Intersection of Artificial Intelligence and the COVID-19 pandemic

A Rapid Review

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SPOR Evidence Alliance operates from the St. Michael's Hospital, Unity Health Toronto which is located on the traditional land of the Huron-Wendat, the Seneca, and the Mississaugas of the Credit. Today, this meeting place is still the home to many Indigenous people from across Turtle Island. COVID-END is housed within McMaster University which is located on the traditional territories of the Mississauga and Haudenosaunee nations, and within the lands protected by the "Dish With One Spoon" wampum, an agreement to peaceably share and care for the resources around the Great Lakes**.**
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Abbreviations and Definitions

Abbreviations

AB	AdaBoost
ADQN	Advance Deep Q-learning network
AE	Auto-encoders
AI	Artificial Intelligence
ANN	Artificial Neural Network (unspecified)
ARIMA	Auto-Regressive Integrated Moving Average Model
BA	Bayesian analysis
BERT	Bidirectional Encoder Representations from Transformers
CBOW	Continuous Bag of Words
CNN	Convolutional neural network
CT	Computerized Tomography
DL	Deep Learning
DNN	Deep neural network
DT	Decision tree
EM	Eureqa Modelling
GA	Genetic algorithm
GAN	Generative adversarial network
GLM	Generalized Logistic growth Model
HAM	Holistic Agent-based Model
ICU	Intensive Care Unit
KNN	K-Nearest Neighbors
LASSO	Least Absolute Shrinkage and Selection Operator
LDA	Linear Discriminant Analysis
LiR	Linear Regression
LM	Language model
LoR	Logistic Regression
MDM	Multi-task deep model
ML	Machine Learning
MLP	Multilayer perceptron
NB	Naive Bayes
NLP	Natural Language Processing
PNN	Polynomial Neural Network
PS	Porter Stemming
Q/A	Quality Assessment
RF	Random Force
RL	Reinforcement learning
RNN	Recurrent Neural Network
SM	Skip-gram model
SVM	Support Vector Machine
TL	Transfer learning
TSF	Time Series Forecasting
USEL	Universal-sentence-encoder-large
VAR	Vector Auto Average

Key Definitions:

Artificial intelligence: computer applications that can perform tasks that normally require human intelligence (1).

Big data: Big data analytics is the use of advanced analytic techniques against very large, diverse big data sets that include structured, semi-structured and unstructured data, from different sources, and in different sizes from terabytes to zettabytes (2).

Computer vision: Training computers to interpret and understand the visual world. Using digital images from cameras and videos and deep-learning methods. Machines can accurately identify and classify objects (3).

Data intensive: Data-intensive is used to describe applications that are input/output bound or with a need to process large volumes of data. Such applications devote most of their processing time to input/output and movement of data. Parallel processing of data-intensive applications typically involves partitioning or subdividing the data into multiple segments which can be processed independently using the same executable application program in parallel on an appropriate computing platform, then reassembling the results to produce the completed output data (4)

Deep learning: A subfield of machine learning that uses algorithms designed as networks of decisions to learn from data. These networks are often called neural networks. When there are many layers in the network, they are called deep neural networks or deep learning networks. Deep learning can identify diseases based on imaging and can predict health status from electronic health records (3).

Expert systems: An expert system is an intelligent computer program that uses knowledge and inference procedures to solve problems that are difficult enough to require significant human expertise for their solution (5).

Fuzzy logic: Fuzzy Logic is an approach to variable processing that allows for multiple possible truth values to be processed through the same variable. Fuzzy logic attempts to solve problems with an open, imprecise spectrum of data and heuristics that makes it possible to obtain an array of accurate conclusions (6).

Machine learning: process of applying training-data to a "learning algorithm." The algorithm generates a set of rules, based on identified data patterns. These rules can then be used to classify new data or predict future data. By using different training-data, the same learning algorithm could be used to generate different models, e.g. pathology prediction etc. (3).

Natural language processing: NLP automates the ability to read, understand, and derive meaning from human language (3).

Neural networks: are a subset of machine learning, comprised of node layers, containing an input layer, one or more hidden layers, and an output layer. Each node, or artificial neuron, connects to another and has an associated weight and threshold. If the output of any individual node is above the specified threshold value, that node is activated, sending data to the next layer of the network. Otherwise, no data is passed along to the next layer of the network (7).

Pattern recognition: Pattern recognition is about assigning objects (also called observations, instances, or examples) to classes. The objects are described by features and represented as points in the feature space. A classifier is an algorithm that assigns a class label to any given point in the feature space. Pattern recognition comprises supervised learning (predefined class labels) and unsupervised learning (unknown class labels). Supervised learning includes choosing a classifier model, training and testing the classifier and selecting relevant features. Classifier ensembles combine the outputs of a set of classifiers for improved accuracy. Unsupervised learning is usually approached by cluster analysis (8).

Virtual agents (chatbots): Also known as "conversational agents". These are software applications that mimic written or spoken human speech to simulate a conversation or interaction with a real person (3).

EXECUTIVE SUMMARY

Objectives: *The purpose of this review was to provide evidence on the following key question: Where can AI and emerging digital technologies potentially add value in COVID responses to mitigate, control, or prevent COVID-19 and its consequences?*
Includes both innovative applications and developments, and new applications of established technologies and processes.

Design: *Rapid review*

Methods: *The search was performed in six bibliographic databases (Medline, Embase, BIREME-LILACS, Cochrane Library, Epistemonikos, McMasterPlus+). Two reviewers selected studies for inclusion, one reviewer extracted data and assessed the quality of systematic reviews using the AMSTAR tool, and primary studies with the Johana Briggs Institute's tools. The results are presented narratively in tables that describe the key findings.*

Results: *The evidence search identified 3,357 studies. After the screening,133 studies were included including: 10 moderate- to high-quality evidence syntheses; four moderate- to high-quality analytical cross-sectional studies; nine moderate- to high-quality prevalence studies; and 82 moderate- to high-quality modelling studies. All included studies were either descriptive or model studies. We did not identify cohorts, case-control, quasi-experimental studies, or randomized trials that had assessed the effectiveness of the thechnologies.* ***Figure 1*** *shows the summary of the public health activities for which we found research literature supporting or describing the use of AI in COVID-19.*

Among the specific outcomes and activities of interest, the one that stands out the most is the prediction of the spread of the pandemic (Broader public-health measures activity) with many publications describing the development of prediction models. Most of them lack validation studies but seem to be promising when compared to traditional models.

Conclusion: *The COVID-19 pandemic has allowed the development of impressive technologies to support public health activities and improve public health outcomes. We identified literature describing experiences with several AI technologies. Of note, we also describe a high number of predictive models that have been developed to determine the course of the pandemic (predicting spread and contact tracing). However, our search did not retrieve comparative studies. Therefore, the evidence to support the use of AI in COVID -19-related public health activities remains scarce.*

Figure 1. Summary of Public health activities covered by the included studies*

Framework category	Studies in areas where AI and other emerging digital technologies can support **to public-health responses**			Studies where AI and emerging digital technologies can support **responses from other parts of the health system**				Studies where Areas where AI and emerging digital technologies can support **economic and social responses**
Broad Public Health Activities of interest	Infection prevention	Infection control	Broader public-health measures	Approach to COVID-19 vaccine roll-out	Approach to population-health management for COVID-19 and for those whose care is disrupted by COVID-19	Service planning for COVID-19 prevention	Service planning for COVID-19 treatment	

** First row presents the overarching framework categories that describe the scope of the activities. Second row presents the categories of public health activities. Activities or outcomes for which there were at least one systematic review assessing its use are presented in green; activities for which we found at last one primary study are presented in yellow; and those for which we did not identify any study are presented in red. A more detailed version of this figure is showed in the results section.*

Introduction

Artificial intelligence (AI) and emerging digital technologies are powerful aids in different areas. In healthcare, they can help the clinical decision-making process by supporting the analysis of medical images and sounds, in the prediction of diseases, in improving the patient experience through using wearables to aid the diagnosis and treatment, and so on. Although the applications of these new technologies are not available worldwide, there are a handful of new initiatives to bring these technologies to the bedside and help the healthcare worker make the best decisions considering different data and knowledge that the individual cannot handle by himself.

During the last two years, in the context of the COVID-19 pandemic, there has been an explosion of AI-related approaches and initiatives to address this threat and help clinicians in their decision-making process. There are many examples where AI can help interpret CT cans and X-rays to diagnose COVID-19 lung involvement (9,10), predict mortality and intensive care unit's admissions using imaging and laboratory data (11,12), and in the identification of new treatments (13).

Decision-makers can use these technologies to bring information to support decisions about public health measures, their effectiveness, and the adherence of citizens to them. There are many applications, but there is uncertainty about where these technologies can help and where they cannot help to tackle the disease. Knowing the landscape of the use of these applications can help policymakers, public and private funders, and investors to detect and fund new and established initiatives to help communities world-wide to hinder the pandemic development.

This rapid review addresses the key question: *Where can AI and emerging digital technologies potentially add value in COVID responses to mitigate, control, or prevent COVID-19 and its consequences?* This includes public health applications in areas where AI and emerging digital technologies can support public health responses, where AI and emerging digital technologies can support responses from another part of the health system related to the COVID-19 pandemic and in areas where AI and emerging technologies can support economic and social responses.

Methods

This rapid review was conducted according to the World Health Organization guide for rapid reviews (14), and reported according to the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) guidelines (15).

The primary research question for this review was as follows: *Where can AI and emerging digital technologies potentially add value in COVID responses to mitigate, control, or prevent COVID-19 and its consequences?* Includes both innovative applications and developments, and new applications of established technologies and processes.

Table 2. Eligibility Criteria

	Inclusion Criteria	Exclusion criteria
Population:	• General population	
Scope	• Studies within public health field or within health systems if focused or aiming to understand or impact on public health interventions or approaches	Clinical applications of the use of artificial intelligence or emerging digital technologies, e.g., in terms of treating patients, predicting their outcomes, or identifying therapeutic options
Intervention *(AI technologies)*	• Studies with an artificial intelligence or emerging digital technologies' intervention that are used for public health • Policy and/or ethical frameworks, community and/or local initiatives, and research initiatives that have looked for artificial intelligence or emerging digital technologies interventions in public health • ***Note: artificial intelligence may include one or more of the following:*** o *Artificial intelligence* o *Natural language processing* o *Machine learning* o *Deep learning* o *Neural networks* o *Pattern recognition* o *Expert systems*	
Outcomes *(Public health activities of interest)*	Public health activities were organized according to a preestablished framework categories of interest (described below), each one containing specific public heath activities. 1. Studies of effectiveness or safety, or studies describing the experience, adoption, or impact of the use of AI in public health initiatives. o Infection prevention (*Vaccination*) o Infection control (*Screening, testing for/detection of cases, contact tracing, Broader public-health measures (e.g., Predicting spread and pandemic tracking, Risk stratification), Stratifying the*	

	population by risk of infection, Outbreak management, Strategies to support adherence to public-health measures, Strategies to identify and address misinformation) 2. Studies of effectiveness, safety, experiences, impact, evidence of the use of AI in health systems aiming to understand or impact on public health measures or strategies. This, includes studies on the: o Approach to COVID-19 vaccine roll-out o Approach to population-health management for COVID-19 and for those whose care is disrupted by COVID-19 o Service planning for COVID-19 prevention o Service planning for COVID-19 treatment	
Design	• Reviews using systematic methods (e.g., systematic reviews, rapid reviews, scoping reviews, overviews) summarizing available primary studies • All primary study designs, including: o Experimental (e.g., randomized controlled trials (RCTs), non-randomized controlled trials) o Mixed methods design studies o Observational (e.g., cohort studies, case control studies, cross-sectional studies o Quasi-experimental (e.g., controlled before after studies, interrupted time series) o Qualitative studies • Documents that synthesize evidence and provide recommendations • Policy / government documents (covered in the jurisdictional scan report accompanying this document)	• Narrative reviews • Literature reviews • Editorials with no primary data • Commentaries/expert opinions with no primary data • Blogs/opinion pieces/personal accounts • Letters to the editor • News articles/books • Case studies • Case series

Literature Search

We developed our searches in two stages. In the first stage, we searched evidence syntheses, including systematic reviews, scoping reviews, and rapid synthesis (from now on 'systematic reviews'). In a second stage, to complement the findings, we conducted a targeted search focused on primary studies that covered the topics not identified by the systematic reviews and to find evidence on the public health activities not covered by the included systematic reviews.

An experienced librarian developed and tested both search strategies through an iterative process in consultation with the review team. Each database was searched using an individualized search strategy; to review the complete strategies, see Appendix 1.

The consulted databases were MEDLINE/PubMed, EMBASE, BIREME-LILACS, The Cochrane Library, Epistemonikos and McMaster PLUS+. Searches were conducted from inception to the period between 17/08/2021 and 28/08/2021 as explained below.

In the first stage, we searched Medline-PubMed and BIREME-LILACS on 17/08/2021. We complemented the search for the first stage with EMBASE (Ovid) on 24/208/2021 and with searches in The Cochrane Library, Epistemonikos and McMaster PLUS+ on 27/08/2021. The second search phase was carried out in Medline-PubMed on 28/08/2021.

Study Selection

Study selection was performed by double-reviewer titles/abstracts screening and double-reviewer full text screening (JCM, PV, AH, AMP). Discrepancies were resolved by discussion, or by a third reviewer, when needed (IF). The online platform 'Covidence' (Covidence systematic review software, Veritas Health Innovation, Melbourne, Australia. Available at www.covidence.org) was used for titles/abstracts and full-text screening steps. Training was provided to all reviewers at the beginning of the review and during the review for consistency purposes.

Data Extraction

The data extraction from the evidence was carried out in a Google Form developed for each study design. The form was tested on five articles by two researchers independently (PVS, JCM) and iteratively improved after discussion.

- For each evidence synthesis included, we documented the following information: title, author, scope, publishing year, date of the last literature search, number of included studies, population, inclusion criteria, country, population, AI technology, intervention, comparators, outcomes (public health activities), and key findings.

- For observational studies we documented the following information: title, authors, publishing date, type of design, setting, population, Artificial Intelligence technology, intervention, comparators, outcomes (public health activities), and key findings.

- For official policy/government documents and documents that provide recommendations: title, country, authors / organization, publishing date, setting, target population, Artificial Intelligence technology, and key findings (or recommendations).

After checking that the Google Forms were exhaustive, training of reviewers was performed. We used a single abstraction approach (JCM, PVS, AH, AMP).

Quality Assessment

We performed a single-reviewer quality assessment (JCM, PVS, AH, AMP) as indicated by the study design below:

- The quality of the evidence syntheses was assessed with the AMSTAR tool (16).
  - AMSTAR rates overall methodological quality on a scale of 0 to 11, where 11/11 represents a review of the highest quality. High-quality reviews were those with scores of eight or higher out of a possible 11 (or higher out of a possible 9 for those reviews that did not perform meta-analysis), moderate quality were those considered those reviews with scores between five and seven, and low-quality reviews were those with scores less than five.
- The Joanna Briggs institute's tools for observational studies and clinical trials (17).
  - The reviewer applied the JBI checklist and then provided a concept on the inclusion and relevance of each study. For prevalence studies: scores from 1-4 were considered as low, from 5-7 as moderate, and from 8-9 as high quality. For analytical cross-sectional studies: scores

from 1-3 as low, from 4-6 as moderate, and from 7- 8 as high. We did not find any additional study designs

- For simulation models: Given the lack of tools for evaluating the quality of simulation studies / models, it was rated based on 5 aspects, considered key elements to the authors:
  1) adequate description of the population and the interventions to be evaluated,
  2) adequate description of the model to be used,
  3) publication of the assumptions of the model,
  4) publication of the formulas associated with the model,
  5) consistency of the results and conclusions of the authors.

  According to the number of these points that the simulation met, we classified these studies as high quality (5 points), moderate quality (3 to 4 points) and low quality (1 to 2 points).

Studies rated as moderate and high-quality are presented in the synthesis. To facilitate visualization of the quality assessment, we created a color label classification to present the quality assessment (Q/A) scores. Regardless of the study design, we present in the Q/A assessment column in the table, in green the studies judged as high quality, and in yellow, those judged as of moderate quality. Studies judged as low quality are described in Appendix 2 and not presented in the results as their results are very uncertain. Completed quality assessments for each included study is available on request.

Data Synthesis

Due to the heterogeneity in study designs and outcomes (public health activities), across included studies, data was synthesized descriptively; meta-analyses were not conducted.

- The introduction and conclusions are presented descriptively.
- The main results of the studies included upon full text screening, are summarized in tables (text) according to their design, after discussion by the research team. The tables highlight the total number of different types of highly relevant documents identified, their key findings, date of last search, and methodological quality.
-

Microsoft Excel for Mac (version 16.53) and R Studio (*RStudio Team (2020). RStudio: Integrated Development for R. RStudio, PBC, Boston, MA URL http://www.rstudio.com/.)* were used for developing the figures presented in the results

Results presentation

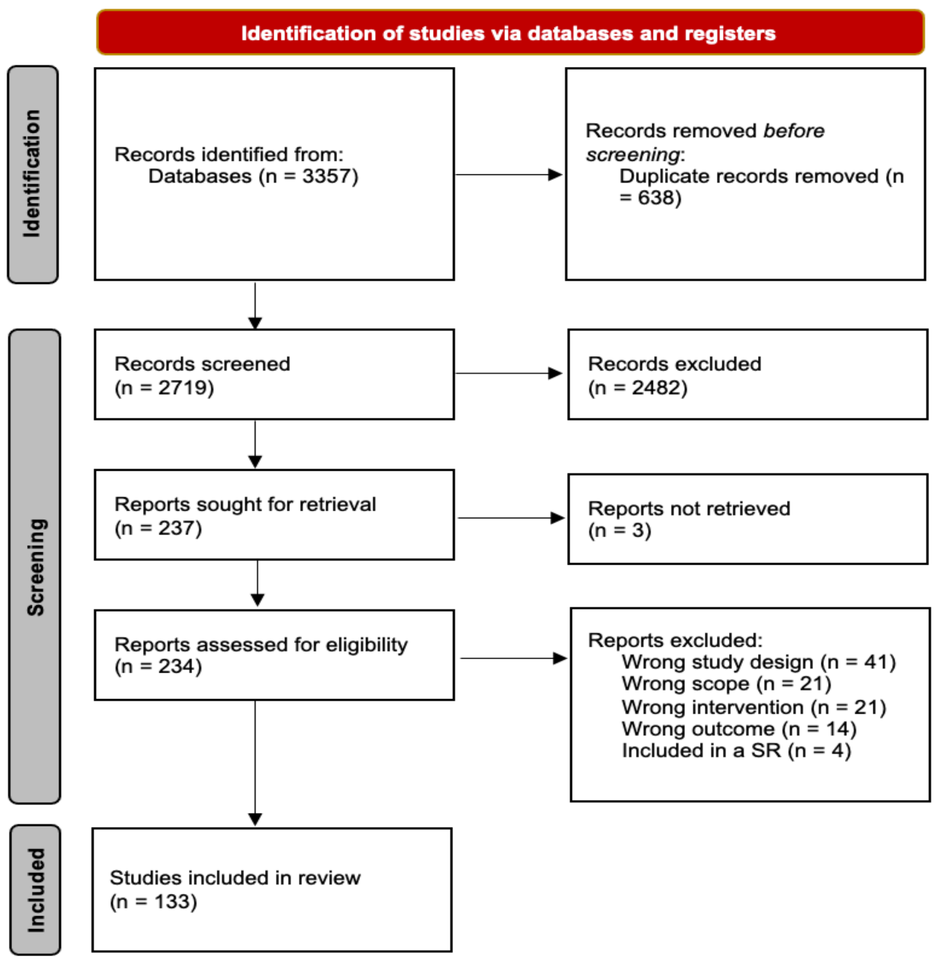
With the aim of facilitating the results visualization and interpretation, we present the results in two sections. First, we present a summary of the Key Findings that focuses only on the studies that were considered of high quality, organized by public health activity. Then, in a more detailed section, we present the Main Results, were we detail the evidence retrieved from all the included studies, along with their quality assessment and the e citations and link to the articles.

Results

Selection process

The search identified 3,357 potential references. After titles and abstracts screening, 237 articles were assessed for eligibility in full text, 104 records were excluded during this process, and the reasons for their exclusion are presented in the PRISMA diagram **(Figure 2)**. We, therefore, included 133 articles.

Figure 2. Modified PRISMA flow diagram



Key findings

The most important findings from the studies assessed as of high-quality, is presented in **tables 3 and 4,** separated by the public health activities to which they are focused

Table 3. Studies in areas where AI and other emerging digital technologies can support to public-health responses

Infection prevention:	
Vaccination	• No moderate or high-quality studies addressing the effectiveness of vaccination when administered at large scale or the Efficacy/effectiveness by population segment found.
Infection control:	
Screening • Targets • Locations (and frequency if applicable) Testing for/detection of cases (not diagnosis or prognosis)	• A high quality cross sectional study (18) found that the best models to predict positiveness in Covid19 IgM/IgG test were logistic regression, gradient boosting and random forest; and that loss of smell, fever, and shortness of breath were independently associated with SARS-CoV-2 infection. • A high-quality study proposed framework (19) that includes a four-level architecture for the monitoring and prediction of COVID-19 virus infection, that comprises COVID-19 Data Collection, COVID-19 Information Classification, COVID-19-Mining and Extraction, and COVID-19 Prediction and Decision Modeling utilizing the temporal recurrent neural network was found to have higher precision when compared with the other strategies of ANN and RFT. • An Artificial Intelligence (AI)-driven mobilization strategy (20) presented in a high-quality study for mobile assessment agents for epidemics/pandemics, showed that on the 15th day following the first confirmed case in the city under the risk of community spread, AI-enabled mobilization of assessment centers can reduce the unassessed population size down to one fourth under the case when assessment agents are randomly deployed over the entire city. • A high-quality study that proposes a fuzzy bases Bayesian model (21) found that detecting viral load in the biomarkers excreted in human urine and feces using Wastewater-Based Epidemiology (WBE) could be a promising approach to investigate the occurrence of COVID-19 in communities, especially at locations with limited clinical testing and could orientate governments to solidify the facilities and make proper sanitization in the targeted locations identified. This study addresses this outcome and predicting spread and pandemic tracking.
Contact tracing	• A high-quality modelling study (22)that assesses the feasibility of annotating and automatically extracting travel history mentions from unstructured clinical documents found that automated text processing models, involving machine learning and neural language models was useful in the early stages of transmission, as it was able to identify mentions of travel to endemic areas. The usefulness of this system for COVID-19 specifically is limited to a relatively short window in the early stages of transmission when containment was possible, and travel was a disruptive risk factor.
Broader public-health measures	
Predicting spread and pandemic tracking	High quality modelling studies' findings • A study that compares different deep learning algorithms (23), found that the Variational AutoEncoder (VAE) method provides better forecasting of COVID-19 confirmed cases in comparison to the other considered models for almost all considered countries except in Italy. • A modelling study (24) showed that Hybrid deep learning models (LSTM-CNN) were found to efficiently forecast COVID-19 cases. Also, that compared to baseline machine learning models (LR and SVR), deep learning models had superior performance even with relatively small-sized data. • A model developed to predict the incidence rate for the coming 2 weeks via a Least-Square Boosting Classification algorithm (25), was able to accurately predict the incidence of COVID-19 within a two-week period USING the cases, recovered and deaths from COVID-19 from each

	region and the dynamics of neighboring regions. The best predicted continental incidence rates were found in South America and Asia, respectively. • In a modelling study (26) that proposes a tool for real-time spatio-temporal analysis using a machine learning approach to predict the distribution of cases and deaths in Brazil linear regression showed the best performance while SVR, kernel RBF presented the worst results. • In a study that proposes an approach using a graph neural network architecture (27) where effective local mechanisms governing a dynamic on a network are learned from time series data, the authors found that deep learning can build effective models of contagion dynamics on networks. • A machine learning hybrid framework (28) that evaluated the impact of mobility on COVID-19 trends, found a weekly pattern of mobility and infections that implied a high number of infections during the following weekend. • The developed CPAIS framework (29) generates Heat maps to represent variations in policy measures for the COVID-19 pandemic over time. In this study 4 ML models were evaluated; ARIMA, a feedforward neural network (FNN), multilayer perceptron neural networks (MLPs), Short-term long-term memory (LSTM) networks. The LSTM performance accuracy was better that the performances of ARIMA, FNN, and the MLP. • In a modelling study (30) the authors develop a model to forecast in real-time the behavior of COVID-19 in the states of United States and it was found that the models based on reproduction number have much better performance than those trained on confirmed cases. In addition, the deterministic LSTM model exhibited better performance than the stochastic LSTM/MDN and linear regression models. • A deep learning–enhanced compartment model (31) that applied standard deep neural networks (DNN) and advanced recurrent neural networks–long short-term memory (RNN-LSTM) to fit the confirmed/dead in-sample time series and predict the further development of confirmed/dead cases for 35 and 42 days was found effective in estimating these stochastic parameters with reduced dependency on data particularity. • A model called COURAGE (COUnty aggRegation mixup AuGmEntation) (32) created to predict COVID-19 related deaths for each count in US, using a transformed based model architecture was found able to produce short-term forecast of COVID-19 deaths at state level and at county level. • An early warning / detection system (33) that works by predicting future confirmed cases daily by RNN with LSTM using the Google Mobility Report and the Facebook movement data sets developed to predict daily change in cases dTCt in South African provinces was found to perform well over the interim period, but not when another COVID-19 case wave is reached. • A study (34) evaluated ML-based models (Long short-term memory and gate recurrent unit) and statistical models (autoregressive and AIRMA) and found that for 14 days predictions the ML based models performed better than the statistical ones. • A study that compares (35) fourteen ANN-based models to predict the COVID-19 outbreak in seven countries found that ANN-based model that considers the previous 14 days (the maximum incubation period) outperforms the other ones. • Additionally, applying only confirmed cases of the very previous day by ANN for estimation daily confirmed cases do not yield to reliable predictions. • A developed hybrid model called spatio-temporal attention network (STAN) (36) was found to have better performance than traditional epidemiological models, and deep learning models on both long-term and short-term predictions and on both state and county levels, achieving up to 87% reduction in mean squared error compared to the best baseline prediction model. • A study that compared SARIMA and ARIMA models (37) to forecast cumulative confirmed COVID-19 cases, recovered cases, and confirmed deaths for 16 main countries found that to capture the seasonality or trends of the data, the SARIMA models were better than the ARIMA models.

	• A study (38) used ANN to analyze the behavior of new cases, deaths and demand for hospital beds that would allow decisions to be made according to the behavior of covid-19 care, the results show that ANNs generate forecasts that should be closer to the data observed in daily variables and hospital beds as new data are inserted into the ANN training data set. • An ANN architecture(39) developed to predict the pandemic outbreak impact in Qatar, Spain, and Italy showed the effects of the measures taken by the government and medical sectors to alleviate the pandemic effect and the effort to decrease the spread of the virus to reduce the death rate. Although the Pandemic spread rate and the number of reported cases were the highest in Qatar compared with Spain and Italy, the low mortality number suggest that the population density, infected people age, social distances precautions, weather conditions, and the responsibilities of individual have a major impact towards the critical pandemic evolution. • In a study (40) the authors developed two types of GNN models, including: (1) graph-theory-based neural networks (GTNN) and (2) neighborhood-based neural networks (NGNN). The results indicated that the GTNN model outperformed both the NGNN and LSTM models for predicting Rt. • A LSTM-SAE model to predict the COVID-19 pandemic (41) trained using countries with similar characteristics as of the Brazilian states. New cases were predicted with more accuracy than the obtained from traditional compartment models. • A ML data driven model (42) found that social demographic features kept high importance through stages of the COVID-19 pandemics; reproduction number (R0), and some social demographic features showed increased importance in the trajectory of the COVID-19 pandemic; some within-county mobility features showed decreased importance across different stages; social distance index (SDI) showed higher importance in county clusters with lower population densities and higher importance in the social distancing and reopening stages. • A study (43) that used machine learning based models (gradient boosting regressor, random forest regressor, limited memory BFGS and convolutional neural network) to estimate the parameters for a classical SEIRD model for forecast the epidemic using a database of the Colombian evolution of the COVID-19 pandemic, found that the resulted model can predict the pandemic development in Colombia with a high coefficient of determination and low error. • A proposed TW-SIR prediction model (44) used machine learning methods to predict the basic number of infections R0 and the exponential growth rate of the epidemic, the study shows that the model can effectively measure the real-time changes of parameters during the spread of epidemics. • A study using a machine learning model (45) found that passively observed measures of aggregate mobility are useful predictors of growth in COVID-19 cases. • A deep learning based model (46) for detecting masks over faces in public place making use of ensemble of single and two stage detectors achieved accuracy and improves detection speed when compared to the model called Retina Face Mask detector. the application of transfer learning on pretrained models resulted in a highly robust and low-cost system • A study (47)that proposes a hybrid model reinforcement learning-based algorithm capable of solving complex optimization problems based on the application of AI and ML was proved in the prediction of the behavior of covid 19 in Quebec, Canada and accurately reflected the future trend of the pandemic with a mean square error of 6.29E−06. • A diffusion prediction model (48) for prediction of number of coronavirus cases in four countries: India, France, China and Nepal forecasts the number of new cases expected to occur in next 4 weeks. The performance was and compared with the prediction results of support vector machine, logistic regression model and convolution neural network showing the efficiency of the proposed model. • Machine learning analysis using the K-means clustering method (49) was adopted to classify patterns of community-acquired outbreaks worldwide. Unsupervised machine learning identified

	five patterns as "controlled epidemic", "mutant propagated epidemic", "propagated epidemic", "persistent epidemic" and "long persistent epidemic". • A study evaluated Data-driven models for the prediction of COVID-19 (50) founding that ANN and ANFIS models showed greater precision and robustness than the MLR models. Air and wastewater temperature played a key role in estimating prevalence using data-driven models, especially MLR models. • A proposed model for the prediction of the COVID-19 spread (51) in different countries taking into account the Hofstede cultural dimensions of 2015, the dynamics of the pandemic, and the non-pharmacological interventions using a machine learning approach using ridge regression, decision tree regression, random forest regression, AdaBoost, and Support vector regression found that the random regression and the AdaBoost models had the lowest mean test error with highest accuracy in the in-distribution method. • A Study (52) that integrates Data Envelopment Analysis (DEA) with four different machine learning (ML) techniques to assess efficiency and assess US COVID-19, showed that 23 states of the 50 evaluated in total, were efficient and urban areas, physical inactivity, number of examinees per population, population density, and total hospital beds per population were the factors that most influenced efficiency. • A proposed Random Forest Classification algorithm (53) was compared with other common machine learning classification methods: Linear Regression Classification (LRC), Support Vector Machine (SVM), k-Nearest Neighbor (K-NN), Decision Tree Classification (DTC). The proposed algorithm based on Random Forest Classification and nine features (coronavirus, pneumonia, cough, fever, nasal congestion, rhinorrhea, cough, diarrhea, fever) performed better compared to other machine learning methods and the models with different numbers of features.
• Risk stratification	• A high-quality modelling study (54) used geographical trend analysis, Local Indicators of Spatial Association (LISA) and performed variable selection using Bayesian Additive Regression Trees (BART), All preliminary and final models indicated that location, densities of the built environment, and socioeconomic variables were important predictors of incidence rates in Germany. The BART, partial dependence, and GAM results indicate that the strongest predictors of COVID-19 incidence at the county scale were related to community interconnectedness, geographical location, transportation infrastructure, and labor market structure.
Outbreak management • Locations (essential services or others) • Rapid-response mechanisms	• A high-quality modelling study (55) that uses Smartphone-based Tracing has shown that the lockdown issue for an intended area could be predicted using machine learning algorithms such as K-Means clustering algorithm to provide a plan for policymakers on how lockdown/mass quarantine can be safely lifted. This study addresses this outcome and contact tracing.
Strategies to support adherence to public-health measures (e.g., distancing, handwashing, vaccination, etc.)	• A high-quality study proposed SRCNet (56) was better than traditional end-to-end image classification methods using deep learning without image super-resolution for the identification of facemask-wearing conditions.
Strategies to identify and address misinformation	• A high-quality scoping review (57) that attempted to identify and analyze social media studies related to COVID-19. Found one study that classified the information related to COVID-19 into seven types of situational information and their predictors and a study in tweets that showed idiosyncratic relationships between bots and hate speech across data sets, emphasizing different network dynamics of racially charged toxicity in the US.

Table 4. Findings from Studies where AI and emerging digital technologies can support responses from other parts of the health system

Approach to COVID-19 vaccine roll-out	
• Administering vaccines that optimize timely uptake • Surveillance, monitoring and reporting	• No high-quality studies addressing COVID-19 vaccine roll out found. However an interesting analysis of the spatiotemporal trend performed using the space-time cube technique, with clustering by emerging hotspot analysis made by a moderate-quality cross-sectional study (58), to assess how the development of vaccination microplans for COVID-19 can benefit from GIS solutions with artificial intelligence (AI) suggest the utility of these technologies to improve these public health activity.
Approach to population-health management for COVID-19 and for those whose care is disrupted by COVID-19	
• Segmenting the population into groups with shared health and social needs	• No high-quality studies addressing population-health management for COVID-19 and for those whose care is disrupted by COVID-19 found.
Service planning for COVID-19 prevention	
• Re-locating hospital-based ambulatory clinics, cancer treatments, etc. • Limiting access to health facilities • Changing hospital-discharge procedures	• No high-quality studies addressing Service planning for COVID-19 prevention found.
Service planning for COVID-19 treatment	
• Scaling up/down testing, emergency-room, ICU, post-ICU recovery, palliative-care, sequelae-management capacity • Surge-management models	• A high-quality model (59) that considers three compartments (I: The number of infectious individuals who show symptoms of COVID-19, C: The number of critically ill people who need an ICU bed, D: The number of individuals who are discharged from the ICU), combines autoregressive, machine learning and epidemiological models to provide a short-term forecast of ICU utilization at the regional level and was frequently associated with smaller errors than those of the individual models. • There was no additional high quality studies, but a moderate-quality interesting study (60) developed a three-stage algorithm to facilitate the near optimal redistribution of medical equipment using LSTM and found performance optimality.

Summary of findings by research study designs

Figure 4 shows the summary of the public health activities for which we found research literature supporting or describing the use of AI in COVID-19, according to the study design. Activities or outcomes for which there is at least one study assessing its use are displayed categorized by study design. In green, those activities for which we found at last one study, in red, those for which we did not identify any study, and in yellow, an activity that was only covered partially by the study. Detailed results are explained in the next sections categorized by study designs along with their quality assessments and main findings.

Figure 4. Summary of Public health activities covered by research studies included

Public health activities and outcomes of interest	**SR**	**Prevalence**	**Analytical Cross sectional**	**Modeling studies**
Areas where AI and other emerging digital technologies can support to **public-health responses**				
○ Infection prevention				
▪ Vaccination				
○ Infection control				
▪ Screening	X			
▪ Testing for/detection of cases (not diagnosis or prognosis)			X	X
▪ Contact tracing	X			X
○ Broader public-health measures				
▪ Predicting spread and pandemic tracking	X		X	X
▪ Risk stratification				X
▪ Outbreak management	x	X		X
▪ Strategies to support adherence to public-health measures (e.g., distancing, hand washing, vaccination, etc.)	X	X		X
▪ Strategies to identify and address mis-information	X	X	X	
Areas where AI and emerging dtechnologies can support **responses from other parts of the health system**				
○ Approach to COVID-19 vaccine roll-out			X	
▪ Administering vaccines that optimize timely uptake			X	
▪ Surveillance, monitoring and reporting			X	
○ Approach to population-health management for COVID-19 and for those whose care is disrupted by COVID-19				
▪ Segmenting the population into groups with shared health and social needs				
○ Service planning for COVID-19 prevention				
▪ Re-locating hospital-based ambulatory clinics, cancer treatments, etc.				
▪ Limiting access to health facilities				
▪ Changing hospital-discharge procedures				
○ Service planning for COVID-19 treatment				X
▪ Scaling up/down testing capacity				
▪ Scaling up/down emergency-room capacity				
▪ Scaling up/down ICU capacity				
▪ Scaling up/down post-ICU recovery capacity (e.g., hospital beds)				
▪ Scaling up/down palliative-care capacity				
▪ Scaling up/down COVID-19 sequelae-management capacity				
▪ Surge-management models				
▪ Triage protocols				
Areas where AI and emerging digital technologies can support economic and social responses	X			X

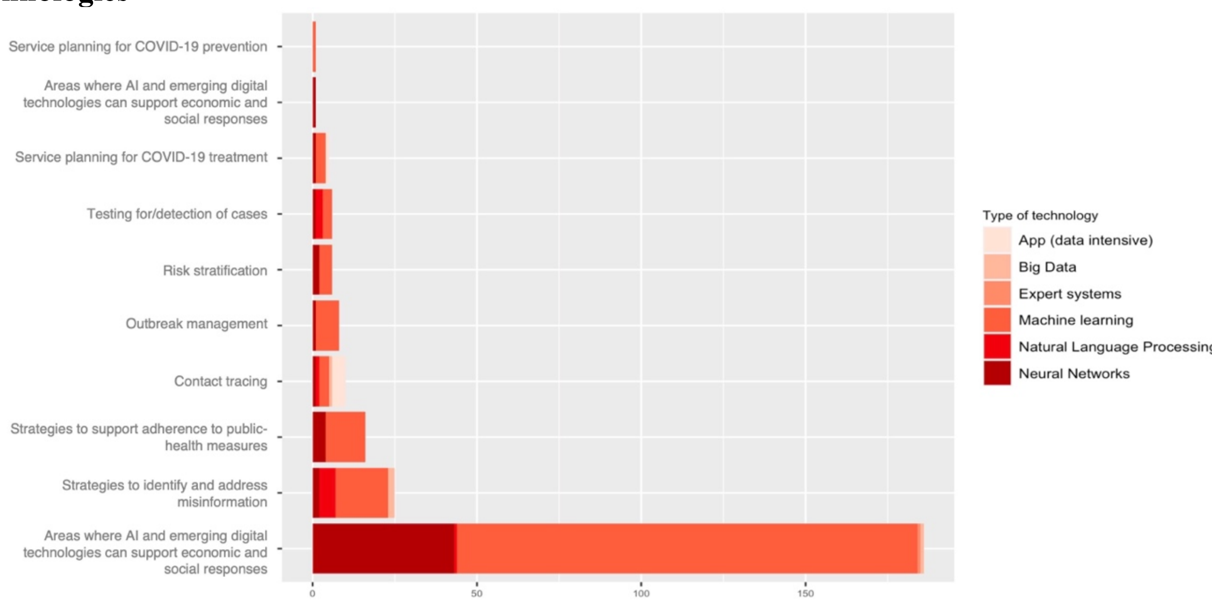
SR: Systematic review or evidence syntheses

Figure 5 and 6 displays the number of studies for each public health activity, by type of technology used. Machine learning was by far the most common technology used, followed by Neural networks, mostly for Predicting spread and pandemic tracking, and for identifying and addressing misinformation.

Figure 5. Amount of literature for each public health framework category

Outcome	App (data intensive)	Big Data	Expert systems	Machine learning	Natural Language Processing	Neural Networks
Areas where AI and emerging digital technologies can support economic and social responses	0	0	0	0	0	1
Contact tracing	4	1	0	3	1	1
Outbreak management	0	0	0	7	0	1
Predicting spread and pandemic tracking	0	1	1	140	1	43
Risk stratification	0	0	0	4	0	2
Service planning for COVID-19 prevention	0	0	0	1	0	0
Service planning for COVID-19 treatment	0	1	0	3	0	1
Strategies to identify and address misinformation	0	2	0	16	5	2
Strategies to support adherence to public-health measures	0	0	0	12	0	4
Testing for/detection of cases	0	0	0	3	2	1

Figure 6. Public health activities and number of studies using or applying different types of technologies



Findings from Evidence Syntheses

The search found 17 evidence syntheses, 10 of them were moderate to high quality reviews, and seven were low quality reviews (61–67). **Table 5** describes the evidence syntheses sorted by quality, i.e., the highest quality studies on top, with the quality assessment -Q/A- scores in the last column. The evidence synthesis provided information about the usefulness of AI in the following public health activities: **Infection control (specifically for contact tracing and screening), and for Broader public-health measures (specifically strategies to support adherence to public-health measures, Strategies to identify and address misinformation, Predicting spread and pandemic tracking, and Outbreak management**).

The available evidence syntheses did not cover the following activities: infection prevention (vaccination), some infection control activities (Screening, testing/detection), some broader public health measures (i.e., risk stratification activities), support to responses from other parts of the health system (approaches to vaccine roll-out, population-health management for COVID-19 and for those whose care is disrupted by COVID-19, Service planning for COVID-19 prevention, and service planning for COVID-19 treatment).

Table 5. Evidence syntheses sorted by their methodological quality (highest quality on top).

Article	Scope	Technology *(Abbreviations in page 4)*	Public health activities	Key findings	Q/A
Anglemyer, 2020 (68)	To assess the benefits, harms, and acceptability of personal digital contact tracing solutions for identifying contacts of an identified positive case of an infectious disease.	Contact tracing apps	Infection control • ***Contact tracing***	Four studies evaluated digital solutions for contact tracing in simulated COVID-19 scenarios. Of the four modelling studies specifically evaluating contact tracing solutions during the COVID-19 outbreak, one modelled scenario within the UK, and three were modelled in non-specific geographic areas with COVID-19. All the modelling studies specifically set in COVID-19 environments evaluated non-specific, automatic smartphone apps to aid in contact tracing. Further, an adapted disease transmission model (susceptible, infectious, or recovered (SIR)) was built by Yasaka and colleagues to evaluate an unnamed smartphone app in an unspecified geographic area (Yasaka 2020). Two additional modelling studies used individual-based models to evaluate nonspecific, passive digital contact tracing apps in the UK (Kucharski 2020), or in an unspecified area (Hinch 2020). Identifying the secondary cases from index cases when compared to traditional contact tracing solutions: Two modelling studies provided low-certainty evidence of a reduction in secondary cases using digital contact tracing (measured as average number of secondary cases per index case - effective reproductive number (R eJ)). Digital solutions in these models do not perform as well as manual contract tracing when compared to each other, however an additional important note is that there are quite strong assumptions about the effectiveness of manual contact tracing (95% to 100% of acquaintances would be traced), and assumptions about the proportion of the population who would have the app (53%). Effectiveness of different types of digital solutions in identifying the secondary cases from index cases when compared to each other: One modelling study (Hinch 2020), provided indirect evidence comparing digital contact tracing with and without recursive contact tracing. The researchers found that contact tracing with an app can only quell epidemic growth rates if strong	**9/9**

				assumptions are made regarding the doubling time, while a contact tracing app with recursive contact tracing could control the epidemic even with much more relaxed assumptions.	
Lahiri, 2020 (57)	Systematic review about effectiveness of Preventive Measures against COVID with Modeling Studies in Indian Context	Artificial Intelligence, Big data, Neural networks	Infection control ● ***Contact tracing*** Broader public-health measures ● ***Strategies to support adherence to public-health measures (e.g., distancing, hand washing, vaccination, etc.)***	In the search for articles, they were finally left with 24 publications, of which 20 were pre-print and 4 were full publications. These studies nested their models and predictions among the Indian population, although not always considering the demographic distribution of the population. The conclusions on the synthesis of the evidence were based on 4 aspects: Predictive models, Effect of inspection at the port of entry, Effect of social distancing and confinement and effect on the combination of interventions. The main use of AI and ML was found in the study by Tomar and Gupta, which found that the total estimated positive cases have been compared with real cases using different values of transmission rate and the public health measures have been found 'hypothetically effective". They found out that in India, value of effective reproduction number for COVID-19 before lockdown was 2.3 and after lockdown it may be reduced to 0.15.	**9/9**
Tsao, 2021 (69)	Studies in areas where AI and other emerging digital technologies can support to public-health responses	Artificial intelligence including: ML: LM, NLP	Broader public-health measures • ***Strategies to identify and address misinformation***	This scoping review included 81 articles that attempted to identify and analyze social media studies related to COVID-19. Of all the articles, only 2 used an AI and ML strategy. Li L et al (2021) classified the information related to COVID-19 into seven types of situational information and their predictors. Uyheng and Carley study using ML hate in tweets showed idiosyncratic relationships between bots and hate speech across data sets, emphasizing different network dynamics of racially charged toxicity in the US.	**8/9**
Abd-Alrazaq, 2020 (70)	Explore how AI technology is being used during the COVID-19 pandemic as reported in the literature.	Artificial intelligence including: DL: ANN, RNN, PNN, AE ML: CNN, RNN, ARIMA, VAR, GLM, EM, HAM, BA, TSF, DT, SVM, CBOW, SM, USEL, PS	Broader public-health measures • ***Predicting spread and pandemic tracking*** • ***Strategies to support adherence to public-health measures (e.g., distancing,***	Purposes or uses of AI Against COVID-19 There were 14 studies that used AI for epidemiological modeling tasks, those studies employed AI for forecasting the epidemic development (e.g., numbers of confirmed, recovered, death, suspected, asymptomatic, and critical cases, and lengths and ending time),. AI has also been used for infodemiology (1 study). Specifically, for raising awareness to use water, sanitation, and hygiene through combining authentic sources of	**5/9**

		NLP	***hand washing, vaccination, etc.)***	information with daily news. Features of AI-Based Techniques Used for COVID-19 In 7 studies AI techniques used against COVID-19 were based on traditional machine learning models and algorithms. The most used machine learning models and algorithms were support vector machine (SVM), random forest, decision tree. In 9 studies, AI techniques used against COVID-19 were based on deep learning models and algorithms. The most used learning models and algorithms in the included studies were convolutional neural network (CNN) and recurrent neural network (RNN). In 1 study, AI techniques used against COVID-19 were based on models related to natural language processing (NLP), such as the continuous bag of words model, skip-gram models, and porter stemming. Although AI techniques were implemented in mobile phones for 1 study, computers were the platform for AI techniques in the remaining studies. Features of Data Sets Used for Development and Validation of AI Models Public resources (e.g., National Center for Biotechnology Information [NCBI], GitHub, and Kaggle) were the most used data source for development and validation of AI models. Other data sources used by the included studies were as follows: government sources (e.g., Chinese Center for Disease Control and Prevention) and news websites. The types of data collected from these data sources were epidemiological data (e.g., number of infected and recovered cases), biological data (e.g., protein and genome sequences), laboratory data, guidelines, and news articles. Only 1 study reported a size of 10,000 samples or more. Three types of validation were used in the included studies: train-test split (3 studies), and external validation (1 study). Authors conclude that "The included studies showed that AI has the potential to fight against COVID-19. However, many of the proposed methods are not yet clinically accepted. Thus, the most rewarding research will be on methods promising value beyond COVID-19.	

				More efforts are needed for developing standardized reporting protocols or guidelines for studies on AI."	
Syrowatka, 2021(71)	Synthesize available literature describing the use of AI to inform public health decision-making	Artificial intelligence including: DL: ANN, RNN, AE, CNN, PNN ML: DT, GBT MLP: RF, NLP, NN, LSTM, RNN, KNN, AE, Transformer NN, CNN ARIMA, VAR, GLM, EM, GBT, SVM, Fuzzy NN, NN, LiR	Broader public-health measures ● ***Predicting spread and pandemic tracking*** ● ***Outbreak management*** ● ***Strategies to support adherence to public-health measures (e.g., distancing, hand washing, vaccination, etc.)***	Summarizes 183 articles related to early in the pandemic ML strategies to support clinical and public health decision-making. In Public health decision making, the authors found that ML has been used to short- term forecast the spread of the epidemic, using this strategy to augment the traditional modelling, or even comparing with it (Dandekar and Yu compared ML approach with traditional modelling and found the ML produces a better approximation to the behavior of the disease). In forecasting, the studies used publicly available databases like the Johns Hopkins COVID-19 map, Worldometer, the World Health Organization, and the Centers for Disease Control and Prevention database. ML can also be used to predict and detect outbreaks. Using natural language processing and deep neural networks, two preprints mined and analyze Twitter post for personal reports of potential exposure to COVID-19. Also, AI can be used to evaluate in real-time the adherence to public health recommendations. The authors found in grey literature that countries such as China and Russia used facial-recognition software and cameras to identify individuals who were not compliant to self-quarantine. Companies have developed software for monitoring and improving adherence to public health recommendations such as wearing face mask, social distancing, and hand sanitization using videos and neural networks.	**5/9**
Golinelli, 2020 (72)	Systematic review on digital technologies for surveillance and prevention early in the pandemic.	Artificial Intelligence including: DL: ANN; DT Big Data	Broader public-health measures • ***Predicting spread and pandemic tracking*** • ***Strategies to identify and address misinformation***	This review found 10 studies reporting digital technologies for surveillance and prevention early in the pandemic. The technologies used in these studies were artificial intelligence (machine learning, deep learning), big data analytics, blockchain, and internet of things. The innovation of these technologies was classified as complementing (1/10), supporting (6/10) and innovating (3/10) with local (4/10) and global (6/10) scalability. This includes the following: - Use of big data analytics in Taiwan merging its national health insurance database with immigration and	**5/9**

				customs database, which generated a real-time alert based on travel history and clinical symptoms (Wang, 2020). - Big data and blockchain to evaluate the diffusion of information related to the virus (Shanlang, 2020). - Quantifying the effect of quarantine control (Dandekar, 2020), outbreak prediction, (Ardabili, 2020) and predict critical events. (Vaid 2020)	
Naseem, 2020 (73)	Scoping Review that aims to explore the use of AI and ML to combat COVID-19 and opportunities for LMIC to adapt and implement from these AI-driven tools to their settings for better outcomes and response to this COVID-19 pandemic	Artificial Intelligence including: ML	Infection control • ***Contact tracing*** • ***Screening*** Broader public-health measures • ***Predicting spread and pandemic tracking***	This study found in13 articles information about the use of AI in the fight against covid-19 and divided into 4 categories: 1. COVID-19 pandemic and the need of AI; 2. The utility of AI in COVID-19 screening, contact tracing, and diagnosis; 3. Use of AI in COVID-19 patient monitoring and drug development 4. AI beyond COVID-19 and opportunities for LowMiddle Income Countries (LMIC) AI has not only reduced the burden on health care systems by cost-effective and faster detection of COVID-19, screening, and diagnosis but it has also helped predict the location of the outbreak and future prediction of such outbreaks	5/9
Payedimarri, 2021(74)	Assess the effectiveness of public health containment measures on the spread of COVID-19	Artificial Intelligence including: DL: ANN ML: ARIMA, GLM, VAR HAM	Broader public-health measures • ***Predicting spread and pandemic tracking***	The authors summarize 8 studies that evaluate containment measures such as quarantine, complete lockdown, flexible lockdown, school closures, restaurant limits, (Wang) social distancing (Delen), time of lockdown, (Pasayat) adoption of lockdown according to the risk of outbreaks (Kumar), quarantine and isolation, (Dandekar) closure of certain public services (Marini) massive lockdown, (Qiuy) and reduction of mobilization (Shao) using ML or AI to model the pandemic spread	5/9
Bareen Syeda, 2021(75)	Systematic review on the role of AI as a comprehensive technology to fight the COVID-19 crisis in the fields of epidemiology, diagnosis, and disease progression.	Artificial intelligence including: ML: LSTM, MLP, NLP; Transformer NN, TSF, RNN DT, SVM DL: PNN	Broader public-health measures • ***Predicting spread and pandemic tracking*** • ***Outbreak management*** • ***Strategies to support adherence to public-health measures (e.g., distancing, hand washing, vaccination, etc.)*** • ***Strategies to identify and address misinformation***	130 publications were selected for further analyses. During the initial days of the COVID-19 outbreak, most published studies focused on predicting the outbreak and potential drug discoveries. -71 studies are classified into the CE theme (models developed to address issues central to epidemiology). - 40 studies that applied AI techniques to detect COVID-19 using patients' radiological images or laboratory test results were grouped under the EDD theme (models that aid the diagnosis of patients with COVID-19). -19 studies that focused on predicting disease progression, outcomes (recovery and mortality), length of stay, and the	5/9

			Areas where AI and emerging digital technologies can support economic and social responses	number of days spent in the intensive care unit (ICU) for patients with COVID-19 were grouped under the DP theme. The 71 studies that focused on epidemiological concerns of COVID-19 were further classified into 3 categories: *(1) COVID-19 disease trajectory (CDT),* *(2) molecular analysis-drug discovery (MADD), and* *(3) facilitate COVID-19 response (FCR) (clinical response).* *In all, 40 studies that focused on predicting COVID-19* peaks and sizes globally and specific to a geographical location, estimating the impact of socioeconomic factors and environmental conditions on the spread of the disease, and effectiveness of social distancing policies in containing disease spread were categorized under CDT. <u>AI Techniques for CDT</u> Yang et al and Moftakhar et al. used DL models to fit both statistical models SEIR and ARIMA. The long-short term memory model proposed by Yang et al and artificial neural network model proposed by Moftakhar et al had a good fit to SEIR and ARIMA, respectively. <u>Impact of Policies on COVID-19 Trajectories</u> The study by Yang et al used a DL technique to predict COVID-19 epidemic peaks and sizes with respect to the containment polices. Their study revealed that the continual enforcement of quarantine restrictions, early detection, and subsequent isolation were the most effective in containment of the disease. Relaxing these policies would likely increase the spread of disease by 3-fold for a 5-day delay in implementation and could cause a second peak. <u>Psychological Impact of the COVID-19 Pandemic</u> Li et al conducted a study using a ML model (support vector machine) and sentiment analysis to explore the effects of COVID-19 on people's mental health and to assist policymakers in developing actionable policies that could aid clinical practitioners. Key findings of the study reveal that after the declaration of the COVID-19 outbreak in China, there has been a significant impact resulting in increased negative emotions (e.g., anxiety and depression) and	

				sensitivity to social risks, and decreased happiness and satisfaction of life. Raamkumar et al used the health belief model (HBM) to determine public perception of physical distancing posts from multiple public health authorities. They used a DL (a variant of recurrent neural network) text classification model to classify Facebook comments related to physical distancing posts into 4 HBM constructs: perceived severity, perceived susceptibility, perceived barriers, and perceived benefits, with accuracy of the model ranging from 0.91 to 0.95.	
Gunasekeran, 2021(76)	Studies where AI and emerging digital technologies can support responses from other parts of the health system	Artificial intelligence including: ML	Broader public-health measures ▪***Predicting spread and pandemic tracking.***	This study provides a search map to analyze how technological applications, including artificial intelligence and machine learning strategies, impact on the response to public policies for the management of covid 19. Until that moment of the pandemic, a single study that described the behavior of the disease according to the self-reported symptoms and the positive tests of each patient included the use of AI to predict the increase in the number of cases (Menni, et al). Despite many reports describing promising applications of artificial intelligence and big data in the pandemic, we found that minimal research has been reported for patient and / or provider acceptance. There was a paucity of reports describing the performance of applied digital health technologies at points of entry and national laboratories. Includes a subjective narrative description of various digital health issues that could potentially be applied in public health responses to COVID-19.	5/9

Findings from primary studies

The targeted searches focused on those public health activities not covered by the evidence syntheses studies retrieved studies from three different designs: analytical cross-sectional studies, prevalence studies, and modelling studies. Searches did not retrieve randomized controlled trials, quasi-experimental, mixed methods, qualitative, case control or cohort studies. Below, we summarize the findings according to the study design.

1. *Analytical Cross-sectional studies*

The search found six analytical cross-sectional studies. Four of them were moderate to high quality studies (presented below) and two of them were low quality studies (not presented in results) (22,23). **Table 6** describes these studies, grouped by public health activities, and then sorted by quality, i.e., the highest quality studies on top; Quality assessment-Q/A- in the last column). The analytical cross-sectional studies provided information about the usefulness of AI in the following public health activities: Infection control (Testing for/detection of cases), and some additional broader public health measures (Predicting spread and pandemic tracking, and Strategies to identify and address misinformation)

2. *Prevalence studies*

The search found nine moderate- to high-quality prevalence studies. **Table 7** describes the studies, grouped by public health activities, and then sorted by quality, i.e., the highest quality studies on top; Quality assessment-Q/A- in the last column). The prevalence studies provided information about the usefulness of AI only for broader public health measures, such as **risk stratification, and as a strategy to support adherence to public-health measures and to identify and address misinformation.**

3. *Modelling studies*

The search found 99 modelling studies, 82 of moderate to high quality (presented below) and 17 of low quality (not presented in the results) (79,80,89–95,81–88). **Table 8** describes the included studies, grouped by public health activities, and then, sorted by quality, i.e., the highest quality studies on top of each public health activity (Quality assessment-Q/A- score displayed in the last column to the right). Quality assessment presented in the last column (assessment criteria created by authors. See *Methods* section, *Quality assessment* subsection, for more information). We present studies judged to be of moderate (cells in yellow in the last column to the right), or of high quality (Cells in green in the last column to the right).

Table 6. Analytical Cross-sectional studies grouped by public health activity and their methodological quality

Article	Technology	Intervention *(Abbreviations in page 4)*	Public health activity	Key findings	Q/A
Dantas, 2021 (18)	Machine learning	LR, NB, RF, RT	Infection control ▪***Testing for/detection of cases***	These authors performed a retrospective analysis of the data from individuals in the app *"Dados do Bem"*, this app works as a symptom tracker in Brazil. Using five machine learning models (Logistic Regression (LR) stepwise, Naïve Bayes (NB), Random Forest (RF), Decision Tree using C5.0 (DT), and eXtreme gradient Boosting) they develop a prediction model of positiveness in Covid19 IgM/IgG test. They found that the best models were logistic regression, gradient boosting and random forest, and loss of smell (OR [95%CI]: 4.6 [4.4–4.9]), fever (2.6 [2.5–2.8]), and shortness of breath (2.1 [1.6–2.7]) were independently associated with SARS-CoV-2 infection.	**7/8**
Dos Santos, 2021(96)	Artificial Intelligence	MLP, GBM, DT, RF, XGBoost, KNN, SVM, and LR	Infection control ▪***Testing for/detection of cases***	The authors used a dataset of 55676 Brazilians who were symptomatic and tested for COVID-19 using RT-PCR. Using MLP, GBM, DT, RF, XGBoost, KNN, SVM, and LR the evaluate predictors of positiveness in the test. They found that the DT model achieved the best results (in precision, accuracy score, recall, and Brier Score), for this model the most significant factors were fever, gender, sore throat, dyspnea, and cough.	**4/8**
Hernandes, 2021(58)	Artificial intelligence	Analysis of the spatiotemporal trend performed using the space-time cube technique, with clustering by emerging hotspot analysis	Broader public-health measures ▪***Predicting spread and pandemic tracking*** Approach to COVID-19 vaccine roll-out Service planning for COVID-19 prevention	To assess how the development of vaccination microplans for COVID-19 can benefit from GIS solutions with artificial intelligence (AI) were structured in four analytical steps: 1) geolocation of UBS with active vaccine room in November 2020; 2) creation of coverage areas and estimation of the population assigned to active vaccine rooms (coverage areas were created for the UBS through isodistance polygons created by analyzing the real street network for all of Brazil for 2020, obtained from OpenStreetMap23); 3) examination of the distance between UBSs with Vaccine room and cell towers capable of supporting mobile internet services; and 4) analysis of the spatiotemporal trend towards an increase in cases of COVID-19, through spatiotemporal clustering of hospitalizations due to SARS linked to COVID-19. Brazil has 32,474 vaccine rooms, distributed in 32,226 UBS. The Northeast Region had the largest number of rooms with 13,203 installations of this nature. From 32,226 UBS it was possible to obtain the geographic coordinates of 31,727. By applying the solution for the construction of coverage areas in each UBS, it was possible to obtain 23,171 coverage areas. Thus, of the 31,727 geolocated UBS, data on the dasimetric population referring to 29,419 UBS were analyzed. In the analysis of 92.72% of the UBS geolocated in the country, it was possible to identify 23,792,907 people over 60 years of age within 4 kilometers of the considered UBS, which represent 82% of the elderly	**5/8**

				population in the country. For the remaining 18%, it will be necessary to travel more than 4 kilometers on foot to access a UBS with the potential to vaccinate against COVID-19. In the South Region, 24% of the elderly lived more than 4 kilometers away from a UBS with a vaccination room. Regarding the proximity to cell phone antennas, 27,388 UBS with vaccine room are within 2.5 kilometers of linear distance of a cell phone tower. The North and Northeast Regions were the ones that presented the largest amount of UBS more than 5 kilometers away from cellular base stations. For the units in these locations, it will be more difficult to electronically register doses and, thus, to monitor the progress of the vaccination campaign. The spatiotemporal clusters referring to the incidence of SARS: The regions categorized as new hot spots are regions that were never classified as hot spots and that in the final moments of the temporal observation started to be classified as such. In these places, the incidence of SARS due to COVID-19 increased at the end of 2020, which suggests a significant potential for exacerbating patients. The three states in the Southern Region were categorized as Oscillating hot spots, meaning that they were cold spot areas of hospitalizations for SARS in the past, but which became hot spots at the most recent points in the analyzed time scale. This situation affected the states of Minas Gerais, Goiás, Tocantins, Rondônia, Acre, eastern Pará, the coast of the Northeast and Mato Grosso. Finally, the states of Amazonas, Mato Grosso do Sul, Sul de Roraima and Amapá were evaluated as a Sporadic hotspot that defines a grouping of municipalities that alternate a non-significant clustering situation, with hotspot classification. It is worth highlighting the situation in the southwest of São Paulo, which presented an Intensifying hotspot cluster that marks the situation of cities classified as hot spots 90% of the time, and that in the last points of the temporal scale the statistical significance of the grouping became more intense. Of the total number of cities analyzed, 3,253 were considered as Oscillating hotspot. Of which 1,102 are in the South region. The Northeast Region had 518 municipalities categorized as New Hot Spot, thus 28% of its cities presented a pattern of SARS increment at the end of 2020.	
Liu, 2021(97)	Machine learning and transfer learning model	Transfer learning model	Broader public-health measures ▪ ***Strategies to identify and address misinformation***	The authors used a ML approach to analyze attitudes and behavioral intentions towards COVID 19 vaccination in tweets posted from Nov 1, 2020, to Jan 31, 2021. The transfer learning model was better to identify tweets that included opinions, attitudes, and behavioral intentions towards COVID 19 vaccinations. The daily prevalence of tweets expressing opinions did not change over time. The daily prevalence of attitudes and behavioral interventions was not stationary. The prevalence of positive behavioral interventions augment over time.	**5/8**

Table 7. Prevalence studies grouped by public health activity and their methodological quality

Article	Technology	Intervention *(Abbreviations in page 4)*	Public health activity	Key findings	Q/A
Galvan, 2020 (98)	Artificial Neural Networks (ANN) of the type of Self-Organizing Maps (SOM)	14 possible factors that can affect the spread of COVID-19: ICU beds, ventilators, physicians, nurses, PPE, hand sanitizer, rapid test, PCR test, vaccines distributed, vaccines applied, chloroquine tablets, oseltamivir capsules, HDI, and federal funds distribution	Broader public-health measures ▪***Risk stratification***	The dataset used in the study was obtained from websites of Brazilian government agencies or institutions. The influence of 14 variables was assessed together by Artificial Neural Networks (ANN) of the type Self-Organizing Maps (SOM), to verify the relationship between numbers of cases and deaths from COVID-19 in Brazilian states for 110 days. The datasets were evaluated using three different approaches. In the first step, two SOM analyses were conducted to verify the distribution of the numbers of cases and deaths from COVID-19 in Brazilian regions and states. In the second step, the distribution of 14 variables for the Brazilian states was verified. The Spearman's rank correlation coefficient is adopted to determine the correlation between variables. All states belonging to the South (S) and Central-West (CW) regions of the country had the lowest rates of cases and deaths by COVID-19 recorded, an average of 180 cases and 4 deaths per 100,000 inhabitants. Most of the Brazilian states with the highest rates of cases and deaths belong to the North (N) region, an average of 954 cases and 43 deaths per 100,000 inhabitants, mainly represented by Acre (AC), Amapá (AP), Amazonas (AM), Pará (PA), and Roraima (RR). The neural network demonstrated that the spread of COVID-19 in Brazil has heterogeneous behavior. The North of the country was more affected by COVID-19 than the South. The Northeast and Southeast differ in case rates but have similar death rates. The SOM analysis showed that the variables that presented a more significant relationship with the numbers of cases and deaths by COVID-19 were influenza vaccine applied, Intensive Care Unit (ICU), ventilators, physicians, nurses, and the Human Development Index (HDI). In general, Brazilian states with the highest rates of influenza vaccine applied, ICU beds, ventilators, physicians, and nurses, per 100,000 inhabitants, had the lowest number of cases and deaths from COVID-19, while the states with the lowest rates were most affected by the disease. According to the SOM analysis, other variables such as Personal Protective Equipment (PPE), tests, drugs, and Federal funds, did not have as significant effect as expected.	**7/9**

Magoo, 2021 (99)	Deep learning	System to detect social distancing	Broader public-health measures ▪***Strategies to support adherence to public-health measures***	These authors created a model using deep learning and tensor flow-based version of YOLOv3 for object detection a system that can be used to detect pedestrians and evaluate if they are complying with the social distancing policy.	**6/9**
Daughton, 2021 (100)	Machine learning	Coding schema for 6 categories and 11 subcategories, which included both a wide number of behaviors as well codes focused on the impacts of the pandemic. Then, used this to develop training data and develop supervised learning classifiers (Logistic Regression, Random Forest) for classes with sufficient labels.	Broader public-health measures ▪***Strategies to identify and address misinformation***	The authors applied the labeling schema to approximately 7200 tweets. The most prevalent category by far was tweets about social distancing. The worst-performing classifiers had F1 scores of only 0.18 to 0.28 when trying to identify tweets about monitoring symptoms and testing. Classifiers about social distancing, however, were much stronger, with F1 scores of 0.64 to 0.66. They applied the social distancing classifiers to over 228 million tweets. They showed temporal patterns consistent with real-world events, and correlations of up to –0.5 between social distancing signals on Twitter and ground truth mobility throughout the United States. The authors found similar performances between random forest (RF) and logistic regression (LR). The exception to this trend was in the personal protective category, where the LR model substantially outperformed the RF. Twitter can provide useful information for parameterizing models that incorporate human behavior, as well as for informing public health communication strategies by describing awareness of and compliance with suggested behaviors.	**7/9**
Li, 2021 (101)	Natural Language Processing	Natural Language Processing	Broader public-health measures ▪***Strategies to identify and address misinformation***	In late April to early May, a larger proportion of tweets were perceived as opposing to reopen. After the opening news of Florida and Texas, the tweets supporting reopening began to accumulate with a gradual increase in the volume. The perception for or against reopening was influenced by political and scientific news that were discussed on Twitter.	**6/9**
Cresswell, 2021 (102)	Deep Learning	An ensemble-based AI model developed by the authors in was adapted and utilized for this study, combining lexicon rule-based and deep learning (DL)–based approaches. Specifically, an average-weighting ensemble of lexicon-based models, including Valence Aware Dictionary and Sentiment	Broader public-health measures ▪***Strategies to identify and address misinformation***	Overall, the average positive sentiments were found to far outnumber the negative sentiments. With a six-fold difference between the sentiment type, with 76% positive and 12% negative sentiments. Key events that are likely to have influenced changes in the public's sentiments toward using contact tracing apps: Apple and Google partnered on developing a decentralized COVID-19 contact tracing technology. Shortly after, the UK government released contact tracing guidance with plans to develop a home-grown app and deploy it through a centralized model, implying that individual information would be shared with health services.	**6/9**

		Reasoner (VADER) and TextBlob, was combined with a state-of-the-art DL-based model Bidirectional Encoder Representations from Transformers (BERT).		In June 2020, the centralized UK app was abandoned. In August 2020, the UK government decided to implement the decentralized contact tracing system developed by Apple and Google, launching the app in September 2020. Since then, there have been concerns around high rates of false-positive COVID-19 cases reported via the app, hindering its uptake among the public. The counties with the most positive sentiment included Lincolnshire, Norfolk, Nottinghamshire, Leicestershire, and Northamptonshire in England, and Stirling, Fife, Dumfries and Galloway, East Ayrshire, and West Lothian in Scotland. Counties with the most negative sentiment were Suffolk, Somerset, Devon, and North Yorkshire—all in England.	
Massey, 2021 (103)	Natural language processing	Natural language processing	Broader public-health measures ▪***Strategies to identify and address misinformation***	Using natural language processing, these authors measured the prevalence of online discussions about topics in COVID-19 related to public health in forums and social media platforms such as Reddit, Facebook, 4 Chan, and comments from news sites from June to November 2020. They found 1836200 posts classified as including discussions regarding COVID-19 public health with the most prevalent topic was wearing face masks, followed by lockdowns and social distancing with a decline in time.	**6/9**
Hussain, 2021 (104)	Natural language processing	NLP with Bidirectional Encoder Representations from Transformers (BERT)	Broader public-health measures ▪***Strategies to identify and address misinformation***	Using a new hierarchical hybrid ensemble-based AI model developed for thematic sentiment analysis for COVID-19 vaccines consisting of average weighting ensemble of 2 lexicon-based methods: Valence Aware Dictionary for Sentiment Reasoning (VADER) [20] and TextBlob with a combination of a pretrained DL-based model, Bidirectional Encoder Representations from Transformers (BERT) [22], using a rule-based ensemble method, this authors analyzed Facebook post and Tweets from March,1, to November 22, 2020, obtained through the CrowdTangle platform and the Twitter API. They found an Overall averaged positive, negative, and neutral sentiments were at 58%, 22%, and 17% in the United Kingdom, compared to 56%, 24%, and 18% in the United States, respectively.	**6/9**
To, 2021 (105)	Natural Language Processing	Bidirectional encoder representations from transformers (BERT) and the bidirectional long short-term memory networks with pre-trained GLoVe embeddings (Bi-LSTM).	Broader public-health measures ▪***Strategies to identify and address misinformation***	Performance on the test set of the BERT model was accuracy = 91.6%, precision = 93.4%, recall = 97.6%, F1 score = 95.5%, and AUC = 84.7%. Bi-LSTM model performance showed: accuracy = 89.8%, precision = 44.0%, recall = 47.2%, F1 score = 45.5%, and AUC = 85.8%. SVM with linear kernel performed at: accuracy = 92.3%, Precision = 19.5%, Recall = 78.6%, F1 score = 31.2%, and AUC = 85.6%. Complement NB demonstrated: accuracy = 88.8%,	**6/9**

				precision = 23.0%, recall = 32.8%, F1 score = 27.1%, and AUC = 62.7%. In conclusion, the BERT models outperformed the Bi-LSTM, SVM, and NB models in this task. Moreover, the BERT model achieved excellent performance and can be used to identify anti-vaccination tweets in future studies.	
Kwok, 2021 (106)	Natural language processing, Machine learning	Latent Dirichlet allocation-LDA (an unsupervised machine learning method that allows observations such as words or documents) topic model to identify commonly discussed topics in a large sample of tweets. The authors also performed sentiment analysis to understand the overall sentiments and emotions related to COVID-19 vaccination in Australia.	Broader public-health measures ▪***Strategies to identify and address misinformation***	The analysis identified 3 LDA topics: (1) attitudes toward COVID-19 and its vaccination, (2) advocating infection control measures against COVID-19, and (3) misconceptions and complaints about COVID-19 control. Nearly two-thirds of the sentiments of all tweets expressed a positive public opinion about the COVID-19 vaccine; around one-third were negative (fear, sadness, anger, and disgust). Among the 8 basic emotions, trust and anticipation were the two prominent positive emotions observed in the tweets, while fear was the top negative emotion. Those who underestimated the risks and severity of COVID-19 may have rationalized their position on COVID-19 vaccination with conspiracy theories. Those who were skeptical about vaccines were affected by misinformation and adverse effects, which are statistically rare. Another topic was baseless claims, conspiracy theories, complaints, and misconceptions about various measures against COVID-19, including vaccines, drugs, virus testing, lockdown, and herd immunity. The major pitfall of these tweets was that their content could not be supported with any valid scientific evidence; further, the complaints were not directly associated with any solutions. Some Twitter users advocated for infection control measures had confidence in COVID-19 vaccine trials and rebutted tweets that were derived from conspiracy theories or misinformation. The authors also noticed that the level of positive sentiment among the public may not be sufficient to increase vaccination coverage to a level high enough to achieve vaccination-induced herd immunity.	**5/9**

Table 8. Modelling studies grouped by public health activity and quality assessment

Article	Technology (*Abbreviations in page 4*)	Public health activity	Key findings	Q/A
Ahanger, 2021 (19)	Temporal recurrent NN (T-RNN)	Infection control ▪***Testing for/detection of cases (not diagnosis or prognosis)***	Based on the simulations, outcomes are nearer to the efficiency line by accomplishing more precision when contrasted with different models. Likewise, the model delivers low errors which are approved by assessing NRMS and MSE rates. Response delay - reaction time estimation of the proposed model is 5.16s per information feature, while the manual checking framework takes mean estimation of 16.36s per information value. Reliability: From the implementation results, it is seen that the introduced model accomplished higher precision when contrasted with others. Authors inferred that the proposed model has higher precision averaging 91% when compared with the other strategies of ANN and RFT.	**High (5/5)**
Simsek, 2020 (20)	AI	Infection control ▪***Testing for/detection of cases***	The first class of analyses have focused on maximum coverage in communities where the results have shown that an average 5 km coverage constraint achieves 99.783% coverage outperforming the random deployment of mobile assessment agents by ≈12%. The second class of analyses assume the worst-case scenario and prove that the minimum number of neurons (i.e., stops) for SOFM (self-organizing feature map) can be achieved on the 15th day following the occurrence of the first confirmed case to be able to detect and isolate all infected individuals whereas the random deployment under the same number of stops over multiple districts fail to detect all cases and leads to non-assessed population remain quadruplicated. AI-enabled mobilization of assessment centers can reduce the unassessed population size down to one fourth of the unassessed population under the case when assessment agents are randomly deployed over the entire city.	**High (5/5)**
Shoer, 2020 (107)	Gradient Boosting Decision Trees models	Infection control ▪***Testing for/detection of cases***	The primary model for prediction of a positive COVID-19 test result was based on the 43,752 integrated responses of which 498 self-reported as being diagnosed with COVID-19. The mod achieved an area under the receiver operating characteristic (auROC) of 0.737 (confidence interval [CI]: 0.712–0.759), and an area under the precision recall (auPR) of 0.144 (CI: 0.119–0.177). To capture nonlinear interactions and interactions among features, authors trained both the primary and the extended features models using a Gradient Boosting Decision Trees algorithm The Gradient Boosting Decision Trees primary model showed similar performance to the Logi Regression primary model, and predictions on the online survey data not used in the model's construction process were highly correlated with the predictions of the primary Logistic Regression model (Pearson r = 0.91, p < 10−8). Loss of taste or smell was the most contributing feature in both the primary model and the extended features model. The contribution of age individually to the probability of being diagnosed with COVID-19 is the highest in the oldest age group (>70 years old). Presence of	**Mode rate (3/5)**

			cough and loss of taste or smell exhibits a sharp transition-type (sigmoid-like) interaction with age, such that above the age of 40 years old; presence of each of these symptoms sharply increases the model's predicted probability of COVID-19 infection.	
Peterson, 2021(22)	ML, NLP	Infection control ▪***Contact tracing***	This study was developed with data from the Corporate Data Warehouse from 2015 to 2017 in more than 6.4 million patients with more than 694 million clinical notes. This study was carried out on American veterans to provide tools that facilitate medical care and bio-surveillance operations. Combining multiple aspects of clinical data with travel information included rapid selection of cases to review in January 2020 for testing and travel regions in a more specific case review. This system was already operational in early 2020, so it could be leveraged in response to the spread of COVID-19 in the United States. This ability was useful in the early stages of transmission, as it was able to identify mentions of travel to endemic areas. The usefulness of this system for COVID-19 specifically is limited to a relatively short window in the early stages of transmission when containment was possible, and travel was a disruptive risk factor.	**High (5/5)**
Maghdid, 2020 (55)	ML, Smartphone-based Tracing	Infection control ▪***Contact tracing*** Broader public-health measures ▪***Outbreak management*** ▪***Risk stratification***	This research has shown that the lockdown issue for an intended area could be predicted using machine learning algorithms such as K-Means clustering algorithm. The time and space complexity of the implemented algorithm on the server is depending on the size of the number of participant users. The weak point of this study is the privacy issue of tracking position information of the users.	**High (5/5)**
Chen, 2020 (108)	Big Data Analytics	Infection control ▪***Contact tracing***	Based on the mobile position information, the study identified 627,386 corresponding possible contact-persons. The symptom monitoring and self-quarantine message was sent though SMS after identifying the contact-person on February 7, 2020. Multiple means were taken for contact tracing by the Central Epidemic Command Center (CECC). These included travelling itinerary arranged by the agency, GPS in shuttle buses, credit card transaction logs, closed-circuit television (CCTV), vehicle license plate recognition system, and mobile positioning data. As of February 29, a total of 67 contacts who were tested by RT-PCR were all negative and no confirmed COVID-19 cases were found. Less cases of respiratory syndrome (age-standardized RR of 0.929- 95% CI 0.923-0.935) and pneumonia (age-standardized RR 0.915, 95% CI 0.869-0.963) were found after the follow-up of the contact population compared with the general population until March 10, 2020. This suggests that smart contract tracing with mobile position data followed by self-quarantine and isolation may be a useful means of preventing the spread of COVID-19. Big data analytics with smart contact tracing, automated alert messaging for self-restriction, and follow-up of the outcome related to COVID-19 using health insurance data could curtail the resources required for conventional epidemiological contact tracing.	**Moderate (4/5)**

Rallapalli, 2021 (21)	Fuzzy Logic, Bayesian networks	Infection control ▪***Testing for/detection of cases*** Broader public-health measures ▪***Predicting spread and pandemic tracking***	The model has the ability to deal with the uncertainty associated with the data and decision maker's opinions using fuzzy logic, which is fused with the Bayesian approach The study establishes that detecting viral load in the biomarkers excreted in human urine and feces using Wastewater-Based Epidemiology (WBE) could be a more promising approach to investigate the occurrence of COVID-19 in communities, especially at locations with limited clinical testing. *Increasing the population of individuals with age more than 50 years has resulted in the increase of severity of COVID-19 spread by 9% in the 'extreme' region, and about 20% in 'high' regions. Hence, the regions that correspond to 'scenario 1' (Region with high population density with 80% individuals above 50 years of age and 50% literacy rate.) and housing a greater number of older adult populations would surely increase the probability of COVID-19 spread. The installation of autosamplers or biosensors at the strategic positions such as domestic sewage, housing estate sewage at identified targeted locations would help in implementing WBE. The advantage of WBE over PCR testing is the use of biomarkers. *Keeping other criteria intact, 'scenario 2' (Diabetes and Cardiovascular comorbidities partake 90% of the COVID infected individuals for a given region) results in an increase of COVID-19 spread from 29.9% to 60.14% under 'high' state and about 3% in the 'extreme state'. This gives immense clarity to the state/local governments to solidify the facilities and make proper sanitization in the targeted locations identified by the model.	**High (5/5)**
Zeroual, 2020 (23)	DL/NN (with comparison of five deep learning methods)	Broader public-health measures ▪***Predicting spread and pandemic tracking***	Deep learning models have promising potential in forecasting COVID-19 cases; this study highlight the superior performance of the Variational AutoEncoder (VAE) compared to the other algorithms. The three models (RNN, LSTM, and GRU) converge very quickly and the RNN is relatively faster than the other models followed by GRU. This is mainly due to the fact that the RNN is a simple model and the GRU use directly all hidden states without control and presents fewer computational parameters compared to LSTM, Bi-LSTM, and VAE. The VAE method provides better forecasting of COVID-19 confirmed cases in comparison to the other considered models for almost all considered countries except in Italy. The VAE model achieved MAPE values of 5.90%, 2.19%, 1.88%, 0.128%, 0.236%, and 2.04% for COVID-19 data from Italy, Spain, France, China, Australia, and the USA, respectively. This is the first time that the VAE model is applied for COVID-19 time series forecasting.	**High (5/5)**
Dairi, 2021 (24)	ML/ DL/NN.	Broader public-health measures ▪***Predicting spread and pandemic tracking***	Hybrid deep learning models can efficiently forecast COVID-19 cases. Also, results confirmed the superior performance of deep learning models compared to the two considered baseline machine learning models (LR and SVR). Furthermore, results showed that LSTM-CNN achieved improved performances with an averaged mean absolute percentage error of 3.718%, among others. By considering all metrics, LSTM-CNN is the best approach with high efficiency and	**High (5/5)**

			satisfying forecasting accuracy due to its capability to learn higher-level features that permit good forecasting precision. Results in this study showed that deep learning models provide satisfying results, even with relatively small-sized data.	
Ahouz, 2021 (25)	ML	Broader public-health measures ▪***Predicting spread and pandemic tracking***	Using the Johns Hopkins COVID-19 Dataset, these authors created a model that uses the cases, recovered and deaths from COVID-19 from each region and the dynamics of neighbouring regions to short-term forecast the epidemic dynamic. They found the number of neighbors ranged from zero to 10. Euclidean distance based on latitude and longitude was used to calculate nearest neighbors. The model was presented for three groups based on the incidence rate: less than 200 (16,825 records), between 200 and 1000 (220 records), and above 1000 (152 records). To predict the incidence of COVID-19 in regions with more than 1000 confirmed cases per day, the proposed model demonstrated the best performance with MAE (mean absolute error) of 6.13%, considering the information of the last 14 to 17 days of the region and its two neighboring areas. For regions with 200 to 1000 cases per day, the proposed model performed best with respect to the 9 nearest neighboring areas and with data from the last 14 to 20 days, with MAE of 8.54% on the validation set. For regions with fewer than 200 cases per day, the proposed model performs best with MAE of 4.71%, considering the region data for the last 14 to 34 days. Prediction of incidence by April 12, 2020: By April 12, 1,134,018 new cases worldwide were expected to be on record. Of these, Europe with 687,665 (60.64%), North America with 272,957 (24.07%) and Asia with 107,000 (9.44%) new cases were the most prevalent, whereas Australia with 14,526 (1.28%), Africa with 19,131 (1.69%) and South America with 32.739 (2.89%) new cases were the least incidence. Comparison of predicted and actual cases from March 30 to April 12, 2020. As shown, the daily percent error is below 20%. The best accuracy of the proposed model in predicting the incidence of COVID-19 was obtained on April 10 with 99.6%, and the worst on April 11 with 81.3%. The best predicted continental incidence rates were found in South America and Asia with 18.15 and 21.04% percent error, respectively. The worst cases, still, were observed in Africa and Australian with more than 80% percent errors.	**High (5/5)**
da Silva, 2021 (26)	ANN Artificial neural networks, linear regression, support vector machines (polynomial kernels and RBF), multilayer perceptrons, and random forests	Broader public-health measures ▪***Predicting spread and pandemic tracking***	In a modelling study that proposes a tool for real-time spatio-temporal analysis using a machine learning approach to predict the distribution of cases and deaths in Brazil and in each federative unit. Four regression methods were investigated: linear regression, support vector machines (polynomial kernels and RBF), multilayer perceptrons, and random forests. For both territories, linear regression showed the best performance while SVR, kernel RBF presented the worst results. In general, for the Brazil's territory, the regressors that showed the best performances were linear regression, and MLP with 20 neurons in the hidden layer. On the other hand, the SVR with RBF kernel showed a bad performance.	**High (5/5)**

Murphy, 2021(27)	ML GNN	Broader public-health measures ▪***Predicting spread and pandemic tracking***	This study proposes a complementary approach based on deep learning where the effective local mechanisms that govern a dynamic in a network are learned from time series data. They illustrate the applicability of the approach using real data from the COVID-19 outbreak in Spain.	**High (5/5)**
Kuo, 2020 (28)	Elastic net (EN), principal components regression (PCR) model, partial least squares regression (PLSR) model, k-nearest neighbors' regression (KNN) model, regression tree (RT) model, random forest (RF) model, gradient boosted tree models (GBM), ANN	Broader public-health measures ▪***Predicting spread and pandemic tracking***	These authors evaluated the impact of mobility on COVID-19 trends, for this data from 3,219 counties in the United States were evaluated and using a ML-based model they found noted that community mobility in metropolitan counties declined substantially since mid-March after the closure was announced and continued to be an increasing trend with an apparent weekly pattern and the weekly pattern and mobility and infections implied a high number of infections during the following weekend.	**High (5/5)**
Yu, 2021(29)	DL	Broader public-health measures ▪***Predicting spread and pandemic tracking***	In this study, CPAIS was developed to explore variations, trends, and forecasts related to the COVID-19 pandemic in various countries. The CPAIS framework: from data acquisition and pre-processing to DL model application, forecasting and data visualization. Mainly use 4 ML models; An Autoregressive Integrated Moving Average (ARIMA) model is a statistical regression analysis that uses time series data to better understand the data set or predict future trends. A feedforward neural network (FNN) is the simplest type of artificial neural network. The FNN algorithm is biologically inspired. It consists of several simple neuron-like units that are organized in layers. Like FNNs, multilayer perceptron neural networks (MLPs) are common deep learning power networks. An MLP neural network is also a supervised learning algorithm used for classification. Short-term long-term memory (LSTM) networks are a special type of recurrent deep learning neural network that learns order dependence in sequence prediction problems. Heat maps can be generated to represent variations in policy measures for the COVID-19 pandemic over time. Gradient colored bars represent changes in measures at different levels and support received in the form of financial assistance and investments. Deep learning and statistical learning models will be used to enable COVID-19 forecasting. The feature makes it easy to forecast 14 days using the four powerful algorithms. CPAIS can help users determine whether policy measures are successful in preventing the transmission of COVID-19.	**High (5/5)**
Davahli, 2021 (30)	***ML***	Broader public-health measures	The authors develop a model to forecast in real-time the behavior of COVID-19 in the states of United States using the data for confirmed cases and the reproduction number from the Centers for Disease and Prevention. For this they first categorized all the states in four groups according to their reproduction number and then used long-short term memory,	**High (5/5)**

		▪***Predicting spread and pandemic tracking*** ▪***Risk stratification***	recurrent neural networks and mixture density networks models which were trained with data of a leading of each group. They found that the models based on reproduction number have much better performance than those trained on confirmed cases. In addition, the deterministic LSTM model exhibited better performance than the stochastic LSTM/MDN and linear regression models.	
Deng, 2020 (31)	DL	Broader public-health measures ▪***Predicting spread and pandemic tracking***	Authors established a SEIR-variety discrete time series on a daily interval as the theoretical foundation for a deep learning–enhanced compartment model. The multistep deep learning methodology to estimate the model's transmission parameters applied 2 deep learning approaches—the standard deep neural networks (DNN) and the advanced recurrent neural networks–long short-term memory (RNN-LSTM)—to fit the confirmed/dead in-sample time series and predict the further development of confirmed/dead cases for 35 and 42 days (out-of-sample time series). They used the US COVID-19 epidemic datasets from John Hopkins University Center for Systems Science and Engineering (JHU CSSE) Github COVID-19 data depository. The results based on data up to July 31, 2020, report that the DNN method predicts that on August 19, 2020, the value of the basic reproduction rate, R0 will fall to <1 and that the spread of COVID-19 in the United States will effectively end on that day. In the 35-day forecast, the RNN-LSTM method gives a prediction that the tide of the US epidemic will turn around the August 17-19, 2020, timeframe. In 35-day forecast, the DNN method predicts that the US "Infected" population will peak on August 18, 2020, at 3,267,907 individual cases. In 35-day forecast, the RNN-LSTM method predicts that the US "Infected" population will peak on August 16, 2020, at 3,228,574 individual cases. The model also predicted that the number of accumulative confirmed cases will cross the 5 million mark around August 7, 2020.	**High (5/5)**
Er, 2021 (32)	ML	Broader public-health measures ▪***Predicting spread and pandemic tracking***	These authors created a model called COURAGE (COUnty aggRegation mixup AuGmEntation) with can predict COVID-19 related deaths for each count in US. For this, they used a transformed based model architecture with data form the Johns Hopkins University and community mobility from Google. They found that this model can produce short-term forecast of COVID-19 deaths at state level and at county level	**High (5/5)**
Stevenson, 2021(33)	RNN with LSTM model.	Broader public-health measures ▪***Predicting spread and pandemic tracking***	This study proposes the development of an early warning / detection system that works by predicting future confirmed cases daily based on a series of characteristics that include mobility and rigor indices, and epidemiological parameters. The model was used between the first and second wave of infections in all the provinces of South Africa. Two georeferencing parameters were used, the first the Google Mobility Report is useful to understand the geospatial movement of people during the pandemic and the second about the Facebook movement data sets were developed to help researchers and experts in public health to monitor and track how populations are responding to social / physical distancing measures. Ten features were chosen as inputs to the RNN model. These features include	**High (5/5)**

			mobility measures, stringency indicators and epidemiological parameters. The model was trained over the interim period between COVID-19 case waves within each province. This configuration caused the model to perform well over the interim period, however when another COVID-19 case wave is reached, the system is unable to predict the values accurately.	
García-Cremades, 2021 (34)	ML	Broader public-health measures ▪***Predicting spread and pandemic tracking***	This study evaluates different models for prediction of COVID 19 cases and deaths using epidemiological and mobility data from Spain. The models evaluated were ML-based models (Long short-term memory and gate recurrent unit) and statistical models (autoregressive and AIRMA). They found that for 14 days predictions the ML based models performed better than the statistical ones with greater R2 and lower MAE and RMSE, but these models were outperformed by the TPOT and PROPHET models which are open ML models available as libraries of Python.	**High (5/5)**
Goic, 2020 (59)	ARIMA and its ARIMAX variants, trend seasonal components (TBATS), time-delay neural networks (TDNNs), ELM, LASSO, GMDH “group method of data handling”.	Broader public-health measures ▪***Predicting spread and pandemic tracking*** Service planning for COVID-19 treatment ▪***Scaling up/down ICU capacity***	Starting from May 16th, authors generated standardized and frequent reports containing the two weeks ahead forecasts. The reports were made publicly available at https://isci.cl/covid19/. In the analysis they only consider results since May 20th, when the routines were fully automatized to generate predictions for all regions. The main body of each report consisted of a summary of the number of beds that were going to be required for each region for a time horizon of two weeks, followed by a graphical summary of the forecast. For the Metropolitan Region on July 24th, the reports indicated that the Region was going to require 937 beds within a week (172 beds less than occupation at that date) and 802 beds within two weeks (307 beds less than the occupancy on that date). From May 20th to July 28th, they produced 30 ICU utilization reports. At the peak of the outbreak, the Metropolitan Region demanded more than 11 times more beds than the second-most congested region. The forecasts exhibited a 4.11% error rate in the first week and a 9.03% error rate in the second week. The ensemble was frequently associated with smaller errors than those of the individual models.	**High (5/5)**
Niazkar, 2020 (35)	NN	Broader public-health measures ▪***Predicting spread and pandemic tracking***	Based on the obtained results, the ANN-based model that considers the previous 14 days outperforms the other ones. This comparison reveals the importance of considering the maximum incubation period in predicting the COVID-19 outbreak. Comparing the ranges of determination coefficients indicates that the estimated results for Italy are the best one. Moreover, the predicted results for Iran achieved the ranges of [0.09, 0.15] and [0.21, 0.36] for the mean absolute relative errors and normalized root mean square errors, respectively, which were the best ranges obtained for these criteria among different countries. As shown, the proposed ANN-based models have different performances. Additionally, applying only confirmed cases of the very previous day by ANN for estimation daily confirmed cases (the 1st model) do not yield to reliable predictions for seven considered countries. After applying fourteen ANN-based models to predict the COVID-19 outbreak in seven	**High (5/5)**

			countries, the values of NRMSE, MARE and R2 were used to calculate the minimum, average and maximum of the three metrics for all models in each country. Comparison of the ranges of R2 demonstrates that the average R2 of the ANN-based models for Italy, Singapore and China are not only more than 0.5 but also better than those of others, while the lowest R2 values were obtained for South Africa.	
Gao, 2021 (36)	DL graph attention network (GAT)	Broader public-health measures ▪***Predicting spread and pandemic tracking in different regions in China***.	STAN outperforms traditional epidemiological models such as susceptible-infectious-recovered (SIR), susceptible-exposed-infectious-recovered (SEIR), and deep learning models on both long-term and short-term predictions and on both state and county levels, achieving up to 87% reduction in mean squared error compared to the best baseline prediction model.	**High (5/5)**
ArunKumar, 2021 (37)	ML	Broader public-health measures ▪***Predicting spread and pandemic tracking in different regions in China***.	This study uses COVID-19 cases that were reported for the period January 22, 2020 to July 24, 2020. They attempted to forecast cumulative confirmed COVID-19 cases, recovered cases, and confirmed deaths for the 16 main countries, where between 70% and 80% of the world cases of COVID19 were concentrated. To capture the seasonality or trends of the data, the SARIMA models outperform the ARIMA models.	**High (5/5)**
Braga, 2021 (38)	ANN	Broader public-health measures ▪***Predicting spread and pandemic tracking***	This study used the ANN as the ML strategy. The proposal was to analyze the behavior of new cases, deaths and demand for hospital beds that would allow decisions to be made according to the behavior of covid-19 care. 6 scenarios were created that allowed us to analyze the data by time sections and compare them with each other. In conclusion, the results show that ANNs generate forecasts that should be closer to the data observed in daily variables and hospital beds as new data are inserted into the ANN training data set.	**High (5/5)**
Shawaqfah, 2021 (39)	NN	Broader public-health measures ▪***Predicting spread and pandemic tracking***	The verified and validated growth model of COVID-19 for these countries showed the effects of the measures taken by the government and medical sectors to alleviate the pandemic effect and the effort to decrease the spread of the virus to reduce the death rate. Similar trends were observed between Spain and Italy but different than Qatar, with Qatar possessing the lowest expected deaths. The highest numbers per million of the population (MN-MIN) was observed in Italy at 2130 followed by Spain in 1701, with no more than 200 deaths in Qatar. The percentage mortality of the infected population was 2.2% for Spain, 3.0% for Italy, and no more than 0.30% for Qatar. The MN-MIN obtained by the ANN showed a very high correlation adjustment coefficient R2, with an almost perfect adaptation to the real values. Although the Pandemic spread rate and the number of reported cases were the highest in Qatar compared with Spain and Italy, the low mortality number suggest that the population density, infected people age, social distances precautions, weather conditions, and the responsibilities of individual have a major impact towards the critical pandemic evolution.	**High (5/5)**

Davahli, 2021(40)	NN	Broader public-health measures ▪***Predicting spread and pandemic tracking***	The authors developed two types of GNN models, including: (1) graph-theory-based neural networks (GTNN) and (2) neighborhood-based neural networks (NGNN). The nodes in both graphs indicated individual states in the United States. While the GTNN model's edges document functional connectivity between states, those in the NGNN model link neighboring states to one another. We trained both models with Rt numbers collected over the previous four days and asked them to predict the following day for all states in the United States. The performance of these models was evaluated with the datasets that included Rt values reflecting conditions from 22 January through 26 November 2020 (before the start of COVID-19 vaccination in the United States). To determine the efficiency, the authors compared the results of two models with each other and with those generated by a baseline Long short-term memory (LSTM) model. The results indicated that the GTNN model outperformed both the NGNN and LSTM models for predicting Rt.	**High (5/5)**
Pereira, 2021 (41)	ML	Broader public-health measures ▪***Predicting spread and pandemic tracking***	The authors used a LSTM-SAE model to predict the COVID-19 pandemic. For this, they created the model and then they trained de model using countries with similar characteristics as of the Brazilian states. This model was used to predict new cases with more prediction than the predictions obtained from traditional compartment models.	**High (5/5)**
Andelic, 2021 (109)	ML (Genetic programming)	Broader public-health measures ▪***Predicting spread and pandemic tracking***	The GP algorithm can produce symbolic expressions for the estimation of the number of confirmed, recovered and deceased patients as well as the epidemiology curve not only for the states but for the entire U.S with very high accuracy. Also, The GP algorithm can be utilized to obtain symbolic expressions for each U.S. state based on the latitude and longitude of their central location and day as an input variable to estimate the number of confirmed/deceased/recovered patients in different states. Each symbolic expression obtained for each U.S. state is estimating the number of confirmed patients in each state with high accuracy; the value of the achieved R 2 score is in range from 0.9406 to 0.9992. The highest accuracy (higher than 0.999) was achieved with the symbolic expressions for New York, North Dakota Oregon, South Carolina, Virginia, West Virginia and Wisconsin. The obtained symbolic expression for estimation of the epidemiology curve follows the trend of the real data with smaller deviations. The most noticeable deviation from real data can be seen in the last 20 days where the estimated number of infected patients is smaller than those obtained from the real data. During Days 60–250, the number of confirmed patients grew from 0 to above 7,000,000. In this period, the public protests in almost every state for anti-lockdown measures and Black Lives Matter were the most contributing factors for increased virus spreading at that time. In the last period of Days 250–317, the number of confirmed patients in the U.S. grew extremely from 7,000,000 to 14,000,000. The most contributing factors for virus spread at that time were presidential rallies and mass gatherings in South Dakota. ▪ Confirmed patients: Were divided into intervals. The first interval can be divided into sub-intervals where in the first (120–150 days) the symbolic expressions are underestimated the number of confirmed patients, while in the second subinterval	**High (5/5)**

			(150–170 days) the symbolic expression overestimated the number of confirmed patients. In the second interval (300–317 days), the symbolic expressions underestimated the number of confirmed patients. ▪ Recovered patients: The R 2 score achieved with symbolic expressions for the estimation of the number of recovered patients for each state was in range from 0.9797 to 0.99955. The symbolic expression for the estimation of the number of recovered patients very accurately follows the number of recovered patients when compared to the real data. Deceased: the value of achieved R 2 score with symbolic expressions for the estimation of the number of deceased patients for each state range from 0.9404 to 0.99984. The curve of deceased patients has a similar trend as the number of confirmed patients' curve.	
Li, 2021 (42)	ML	Broader public-health measures ▪***Predicting spread and pandemic tracking***	In the models including all 2787 counties, (1) social demographic features, such as GDP and population density, and the feature reflecting social interaction strength, social connectedness index, kept high importance through stages of the COVID-19 pandemics; (2) a virus attribute feature, reproduction number (R0), and some social demographic features, including minority status, socioeconomic status, and COVID-19 community vulnerability index (CCVI) showed increased importance in the trajectory of the COVID-19 pandemic; (3) within-county mobility features, Cuebiq county mobility index (CMI) and shelter-in-place (SIP), showed decreased importance across different stages; while in the models with different population densities, the level of importance varied; (4) within-county mobility features showed higher importance in county clusters with higher population densities; (5) GDP and R0 did not show the same importance within the models encompassing 2787 counties, while the minority status feature still showed an initial low level and increasing importance across stages; and (6) social distance index (SDI) showed higher importance in county clusters with lower population densities and higher importance in the social distancing and reopening stages. The results showed that the data-driven machine learning models could provide important insights to inform policymakers regarding feature importance for counties with various population densities and at different stages of a pandemic life cycle.	**High (5/5)**
Quintero, 2021 (43)	ML	Broader public-health measures ▪***Predicting spread and pandemic tracking***	The authors of this study used machine learning based models (gradient boosting regressor, random forest regressor, limited memory BFGS and convolutional neural network) to estimate the parameters for a classical SEIRD model for forecast the epidemic using a database of the Colombian evolution of the COVID-19 pandemic. Using this approach, they found that the resulted model can predict the pandemic development in Colombia with a high coefficient of determination and low error.	**High (5/5)**
Rios, 2021 (110)	AI	Broader public-health measures ▪***Predicting spread and pandemic tracking***	The authors analyzed how some countries with the greatest numbers of confirmed cases per million inhabitants transitioned along groups. Brazil, Canada, China, France, Germany, India, Russia, USA, UK, Belgium, Iran, Spain, and Italy were analyzed. The study shows the historical infection path taken by specific countries and emphasizes	**High (5/5)**

		▪***Risk stratification***	changing points that occur when countries move between clusters with small, medium, or a large number of cases; also the authors estimate new waves for specific countries using the transition index. The number of cases of a country is indeed useful to analyze possible outcomes in other regions. The closer to 100% the transition index is, the greater is the probability of moving to another group. The study noticed that some transitions between groups happened even without having this index close to 100%. This situation is expected once the whole environment is episodic and dynamic, i.e., while analyzing a country, the recorded numbers of others may also change. Another important information highlighted by the visual transition is the line width of Brazil, France, Germany, the USA, and the UK that got wider as new cases were reported, indicating those countries were moving to high-incidence groups.	
Majhi, 2020 (111)	ML, RF	Broader public-health measures ▪***Predicting spread and pandemic tracking***	In this article, the authors explain the advantages of using machine learning systems in the prediction of deaths, cases and the impact of political decisions such as population closures on the control of COVID 19 management. It uses a comparison with a proprietary algorithm based on Random Forrest in Indian population. Finding that the method is effective in preventing cases and can be a useful tool in controlling the spread of the virus.	**High (5/5)**
Liao, 2020 (44)	ML	Broader public-health measures ▪***Predicting spread and pandemic tracking***	This study proposed a TW-SIR prediction model which is able to reflect the real-time trend of the epidemic in the process of infection for different areas, different policies and different epidemic diseases. Machine learning methods are applied to predict the basic number of infections R0 and the exponential growth rate of the epidemic The numerical results shows that the model can effectively measure the real-time changes of parameters during the spread of epidemics, including the basic number of infections R0(t) and exponential growth rate Ex(t). And the results will provide some advice for the follow-up epidemic prevention and control.	**High (5/5)**
Ilin, 2021 (45)	ML	Broader public-health measures ▪***Predicting spread and pandemic tracking***	The authors created a machine learning model that analyzed and demonstrated that freely available mobility data can be used in simple models to generate practically useful forecasts. This model used data collected from the Johns Hopkins Center Epidemiological Surveillance Center, mobility data from google, Facebook and Baidoo and policy data prepared and made available for academic research by Global Policy Laboratory. They found that passively observed measures of aggregate mobility are useful predictors of growth in COVID-19 cases. However, this does not imply that population mobility itself is the only fundamental cause of transmission. The measures of mobility we observe capture a degree of "mixing" that is occurring within a population, as populations move about their local geographic context.	**High (5/5)**
Sethi, 2021 (46)	DL	Broader public-health measures ▪***Predicting spread and pandemic tracking***	It is observed that the proposed technique achieves high accuracy (98.2%) when implemented with ResNet50. Besides, the proposed model generates 11.07% and 6.44% higher precision and recall in mask detection when compared to the recent public baseline model published as Retina Face Mask detector. The outstanding performance of the	**High (5/5)**

		▪***Strategies to support adherence to public-health measures***	proposed model is highly suitable for video surveillance devices. The proposed technique efficiently handles occlusions in dense situations by making use of an ensemble of single and two stage detectors at the pre-processing level. The ensemble approach not only helps in achieving high accuracy but also improves detection speed considerably. Furthermore, the application of transfer learning on pretrained models with extensive experimentation over an unbiased dataset resulted in a highly robust and low-cost system. The identity detection of faces, violating the mask norms further, increases the utility of the system for public benefits. The proposed technique can be integrated into any high-resolution video surveillance devices and not limited to mask detection only. Also, the model can be extended to detect facial landmarks with a facemask for biometric purposes.	
Khalilpourazari, 2020 (47)	ML, RL, EC	Broader public-health measures ▪***Predicting spread and pandemic tracking***	This study proposes a hybrid model that is based on the application of AI and ML in the prediction of the behavior of covid 19 in Quebec, Canada. The period (from January 25, 2020 (day 1) to July 19, 2020 (day 176)) was divided into six stages in which the government of Quebec applied specific restrictions to control the pandemic (closures, blockades, social distancing, etc.) With the application of the method and based on the results, considering social distancing and current limitations, they experienced a significant decrease in the number of cases in the coming months if and only if strict measures such as the partial blockage.	**High (5/5)**
Raheja, 2021(48)	ML: diffusion prediction model	Broader public-health measures ▪***Predicting spread and pandemic tracking***	The results proved the efficacy of proposed model as the actual confirmed cases and the cases predicted by the proposed model are mostly walking together. In future, if more attributes will be available, the model can be expanded to predict more attributes and can also be implemented for other countries.	**High (5/5)**
Wang, 2021 (49)	ML	Broader public-health measures ▪***Predicting spread and pandemic tracking***	The global estimated Rt declined after the first surge of COVID-19 pandemic but there were still two major surges of epidemics occurring in September 2020 and March 2021, respectively, and numerous episodes due to various extents of Non-pharmaceutical Interventions (NPIs). Unsupervised machine learning identified five patterns as “controlled epidemic”, “mutant propagated epidemic”, “propagated epidemic”, “persistent epidemic” and “long persistent epidemic” with the corresponding duration and the logarithm of case load from the lowest (18.6 11.7; 3.4 1.8)) to the highest (258.2 31.9; 11.9 2.4). Countries like Taiwan outside five clusters were classified as no community-acquired outbreak. Data-driven models for the new classification of community-acquired outbreaks are useful for global surveillance of uninterrupted COVID-19 pandemic and provide a timely decision support for the distribution of vaccine and the optimal NPIs from global to local community.	**High (5/5)**
Li, 2021 (50)	ML, ANN	Broader public-health measures	It is a study that includes a hydride model between a systematic review of the literature and the creation of a data analysis model that makes it possible to relate the detection of covid-19 by ANR in wastewater and the prevalence of the disease. In general, the ANN and ANFIS models showed greater precision and robustness than the MLR models. Air and	**High (5/5)**

		▪***Predicting spread and pandemic tracking***	wastewater temperature played a key role in estimating prevalence using data-driven models, especially MLR models. Using unseen data sets, the ANN model reasonably estimated the prevalence of COVID-19 (cumulative cases) in the early phase and predicted the next new cases in 2-4 days in the post-peak phase of the COVID-19 outbreak.	
Yeung, 2021 (51)	ML	Broader public-health measures ▪***Predicting spread and pandemic tracking***	This authors proposed a model for the prediction of the COVID-19 spread in different countries taking into account the Hofstede cultural dimensions of 2015 (this dimensions are: Power distance index, Individualism versus collectivism, Uncertainty avoidance, Masculinity versus femininity, Long-term versus short-term orientation, and Indulgence versus restraint), the dynamics of the pandemic, and the non-pharmacological interventions using a machine learning approach using ridge regression, decision tree regression, random forest regression, AdaBoost, and Support vector regression with data from the Johns Hopkins University. They found the random regression and the AdaBoost models had the lowest mean test error with highest accuracy in the in-distribution method.	**High (5/5)**
Xu, 2021(52)	ML: Classification and Regression Tree (CART), Boosted Tree (BT), RF and LR	Broader public-health measures ▪***Predicting spread and pandemic tracking***	This study integrates Data Envelopment Analysis (DEA) with four different machine learning (ML) techniques to assess efficiency and assess US COVID-19. Various parameters were taken to evaluate efficiency such as number of tests, public funding, number of healthcare employees, number of hospital beds. Then, the number of recovered COVID-19 cases is considered as a desirable outcome and the number of confirmed COVID-19 cases as an undesirable outcome. The results showed that 23 states of the 50 evaluated in total, were efficient with an average efficiency score of 0.97. Finally, urban areas, physical inactivity, number of examinees per population, population density, and total hospital beds per population were the factors that most influenced efficiency. The results of this study may be of interest to healthcare decision makers involved in COVID-19 response management planning and wanting to maximize performance across the state.	**High (5/5)**
Peng, 2020 (53)	ML	Broader public-health measures ▪***Predicting spread and pandemic tracking***	The model performed well in 154 (76.2%) countries, of which each had no more than four misclassified samples. In these 154 countries, the accuracy was 0.8133, and the kappa coefficient was 0.6828. While in all 202 countries, the accuracy was 0.7527, and the kappa coefficient was 0.5841. For the real-time prediction of weekly alert level, the proposed Random Forest Classification algorithm was compared with other common machine learning classification methods: Linear Regression Classification (LRC), Support Vector Machine (SVM), k-Nearest Neighbor (K-NN), Decision Tree Classification (DTC). The results show the Random Forest Classification algorithm achieved much better results in terms of all quantitative metrics compared to others. The proposed algorithm based on Random Forest Classification and nine features (coronavirus, pneumonia, cough, fever, nasal congestion, rhinorrhea, cough, diarrhea, fever) performed better compared to other machine learning methods and the models with different numbers of features.	**High (5/5)**

Peng, 2021 (112)	ML	Broader public-health measures ▪***Predicting spread and pandemic tracking***	The models accurately predict the daily new confirmed cases of COVID-19 in most countries and territories. Of the 215 countries and territories under study, 198 (92.1%) had MAEs <10 and 187 (87.0%) had Pearson correlation coefficients >0.8. For the 215 countries and territories, the mean MAE was 5.42 (range 0.26-15.32), the mean RMSE was 9.27 (range 1.81-24.40), the mean Pearson correlation coefficient was 0.89 (range 0.08-0.99), and the mean Spearman correlation coefficient was 0.84 (range 0.2-1.00). The results show that the longer the training time and the greater the amount of available data, the higher the prediction accuracy	**High (5/5)**
Yang, 2020 (113)	NN	Broader public-health measures ▪***Predicting spread and pandemic tracking***	The authors found that the epidemic of China should peak by late February with 59,764 (95% CI: 51,979–70,172) cases, showing gradual decline by end of April 2020. A five-day delay in implementation would have increased epidemic size in mainland China three-fold. Lifting the Hubei quarantine would lead to a second epidemic peak in Hubei province in mid-March and extend the epidemic to late April 2020 a result corroborated by the machine learning prediction. The dynamic SEIR model was effective in predicting the COVID-19 epidemic peaks and sizes. The implementation of control measures on January 23, 2020, was indispensable in reducing the eventual COVID-19 epidemic size. The total epidemic size is predicted to be 122,122 (95% CI: 89,741–156,794) cases. There was a remarkable fit between the actual number of new confirmed cases and the LSTM-predicted curve between January 22 and the February 10. Both the SEIR and LSTM model predicted a peak of 4,000 daily infection between February 4 and 7 of 2020.	**High (5/5)**
Mao, 2021 (114)	Big data/Digital contact tracing	Broader public-health measures ▪***Predicting spread and pandemic tracking***	Quickly and accurately identify and trace 10,871 contacts among hundreds of thousands of epidemic data records; 378 closest contacts and several public places with high risk of infection were identified. A confirmed patient was found after quarantine measures were implemented by all contacts. The study provides a graphical representation of the contact tracing: (A) contacts associated with travel, (B) contacts associated with >2 confirmed cases, and (C) contacts associated with private cars. The results show that the digital contact tracing in Hainan Province is compatible with multisource heterogeneous epidemic big data; it can quickly and accurately find close, second-degree, or third-degree contacts, and it can identify public places with high risk of infection.	**High (5/5)**
Gomes da Silva, 2020 (115)	Bayesian regression neural network, cubist regression, k-nearest neighbors, quantile random forest, and support vector regression	Broader public-health measures ▪***Predicting spread and pandemic tracking***	In this experiment, regarding the Brazilian states, 150 scenarios (5 datasets, 3 forecasting horizons, and 10 models) were evaluated for the task of forecasting cumulative COVID-19 cases. In an overview, the best models for each state, obtained sMAPE ranged between 1.14% - 3.05%, 1.06% - 2.79%, and 1.05% - 3.03% for ODA, TDA, and SDA forecasting, respectively. In the Brazilian context, the ranking of the model in all scenarios is VMD–CUBIST, VMD–BRNN, SVR, CUBIST, VMD–SVR, BRNN, VMD–QRF, QRF, VMD–KNN, and KNN. USA: In an overview, the best models for each state, obtained sMAPE ranged between 0.54% - 1.90%, 0.55% - 1.59%, and 0.62% - 3.08% for ODA, TDA, and	**Mode rate (4/5)**

			SDA forecasting, respectively. In the American context, the ranking of the models in all scenarios is VMD–CUBIST, BRNN, CUBIST, SVR, VMD–BRNN, VMD–SVR, VMD–QRF, QRF, KNN, and VMD–KNN model. In general, the hybridization of VMD outperformed single forecasting models regarding the accuracy, specifically when the horizon is six-days-ahead, the hybrid VMD–single models achieved better accuracy in 70% of the cases. Regarding the exogenous variables, the importance ranking as predictor variables is, from the upper to the lower, past cases, temperature, and precipitation.	
Guo, 2021 (116)	ANN	Broader public-health measures ▪***Predicting spread and pandemic tracking***	With data of the confirmed cases and deaths from COVID-19 from the WHO form January 21,2020 to November 11,2020, these authors developed a model using artificial neural networks with one hidden layer to predict the number of new cases and death. They found that the best simulating model with performance indices of RMSE, R, and MAE is realized using the 7 past days' cases as input variables in the training and test dataset. And, using the ANN model, they predicted the confirmed cases and deaths of COVID-19 from June 5, 2020, to November 11, 2020.	**Moderate (4/5)**
Khan, 2021 (117)	ML	Broader public-health measures ▪***Predicting spread and pandemic tracking***	Using data from each prefecture in China which includes case counts, mortality, recovery, temperature, population density, and demographic information, the authors created a model using unsupervised machine learning. They found R0 may be affected (i.e., worsened) by higher temperature, and the prefectures having older population likely favored its transmission. The mean R0 for the COVID-19 ranges from 1.58 to 2.24 and is significantly larger than 1 and is consistent with the other estimations for the human-to-human (direct) transmission ranged from 1.3 to 7.7.	**Moderate (4/5)**
Kwak, 2021 (118)	Dueling Double Deep Q-Network (D3QN) which is a variant of Deep Q-Network among deep RL algorithms	Broader public-health measures ▪***Predicting spread and pandemic tracking***	Full lockdowns (L2) and closure of all borders (T2) were always only applied after index case date in each country or territory. Overall, early implementation of any or full lockdown and travel restriction policies were associated with progressively lower levels of crisis severity. In general, the agent proposed lockdown or travel restriction policy at level one earlier than when it was implemented by governments. The agent suggested to initiate at least minimal intensity of lockdown or travel restriction even before or on the day of the index case in each country and territory. In addition, proposed action timing from the agent did not deviate from the actual implementation dates for some countries and territories. In contrast, for some countries and territories, the agent suggested to delay policy implementation whereas governments took early action even though the number of cases did not grow exponentially. In general the intensity of both lockdown and travel restriction policies suggested by the agent were higher than government policies until April 2020. Overall, the agent opted for an earlier and shorter maximum lockdown and travel restriction (L2, T2) than governments. In general, earlier agent lockdowns when compared to government lockdown policy was related to a more rapid acceleration in cases. In contrast, earlier government closure of border compared to agent was not necessarily associated with slower acceleration of cases.	**Moderate (4/5)**

Andelic, 2021 (119)	Genetic programming	Broader public-health measures ▪***Predicting spread and pandemic tracking***	These authors created a model using genetic programming using data from the Johns Hopkins University from January 22, 2020, to April 8, 2020. With this data, the authors used the model to predict the pandemic spread in China, Italy, Spain, USA and in the world with R2 scores greater than 0.9 for confirmed, deceased, and recovered in the five predictions.	**Moderate (4/5)**
Malki, 2021 (120)	ML: decision tree algorithm	Broader public-health measures ▪***Predicting spread and pandemic tracking***	The proposed method has forecasted the possible confirmed cases for the upcoming 7 days for the USA. Experimental results showed that the confirmed cases are exponentially increasing from a few hundreds of thousands to nearly two and a half million. Similarly, the confirmed cases of the pandemic are forecasted and indicate that the predicted values are close to the test values. The prediction of the deadline for India show that the predicted number of confirmed cases will be 548,318 on August 05, 2021, and after three months, that is, on November 15, 2021, the number of confirmed cases will remain 156. USA will have 2,379,799 confirmed cases on August 17, 2021, and three months (on November 30, 2021), the expected number of positive cases in 1147 patients. The results forecasted that the COVID-19 infections will greatly decline during the first week of September 2021 when it will be going to an end shortly afterward. The experimental results of the proposed model showed that the overall R2 is 0.99 from the perspective of confirmed cases and R2 values for deaths, recoveries are 0.99 and 0.99, respectively. To validate the performance of the proposed method, authors used root mean square error on each of the three attributes namely confirmed cases, recoveries and death.	**Moderate (4/5)**
Pourghasemi, 2020 (121)	ML: ARMA, LASSO, RF	Broader public-health measures ▪***Predicting spread and pandemic tracking***	The results show that from February 19 to June 14, 2020, the average growth rates (GR) of COVID19 deaths and the total number of COVID-19 cases in Iran were 1.08 and 1.10, respectively. Iran's fatality rate is 10.53. Other countries' fatality rates were, for comparison, Belgium – 83.32, UK – 61.39, Spain – 58.04, Italy – 56.73, Sweden – 48.28, France – 45.04, USA – 35.52, Canada – 21.49, Brazil – 20.10, Peru – 19.70, Chile – 16.20, Mexico– 12.80, and Germany – 10.58. The fatality rate for China is 0.32. Over time, the heatmap of the infected areas identified two critical time intervals for the COVID-19 outbreak in Iran. The heatmap of countries of the world shows that China and Italy were distinguished from other countries in terms of nine viral infection related parameters. The regression models for death cases showed an increasing trend but with some evidence of turning. The third-degree polynomial regression model for deaths showed an increasing trend recently, indicating that subsequent measures taken to cope with the outbreak have been insufficient and ineffective. The general trend of deaths in Iran is similar to the world's, but Iran's shows lower volatility. Change detection of COVID-19 risk maps for the period from March 11 to March 18 showed an increasing trend of COVID-19 in Iran's provinces. The most important variables were the distance from bus stations, bakeries, hospitals, mosques, ATMs (automated teller machines), banks, and the minimum temperature of the coldest month.	**Moderate (4/5)**

Rashed, 2021 (122)	ML	Broader public-health measures ▪***Predicting spread and pandemic tracking***	Using a LSTM based neural network model with data of the cases from the Japanese Ministry of Health, Labour, and Welfare, meteorological data from the Japan Meteorological Agency and mobility from NTT DoCoMo, Inc., the authors created and validated a forecasting model with an average relative error ranging from 16.1% to 22.6% in major regions of Japan.	**Moderate (4/5)**
Ohi, 2020 (123)	RL	Broader public-health measures ▪***Predicting spread and pandemic tracking***	Describe the use of a model based on RL to try to predict the result applying restrictive measures regarding the increase in the number of covid-19 cases. They introduce a virtual environment that mostly relates to a pandemic situation, and sedulously investigate new tactics to mitigate disease by applying reinforcement learning. In what follows, they perform a pensive analysis of the impact of lockdown, social-distancing, and using agent-based solutions to prevent the mitigation of disease. They find the proposed scheme to be convincing in achieving optimal decision balancing the overweening pandemic and economic situation.	**Moderate (4/5)**
Alzayed, 2020 (124)	ANN	Broader public-health measures ▪***Predicting spread and pandemic tracking***	As the main public concern in Malaysia is whether the COVID-19 spread will continue for the upcoming few months, the authors provide information on predicting the epidemic peak using the SEIR model, estimating the infection rate using the GA algorithm, and short-time forecasting using the ANFIS model. The results also show that the infection rate is 0.228 ± 0.013, while the basic reproductive number is 2.28 ± 0.13	**Moderate (4/5)**
Jung, 2020 (125)	DL, NN	Broader public-health measures ▪***Predicting spread and pandemic tracking***	New model of this study could be employed for short-term prediction of COVID-19, which could help the government prepare for a new outbreak. In addition, from the perspective of measuring medical resources, our model has powerful strength because it assumes all the parameters as time-dependent, which reflects the exact status of viral spread. Research technical advantages: 1) It computes the effective and time-dependent reproduction numbers without any assumptions. 2) No need to artificially divide the phases because the results including S, I, and R and the parameters are naturally time dependent. 3) Rather than using statistical inference techniques as in previous research, the authors applied a neural network to solve the forward-inverse problem consisting of the SIR model and its parameters. Therefore, this method gives deterministic and more accurate values without any statistical uncertainty.	**Moderate (4/5)**

Vaid, 2020 (126)	ML	Broader public-health measures ▪***Predicting spread and pandemic tracking***	First, the effective growth rate of covid-19 infections dropped in response to the approximate dates of key policy interventions. We find that the change points for spreading rates approximately coincide with the timelines of policy interventions across respective countries. Second, forecasted trend until mid-June in the USA was downward trending, stable, and linear. Sweden is likely to be heading in the other direction. That is, Sweden's forecasted trend until mid-June (2020) appears to be non-linear and upward trending. Canada appears to fall somewhere in the middle—the trend for the same period is flat. Third, a Kalman filter-based robustness check indicates that by mid-June the USA will likely have close to two million virus cases, while Sweden will likely have over 44,000 covid-19 cases. The findings suggest that infections did not slow down as rapidly in Sweden compared with USA and Canada. We infer that the likely reason is Sweden's relatively relaxed policy intervention.	**Moderate (4/5)**
Shastri, 2021 (127)	DL (long short-term memory (LSTM))	Broader public-health measures ▪***Predicting spread and pandemic tracking***	The forecasted Covid-19 confirmed cases of India shows significant upward trend for some more time in the future. For Covid-19 confirmed cases the model achieved an accuracy of 97.59% and for death cases, it is 98.88%. MAPE value for both the experiments aimed Covid-19 confirmed and death cases are 2.40 and 1.11 respectively. Contactless treatment is possible only with the help of AI assisted automated health care systems. Furthermore, remote location self-treatment is one of the key benefits provided by AI based systems	**Moderate (4/5)**
Wang, 2020 (128)	Tuple-based Multi-Task NN (TMT-NN)	Broader public-health measures ▪***Predicting spread and pandemic tracking***	From the results, the authors conclude that the model obtains strong performance for patient information task, and event and social relation extraction are more challenging than patient information extraction. Regarding to social relation task, its performance looks worse since social relation terms are very sparse in the dataset. For the second task - infection network inference and infection source identification, they totally select 316 case reports from Shenzhen city and 35 case reports from Tianjin city to validate the implementation of epidemiological inference engine. For Shenzhen dataset, they got 316 nodes, and 100 edges in Step 1. In Step 2, they got 217 groups, among them 61 groups with more than one patient. The max group in Shenzhen data is 8-patient group. In Step 3, for the maximum group, they generated 52 alternative subgraphs and after comparing them by using 4 rules, they got the final inferred infection graph with one source node, 7 edges. Authors conclude that in Shenzhen, most of infections happen among social relations, mainly within family.	**Moderate (4/5)**
Watson, 2021 (129)	ML	Broader public-health measures ▪***Predicting spread and pandemic tracking***	The authors created a random forest algorithm embed with a Bayesian time series model within an epidemiological compartmental model (SIRD) for empirically grounded COVID-19 predictions using the COVID Tracking Project database of confirmed and death cases in the US. This model was used to project infections and death through April 1, 2020, in the states of New York, Colorado and West Virginia with good accuracy. This model cannot account the influence of public health interventions.	**Moderate (4/5)**

Huang, 2021 (130)	ML	Broader public-health measures ▪***Predicting spread and pandemic tracking***	The results show that the number of daily confirmed cases, number of active cases, or growth rate of daily confirmed cases of COVID-19 are exhibiting a significant downward trend in Qatar, Egypt, Pakistan, and Saudi Arabia under the current interventions (school closures, stay-at-home requirements, workplace closures, restrictions on public gatherings, public information campaigns, closures of public transport, restrictions on internal movements, cancellation of public events, and international travel controls), although the total number of confirmed cases and deaths is still increasing. Iran and Iraq may continue to rise in active cases and total confirmed cases with no significant downward trend in the daily growth rate, which indicates that one cannot be optimistic and the response must be further strengthened.	**Moderate (4/5)**
Amaral, 2020 (131)	ANN	Broader public-health measures ▪***Predicting spread and pandemic tracking***	Quantitative and Qualitative Analyses: The analysis was performed in terms of the following Covid-19 indicators: accumulated, recovered and deceased cases. São Paulo State Regions: All the MAPE errors were lower than 1, except the Coastal region, where a MAPE of 1.2 was calculated. Regarding RMSE, regions presented very low errors, whose values were on the order of 10−2 on average. The proposed model reached a very accurate agreement between the true data and the forecasts of accumulated, recovered and deceased cases in São Paulo state. Brazilian Regions: The MAPE and RMSE, for the accumulated, recovered and deaths were numerically consistent and reliable. To provide further evidence concerning the feasibility of the current methodology, authors investigated the spread of Covid-19 for three different data sets: Italy, Portugal and Ukraine, considering the data provided by Johns Hopkins University, from 25 October to 3 December. The results confirm that the SIRD model enhanced by a learning scheme can be successfully applied to inspect the Covid-19 spread in several regions of the world.	**Moderate (4/5)**
Ahmad, 2020 (132)	ANN	Broader public-health measures ▪***Predicting spread and pandemic tracking***	This study utilized a supervised ANN is used which is trained based on the collected data of past few days and is used to make predictions of increasing rate of coronavirus confirmed cases, deaths and number of people who have recovered from this disease. The data gathered in this research study have been collected from the repository of Centre for System Science and Engineering (CSSE) at Johns Hopkins University and divided into three different categories with time interval of 24 h cumulative total number of confirmed cases of coronavirus-infected people increasing daily; second, the total counted deaths due to the virus and third is those who have recovered from the virus and discharged from hospitals. This study aims to presented and future predictions for the next 7 days and help to make decisions about public health. the effect of variable parameters on three different cases infected, deaths and recoveries on daily basis are shown which would help the Government for the future safety of people and to control the spread of pandemic if the same practice remains continues.	**Moderate (4/5)**

Chen, 2021 (133)	NN	Broader public-health measures ▪***Predicting spread and pandemic tracking***	These authors developed a short-term forecasting model to predict the COVID-19 pandemic in Canada, for this, they used an open access database from February 24, 4040 to August 16,2020 with the infected cases and deaths for each jurisdiction in Canada. Then, they applied three models: smooth transition autoregressive (STAR) models, neural network (NN) models, and susceptible-infected-removed (SIR) models. They found the NN model provided a more accurate values than the other models, with a bigger prediction error as the period of prediction increased,	**Moderate (3/5)**
Khalilpourazari, 2021 (134)	ES	Broader public-health measures ▪***Predicting spread and pandemic tracking***	These authors proposed a method based on Gradient-based grey wolf optimizer with Gaussian walk to solve complex optimization problems using metaheuristics. With this method they apply the algorithm to forecast the spread of COVID-19 in the US in mid-to-end November 2020 in terms of infected and hospitalized cases using as a base a differential equations model (SIDARTHE) with a solution with better accuracy and less error.	**Moderate (3/5)**
Kim, 2021 (135)	NN	Broader public-health measures ▪***Predicting spread and pandemic tracking***	With datasets of COVID-19 cases, mobility and environment from different cities of Japan and in different timeframe per city these authors created a random forest regression-based model for forecasting the pandemic in Japan which provided the input for a SEIR. This model could predict the number of cases in these cities of Japan despite the variation in climate, and population dynamics.	**Moderate (3/5)**
Alanazi, 2020 (136)	ML	Broader public-health measures ▪***Predicting spread and pandemic tracking***	The reproductive rate shows that measures such as government lockdowns and isolation of individuals are not enough to stop the pandemic. Despite the reproductive rate being low, the pandemic will increase, and the trend lines explain that the interventions by governments or individual isolation are not enough to stop the pandemic. The lockdown case delays the peak point by decreasing the infection and affects the area equality rule of the infected curves. On the other side, new medicines have a significant impact on infected curve by decreasing the number of infected people about time.	**Moderate (3/5)**
Shahid, 2020 (137)	AI	Broader public-health measures ▪***Predicting spread and pandemic tracking***	These authors created a model for short-term forecast the COVID-19 epidemic using an ARIMa, support vector regression, LSTM, and Bi-LSTM models using a global dataset form January 22, 2020, to June 27, 2020 using the first 110 days to train the model and the other 48 days to validate. The Bi-LSTM model outperforms in terms of endorsed indices with a MAE and RMSE values of 0.0070 and 0.0077, respectively, for deaths in China.	**Moderate (3/5)**
Lmater, 2020 (138)	ML	Broader public-health measures ▪***Predicting spread and pandemic tracking***	Authors conducted a comparative simulation to evaluate the effectiveness of the drastic control measures taken by the Moroccan government. After the first period (15 days from the first diagnosed case), the Moroccan government has decided to shut down schools' cafes and mosques, one day after suspending international flights, this period was considered to represent the spread of the virus with no countermeasures, the number of diagnosed cases would have reached the peak in about 116 days (15 June) instead of 53 (23 April) and with several positive cases approaching 600 K. The simulation proves that the control measures helped contain the pandemic, thus flattening the curve and reducing the virus's spread speed. The full control measures include	**Moderate (3/5)**

			imposing full quarantine except for necessary businesses with social distancing on March 20th, followed by the prohibition of movement between cities which made containing and dismantling small contagion areas and preventing mass spread, the third measures consisted in making the use of facemasks mandatory which reduced the probability of contagion.	
Zhang, 2021 (139)	Genetic algorithm	Broader public-health measures ▪***Predicting spread and pandemic tracking***	This study presents a hybrid model for prediction of the COVID-19 spread dynamics, for this the authors used a SIQR model with GA used to optimize the parameter of the model and to model the effect of different public health actions (such as government investment, media publicity, medical treatment, and law enforcement) to limit the rate of spreading, using data from Brazil (from February 26 to October 13, 2020) to predict the number of confirmed per day (of the last 17 days before October 13,2020), with accurate estimates.	**Mode rate (3/5)**
Bird, 2020 (140)	ML	Broader public-health measures ▪***Risk stratification***	In this study, the authors used a machine learning approach to classify the countries according to their pandemic risk and preparedness. For this, the authors used the strategy of Leave One Out-cross validation (LOO-Cv) to find the better model using Stack of Gradient Boosting and Decision Tree algorithms for risk of transmission, a Stack of Support Vector Machine and Extra Trees for risk of mortality, and a Gradient Boosting algorithm for the risk of inability to test. Using data from September 2020 they classify the countries in four groups (low, med-low, med-high, high) with similar characteristics.	**High (5/5)**
Scarpone, 2020 (54)	Bayesian Additive Regression Trees (BART)	Broader public-health measures ▪***Risk stratification***	Natural log-transformed age-adjusted incidence rates indicated spatial variation between the northeast and south-southwest of the study area, facilitating an empirical classification of the study area into two epidemic subregions. The results of the trend analysis indicate no apparent correlation between longitude and incidence rates. The LISA results indicate a large cluster of high rates was observed in the south, whereas the northern and eastern regions exhibit a cluster of low rates. These trend analysis and LISA results indicate the presence of two distinct spatial patterns within Germany, enabling the classification of all federal states into two regions for the subsequent analysis: High-Rate Regions (HRR, referring to the southern cluster) and Low-Rate Regions (LRR, referring to the northern cluster). The North/LRR accounts for 48.5% (173,287 km2) of the total land area and 35.6% of the population, and the South/HRR for 51.5% (183,887 km2) of the total land area and 74.4% of the total population of Germany. The southwestern region has a greater representation of higher incidence rates where X = 98.96 cases per 100,000 and σ = 70.73 and minimum and maximum incidence rates of 20.60 and 673.93. The northern region has less proportion of counties, with the X = 41.92 and σ = 25.95 with county-level rates ranging from 5.76 to 139.10. All preliminary and final models indicated that location, densities of the built environment, and socioeconomic variables were important predictors of incidence rates in Germany. The BART, partial dependence, and GAM results indicate that the strongest predictors of COVID-19 incidence at the county scale were related to community interconnectedness, geographical location, transportation infrastructure, and labor market structure.	**High (5/5)**

Haug, 2020 (141)	ML: LASSO, RF and TF.	Broader public-health measures ▪***Outbreak management***	The results indicate that a suitable combination of NPIs is necessary to curb the spread of the virus. Less disruptive and costly NPIs can be as effective as more intrusive, drastic, ones (for example, a national lockdown). Global approach. Social distancing and travel restrictions are top ranked in all methods, whereas environmental measures (for example, cleaning and disinfection of shared surfaces) are ranked least effective. Six NPI categories show significant impacts on Rt in all four methods. Among the six full consensus NPI categories in the CCCSL, the largest impacts on Rt are shown by small gathering cancellations (83%, ΔRt between −0.22 and –0.35), the closure of educational institutions (73%, and estimates for ΔRt ranging from −0.15 to −0.21) and border restrictions (56%, ΔRt between −0.057 and –0.23). The consensus measures also include NPIs aiming to increase healthcare and public health capacities (increased availability of personal protective equipment (PPE): 51%, ΔRt −0.062 to −0.13), individual movement restrictions (42%, ΔRt −0.08 to −0.13) and national lockdown (including stay-at-home order in US states) (25%, ΔRt −0.008 to −0.14). Among the least effective interventions they found: government actions to provide or receive international help, measures to enhance testing capacity or improve case detection strategy, tracing and tracking measures as well as land border and airport health checks and environmental cleaning. Findings on NPI effectiveness in a co-implementation network: A pattern where countries first cancel mass gatherings before moving on to cancellations of specific types of small gatherings, where the latter associates on average with more substantial reductions in Rt. Education and active communication: Within the CC approach, the most effective communication strategies include warnings against travel to, and return from, high-risk areas and several measures to actively communicate with the public. Validation with external datasets: The CCCSL results were compatible with findings from the CoronaNet dataset2 and the WHO-PHSM. Country-level approach: In general, social distancing measures and travel restrictions show a high entropy (effectiveness varies considerably across countries) whereas case identification, contact tracing and healthcare measures show substantially less country dependence. It was found a robust tendency that NPI effectiveness correlates negatively with indicator values for governance-related accountability and political stability (as quantified by World Governance Indicators provided by the World Bank).	**Moderate (4/5)**
Eastman, 2021 (142)	ML	Broader public-health measures ▪***Predicting spread and pandemic tracking***	A key result of the model, following from the variable transmission rate, is the prediction of the occurrence of a second wave using the most current infection data and disease-specific traits. The qualitative behavior of different future transmission-reduction strategies is examined, and the time-varying reproduction number is analyzed using existing epidemiological data and future projections. Importantly, the effective reproduction number, and thus the course of the pandemic, is found to be sensitive to the adherence to public health policies, illustrating the need for vigilance as the economy continues to reopen. Importantly, the appearance of a second wave is found to depend sensitively on the public	**High (5/5)**

		▪***Strategies to support adherence to public-health measures***	response. Indeed, a slight decrease from the critical value of θ(t) leads to a significant second wave of infections that continues to peak for many months into the future. Importantly, the method for calculating θ critical developed here can be used as a benchmark to calculate the approximate level of adherence to public health policies. Importantly, the significance of θ critical in distinguishing the nature of the future pandemic progression was reflected in our projections of the pandemic. We saw that maintaining supercritical public adherence, i.e., θ(t) > θ critical, leads to a decrease in active infections, while reducing public adherence below θ critical can lead to an exponential increase in infections and a surge in case fatalities over a period of several months. Increasing θ(t) well beyond θ critical leads quickly to a decline in active cases and a saturation in case fatalities. This means that a near perfect adherence to public health advice could efficiently dampen the pandemic over a period of months. One of the main tactics the public can employ to combat the SARS-CoV-2 virus is social distancing: Indeed, the effective reproduction number of the virus is highly sensitive to the public response. One particularly effective strategy supported by this work is the pulsing of public response measures, at two-week intervals, between two different values of public adherence. This situation leads to a decay in active case numbers over a period of a few months, while still permitting a degree of socialization.	
Qin, 2020 (56)	DL, NN.	Broader public-health measures • ***Strategies to support adherence to public-health measures***	The proposed SRCNet achieved 98.70% accuracy and outperformed traditional end-to-end image classification methods using deep learning without image super-resolution by over 1.5% in kappa. These findings indicate that the proposed SRCNet can achieve high-accuracy identification of facemask-wearing conditions, thus having potential applications in epidemic prevention involving COVID-19. The SRCNet identifies different types of facemask-wearing conditions with high accuracy, like: CFW=correct facemask-wearing (green), IFW=Incorrect facemask-wearing (yellow), NFW= No facemask-wearing (red). The SRCNet can also identify facemask-wearing condition with different facemask colors, which means that the SRCNet is robust. As analyzed from failed cases, the critical states (wearing facemask between CFW and IFW), image quality, and blocked faces were the three main reasons for identification errors. The ways of wearing facemasks were continuous variables, while the classification results were discrete; hence, critical states were one of the main causes of misidentification. *Besides, when the image quality was low (e.g., low-resolution, blocking artifacts, ringing effects, and blurring) or when the faces were partly occluded by objects or other faces, SRCNet had a higher error rate. In addition, SRCNet was likely to make bias errors when the color of a facemask was close to the facial skin color.	**High (5/5)**
Roma, 2020 (143)	ML	Broader public-health measures	Significantly lower scores in behavioral compliance than efficacy perception. Risk perception and civic attitudes as moderators rendered the mediating effect of self-efficacy insignificant. Perceived efficacy on the adoption of recommended behaviors varied in	**Mode rate (4/5)**

		Strategies to support adherence to public-health measures	accordance with risk perception and civic engagement. The 14 collected variables, entered as predictors in machine learning models, produced an ROC area in the range of 0.82–0.91 classifying individuals as high versus low compliance. This underline that the most important variable for compliance with the recommended health behaviors is perceived efficacy, as has been consistently indicated by previous studies on behavioral responses to epidemics. Individuals who perceive themselves as able to carry out (i.e., those with self-efficacy) those behaviors judged as effective in reducing the threat (i.e., behaviors with perceived efficacy) are more likely to comply with the government measures. Younger persons and those with higher education levels are less likely to comply with the recommended measures, especially those related to hygiene. Overall personality functioning may be significant in influencing individuals to adopt the protective measures recommended by authorities. For this reason, personality functioning should be assessed more frequently, and those already known to have a personality impairment (e.g., clinical patients) should be supported and controlled more promptly than others. Both risk perception and civic attitudes were found to significantly moderate the relationship between perceived efficacy and compliance. The current finding of a link between civic attitudes and preventive health actions suggests the importance, for instance, of teaching civic education in the early school grades.	
Rahim, 2021 (144)	DL	Broader public-health measures ***Strategies to support adherence to public-health measures***	The model exhibited overall good performance in low light environments, no false positive is detected in any of the frames, whereas the number of false negatives is also low. Precision values remained constant from Frame 1 to Frame 15. To evaluate the performance of the social distance monitoring solution, they perform few tests at three different fixed camera distances 400 cm, 500 cm, and 600 cm. At each specific fixed camera distance, they tested 2 scenarios one above the specified safety threshold (100 cm) at 140 cm and one below the specified safety threshold at 52 cm. The model exhibited overall good performance. People violating the safety distance are highlighted by red bounding boxes, whereas green bounding boxes show people following safety distance criteria. Experimental results show that the proposed model exhibits good performance with 97.84% mean average precision (mAP) score and the observed mean absolute error (MAE) between actual and measured social distance values is 1.01 cm.	**Moderate (4/5)**
Yang, 2021 (145)	Convolutional NN (CNN)	Broader public-health measures ***Strategies to support adherence to public-health measures***	Real-Time Pedestrian Detection The authors experimented with two different deep-CNN-based object detectors: Faster R-CNN and YOLOv4, both detectors achieved an inference time of about 0.1s per frame. Social Distancing Violation Detection The change of pedestrian density ρ and the number of violations v as time evolves indicates a positive correlation between ρ and v. This correlation leads to the subsequent proposed linear regression method to identify critical social density. The precision, recall, and	**Moderate (4/5)**

			accuracy of the violation detection compared over the methods of End-to-End CNN, BB-center, and BB-bottom, shows that the BB-bottom method performs better than the other two methods in all three metrics. Critical density ρc v increases with an increase in ρ, which shows a linear relationship with a positive correlation. The skewness values of ρ for the Oxford Town Center Dataset, Mall Dataset, and Train Station Dataset are 0.32, 0.16, and −0.14, respectively, indicating the distributions of ρ are symmetric. The obtained critical density values for all datasets are similar. To evaluate the effect of social distancing detection on determining the critical density, authors conducted the linear regression on the data of ground truth pedestrian positions in the Oxford Town Center Dataset. The obtained regression result over ground truth pedestrian positions are β0, gt = 0.0217 and ρc, gt = 0.0086. The critical density ρc only has an error of 2%.	
Shams, 2021 (146)	ML	Broader public-health measures ***Strategies to identify and address misinformation***	This study's main objective was to evaluate the potential ML-based approach integrated with search engine extension for notifying any public health misinformation during this COVID-19 pandemic. This numerical data is then inputted into a trained ML algorithm that classifies the query's integrity and notifies its authenticity to the user using a message box on the screen. The overall procedure transpires in real-time to alert the user of potential misinformation pitfalls before clicking on any search results. This may significantly help to prevent the spread of misinformation. SEMiNExt can successfully prevent the depletion of healthcare resources: in novel disease outbreaks, resource management in healthcare can be overwhelming because the demand is dynamic. They proposed method can be extended to real-time healthcare resource management	**Mode rate 4/5**
Liu, 2020 (147)	NN	Service planning for COVID-19 treatment	Different formats of forecasted sales values, such as decimal or integer, can lead to significantly different performance in small demand problems. Six other benchmark methods are also applied, namely Syntetos and Boylan's method, GM, SVM, MS, ELM and NN. The experimental of this study results show that the performance of the proposed method outperforms others. The findings suggest that due to the complexity of sales data, managers should consider model selection, and sMDL-NN is an ideal candidate model to achieve this goal. Different formats of forecasted sales values, such as decimal or integer, can lead to significantly different performance in small demand problems. Although it is common for forecasting methods to use decimal number sales values, only integers can be used because we cannot order or deliver a part of the Stock Keeping Unit (SKU)	**Mode rate (4/5)**
Bednarski, 2021 (60)	DL	Service planning for COVID-19 treatment	This study aims to facilitate the near optimal redistribution of medical equipment in order to bolster public health responses to future crises similar to the COVID-19 pandemic. These authors created a three-stage algorithm where input data (derived from the current demand of medical supplies) are processed, the demand were inferenced using LSTM and then the final needs for medical supplies. They found this algorithm demonstrates performance optimality ranging from 93% to 95%. Performance improves consistently with	**Mode rate (3/5)**

			the number of random states participating in exchange, demonstrating average shortage reductions of 78.74 6 30.8% in simulations with 5 states to 93.50 6 0.003% with 50 states.	
Chandra, 2021 (148)	Bayesian NN	Areas where AI and emerging digital technologies can support economic and social responses	In general, RMSE for all the given stocks improved by reducing for Setup-2. Setup-2 gives a better performance with much lower error (RMSE) when compared to Setup-1. Given that authors add the first half of period affected by COVID-19 into the training set, the error during Setup-2 significantly decreases, but become larger with the prediction horizon. Among the respective stocks, the prediction of stock 600118.SS performs the best for Setup-2. ed to Setup 1. The stocks show high volatility in general during COVID-19. The results indicate that due to high volatility in the stock-price during COVID-19, it is more challenging to provide forecasting. However, Bayesian neural networks could provide reasonable predictions with uncertainty quantification despite high market volatility during the first peak of the COVID-19 pandemic.	**High (5/5)**

Conclusions

The COVID-19 pandemic has been the setting in which a large amount of research and publications demonstrate how artificial intelligence and emerging digital technologies can improve public health outcomes. One of the most prominent examples in the literature is the development of prediction models to determine the course of the pandemic, mainly the spread and pandemic tracking. These models have used different approaches with different types of machine learning and neural networks with mixed results. The models for the prediction of the COVID-19 dynamic have used different variables including the trend of cases, recovered and deaths, mobility data, environmental and sociocultural to augment the precision of these models. We identified many new models to predict the dynamics of COVID-19 in different scenarios, but there is a lack of validation studies.

The pandemic also highlights impressive technological advances using image analysis and web applications. There have been multiple research initiatives to use AI and derived imaging recognition technologies to support the adherence to public health measures. This includes the use of software in close caption cameras (in streets and indoors) to identify the use of face masks, to evaluate whether people are enforcing social distancing measures, and to identify people with high body temperature (as a proxy to the identification of the fever of the COVID-19 disease).

There are important global initiatives to share large databases that allow researchers and decision makers to guide the response to the pandemic. There have been a lot of new initiatives to use big data and AI to forecast and contact tracing the COVID-19 epidemic, using public databases such as the US 'Centers for Disease Control and Prevention and the Johns Hopkins University databases as well as local and regional data from public health authorities.

We did not identify any research focused on the following public health activities: **infection prevention (Vaccination), approach to population-health management for COVID-19 and for those whose care is disrupted by COVID-19, service planning for COVID-19 prevention, or treatment** (except for supporting medical equipment processes). These are gaps in the current literature.

There are some limitations to this review to highlight. We did not retrieve any comparative study such as cohorts, case-control, quasi-experimental studies, or randomized trials, that had measured differences in public health outcomes. Therefore, the evidence to support its use of AI in COVID -19-related public health activities remains scarce. Appropriately designed comparative studies, ideally randomized trials, are warranted, in this field. Also, as this is a rapid review, and as such we initially focused on evidence synthesis, and complement them with targeted searches to activities not covered by them, we cannot guarantee we have not missed relevant evidence related to public health activities published after the evidence syntheses search dates

Summary statements for decision makers

Some AI strategies that might be considered by decision makers for supporting public health decisions or some health policies related to COVID-19. Below, we present a summary of them and their potential uses.

1. *Logistic regression, gradient boosting and random forest* are promising artificial intelligence approaches may improve testing /detection of cases activities.
2. *Mining social media using natural language processing* may be a successful resource for identifying and addressing misinformation.
3. *Automated text processing models, involving machine learning and neural language models* could be useful for increasing the efficiency of contact tracing.
4. Strategies involving *Smartphone-based tracing and machine learning algorithms, such as K-Means clustering* may be an effective approach to guide decision makers on how lockdown/mass quarantine can be safely lifted.
5. Since high-quality studies addressing the effectiveness of vaccination when administered at large scale or by population segment, population-health management or Service planning for COVID-19 prevention were not found, statements about their use cannot be made for these public health activities.
6. There is an urgent need of comparative studies that may determine the real effectiveness of the strategies and technologies described in points 1 to 5 that could measure public health outcomes, Decision-makers may want to consider funding comparative research to assess the effectiveness, cost-effectiveness and implementability of the AI strategies for supporting public health activities in Canada

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Appendix 1. Search strategies

First stage search

Medline-PubMed
Date: 17/08/2021

1. "Severe Acute Respiratory Distress Syndrome"[Title/Abstract] OR "SARS"[Title/Abstract] OR "MERS"[Title/Abstract] OR "sars cov"[Title/Abstract] OR "SARS-CoV-2"[Title/Abstract] OR "SARSCOV-2"[Title/Abstract] OR "SARSCOV2"[Title/Abstract] OR "COVID-19"[Title/Abstract] OR "COVID19"[Title/Abstract] OR "COVID"[Title/Abstract] OR "coronavirus disease"[Title/Abstract] OR "novel coronavirus"[Title/Abstract] OR "novel 2019 coronavirus"[Title/Abstract] OR "nCoV"[Title/Abstract] OR "2019nCoV"[Title/Abstract] OR "19nCoV"[Title/Abstract] OR "severe acute respiratory syndrome coronavirus 2"[Supplementary Concept] OR "COVID-19"[Supplementary Concept] OR "COVID-19"[MeSH Terms] OR "SARS-CoV-2"[MeSH Terms]	**177,424**
2. ("Artificial Intelligence"[MeSH Terms] OR "Machine Learning"[MeSH Terms] OR "Data Mining"[MeSH Terms] OR "Big Data"[MeSH Terms] OR "Data Science"[MeSH Terms] OR "Digital Technology"[MeSH Terms] OR "Artificial Intelligence"[Title/Abstract] OR "Machine Learning"[Title/Abstract] OR "Computational Intelligence"[Title/Abstract] OR "Machine Intelligence"[Title/Abstract] OR "Expert Systems"[Title/Abstract] OR "Fuzzy Logic"[Title/Abstract] OR "Knowledge Bases"[Title/Abstract] OR "Natural Language Processing"[Title/Abstract] OR "computer neural network*"[Title/Abstract] OR "artificial general intelligence"[Title/Abstract] OR "artificial narrow intelligence"[Title/Abstract] OR "AI technology"[Title/Abstract] OR "ML technology"[Title/Abstract] OR "computer reasoning"[Title/Abstract] OR "Deep Learning"[Title/Abstract] OR "computer vision system"[Title/Abstract] OR "support vector machine"[Title/Abstract] OR "hierarchical learning"[Title/Abstract] OR "Intelligent Assistive Technologies"[Title/Abstract] OR "Data Mining"[Title/Abstract] OR "Big Data"[Title/Abstract] OR "Data Science"[Title/Abstract] OR "neural network*"[Title/Abstract] OR "computer understanding"[Title/Abstract] OR "digital tech*"[Title/Abstract] OR "digital tool*"[Title/Abstract] OR "Transfer Learning"[Title/Abstract] OR "algorithm*"[Title/Abstract] OR "spatial-temporal"[Title/Abstract] OR "multisource Data"[Title/Abstract] OR "data-driven"[Title/Abstract] OR "IoMT"[Title/Abstract] OR "computational simulation"[Title/Abstract] OR "pattern recognition"[Title/Abstract])	**490,294**
3. 1 and 2	**6,118**
4. **(Applying the "Review" filter)**	**671**

BIREME-LILACS
Date 17/08/2021

1. ("Machine Learning") OR ("Artificial Intelligence") AND (covid-19) AND (db:("LILACS" OR "IBECS" OR "MULTIMEDIA" OR "PAHOIRIS" OR "SES-SP" OR "CUMED" OR "PREPRINT-SCIELO"))	**23**

Cochrane Library
Date: 27/08/2021

1. "machine learning" in Title Abstract Keyword OR "artificial intelligence" in Title Abstract Keyword AND covid-19 in Title Abstract Keyword - (Word variations have been searched)	**1**

Epistemonikos
Date: 27/08/2021

1. (title:(Artificial Intelligence) OR abstract:(Artificial Intelligence)) OR (title:(Machine Learning) OR abstract:(Machine Learning)) AND (title:(covid-19) OR abstract:(covid-19))	**26 6**

McMaster PLUS+
Date: 27/08/2021

1. ("Artificial Intelligence" OR "Machine Learning")	**319**

EMBASE (Ovid)
Date: 24/08/2021

1. (Severe Acute Respiratory Distress Syndrome or SARS or MERS or sars cov or SARS-CoV-2 or SARSCOV-2 or SARSCOV2 or COVID-19 or COVID19 or COVID or coronavirus disease or novel coronavirus or novel 2019 coronavirus or nCoV or 2019nCoV or 19nCoV).tw. 2. exp coronavirus disease 2019/ or exp Severe acute respiratory syndrome coronavirus 2/ 3. 1 or 2 4. (Artificial Intelligence or Machine Learning or Computational Intelligence or Machine Intelligence or Expert Systems or Fuzzy Logic or Knowledge Bases or Natural Language Processing or computer neural network$ or artificial general intelligence or artificial narrow intelligence or AI technology or ML technology or computer reasoning or Deep Learning or computer vision system or support vector machine or hierarchical learning or Intelligent Assistive Technologies or Data Mining or Big Data or Data Science or neural network$ or computer understanding or digital tech$ or digital tool$ or Transfer Learning or algorithm$ or spatial-temporal or multisource Data or data-driven or IoMT or computational simulation or pattern recognition).tw. 5. exp Artificial Intelligence/ or exp Machine Learning/ or exp Data Mining/ or exp Big Data/ or exp Data Science/ or exp Digital Technology/ 6. 4 or 5 7. 3 and 6 8. review.pt. 9. 7 and 8	**780**

Second stage search

Medline-PubMed
Date: 28/08/2021

"Severe Acute Respiratory Distress Syndrome"[Title/Abstract] OR "SARS"[Title/Abstract] OR "MERS"[Title/Abstract] OR "sars cov"[Title/Abstract] OR "SARS-CoV-2"[Title/Abstract] OR "SARSCOV-2"[Title/Abstract] OR "SARSCOV2"[Title/Abstract] OR "COVID-19"[Title/Abstract] OR "COVID19"[Title/Abstract] OR "COVID"[Title/Abstract] OR "coronavirus disease"[Title/Abstract] OR "novel coronavirus"[Title/Abstract] OR "novel 2019 coronavirus"[Title/Abstract] OR "nCoV"[Title/Abstract] OR "2019nCoV"[Title/Abstract] OR "19nCoV"[Title/Abstract] OR "severe acute respiratory syndrome coronavirus 2"[Supplementary Concept] OR "COVID-19"[Supplementary Concept] OR "COVID-19"[MeSH Terms] OR "SARS-CoV-2"[MeSH Terms] AND ("Artificial Intelligence"[MeSH Terms] OR "Machine Learning"[MeSH Terms] OR "Data Mining"[MeSH Terms] OR "Big Data"[MeSH Terms] OR "Data Science"[MeSH Terms] OR "Digital Technology"[MeSH Terms] OR "Artificial Intelligence"[Title/Abstract] OR "Machine Learning"[Title/Abstract] OR "Computational Intelligence"[Title/Abstract] OR "Machine Intelligence"[Title/Abstract] OR "Expert Systems"[Title/Abstract] OR "Fuzzy Logic"[Title/Abstract] OR "Knowledge Bases"[Title/Abstract] OR "Natural Language Processing"[Title/Abstract] OR "computer neural network*"[Title/Abstract] OR "artificial general intelligence"[Title/Abstract] OR "artificial narrow intelligence"[Title/Abstract] OR "AI technology"[Title/Abstract] OR "ML technology"[Title/Abstract] OR "computer reasoning"[Title/Abstract] OR "Deep Learning"[Title/Abstract] OR "computer vision system"[Title/Abstract] OR "support vector machine"[Title/Abstract] OR "hierarchical learning"[Title/Abstract] OR "Intelligent Assistive Technologies"[Title/Abstract] OR "Data Mining"[Title/Abstract] OR "Big Data"[Title/Abstract] OR "Data Science"[Title/Abstract] OR "neural network*"[Title/Abstract] OR "computer understanding"[Title/Abstract] OR "digital tech*"[Title/Abstract] OR "digital tool*"[Title/Abstract] OR "Transfer Learning"[Title/Abstract] OR "algorithm*"[Title/Abstract] OR "spatial-temporal"[Title/Abstract] OR "multisource Data"[Title/Abstract] OR "data-driven"[Title/Abstract] OR "IoMT"[Title/Abstract] OR "computational simulation"[Title/Abstract] OR "pattern recognition"[Title/Abstract]) AND (("health policy"[MeSH Terms] OR "implementation science"[MeSH Terms] OR "health plan implementation"[MeSH Terms] OR "policy"[MeSH Terms] OR "public polic*"[Title/Abstract] OR "public polit*"[Title/Abstract] OR "public health"[Title/Abstract] OR "social polic*"[Title/Abstract] OR "social polit*"[Title/Abstract] OR "health polic*"[Title/Abstract] OR "health polit*"[Title/Abstract] OR "healthcare polic*"[Title/Abstract] OR "health care polic*"[Title/Abstract] OR "healthcare polit*"[Title/Abstract] OR "health care polit*"[Title/Abstract] OR "international health"[Title/Abstract] OR "universal healthcare"[Title/Abstract] OR "global healthcare"[Title/Abstract] OR "global health"[Title/Abstract] OR "universal health"[Title/Abstract] OR "health management"[Title/Abstract] OR "health system*"[Title/Abstract] OR "healthcare system*"[Title/Abstract] OR "health care system*"[Title/Abstract] OR "healthcare program*"[Title/Abstract] OR "health care program*"[Title/Abstract] OR "health program*"[Title/Abstract] OR "infodem*"[Title/Abstract] OR "misinformation"[Title/Abstract] OR "disinformation"[Title/Abstract]) AND ("prevention and control"[MeSH Subheading] OR "diagnosis"[MeSH Subheading] OR "strateg*"[Title/Abstract] OR "plan*"[Title/Abstract] OR "intervention*"[Title/Abstract] OR "program*"[Title/Abstract] OR "prevention"[Title/Abstract] OR "control"[Title/Abstract] OR "mitig*"[Title/Abstract] OR "implementat*"[Title/Abstract] OR "vaccin*"[Title/Abstract] OR "screen*"[Title/Abstract] OR "test*"[Title/Abstract] OR "surveillance"[Title/Abstract] OR "diagnos*"[Title/Abstract] OR "outbreak	**1533**

management"[Title/Abstract] OR "risk stratification"[Title/Abstract] OR "predict*"[Title/Abstract] OR "forecasting"[Title/Abstract] OR "contact tracing"[Title/Abstract] OR "drug development"[Title/Abstract])))	

Appendix 2. Additional studies not presented in the results

Design	Article	Q/A
Systematic reviews	Gnanvi , 2021(62)	4/9
	Chen, 2020 (65)	4/9
	Mbunge, 2021(61)	3/9
	Musulin, 2021(63)	3/9
	Rodríguez-Rodríguez, 2021 (64)	1/9
	Corsi, 2020 (66)	1/9
	Alabool, 2020 (67)	1/9
Analytical Cross-sectional	Shearston, 2021 (77)	3/7
	Sitharthan, 2021 (78)	0/8
Modelling studies	Saba, 2021(92)	2/5
	Gray, 2021(90)	2/5
	Asgary 2020 (89)	2/5
	Zawbaa, 2020 (82)	2/5
	Sun, 2020 (83)	2/5
	Shen, 2020 (95)	2/5
	Jombart, 2021(85)	2/5
	Nguyen, 2020 (88)	2/5
	Tomar, 2020 (94)	2/5
	Toga, 2021(93)	1/5
	Tiwari, 2020 (91)	1/5
	Noh, 2021(79)	1/5
	Kasilingam, 2020 (81)	1/5
	Liu, 2020 (80)	0/5
	Aljaaf, 2020 (84)	0/5
	Fokas, 2020 (86)	0/5
	Villanustre, 2021(87)	0/5

Q/A: Quality assessment