Appendix

1 Glossary of model architectures

Model architectures were grouped into eight categories: graph neural network (GNN), recurrent neural network (RNN, including LSTM and GRU variants), convolutional neural network (CNN), transformer, hybrid mechanistic-ML models (models combining a physics-based model with ML), probabilistic/Bayesian model, classical machine learning (not based on neural networks e.g., random forest, XGBoost, support vector machine, naive Bayes, symbolic regression) and "other" for approaches fitting none of these (generative adversarial networks, radial basis function networks, pseudo-grouping adversarial learning, and a multilayer perceptron).

1.1 LSTM/GRU/RNN based models used in the included studies.

Model	Definition	Reference
Recurrent neural network (RNN)	Neural network that processes temporal, sequential data	[1]
Long short-term memory (LSTM)	Type of RNN which learns longer term dependencies in data	[2]
Bidirectional LSTM	Type of LSTM that processes sequences forwards and backwards	[3]
Gated recurrent unit (GRU)	RNN which uses gates to control information flow	[4]
Sequence-to-sequence model	Encoder-decoder network, captures temporal dependencies in data	[5]

Table 1: Glossary of LSTM/GRU/RNN based models used in the included studies.

1.2 Graph neural network based models used in the included studies.

Model	Definition	Reference
Graph neural network (GNN)	Neural networks that process graph structured data	[6, 7]
Graph convolutional network (GCN)	A GNN that aggregates neighbour information using a convolution operation	[8]

Model	Definition	Reference
Graph attention network (GAT)	GNN variant that uses attention to weight the importance of nodes	[9]
Message passing neural network	GNN where each node updates iteratively	[10]
Diffusion graph convolution	A GCN variant that models propagation as a diffusion process	[11]
Graph transformer	GNN with transformer attention	[12]

Table 2: Glossary of graph neural network based models based models used in the included studies.

1.3 CNN based models used in the included studies.

Model	Definition	Reference
Convolutional neural network	A neural network which uses convolutional filters	[13]
Residual network	A CNN architecture that introduces residual connections	[14]
U-Net	A convolutional encoder-decoder architecture	[15]

Table 3: Glossary of CNN based models used in the included studies.

1.4 Hybrid mechanistic ML models used in the included studies.

Model	Definition	Reference
Physics-informed neural network	Neural network augmented with a loss function which embeds differential equations	[16]
Hybrid mechanistic statistical and ML	Couples a ML model with a statistical model	
Ising dynamics informed deep learning model	Individuals represented as state ”spins” whose interactions simulate contagion dynamics	[17]

Table 4: Glossary of hybrid models based models used in the included studies.

1.5 Transformer based models used in the included studies.

Model	Definition	Reference
Transformer	A neural network which processes inputs using self-attention mechanisms	[18]
State space model	Process data through linear state space representation	[19]

Table 5: Glossary of transformer-based models based models used in the included studies.

1.6 Probabilistic/Bayesian based models used in the included studies

Model	Definition	Reference
Bayesian neural network	Neural network where weights are treated as probability distributions	[20]
Gaussian process	Defines a probability distribution over functions.	[21]
Integrated nested Laplace approximation (INLA)	Bayesian inference method for gaussian models.	[22]
Distributional regression	Regression models that predict the full conditional distribution.	[23]
Naive Bayes classifier	A probabilistic classifier based on Bayes' theorum. "Naive" as it is assumed that the features are independent.	[24]

Table 6: Glossary of probabilistic/bayesian based models used in the included studies.

1.7 Classical ML based models used in the included studies

Model	Definition	Reference
Random forest	Builds many decision trees and combines the outputs.	[25]

Model	Definition	Reference
Gradient boosting	Builds trees sequentially. Each new tree corrects the errors of the previous trees.	[26]
XGBoost	Optimised implementation of gradient boosting	[27]
CatBoost	Gradient boosting on decision trees.	[28]
Support vector machine	Used for classification tasks. Finds the optimal hyperplane to separate data points.	[29]
LASSO regression	Linear regression with a penalty on coefficients.	[30]
Generalised linear model	Extends linear regression to handle non-normal data.	[31]
ARIMA/SARIMA	Predicts future values based on historical data. SARIMA explicitly models seasonal trends.	
Vector autoregression	Forecast multiple variables simultaneously.	
Symbolic regression	Searches over mathematical expressions to find the one that best fits the data.	[32]

Table 7: Glossary of classical ML based models used in the included studies.

1.8 Other models used in the included studies

Model	Definition	Reference
Generative adversarial networks	Two neural networks are trained. The first is the generator which creates synthetic data. The second is the discriminator which learns to distinguish real and fake data.	[33]
Radial basis function neural network	Neural network where each hidden layer computes a radial basis function.	[34]
Pseudo-grouping adversarial learning	Clusters hidden group patterns and conceals these from the model.	[35]
Multilayer Perceptron	Feedforward neural network.	[1]

Table 8: Glossary of "other" models used in the included studies. These models did not fit into any of the defined categories.

2 Search terms for each database

2.1 PubMed

Date: 20/11/25
Restrictions: None

("Infectious disease*"[All Fields] OR "epidemic"[All Fields] OR "pandemic"[All Fields] OR "COVID-19"[All Fields] OR "malaria"[All Fields] OR "Dengue"[All Fields] OR "Influenza"[All Fields] OR "virus"[All Fields] OR "bacteria"[All Fields] OR "tuberculosis"[All Fields] OR "Zika"[All Fields] OR "chikungunya"[All Fields] OR "HIV"[All Fields] OR "measles"[All Fields] OR "vector-borne disease"[All Fields] OR "respiratory infection"[All Fields]) AND ("forecast"[All Fields] OR "predict"[All Fields]) AND ("spatiotemporal"[All Fields] OR "spatio-temporal"[All Fields]) AND ("machine learning"[All Fields] OR "deep learning"[All Fields] OR "artificial intelligence"[All Fields] OR "neural network*"[All Fields] OR "graph neural network*"[All Fields] OR "convolutional neural network*"[All Fields] OR "recurrent neural network"[All Fields] OR "transformers"[All Fields] OR "attention model"[All Fields] OR "support vector machine"[All Fields] OR "random forest*"[All Fields])

2.2 Scopus

Date: 20/11/25
Restrictions: None

TITLE-ABS-KEY("Infectious disease*" OR "epidemic" OR "pandemic" OR "COVID-19" OR "malaria" OR "Dengue" OR "Influenza" OR "virus" OR "bacteria" OR "tuberculosis" OR "Zika" OR "chikungunya" OR "HIV" OR "measles" OR "vector-borne disease" OR "respiratory infection") AND TITLE-ABS-KEY("forecast*" OR "predict*") AND TITLE-ABS-KEY("spatiotemporal" OR "spatio-temporal") AND TITLE-ABS-KEY("machine learning" OR "deep learning" OR "artificial intelligence" OR "neural network*" OR "graph neural network*" OR "convolutional neural network*" OR "recurrent neural network" OR "transformers" OR "attention model" OR "support vector machine" OR "random forest*")

2.3 IEEE Xplore

Field searched: All Metadata
Date: 20/11/25
Restrictions: None

("Infectious disease*" OR "epidemic" OR "pandemic" OR "COVID-19" OR "malaria" OR "Dengue" OR "Influenza" OR "virus" OR "bacteria" OR "tuberculosis" OR "Zika" OR "chikungunya" OR "HIV" OR "measles" OR "vector-borne disease" OR "respiratory infection") AND ("forecast*" OR "predict*") AND ("spatiotemporal" OR "spatio-temporal") AND ("machine learning" OR "deep learning" OR "artificial intelligence" OR "neural network*" OR "graph neural network*" OR "convolutional neural network*" OR "recurrent neural network" OR "transformers" OR "attention model" OR "support vector machine" OR "random forest*")

2.4 Web of Science

Date: 20/11/25
Restrictions: None

TS=(”Infectious disease*” OR ”epidemic” OR ”pandemic” OR ”COVID-19” OR ”malaria” OR ”Dengue” OR ”Influenza” OR ”virus” OR ”bacteria” OR ”tuberculosis” OR ”Zika” OR ”chikungunya” OR ”HIV” OR ”measles” OR ”vector-borne disease” OR ”respiratory infection”) AND TS=(”forecast*” OR ”predict*”) AND TS=(”spatiotemporal” OR ”spatio-temporal”) AND TS=(”machine learning” OR ”deep learning” OR ”artificial intelligence” OR ”neural network*” OR ”graph neural network*” OR ”convolutional neural network*” OR ”recurrent neural network” OR ”transformers” OR ”attention model” OR ”support vector machine” OR ”random forest*”)

2.5 Compendex

Field searched: All metadata
Date: 20/11/25
Restrictions: None

(”Infectious disease$” OR ”epidemic” OR ”pandemic” OR ”COVID-19” OR ”malaria” OR ”Dengue” OR ”Influenza” OR ”virus” OR ”bacteria” OR ”tuberculosis” OR ”Zika” OR ”chikungunya” OR ”HIV” OR ”measles” OR ”vector-borne disease” OR ”respiratory infection”) AND (”forecast$” OR ”predict$”) AND (”spatiotemporal” OR ”spatio-temporal”) AND (”machine learning” OR ”deep learning” OR ”artificial intelligence” OR ”neural network$” OR ”graph neural network$” OR ”convolutional neural network$” OR ”recurrent neural network” OR ”transformers” OR ”attention model” OR ”support vector machine” OR ”random forest$”)

3 Glossary of Model Evaluation Metrics

We provide definitions and formulas for all model evaluation metrics identified across the included studies for completeness. Metrics are grouped by six categories - scale-dependent error metrics, percentage and scale-free error metrics, agreement and correlation metrics, information criteria and Bayesian model comparison, probabilistic and distributional metrics and classification performance metrics.

We use y_i to denote the actual (observed) value, $\hat{y}_i$ the predicted value, n the number of observations, $\bar{y}$ the mean of observed values, and $\bar{\hat{y}}$ the mean of predicted values, unless otherwise stated.

3.1 Scale-Dependent Error Metrics

Scale dependent error metrics are defined as error metrics expressed in the same units as the data, providing an interpretable measure of error. However, it is challenging to use scale dependent error metrics to compare model performance across different diseases, times and locations.

Metric	Acronym	Formula	Definition
Mean Absolute Error	MAE	$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\lvert y_i - \hat{y}_i\rvert$	Average of the difference between observed and predicted values.
Mean Squared Error	MSE	$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$	Average of the squared difference between observed and predicted values. Larger errors are penalised more since errors are squared.
Root Mean Squared Error	RMSE	$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$	Square root of MSE, converting MSE to the original units to make it more interpretable.
Normalised RMSE	NRMSE	$\mathrm{NRMSE} = \frac{\mathrm{RMSE}}{y_{\max} - y_{\min}}$ where $y_{\max}$ and $y_{\min}$ are the maximum and minimum observed values.	RMSE scaled so results can be interpreted across different datasets.
Root mean squared log error	RMSLE	$\mathrm{RMSLE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\log(1+\hat{y}_i) - \log(1+y_i))^2}$	RMSE computed on log-transformed values.
Mean squared log error	MSLE	$\mathrm{MSLE} = \frac{1}{n}\sum_{i=1}^{n}(\log(1+\hat{y}_i) - \log(1+y_i))^2$	Unrooted version of RMSLE.
Normalised deviation	ND	$\mathrm{ND} = \frac{\sum_{i=1}^{n}\lvert y_i - \hat{y}_i\rvert}{\sum_{i=1}^{n}\lvert y_i\rvert}$	Total error normalised by the sum of observed values.

3.2 Percentage and Scale-Free Error Metrics

Percentage and scale free error metrics are relative to the actual value, expressed as a percentage, allowing for models to be compared across diseases, times and locations.

Metric	Acronym	Formula	Definition
Mean Absolute Percentage Error	MAPE	$\mathrm{MAPE} = \frac{100\%}{n}\sum_{i=1}^{n}\left\lvert\frac{y_i - \hat{y}_i}{y_i}\right\rvert$	Measures the average percentage difference between predicted and observed values.

Metric	Acronym	Formula	Definition
Symmetric MAPE	SMAPE	$\mathrm{SMAPE} = \frac{100\%}{n} \sum_{i=1}^{n} \frac{\lvert y_i - \hat{y}_i \rvert}{(\lvert y_i \rvert + \lvert \hat{y}_i \rvert)/2}$	Average percentage error which penalises under and over prediction equally.
Root Mean Squared Percentage Error	RMSPE	$\mathrm{RMSPE} = 100\% \times \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(\frac{y_i - \hat{y}_i}{y_i} \right)^2}$	RMSE expressed as a percentage of the observed values.
Mean Absolute Scaled Error	MASE	$\mathrm{MASE} = \frac{\frac{1}{n} \sum_{i=1}^{n} \lvert y_i - \hat{y}_i \rvert}{\frac{1}{n-1} \sum_{i=2}^{n} \lvert y_i - y_{i-1} \rvert}$	MAE scaled by the MAE of a naive (one-step lag) forecast. A MASE value below 1 indicate the model outperforms a naive baseline.
Relative Squared Error	RSE	$\mathrm{RSE} = \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2}$	Sum of squared errors normalised by total variance in the observed data.
Mean Relative Prediction Error	MRPE	$\mathrm{MRPE} = \frac{1}{n} \sum_{i=1}^{n} \frac{y_i - \hat{y}_i}{y_i}$	Average relative error that keeps its sign.

3.3 Agreement and Correlation Metrics

Agreement and correlation metrics measure how well the observed and predicted values match in terms of value and direction.

Metric	Acronym	Formula	Definition
Coefficient of Determination	R^2	$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2}$	Proportion of variance in the observed data explained by the model.
Explained Variance	EV	$\mathrm{EV} = 1 - \frac{\mathrm{Var}(y - \hat{y})}{\mathrm{Var}(y)}$ where $\mathrm{Var}(y - \hat{y})$ is the variance of the prediction residuals and $\mathrm{Var}(y)$ is the variance of the observed values.	Similar to R^2, but calculated from the variance of the residuals rather than their sum of squares, meaning it does not penalise systematic over or under prediction.

Metric	Acronym	Formula	Definition
Pearson Correlation Coefficient	r	$r = \frac{\sum_{i=1}^{n}(y_i - \bar{y})(\hat{y}_i - \bar{\hat{y}})}{\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}\sqrt{\sum_{i=1}^{n}(\hat{y}_i - \bar{\hat{y}})^2}}$	Measures the strength and direction of the linear association between predicted and observed values.
Concordance Correlation Coefficient	CCC	$\mathrm{CCC} = \frac{2\rho\,\sigma_y\sigma_{\hat{y}}}{\sigma_y^2 + \sigma_{\hat{y}}^2 + (\mu_y - \mu_{\hat{y}})^2}$ where ρ is the Pearson correlation coefficient between y and $\hat{y}$; σ_y, $\sigma_{\hat{y}}$ are the standard deviations of the observed and predicted values; and μ_y, $\mu_{\hat{y}}$ are their means.	Measures the linear association between predicted and observed values.
Spearman's Rank Correlation	Spearman's ρ	$\rho_s = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n(n^2-1)}$ where $d_i = \mathrm{rank}(y_i) - \mathrm{rank}(\hat{y}_i)$ is the difference between the rank of the i-th observed and predicted value.	Measures the strength of a monotonic association between predicted and observed values, by comparing their relative rankings rather than their magnitudes.
Kendall's Tau	Kendall's τ	$\tau = \frac{(\text{concordant pairs}) - (\text{discordant pairs})}{\binom{n}{2}}$ where a pair of observations $(y_i, \hat{y}_i)$ and $(y_j, \hat{y}_j)$ is concordant if the ranks agree in direction and discordant if they disagree; $\binom{n}{2}$ is the total number of possible pairs.	Measures rank agreement between predicted and observed values based on the proportion of pairs that are ranked in the same order versus reversed order.

3.4 Information Criteria and Bayesian Model Comparison

Information criteria and Bayesian model comparison metrics measure the accuracy of models and penalise models which are unnecessarily complex.

Metric	Acronym	Formula	Definition
Watanabe-Akaike Information Criterion	WAIC	$\mathrm{WAIC} = -2\left(\mathrm{lppd} - p_{\mathrm{WAIC}}\right)$ where $\mathrm{lppd} = \sum_{i=1}^{n} \log\left(\frac{1}{S}\sum_{s=1}^{S} p(y_i \mid \theta^s)\right)$ is the log pointwise predictive density summed over n observations and S posterior draws θ^s, and $p_{\mathrm{WAIC}} = \sum_{i=1}^{n} \mathrm{Var}_s\left(\log p(y_i \mid \theta^s)\right)$ is the effective number of parameters, estimated as the variance of the log predictive density across posterior draws.	Scores how well a Bayesian model would predict new data. Penalises overly complex models.
Deviance Information Criterion	DIC	$\mathrm{DIC} = \bar{D}(\theta) + p_D, \quad p_D = \bar{D}(\theta) - D(\bar{\theta})$ where $\bar{D}(\theta)$ is the average deviance across posterior samples of θ, $D(\bar{\theta})$ is the deviance evaluated at the posterior mean parameter estimate $\bar{\theta}$, and p_D is the effective number of parameters (the difference between the two).	Balances how well a model fits with how complex it is.
Bayesian Model Averaging Weight	BMA	$w_k = \frac{\exp(-\frac{1}{2}\Delta_k)}{\sum_m \exp(-\frac{1}{2}\Delta_m)}$ where Δ_k is the difference in information criterion value (e.g. AIC or BIC) between model k and the best-fitting model in the candidate set, and the sum in the denominator runs over all m candidate models being compared.	How much weight a model gets when combining predictions from multiple models.
Log Score / Log Predictive Score	LS	$\mathrm{LS} = \frac{1}{n}\sum_{i=1}^{n} \log f(y_i \mid \hat{\theta})$ where y_i is the i-th observed value, $\hat{\theta}$ is the fitted (or posterior mean) parameter estimate, $f(\cdot \mid \hat{\theta})$ is the model's predictive density, and n is the number of observations.	Measure of how likely the observed data is under the model's predictions.
Bayesian P-value		$p_B = \Pr\left(T(y^{\mathrm{rep}}, \theta) \geq T(y, \theta) \mid y\right)$ where y is the observed data, y^{rep} is data replicated (simulated) from the model's posterior predictive distribution, and $T(\cdot, \theta)$ is a chosen test statistic (e.g. mean, variance) computed on either the observed or replicated data given parameters θ.	Checks whether the model's simulated data looks like the real data.

3.5 Probabilistic and Distributional Metrics

Probabilistic metrics assess over a range of predictions, rather than a single prediction, providing a quantification of uncertainty in the models predictions.

Metric	Acronym	Formula	Definition
Continuous Ranked Probability Score	CRPS	$\mathrm{CRPS}(F, y) = \int_{-\infty}^{\infty} (F(x) - 1\{x \geq y\})^2 \, dx$ where F is the model's predicted cumulative distribution function, y is the observed value, and $1\{x \geq y\}$ is 1 if $x \geq y$ and 0 otherwise.	Like MAE, but for models which predict a range of outcomes rather than one.
Weighted Interval Score	WIS	$\mathrm{WIS} = \frac{1}{K + \frac{1}{2}} \left(\frac{1}{2}\lvert y - m \rvert + \sum_{k=1}^{K} \frac{\alpha_k}{2} \mathrm{IS}_{\alpha_k}(y) \right)$ where y is the observed value, m is the model's median predicted value, K is the number of central prediction intervals reported, and for each interval k, α_k is its miscoverage level (e.g. $\alpha_k = 0.1$ for a 90% interval) and $\mathrm{IS}_{\alpha_k}(y) = (u_k - l_k) + \frac{2}{\alpha_k}(l_k - y)1\{y < l_k\} + \frac{2}{\alpha_k}(y - u_k)1\{y > u_k\}$ is the interval score, with l_k, u_k the lower and upper bounds of that interval.	Scores how good a model's predicted ranges are, rewarding both narrow intervals and intervals that contain the true value.
Freeman-Tukey Statistic		$FT = \sum_{i=1}^{n} \left(\sqrt{y_i} - \sqrt{\hat{y}_i} \right)^2$	Measure the gap between predicted and observed data.

3.6 Classification Performance Metrics

Classification performance metrics are used when the outcome of the model is a category rather than a number.

Metric	Acronym	Formula	Definition
Accuracy		$\mathrm{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$ where TP, TN, FP, FN denote the number of true positives, true negatives, false positives, and false negatives respectively.	The proportion of predictions the model got correct.
Precision		$\mathrm{Precision} = \frac{TP}{TP + FP}$	Proportion of predicted positives that are true positives.
Recall		$\mathrm{Recall} = \frac{TP}{TP + FN}$	Proportion of actual positives correctly identified by the model.

Metric	Acronym	Formula	Definition
F-score	F_1	$F_1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$	One score that combines precision and recall.
Area Under the ROC Curve	AUC	$\text{AUC} = \int_0^1 \text{TPR}(\text{FPR}^{-1}(x))\, dx$	Performance metric for binary classification models. Evaluates models ability to distinguish between classes.

References

[1] David E. Rumelhart, Geoffrey E. Hinton, and Ronald J. Williams. "Learning representations by back-propagating errors". In: *Nature* 323.6088 (Oct. 1986), pp. 533–536. ISSN: 1476-4687. DOI: 10.1038/323533a0. URL: http://dx.doi.org/10.1038/323533a0.

[2] Sepp Hochreiter and Jürgen Schmidhuber. "Long Short-Term Memory". In: *Neural Computation* 9.8 (Nov. 1997), pp. 1735–1780. ISSN: 1530-888X. DOI: 10.1162/neco.1997.9.8.1735.

[3] Alex Graves and Jürgen Schmidhuber. "Framewise phoneme classification with bidirectional LSTM and other neural network architectures". In: *Neural Networks* 18.5-6 (July 2005), pp. 602–610. ISSN: 0893-6080. DOI: 10.1016/j.neunet.2005.06.042. URL: http://dx.doi.org/10.1016/j.neunet.2005.06.042.

[4] Junyoung Chung et al. *Empirical Evaluation of Gated Recurrent Neural Networks on Sequence Modeling*. Tech. rep. 2014. DOI: 10.48550/ARXIV.1412.3555. URL: https://arxiv.org/abs/1412.3555.

[5] Ilya Sutskever, Oriol Vinyals, and Quoc V. Le. *Sequence to Sequence Learning with Neural Networks*. Tech. rep. 2014. DOI: 10.48550/ARXIV.1409.3215.

[6] Zewen Liu et al. *A Review of Graph Neural Networks in Epidemic Modeling*. Tech. rep. 2024. DOI: 10.48550/ARXIV.2403.19852.

[7] F. Scarselli et al. "The Graph Neural Network Model". In: *IEEE Transactions on Neural Networks* 20.1 (Jan. 2009), pp. 61–80. ISSN: 1941-0093. DOI: 10.1109/tnn.2008.2005605. URL: http://dx.doi.org/10.1109/TNN.2008.2005605.

[8] Thomas N. Kipf and Max Welling. *Semi-Supervised Classification with Graph Convolutional Networks*. Tech. rep. 2016. DOI: 10.48550/ARXIV.1609.02907. URL: https://arxiv.org/abs/1609.02907.

[9] Petar Veličković et al. *Graph Attention Networks*. Tech. rep. 2017. DOI: 10.48550/ARXIV.1710.10903. URL: https://arxiv.org/abs/1710.10903.

[10] Justin Gilmer et al. *Neural Message Passing for Quantum Chemistry*. Tech. rep. 2017. DOI: 10.48550/ARXIV.1704.01212. URL: https://arxiv.org/abs/1704.01212.

[11] Yaguang Li et al. *Diffusion Convolutional Recurrent Neural Network: Data-Driven Traffic Forecasting*. Tech. rep. 2017. DOI: 10.48550/ARXIV.1707.01926. URL: https://arxiv.org/abs/1707.01926.

[12] Vijay Prakash Dwivedi and Xavier Bresson. *A Generalization of Transformer Networks to Graphs*. Tech. rep. 2020. DOI: 10.48550/ARXIV.2012.09699. URL: https://arxiv.org/abs/2012.09699.

[13] Keiron O'Shea and Ryan Nash. *An Introduction to Convolutional Neural Networks*. Tech. rep. 2015. DOI: 10.48550/ARXIV.1511.08458. URL: https://arxiv.org/abs/1511.08458.

[14] Kaiming He et al. *Deep Residual Learning for Image Recognition*. Tech. rep. 2015. DOI: 10.48550/ARXIV.1512.03385. URL: https://arxiv.org/abs/1512.03385.

[15] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. *U-Net: Convolutional Networks for Biomedical Image Segmentation*. Tech. rep. 2015. DOI: 10.48550/ARXIV.1505.04597. URL: https://arxiv.org/abs/1505.04597.

[16] M. Raissi, P. Perdikaris, and G.E. Karniadakis. "Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations". In: *Journal of Computational Physics* 378 (Feb. 2019), pp. 686–707. ISSN: 0021-9991. DOI: 10.1016/j.jcp.2018.10.045.

[17] Junyi Gao et al. "Evidence-Driven Spatiotemporal COVID-19 Hospitalization Prediction with Ising Dynamics". In: *Nature Communications* 14.1 (May 2023), p. 3093. ISSN: 2041-1723. DOI: 10.1038/s41467-023-38756-3.

[18] Ashish Vaswani et al. *Attention Is All You Need*. Tech. rep. 2017. DOI: 10.48550/ARXIV.1706.03762.

[19] Albert Gu and Tri Dao. *Mamba: Linear-Time Sequence Modeling with Selective State Spaces*. Tech. rep. 2023. DOI: 10.48550/ARXIV.2312.00752. URL: https://arxiv.org/abs/2312.00752.

[20] Ethan Goan and Clinton Fookes. *Bayesian Neural Networks: An Introduction and Survey*. Tech. rep. 2020. DOI: 10.48550/ARXIV.2006.12024. URL: https://arxiv.org/abs/2006.12024.

[21] Christopher Williams and Carl Rasmussen. "Gaussian Processes for Regression". In: *Advances in Neural Information Processing Systems*. Ed. by D. Touretzky, M.C. Mozer, and M. Hasselmo. Vol. 8. MIT Press, 1995. URL: https://proceedings.neurips.cc/paper_files/paper/1995/file/7cce53cf90577442771720a370c3c723-Paper.pdf.

[22] Håvard Rue, Sara Martino, and Nicolas Chopin. "Approximate Bayesian Inference for Latent Gaussian models by using Integrated Nested Laplace Approximations". In: *Journal of the Royal Statistical Society Series B: Statistical Methodology* 71.2 (Apr. 2009), pp. 319–392. ISSN: 1467-9868. DOI: 10.1111/j.1467-9868.2008.00700.x. URL: http://dx.doi.org/10.1111/j.1467-9868.2008.00700.x.

[23] R. A. Rigby and D. M. Stasinopoulos. "Generalized Additive Models for Location, Scale and Shape". In: *Journal of the Royal Statistical Society Series C: Applied Statistics* 54.3 (Apr. 2005), pp. 507–554. ISSN: 1467-9876. DOI: 10.1111/j.1467-9876.2005.00510.x. URL: http://dx.doi.org/10.1111/j.1467-9876.2005.00510.x.

[24] Pedro Domingos and Michael Pazzani. "On the Optimality of the Simple Bayesian Classifier under Zero-One Loss". In: *Machine Learning* 29.2-3 (Nov. 1997), pp. 103–130. ISSN: 1573-0565. DOI: 10.1023/a:1007413511361. URL: http://dx.doi.org/10.1023/A:1007413511361.

[25] Leo Breiman. "Random Forests". In: *Machine Learning* 45.1 (Oct. 2001), pp. 5–32. ISSN: 1573-0565. DOI: 10.1023/a:1010933404324. URL: http://dx.doi.org/10.1023/A:1010933404324.

[26] Jerome H. Friedman. "Greedy Function Approximation: A Gradient Boosting Machine". In: *The Annals of Statistics* 29.5 (2001), pp. 1189–1232. ISSN: 00905364, 21688966. URL: http://www.jstor.org/stable/2699986.

[27] Tianqi Chen and Carlos Guestrin. "XGBoost: A Scalable Tree Boosting System". In: (2016). DOI: 10.48550/ARXIV.1603.02754. URL: https://arxiv.org/abs/1603.02754.

[28] Liudmila Prokhorenkova et al. *CatBoost: unbiased boosting with categorical features*. Tech. rep. 2017. DOI: 10.48550/ARXIV.1706.09516. URL: https://arxiv.org/abs/1706.09516.

[29] Javier M. Moguerza and Alberto Muñoz. "Support Vector Machines with Applications". In: (2006). DOI: 10.48550/ARXIV.MATH/0612817. URL: https://arxiv.org/abs/math/0612817.

[30] Robert Tibshirani. "Regression Shrinkage and Selection Via the Lasso". In: *Journal of the Royal Statistical Society Series B: Statistical Methodology* 58.1 (Jan. 1996), pp. 267–288. ISSN: 1467-9868. DOI: 10.1111/j.2517-6161.1996.tb02080.x. URL: http://dx.doi.org/10.1111/j.2517-6161.1996.tb02080.x.

[31] P. McCullagh and J.A. Nelder. *Generalized Linear Models*. Routledge, Jan. 2019. ISBN: 9780203753736. DOI: 10.1201/9780203753736. URL: http://dx.doi.org/10.1201/9780203753736.

[32] Nour Makke and Sanjay Chawla. "Interpretable Scientific Discovery with Symbolic Regression: A Review". In: (2022). DOI: 10.48550/ARXIV.2211.10873. URL: https://arxiv.org/abs/2211.10873.

[33] Ian J Goodfellow et al. *Generative Adversarial Networks*. Tech. rep. 2014. eprint: 1406.2661 (stat.ML).

[34] D. S. Broomhead and D. Lowe. “Multivariable Functional Interpolation and Adaptive Networks”. In: *Complex Systems* 2.3 (1988), pp. 321–355.

[35] Gang Xue et al. “Improving the Spatial Fairness of Spatiotemporal Sequence Forecasting Service Systems”. In: *Production and Operations Management* 35.3 (Mar. 2026), pp. 876–898. ISSN: 1059-1478. DOI: 10.1177/10591478251356940.

D1. Citation information for the included studies.

ID	Title	Author	Journal	Year	Volume	Issue	Pages	doi
1	A Bayesian machine learning approach for spatio-temporal prediction of COVID-19 cases.	Niraula P and Mateu J and Chaudhuri S	Stochastic environmental research and risk assessment : research journal	2022	36	8	2265-2283	10.1007/s00477-021-02168-w
2	A deep learning approach for Spatio-Temporal forecasting of new cases and new hospital admissions of COVID-19 spread in Reggio Emilia, Northern Italy	Sciannameo, V and Goffi, A and Maffeis, G and Gianfreda, R and Pagliari, DJ and Filippini, T and Mancuso, P and Giorgi-Rossi, P and Dal Zovo, LA and Corbari, A and Vinceti, M and Berchialla, P	JOURNAL OF BIOMEDICAL INFORMATICS	2022	132	NA	NA	10.1016/j.jbi.2022.104132
3	A Deep Residual Network Integrating Spatial-temporal Properties to Predict Influenza Trends at an Intra-urban Scale	Xi, GK and Yin, L and Li, Y and Mei, SJ	PROCEEDINGS OF THE 2ND ACM SIGSPATIAL INTERNATIONAL WORKSHOP ON AI FOR GEOGRAPHIC KNOWLEDGE DISCOVERY (GEOAI 2018)	2018	NA	NA	19-28	10.1145/3281548.3281558
4	A Geo-AI-Based Approach for Spatiotemporal Prediction of Infectious Diseases With Cluster Distribution Pattern in Urban Environments	Samani, ZN and Alesheikh, AA and Kalantari, M	TRANSACTIONS IN GIS	2025	29	7	NA	10.1111/tgis.70132
5	A mobility-aware and patch-based transformer for predicting spatiotemporal transmission patterns of epidemics	Zhou, Z. and Wang, P. and Su, H. and Liu, D. and Zheng, X.	Physica A: Statistical Mechanics and its Applications	2026	681	NA	NA	10.1016/j.physa.2025.131069
6	A Multivariate Spatiotemporal Model of COVID-19 Epidemic Using Ensemble of ConvLSTM Networks	Paul, Swarna Kamal and Jana, Saikat and Bhaumik, Parama	Journal of The Institution of Engineers (India): Series B	2021	102	6	1137-1142	10.1007/s40031-020-00517-x
7	A Novel Data-Driven Model for Real-Time Influenza Forecasting	S. R. Venna and A. Tavanaei and R. N. Gottumukkala and V. V. Raghavan and A. S. Maida and S. Nichols	IEEE Access	2019	7	NA	7691-7701	10.1109/ACCESS.2018.2888585
8	A Novel Early Warning Model for Hand, Foot and Mouth Disease Prediction Based on a Graph Convolutional Network.	Ji TJ and Cheng Q and Zhang Y and Zeng HR and Wang JX and Yang GY and Xu WB and Liu HT	Biomedical and environmental sciences : BES	2022	35	6	494-503	10.3967/bes2022.065
9	A probabilistic spatio-temporal neural network to forecast COVID-19 counts	Ravenda, F and Cesarini, M and Peluso, S and Mira, A	INTERNATIONAL JOURNAL OF DATA SCIENCE AND ANALYTICS	2025	20	2	1255-1262	10.1007/s41060-024-00525-w
10	A prospective prediction tool for understanding Crimean-Congo haemorrhagic fever dynamics in Turkey	Ak Ç, Ergönül Ö, Gönen M.	CLINICAL MICROBIOLOGY AND INFECTION	2020	26	1	NA	10.1016/j.cmi.2019.05.006
11	A reproducible ensemble machine learning approach to forecast dengue outbreaks	Sebastianelli, A and Spiller, D and Carmo, R and Wheeler, J and Nowakowski, A and Jacobson, LV and Kim, D and Barlevi, H and Cordero, ZE and Colon-Gonzalez, FJ and Lowe, R and Ullo, SL and Schneider, R	SCIENTIFIC REPORTS	2024	14	1	NA	10.1038/s41598-024-52796-9
12	A spatiotemporal machine learning approach to forecasting COVID-19 incidence at the county level in the USA	Lucas, B and Vahedi, B and Karimzadeh, M	INTERNATIONAL JOURNAL OF DATA SCIENCE AND ANALYTICS	2023	15	3	247-266	10.1007/s41060-021-00295-9
13	A Stochastic Model of an Early Warning System for Detecting Anomalous Incidence Values of COVID-19	Duarte, AF and Soares, A and Pereira, MJ and Peralta-Santos, A and Leite, PP and Azevedo, L	MATHEMATICAL GEOSCIENCES	2024	56	1	41-54	10.1007/s11004-023-10096-4
14	An Epidemiological Neural Network Exploiting Dynamic Graph Structured Data Applied to the COVID-19 Outbreak	La Gatta, V and Moscato, V and Postiglione, M and Sperli, G	IEEE TRANSACTIONS ON BIG DATA	2021	7	1	45-55	10.1109/TBDATA.2020.3032755
15	An explainable covariate compartmental model for predicting the spatio-temporal patterns of dengue in Sri Lanka	Liu, YC and Fransson, P and Heidecke, J and Liyanage, P and Wallin, J and Rocklv, J	PLOS COMPUTATIONAL BIOLOGY	2025	21	9	NA	10.1371/journal.pcbi.1013540
16	BaSTRoN: a Bayesian model for predicting infectious disease spread using socio-economic and environmental factors	Swaminatha Rao, L.P. and Suresh, A. and Muthukumar, A.	International Journal of Information Technology (Singapore)	2025	17	8	4805-4821	10.1007/s41870-025-02695-7
17	CausalGNN: Causal-Based Graph Neural Networks for Spatio-Temporal Epidemic Forecasting	Wang, L. and Adiga, A. and Chen, J. and Sadilek, A. and Venkatramanan, S. and Marathe, M.	NA	2022	36	NA	12191-12199	10.1609/aaai.v36i11.21479
18	Challenges and implications of predicting the spatiotemporal distribution of dengue fever outbreak in Chinese Taiwan using remote sensing data and deep learning	Anno, S and Tsubasa, H and Sugita, S and Yasumoto, S and Lee, MA and Sasaki, Y and Oyoshi, K	GEO-SPATIAL INFORMATION SCIENCE	2024	27	4	1155-1161	10.1080/10095020.2022.2144770
19	Combining graph neural networks and spatio-temporal disease models to improve the prediction of weekly COVID-19 cases in Germany	Fritz, C. and Dorigatti, E. and Rugamer, D.	Scientific Reports	2022	12	1	NA	10.1038/s41598-022-07757-5
20	Correlating dynamic climate conditions and socioeconomic-governmental factors to spatiotemporal spread of COVID-19 via semantic segmentation deep learning analysis	Chew, AWZ and Wang, Y and Zhang, LM	SUSTAINABLE CITIES AND SOCIETY	2021	75	NA	NA	10.1016/j.scs.2021.103231
21	Countrywide Origin-Destination Matrix Prediction and Its Application for COVID-19	Jiang, RH and Wang, ZN and Cai, ZK and Yang, C and Fan, ZP and Xia, TQ and Matsubara, G and Mizuseki, H and Song, X and Shibasaki, R	MACHINE LEARNING AND KNOWLEDGE DISCOVERY IN DATABASES, ECML PKDD 2021: APPLIED DATA SCIENCE TRACK, PT IV	2021	12978	NA	319-334	10.1007/978-3-030-86514-6_20
22	Customizing Spatial-Temporal Graph Mamba Networks forÂ Pandemic Forecasting	Xu, H. and Gao, C. and Li, X. and Wang, Z. and Tanimoto, T.	Lecture Notes in Computer Science	2025	15281 LNAI	NA	236-242	10.1007/978-981-96-0116-5_19
23	Data Assimilation Predictive GAN (DA-PredGAN) Applied to a Spatio-Temporal Compartmental Model in Epidemiology	Silva, VLS and Heaney, CE and Li, YQ and Pain, CC	JOURNAL OF SCIENTIFIC COMPUTING	2023	94	1	NA	10.1007/s10915-022-02078-1
24	Decoupling Local and Cross-Regional Transmission Dynamics for Enhanced COVID-19 Forecasting	J. Fei and Z. Cao and T. Luo and J. Wang	2025 International Joint Conference on Neural Networks (IJCNN)	2025	NA	NA	01-Sep	10.1109/IJCNN64981.2025.11228555
25	Deep diffusion-based forecasting of COVID-19 by incorporating network-level mobility information	Roy, P and Sarkar, S and Biswas, S and Chen, FL and Chen, ZQ and Ramakrishnan, N and Lu, CT	PROCEEDINGS OF THE 2021 IEEE/ACM INTERNATIONAL CONFERENCE ON ADVANCES IN SOCIAL NETWORKS ANALYSIS AND MINING, ASONAM 2021	2021	NA	NA	168-175	10.1145/3487351.3488334
26	Deep neural networks for endemic measles dynamics: Comparative analysis and integration with mechanistic models	Madden, WG and Jin, W and Lopman, B and Zufle, A and Dalziel, B and Metcalf, CJE and Grenfell, BT and Lau, MSY	PLOS COMPUTATIONAL BIOLOGY	2024	20	11	NA	10.1371/journal.pcbi.1012616

27	Deep Reinforcement Learning Interdependent Healthcare Critical Infrastructure Simulation model for Dynamically Varying COVID-19 scenario - A case study of a Metro City	G. Srikanth and N. Nukavarapu and S. Durbha	2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS	2021	NA	NA	8499-8502	10.1109/IGARSS47720.2021.9554875
28	Deep Spatiotemporal Model for COVID-19 Forecasting	Munoz-Organero, M. and Queipo-<c3>lvarez, P.	Sensors	2022	22	9	NA	10.3390/s22093519
29	DeepEVD: Integrating Epidemiological data into deep learning frameworks based on spatio-temporal feature learning for EVD forecasting	Fofanah, AJ and Kamara, AA and Sankoh, AP and Gao, TG and Dumbuya, I and Conteh, ZB	SPATIAL AND SPATIO-TEMPORAL EPIDEMIOLOGY	2025	54	NA	NA	10.1016/j.sste.2025.100741
30	Design and Analysis of a Prediction System About Influenza-Like Illness From the Latent Temporal and Spatial Information	Guo, XX and Xiong, NN and Wang, HY and Ren, JL	IEEE TRANSACTIONS ON SYSTEMS MAN CYBERNETICS-SYSTEMS	2022	52	1	66-77	10.1109/TSMC.2020.3048946
31	Enhance COVID-19 Mortality Prediction with Human Mobility Trend and Medical Information	Y. Chaudhari and I. Javeri and I. Arpinar and J. A. Miller and X. Li and B. Li and Y. Ke and M. Toutiaee and N. Lazar	2021 IEEE 23rd Int Conf on High Performance Computing & Communications; 7th Int Conf on Data Science & Systems; 19th Int Conf on Smart City; 7th Int Conf on Dependability in Sensor, Cloud & Big Data Systems & Application (HPCC/DSS/SmartCity/DependSys)	2021	NA	NA	1245-1252	10.1109/HPCC-DSS-SmartCity-DependSys53884.2021.00190
32	Enhancing COVID-19 Prevalence Forecasting: A Hybrid Approach Integrating Epidemic Differential Equations and Recurrent Neural Networks	Kong, L and Guo, YH and Lee, CW	APPLIEDMATH	2024	4	2	427-441	10.3390/appliedmath4020022
33	Ensemble forecasting of the Zika space-time spread with topological data analysis	Soliman, M. and Lyubchich, V. and Gel, Y.R.	Environmetrics	2020	31	7	NA	10.1002/env.2629
34	Epidemic-guided deep learning for spatiotemporal forecasting of tuberculosis outbreak	Barman, M. and Panja, M. and Mishra, N. and Chakraborty, T.	Machine Learning	2025	114	10	NA	10.1007/s10994-025-06848-4
35	Epidemiology-informed Spatiotemporal Graph Neural Network for heterogeneity-driven interpretable epidemic forecasting	Han, S and Stelz, L and Sokolowski, TR and Zhou, K and Stocker, H	ENGINEERING APPLICATIONS OF ARTIFICIAL INTELLIGENCE	2025	162	NA	NA	10.1016/j.engappai.2025.112764
36	Evidence-driven spatiotemporal COVID-19 hospitalization prediction with Ising dynamics	Gao, JY and Heintz, J and Mack, C and Glass, L and Cross, A and Sun, JM	NATURE COMMUNICATIONS	2023	14	1	NA	10.1038/s41467-023-38756-3
37	Examining Deep Learning Models with Multiple Data Sources for COVID-19 Forecasting	L. Wang and A. Adiga and S. Venkatramanan and J. Chen and B. Lewis and M. Marathe	2020 IEEE International Conference on Big Data (Big Data)	2020	NA	NA	3846-3855	10.1109/BigData50022.2020.9377904
38	Exploiting mobility data to forecast Covid-19 spread	M. P. Canino and E. Cesario and A. Vinci and S. Zarin	2022 IEEE Intl Conf on Dependable, Autonomic and Secure Computing, Intl Conf on Pervasive Intelligence and Computing, Intl Conf on Cloud and Big Data Computing, Intl Conf on Cyber Science and Technology Congress (DASC/PiCom/CBDCom/CyberSciTech)	2022	NA	NA	01-Apr	10.1109/DASC/PiCom/CBDCom/Cy55231.2022.9927898
39	Forecasting COVID-19 Dynamics: Clustering, Generalized Spatiotemporal Attention, and Impacts of Mobility and Geographic Proximity	T. Shen and Y. Li and J. M. F. Moura	2023 IEEE 39th International Conference on Data Engineering (ICDE)	2023	NA	NA	2892-2904	10.1109/ICDE55515.2023.00221
40	Forecasting Epidemic Spread With Recurrent Graph Gate Fusion Transformers	M. Kim and J. H. Kim and B. Jang	IEEE Journal of Biomedical and Health Informatics	2025	29	2	1546-1559	10.1109/JBHI.2024.3488274
41	Forecasting the Spread of COVID-19 Based on Differential Transfer Graph Neural Network	C. Qin and M. Ma	2021 CIE International Conference on Radar (Radar)	2021	NA	NA	2395-2398	10.1109/Radar53847.2021.10027962
42	Gaussian process modelling of infectious diseases using the Greta software package and GPUs	Gunn, E and Sengupta, N and Swallow, B	JOURNAL OF THEORETICAL BIOLOGY	2026	616	NA	NA	10.1016/j.jtbi.2025.112278
43	Geographic Ensembles of Observations using Randomised Ensembles of Autoregression Chains: Ensemble methods for spatio-temporal Time Series Forecasting of Influenza-like Illness	Poonawala-Lohani, N and Riddle, P and Adnan, M and Wicker, J	13TH ACM INTERNATIONAL CONFERENCE ON BIOINFORMATICS, COMPUTATIONAL BIOLOGY AND HEALTH INFORMATICS, BCB 2022	2022	NA	NA	NA	10.1145/3535508.3545562
44	Graph Representation Learning for Dengue Forecasting	J. Weng and D. Qiu and E. Cruz and M. Magdon-Ismail and T. Munasinghe and J. C. Wei and A. Pathirana and M. Pasarkar	2024 IEEE International Conference on Big Data (BigData)	2024	NA	NA	4448-4456	10.1109/BigData62323.2024.10825335
45	Hierarchical Spatio-Temporal Graph Neural Networks for Pandemic Forecasting	Ma, YH and Gerard, P and Tian, YJ and Guo, ZC and Chawla, NV	PROCEEDINGS OF THE 31ST ACM INTERNATIONAL CONFERENCE ON INFORMATION AND KNOWLEDGE MANAGEMENT, CIKM 2022	2022	NA	NA	1481-1490	10.1145/3511808.3557350
46	Hybrid Modeling of Regional COVID-19 Transmission Dynamics in the U.S	Y. Bai and A. Safikhani and G. Michailidis	IEEE Journal of Selected Topics in Signal Processing	2022	16	2	261-275	10.1109/JSTSP.2022.3140703
47	Improving the Spatial Fairness of Spatiotemporal Sequence Forecasting Service Systems	Xue, G. and Ren, L. and Yan, X. and Cui, Z. and Gong, D. and Chen, J.	Production and Operations Management	2025	NA	NA	NA	10.1177/10591478251356940
48	Incorporating variant frequencies data into short-term forecasting for COVID-19 cases and deaths in the USA: a deep learning approach	Du, HR and Dong, ES and Badr, HS and Petrone, ME and Grubaugh, ND and Gardner, LM	EBIOMEDICINE	2023	89	NA	NA	10.1016/j.ebiom.2023.104482
49	Interpretable spatial identity neural network-based epidemic prediction	Luo, LJ and Li, BX and Wang, XY and Cui, L and Liu, G	SCIENTIFIC REPORTS	2023	13	1	NA	10.1038/s41598-023-45177-1
50	Large-scale multivariate forecasting models for Dengue - LSTM versus random forest regression	Mussumeci, E and Coelho, FC	SPATIAL AND SPATIO-TEMPORAL EPIDEMIOLOGY	2020	35	NA	NA	10.1016/j.sste.2020.100372
51	LSTM-based Estimation of Time-Varying Parameters in a Spatiotemporal PDE Model for Prediction of Epidemic Spread	David, DA and Street, L and Ramakrishnan, S and Kumar, M	IFAC PAPERSONLINE	2024	58	28	468-473	10.1016/j.ifacol.2025.01.090
52	Machine learning approach as an early warning system to prevent foodborne Salmonella outbreaks in northwestern Italy	Garcia-Vozmediano, A. and Maurella, C. and Ceballos, L.A. and Crescio, E. and Meo, R. and Martelli, W. and Pitti, M. and Lombardi, D. and Meloni, D. and Pasqualini, C. and Ru, G.	Veterinary Research	2024	55	1	72	10.1186/s13567-024-01323-9

53	Multi-Model Prediction of West Nile Virus Neuroinvasive Disease With Machine Learning for Identification of Important Regional Climatic Drivers	Holcomb, KM and Staples, JE and Nett, RJ and Beard, CB and Petersen, LR and Benjamin, SG and Green, BW and Jones, H and Johansson, MA	GEOHEALTH	2023	7	11	NA	10.1029/2023GH000906
54	Multi-relational Graph Attention-Based Depth Wise Separable Convolutional Neural Network for Spatio-Temporal Epidemic Forecasting	Suggala, Ravi Kumar and Hema, B. and Naga Jahnavi, B. and Anannya Sai, Ch. and Saumya Prasanna, Ch. and Hari Keerthi, J.	Lecture Notes in Networks and Systems	2026	1465 LNNS	NA	311-320	10.1007/978-981-96-7517-3_26
55	Novel spatiotemporal feature extraction parallel deep neural network for forecasting confirmed cases of coronavirus disease 2019	Huang, CJ and Shen, YM and Kuo, PH and Chen, YH	SOCIO-ECONOMIC PLANNING SCIENCES	2022	80	NA	NA	10.1016/j.seps.2020.100976
56	Optimal resource allocation with spatiotemporal transmission discovery for effective disease control	Ren, JF and Liu, MT and Liu, Y and Liu, JM	INFECTIOUS DISEASES OF POVERTY	2022	11	1	NA	10.1186/s40249-022-00957-1
57	Predicting Disease Outbreaks with Spatio-Temporal Machine Learning Models and Epidemiological Data	S. Chittipothu and P. K. Gutta and N. Aravind and S. Rajalakshmi and A. Reddy Neravetla and N. V. Gangabathula and S. Reddy Chaganti	2025 4th International Conference on Innovative Mechanisms for Industry Applications (ICIMIA)	2025	NA	NA	891-898	10.1109/ICIMIA67127.2025.11200528
58	Predicting regional influenza epidemics with uncertainty estimation using commuting data in Japan	Murayama, T. and Shimizu, N. and Fujita, S. and Wakamiya, S. and Aramaki, E.	PLOS ONE	2021	16	04-Apr	NA	10.1371/journal.pone.0250417
59	Prediction of the Prevalence of COVID-19 Using Epidemic Differential Equations and Deep Learning Network	Kong, Liang and Guo, Yanhui and Lee, Chung-Wei	Smart Innovation, Systems and Technologies	2025	410 SIST	NA	305-316	10.1007/978-981-97-7786-0_25
60	Research on the Forecast of the Spread of COVID-19	Guo, Lihao and Yang, Yuxin	ACM International Conference Proceeding Series	2021	NA	NA	47-51	10.1145/3460238.3460246
61	Research on the regional prediction model of urban raster infectious diseases based on deep learning	Han, B and Mao, Y and Liu, ZH and Wang, LA	SUSTAINABLE ENERGY TECHNOLOGIES AND ASSESSMENTS	2023	60	NA	NA	10.1016/j.seta.2023.103518
62	RESEAT: Recurrent Self-Attention Network for Multi-Regional Influenza Forecasting	J. Moon and S. Jung and S. Park and E. Hwang	IEEE Journal of Biomedical and Health Informatics	2023	27	5	2585-2596	10.1109/JBHI.2023.3247687
63	Space-Distributed Traffic-Enhanced LSTM-Based Machine Learning Model for COVID-19 Incidence Forecasting	MuÃ±oz-Organero, M	COMPUTATIONAL INTELLIGENCE AND NEUROSCIENCE	2022	2022	NA	NA	10.1155/2022/4307708
64	SpatialâTemporal Synchronous Graph Transformer network (STSGT) for COVID-19 forecasting	Banerjee, S. and Dong, M. and Shi, W.	Smart Health	2022	26	NA	NA	10.1016/j.smhl.2022.100348
65	Spatio-temporal epidemic forecasting using mobility data with LSTM networks and attention mechanism	Jiao, S. and Wang, Y. and Ye, X. and Nagahara, L. and Sakurai, T.	Scientific Reports	2025	15	1	NA	10.1038/s41598-025-94089-9
66	Spatio-temporal prediction of the COVID-19 pandemic in US counties: modeling with a deep LSTM neural network	Nikparvar, B and Rahman, MM and Hatami, F and Thill, JC	SCIENTIFIC REPORTS	2021	11	1	NA	10.1038/s41598-021-01119-3
67	Spatio-temporal predictions of COVID-19 test positivity in Uppsala County, Sweden: a comparative approach	van Zoest, V and Varotsis, G and Menzel, U and Wigren, A and Kennedy, B and Martinell, M and Fall, T	SCIENTIFIC REPORTS	2022	12	1	NA	10.1038/s41598-022-19155-y
68	Spatiotemporal Dengue Forecasting for Sustainable Public Health in Bandung, Indonesia: A Comparative Study of Classical, Machine Learning, and Bayesian Models	Mindra Jaya, I.G.N.M. and Andriyana, Y. and Tantular, B. and Pangastuti, S.S. and Kristiani, F.	Sustainability (Switzerland)	2025	17	15	NA	10.3390/su17156777
69	Spatiotemporal forecasting for dengue, chikungunya fever and Zika using machine learning and artificial expert committees based on meta-heuristics	da Silva, Cecilia Cordeiro and de Lima, Clarisse Lins and da Silva, Ana Clara Gomes and Moreno, Giselle Machado Magalhaes and Musah, Anwar and Aldosery, Aisha and Dutra, Livia and Ambrizzi, Tercio and Borges, Iuri V. G. and Tunali, Merve and Basibuyuk, Selma and Yenigun, Orhan and Massoni, Tiago Lima and Jones, Kate and Campos, Luiza and Kostkova, Patty and da Silva Filho, Abel Guilhermino and dos Santos, Wellington Pinheiro	Research on Biomedical Engineering	2022	38	2	499-537	10.1007/s42600-022-00202-6
70	Spatiotemporal Prediction of Chickenpox Cases using Graph Attention Network	N. Aggarwal and I. Pundir and U. Shukla and S. Singh	2022 IEEE 19th India Council International Conference (INDICON)	2022	NA	NA	01-May	10.1109/INDICON56171.2022.10040199
71	Spatiotemporal prediction of COVID-19 cases using inter- and intra-county proxies of human interactions	Vahedi, B and Karimzadeh, M and Zoraghein, H	NATURE COMMUNICATIONS	2021	12	1	NA	10.1038/s41467-021-26742-6
72	Spatiotemporal prediction of infectious diseases using structured Gaussian processes with application to Crimean-Congo hemorrhagic fever	Ak, C and Erg<c3><b6>n<c3><bc>l, <c3> and Sencan, I and Torunoglu, MA and G<c3><b6>nen, M	PLOS NEGLECTED TROPICAL DISEASES	2018	12	8	NA	10.1371/journal.pntd.0006737
73	ST-COVID: a Deep Multi-View Spatio-temporal Model for COVID-19 Forecasting	C. Ju and J. Wang and Y. Zhang and H. Yin and H. Huang and H. Xu	2022 Asia Conference on Algorithms, Computing and Machine Learning (CACML)	2022	NA	NA	769-776	10.1109/CACML55074.2022.00133
74	STG-Net: A COVID-19 prediction network based on multivariate spatio-temporal information	Song, YC and Chen, HY and Song, XM and Liao, ZF and Zhang, Y	BIOMEDICAL SIGNAL PROCESSING AND CONTROL	2023	84	NA	NA	10.1016/j.bspc.2023.104735
75	STOPPAGE: Spatio-temporal data driven cloud-fog-edge computing framework for pandemic monitoring and management	Ghosh, S and Mukherjee, A and Ghosh, SK and Buyya, R	SOFTWARE-PRACTICE & EXPERIENCE	2022	52	12	2700-2726	10.1002/spe.3144
76	TDEFSI: Theory-guided Deep Learning-based Epidemic Forecasting with Synthetic Information	Wang, L. and Chen, J. and Marathe, M.	ACM Transactions on Spatial Algorithms and Systems	2020	6	3	NA	10.1145/3380971
77	Universal risk phenotype of US counties for flu-like transmission to improve county-specific COVID-19 incidence forecasts	Huang, Y. and Chattopadhyay, I.	PLOS Computational Biology	2021	17	10	NA	10.1371/journal.pcbi.1009363
78	Unlocking the potential of Naive Bayes for spatio temporal classification: a novel approach to feature expansion	Prasetiyowati, SS and Sibaroni, Y	JOURNAL OF BIG DATA	2024	11	1	NA	10.1186/s40537-024-00958-x

79	Using a Layered Ensemble of Physics-Guided Graph Attention Networks to Predict COVID-19 Trends	Sun, C and Kumarasamy, VK and Liang, Y and Wu, DL and Wang, YF	APPLIED ARTIFICIAL INTELLIGENCE	2022	36	1	NA	10.1080/08839514.2022.2055989
80	Physics-informed epidemic prediction for irregularly sampled spatio-temporal sequence with missing values	Cheng, H and Mao Y	Applied Intelligence	2025				
81	Transfer graph neural networks for pandemic forecasting	Panagopoulos, G, and Nikolentzos G and Vazirgiannis, M	PROCEEDINGS OF THE AAAI CONFERENCE ON ARTIFICIAL INTELLIGENCE	2021	35	6	NA	10.1609/aaai.v35i6.16616
82	TG-PhyNN: An Enhanced Physically-Aware Graph Neural Network framework for forecasting Spatio-Temporal Data	Elabid, Z., Sasal L, and Busby Daniel	PRICAI 2024: Trends in Artificial Intelligence	2024			42-48	10.1007/978-981-96-0119-6
83	MepoGNN: Metapopulation epidemic forecasting with graph neural networks	Cao Q, and Yang, C, and Fan Z, and Song X and Shibaski R		2023			453-468	10.1007/978-3-031-26422-1_
84	Backbone based dynamic spatiotemporal GNN for epidemic forecasting	Mao J, and Han Y, and Tanaka G, and Wang B	Knowledge based systems	2024	296			
85	A novel graph neural network based approach for influenza like illness nowcasting; exploring the interplay of temporal, geographical and functional spatial features	Luo, J, and Wang, X, and Fan X and He Y, and Du X and Chen Y-Q and Zhao Y	BMC Public Health	2025	25	408		10.1186/s12889-025-21618-6
86	EpiGNN: Exploring spatial transmission with graph neural network for regional epidemic forecasting	Xie, F, and Zhang Z, and Li L, and Zhou B and Tan Y		2023			469 - 485	10.1007/978-3-031-26422-1_29
87	Forecasting dengue across Brazil with LSTM neural networks and SHAP driven lagged climate and spatial effects	Chen X, and Moragag P	BMC Public Health	2025	25	1		10.1186/s12889-025-22106-7
88	Enhancing epidemic forecasting with a physics informed spatial identity neural network+A90:D90	Fujita S, and Akutsu T	PLOS One	2025	20	9	NA	10.1371/journal.pone.0331611
89	Multi-region infectious disease prediction modelling based on spatiotemporal GNN and the dynamic model	Wang X and Jin Z	PLOS Computational Biology	2025	21	1	NA	10.1371/journal.pcbi.1012738
90	Epidemiology aware deep learning for infectious disease dynamics predictions	Liu, M and Liu Y, and Liu J	Proceedings of the 32nd ACM International Conference on Information and Knowledge Management (CIKM '23), October 21–25, 2023, Birmingham, United Kingdom.	2023				10.1145/3583780.3615139
91	Dynamic adaptive spatiotemporal Graph neural network for COVID-19 forecasting	Pu X, Zhu, J, Wu, Y, Leng, C, Bo, Z and Wang H	CAAI Transactions on Intelligence Technology	2023				10.1049/cit2.12238
92	Spatiotemporal graph learning for epidemic prediction	Yu S, Xia, F, Li S, Hou, M and Sheng Q	ACM Transactions on Intelligent Systems and Technology	2023	14	2	NA	10.1145/3579815
93	Forecasting infections with spatio-temporal graph neural networks : a case study	Croft, V, Iersel S and Santina C	Frontiers in Physics	2023	11	NA	NA	10.3389/fphy.2023.1277052

D2. Characteristics of included studies.

ID	Disease	Region	Spatial scale	Temporal resolution	Forecast horizon	Code available? (Y/N)	Size of Dataset	Software used
1	COVID-19	Castilla-Leon, Spain	Health zones -	Daily	7-day forecasts	Available on request	March 1, 2020, to February 5 2021, 245 health zones	R
2	COVID-19	Regio Emilia, Italy	12km x 12km g	Daily	7-day forecasts	No	1st August 2020 to 20th September 2021	R
3	Influenza	Shenzen city, China	District	Daily	One week and two-week predictions	No	1 January 2015 to 30 August 2017, over 716 hospitals (no.days x no. hospitals (973 x 716)	Not mentioned
4	COVID-19	Tehran, Iran	30m spatial cells	Daily	Didn't say	No	20 Feb 2021 - 20 Feb 2022	MATLAB, ArcGIS
5	COVID-19	USA states	State	Daily	7, 15, 30, 60 days	No	August 2020 to October 2022. 783 days x 48 states	Python
6	COVID-19	Regions, USA and Italy	Regions by grid	Daily	5 and 10 days for USA, 5 and 8 days for Italy	No	USA = 9 March 2020 - 8 April 2020. Italy = 5 Feb 2020 to 10 April 2020	Not mentioned
7	Influenza	Regions and cities USA	US department of health and human services region	Weekly	1 - 5 weeks	No	CDC = 2002 - 2016. GFT = 2003 - 2014	R
8	Hand, foot and mouth disease	Guangdon and Shandon, Ch	Prefecture	Doesn't say	4, 8, 12 weeks forecasts	No	1 Jan 2011 to 31 Dec 2019	Not mentioned
9	COVID-19	Italy	Region	Daily	7, 14, 21, 28 day forecasts	https://github.com/Fede-stack/Probabilistic-COVID19	Jan 2020 - Jan 2024	Python
10	Crimean-Congo Hemorrhagic fever	Turkey	Province	Monthly	Monthly	No	Jan 2004 - Dec 2015	R
11	Dengue	Brazil, Peru	Federal unit, d	Monthly	Monthly	https:// github.com/ ESA-PhiLab/ ESA-UNICEF_ Dengu eFore castP roject	19 years. 2001 - 2019	Python
12	COVID-19	USA	County	Weekly	1, 2, 3, 4 weeks for 17 weeks	https://github.com/geohai/covid-lstm.	1 April 2020 to 20 Feb 2021. 3000 counties	Python
13	COVID-19	Portugal	Municipality	Daily	14 days for 5 months	Not available	September 2020 to May 2021 x 19 spatial units	Not mentioned
14	COVID-19	Italy	Region	Daily	"short term"	https://github.com/pcm-dpc/COVID-19	24th Feb - 5th May 2020	Python
15	Dengue	Sri Lanka	District	Weekly	Weekly over a yea	Not available	2011-2018	Not mentioned
16	Influenza, Cholera,	India	State	Weekly	6 weeks	Not available	12 years	R, Python
17	COVID-19	USA	Global, US stat	Daily	Daily	Not available	3 May 2020 - April 23 2021. 355 days	Python
18	Dengue	Taiwan	Town/village	Daily	1/1/2019 - 22/9/2020	https://github.com/thirakawa/dengue feverPredictionUNet.	16/2/2002 - 22/9/2020	Python
19	COVID-19	Germany	District	Weekly	Weekly	Not available	Didn't say	R
20	COVID-19	Global	Country	Daily	7 days	Not available	January - October 2020	Python
21	COVID-19	Japan	Prefecture	Daily	7 days	https://github.com/deepkashiwa20/ODCRN	1/1/2020 - 28/2/2021	Python
22	COVID-19	Italy, England, France, Spain	NUTS3	Daily	3 days, 7 days	Not available	Italy = 24/2 - 12/5, England = 13/3 - 12/5, Spain = 12/2 - 12/5, France = 10/3 - 12/5. 105 regions Italy, 129 England, 35 Spain, 81 France	Doesn't say
23	COVID-19	n/a	Idealized tows	Daily	45.5 days	Not available	N/A	Python

24	COVID-19	Japan, USA	States and prefectures	Daily	3, 7, 14 days	Not available	USA = 12/4/2020 - 15/4/2021, Japan = 2/4/2020 - 24/9/2021	Didn't say
25	COVID-19	USA	County	Daily	7 days	https://github.com/padmaksha18/ARM3Dnet	May to December 2020	Python
26	Measles	England and Wales	Cities and tow	Biweekly	1-52 biweekly time steps ahead	https://github.com/WyattGMadden/deep_measles_dynamics.	1944 - 1965, 1452 regions	Python
27	COVID-19	Mumbai, India	City ward level	Daily	7 days	Not available	N/A	Python
28	COVID-19	Madrid. Spain	Primary care centers - 286	Weekly	Weekly	Not available	Feb 2020 - March 2022	Python
29	Ebola	West Africa and Sierra Leone	Cities and villa	Doesn't say	Weekly	https://github.com/afofanah/DeepEVDMob.	2014 - 2016 - West Africa and 2015 -2016 Sierra Leone	Python
30	Influenza like illness	USA	Health and hu	Weekly	1 year	Not available	2010-2018 for 469 weekly observations	MATLAB.
31	COVID-19	USA	National and s	Daily	14 days	Not available	Jan 22 2020 - 25 Aug 2021	Python
32	COVID-19	Italy	Region	Daily	3 days	Not available	24 Feb 2020 - 18 June 2020. 113 days x 7 regions	Python
33	Zika	Brazil	State	Weekly (aggregated to monthly)	Year	Not available	2017 - 2018	Doesn't say
34	Tuberculosis	Japan, China	Prefecture	Monthly	3, 6, 9, 12 months	Not available	China = Jan 2014 - Dec 2018. Japan = Jan 1998 - Dec 2015	Python, R
35	COVID-19	Germany, China	Province, state	Daily	7, 14, 21, 28 days	t https://github.com/ichbinshhan/Epi-Spatio-Temporal-Teilen.	365 days	Python
36	COVID-19	USA	County	Daily	1-5 weeks	https://github.com/v1xerunt/HOIST.	September 2020 to May 2022	Python
37	COVID-19	USA and global	Global, US state, US county	Daily	4 weeks	Not available	25 weeks	Not mentioned
38	COVID-19	USA	State	Daily	Daily	Not available	18 April 2020 - 20 December 2021	Python
39	COVID-19	USA	County	Daily	7 days	Not available	6th Jan 2020 - 23rd Jan 2022	Not mentioned
40	COVID-19	UK, USA	State	Daily	1, 14, 28, 42-day f	Not available	1 March 2020 - 1 March 2022	Python
41	COVID-19	Spain, Italy, France, England	Regions	Daily	7, 14, 21-day forecasts	Not available	Italy - 24/2/2020 - 15/5/2020. France 10/3/2020 - 15/5/2020. England - 13/3/2020 - 15/5/2020. Spain - 12/3/2020 - 15/5/2020	Doesn't say
42	Tuberculosis	England	Country	Daily	"Short term" - up t	Not available	2022 - 2024	R
43	ILI	New Zealand	District health	Daily	14 days	Not available	2019 x 7 regions	Doesn't sat
44	Dengue	Sri Lanka	District	Weekly	3 weeks ahead	Not available	2013 - 2022	Python
45	COVID-19	USA	County and re	Weekly	1, 2, 3 weeks	Not available	6/4/2020 - 12/7/2021	Not mentioned
46	COVID-19	USA	States and counties	Daily	2 weeks	Not available	1 March 2020 - 31 March 2021	Not mentioned
47	Chickenpox	Hungary	Regions	Weekly	10 and 20 steps ahead	Not available	2005 - 2015, 20 regions	Doesn't say
48	COVID-19	USA	State	Weekly	1 - 4 weeks	https://github.com/hongru94/multi_stage_LSTM.	2/8/2020 - 1/8/2021	Python
49	Influenza	USA, Japan	Region, prefectures	Weekly	3, 5, 10 timesteps	https://github.com/minasora/ISID	USA - 2002 - 2017. Japan Aug 2012 - March 2019	Python
50	Dengue	Brazil	Cities - 790	Weekly	4 weeks	Not available	Jan 2010 - June 2016. 790 x 442 weeks	Not mentioned
51	COVID-19	USA	State and counties	5 or 10 days	1-15 days	Not available	20 April 2020 - 5 June 2020, 45 days	MATLAB

52	Salmonella	Italy	Municipality	Monthly	Not explicitly rep	https:// doi.org/ 10. 1186/ s13567- 024- 01323- 9.	2014 - 2018	R, stata, QGIS
53	West Nile neuroinvasive disease	Continental US	9 climate regio	Annual	1 year	Not available	2005 - 2021	R
54	COVID-19	Global and US	Global, US stat	Daily	1 - 4 weeks	Not available	3 May 2020 - 23 April 2021	Not mentioned
55	COVID-19	Germany, Italy, Spain	Country	Daily	10 days	Not available	22 Jan 2020 - 28 April 2020	Python
56	COVID-19	Hong Kong, China	District = 18	Daily	1 day	Not available	27 December 2021 - 17 July 2022	Not mentioned
57	COVID-19, Dengue, Influenza	Not specified	Multiple regio	Weekly	1 week head	Not available	Not reported	Not mentioned
58	Influenza	Japan	Prefecture	Weekly	1 - 5 weeks	Not available	37th week 2014 to 30th week 2020	Not mentioned
59	COVID-19	Italy	Regions	Daily	3 days	Not available	24/2/2020 - 18/6/2020. 113 days	Python
60	COVID-19	USA	Counties	Daily	7 days	Not available	1 May 2020 - 30 November 2020. 221 days	Not mentioned
61	Tuberculosis	China	City, 50 by 50 g	Monthly	6 months	Not available	2005 - 2015	Python
62	Influenza and COVID	USA, Japan and multiple European nations	States, regions, prefectures	Daily for COVID-19, Weekly for influenza	2 - 5 weeks, 10-26 weeks for influenza, 7 days for COVID-19	Not available	US states = 40th week 2020 - 20th week 2021. US regions = 1st week 2002 - 18th week 2020. Japan = 31st week 2012 - 20th week 2020. COVID-19 = 24th Jan 2020 - 9 May 2021	Python
63	COVID-19	Madrid. Spain	District	Weekly	One week	Not available	Feb 25, 2020 - March 29, 2022	Python
64	COVID-19	USA	State and counties	Daily	up to 12 days	https://github.com/s	15 March 2020 - 30 November 2021 - Johns Hopkins. 18 March 2020 - 30 November 2021 NYT	Python
65	COVID-19	Japan	Prefecture	Daily	1 - 4 weeks	Not available	6 December 2020 - 16 October 2021	Python
66	COVID-19	USA	Counties	Daily	1 - 4 weeks	https:// github. com/ behna mnkp/Covid-19- Predi ction. git.	26th January 2020 - 12 September 2020	Python
67	COVID-19	Uppsala, Sweden	Service point a	Weekly	1 week	https://github. com/MolEpicU U/spatiotempo ral_predictions _COVID19	29 June 2020 - 4 July 2021	R
68	Dengue	Bandung city, Indonesia	District	Monthly	2 years	https://githu b.com/mind ra-bit/Dengue_ Forecasting	2009 - 2023	R
69	Dengue, Chikungunya, Zika	Recife, Brazil	City	Monthly	2 months	Not available	2013 - 2016	QGIS, python
70	Chickenpox	Hungary	County	Weekly	10 weeks, 20 wee	Not available	2005 - 2014	Not mentioned
71	COVID-19	USA	County	Weekly	1 - 4 weeks	https://githu b.com/geoh ai/COVID19-STGXB63	43 weeks x 3103 counties	Python
72	Crimean-Congo Hae	Türkiye	Province	Monthly	2 years	Not available	2004 - 2015	R
73	COVID-19	USA	State and counties	Daily	2, 5, 10, 15 days	Not available	23 March 2020 - 18 September 2020	Python
74	COVID-19	China, Australia, UK, France, Netherlands	Province	Daily	3, 7, 14, 28 days	Not available	22 January 2020 - 6 October 2022	Python
75	COVID-19	West Bengal, India	Regional grids	Weekly	Near future	Not available	6 months	QGIS, Python
76	ILI	USA	State and counties	Weekly	1, 2, 3, 4, 5 weeks	Not available	Epidemiological week 40 2010 to epidemiological week 18 2018	Python
77	ILI, COVID-19	USA	County	Weekly	Weekly	https://githu b.com/zerok nowledgedis covery/unitc ov	471 weeks Jan 2003 - 2011 ILI. COVID data March 2020until end of May 2021	Python
78	Dengue	Indonesia	District	Annual	Annual	https://drive.google .com/file/d/1YvkKs Z- 7yVMancoSBDxKi vZsuljpaz- k/view?pli=1	2012 - 2018	Python
79	COVID-19	UK, USA	Country, continent, global	Daily	14 days	Not available	January 2021 - May 2021	

80	COVID-19	USA	County	Daily	5, 15, 20 days	Available on request	22 March 2020 - 10 June 2020	Not mentioned
81	COVID-19	Italy, France, Spain, England	NUTS3 regions	Daily	1 - 14 days	https://github.com/geopanag/pandemic_tgnn	Italy = 24/2 - 12/5. England = 13/3 - 12/5. Spain = 12/3 - 12/5. France 10/3 - 12/5	Python
82	COVID-19, Chicken	England, Hungary	Region	Daily for COVID, weekly for Chickenpox	1 day for COVID, 1 week for Chickenpox	Not available	COVID = March - May 2020. Chickenpox = 2004 - 2014	Not mentioned
83	COVID-19	Japan	Prefecture	Daily	3, 7, 14 days	https://github	1/4/2020 - 21/9/2021 x 47 prefecture	Python
84	COVID-19	Japan, USA	State, prefecture	Daily	5, 10, 15, 20 days	https://github.com/JkMaoya/BDSTG_NN.	USA = 1 May 2020 - 31 December 2020 - 245 days. Japan = 15 January 2022 - 14 June 2022 - 151 days	Python
85	ILI	Taiwan	County	Weekly	1 week	Not available	Week 14 2008 - week 10 2020	Not mentioned
86	Influenza and COVID	Japan, USA, Australia, Spain	Prefecture, region, state	Daily/weekly	3, 5, 7, 10, 14, 15	https://github.	Japan Prefectures = Aug 2012 - March 2019. US regions = 2002 - 2017. US States = 2010 - 2017. Australia = 27 Jan 2020 - 4 Aug 2021. Spain = 20 Feb 2020 - 20 June 2020	Python
87	Dengue	Brazil	State	Weekly	4 or 12 months	https://github.com/ChenXiang1998/LSTM-Based-Dengue-Prediction-Across-Brazil.	3/1/16 to the last epidemiological week of 2023	Not mentioned
88	COVID-19	USA	County	Daily	5, 15, 20 days	Not available.	January 16, 2020, to May 8, 2023, Japan, January 22, 2020, to March 9, 2023. USA	Not mentioned
89	COVID-19	China	Province	Daily	3 - 7 days	github.com/	334 days 1 Jan 2022 - 30 Nov 2022	Python
90	Influenza -like-illness	USA	District	Weekly	Not mentioned	Not available	2010 - last week 2016 = 364 weeks x 10 regions	Python
91	COVID-19	China, Brazil, Austria	State or province	Daily	7 days	Not available	2020 COVID-19 data	Python
92	COVID-19	USA	States	Daily	30, 60 days	Not available	1 May.- 30 October 2021 x 51 states	Not mentioned
93	COVID-19	The Netherlands	Municipality	Daily	1 week, 2 weeks	Not available	1 June 2020 - 10 April 2022	Python

D3. Model architectures used in the included studies.

ID	Core model (LSTM / GNN / Transformer / Hybrid)	Graph type (static / dynamic / adaptive / hierarchical)	Mechanistic model embedded? (SIR / SEIR / Rt)	Parameter learning (direct / inferred / Bayesian)	Attention mechanism?	Multigraph?	Decoupled transmission?	Surrogate model?
1	Hybrid - LSTM and Bayesian neural network layers	N/A	No	Bayesian	No	No	No	No
2	LSTM, CNN	N/A	No	Direct	No	No	No	No
3	Feedforward convolutional residual architecture	N/A	No	Direct	No	No	No	No
4	CNN	N/A	No	Direct	Yes	No	No	No
5	Transformer, GCN	Dynamic	No	Direct	Yes	Yes	No	No
6	Convolutional neural network, LSTM	N/A	No	Direct	No	No	No	No
7	LSTM	N/A	No	Direct	No	No	No	No
8	GCN	Static	No	Direct	No	No	No	No
9	CNN-LSTM	N/A	No	Direct	No	No	No	No
10	Gaussian process	N/A	No	Bayesian	No	No	No	No
11	LSTM, CatBoost, SVM	N/A	No	Direct	No	No	No	No
12	LSTM	N/A	No	Direct	No	No	No	No
13	Symbolic regression and geostatistical model	N/A	No	Direct	No	No	No	No
14	GCN + LSTM	Dynamic	Yes	Direct	No	Yes	No	No
15	Compartmental and LSTM	N/A	Yes	Direct	No	No	No	No
16	Bayesian modelling + RNN	N/A	No	Hybrid	No	No	No	No
17	GCN	Dynamic	Yes	Direct	Yes	No	No	No
18	U-Net based encoder	N/A	No	Direct	No	No	No	No
19	GNN + Distributional regression	Static	No	Direct	No	No	No	No
20	Encoder decoder model	N/A	No	Direct	No	No	No	No
21	Convolutional recurrent neural network	Static and Dynamic	Yes	Direct	No	No	No	No
22	State space model	Dynamic	No	Direct	No	No	No	No
23	Generative adversarial network	N/A	Yes	Direct	No	No	No	No

24	GRU and self-attention	Dynamic	No	Direct	Yes	No	Yes	No
25	Diffusion graph convolution, autoregressive LSTM, mixture density network	Dynamic	No	Direct	No	No	No	No
26	Feedforward neural network and PINN	N/A	Yes	Direct	No	No	No	No
27	LSTM and reinforcement learning	N/A	No	Direct	No	No	No	No
28	CNN and LSTM	N/A	No	Direct	No	No	No	No
29	GCN and LSTM	Dynamic	Yes	Direct	Yes	No	No	No
30	Radial basis function neural network	N/A	No	Direct	No	No	No	No
31	SARIMAX, minimax concave probability, vector autoregressive, GCN-LSTM, Wavelet ANN, Augmented NN, Deep AR, GRU + LSTM, random walk	Static	No	Direct	No	No	No	No
32	Hybrid compartmental and LSTM	N/A	Yes	Direct	No	No	No	No
33	random forest, gradient boosted regression, deep neural network	N/A	No	Direct	No	No	No	No
34	Hybrid mechanistic deep learning model. Modified network SIR model	Static	Yes	Inferred	Yes	No	No	No

35	Hybrid mechanistic deep learning model. Spatiocontact SIR model	Static and Dynamic	Yes	Direct	No	No	No	No
36	Ising dynamics based deep learning model	N/A	Yes	Direct	No	No	No	No
37	RNN, GRU, LSTM	N/A	No	Direct	No	No	No	No
38	LSTM	N/A	No	Direct	No	No	No	No
39	Hybrid spatiotemporal neural architecture with generalized attention	N/A	No	Direct	Yes	No	No	No
40	Graph neural network and LSTM	Dynamic	No	Direct	Yes	Yes	No	No
41	GNN	Static	No	Direct	No	No	No	No
42	Gaussian process	N/A	No	Inferred	No	No	No	No
43	Ensemble of autoregressive chains	N/A	No	Direct	No	No	No	No
44	GNN	Static	No	Direct	No	No	No	No
45	GNN and transformer	Dynamic	No	Direct	No	No	No	No
46	Peicewise stochastic SIR model and vector autoregressive model	N/A	Yes	Direct	No	No	No	No
47	Psuedogrouping adversarial ML	Static	No	Direct	Yes	No	No	No
48	LSTM	N/A	No	Direct	No	No	No	No
49	Neural network	N/A	No	Direct	No	No	No	No
50	LSTM, random forest, LASSO regression	N/A	No	Direct	No	No	No	No
51	LSTM	N/A	Yes	Inferred	No	No	No	No
52	tree regression, random forest and gradient boosting	N/A	No	Direct	No	No	No	No

53	Always absent, negative binomial, autoregressive, random forest, neural network	N/A	No	Direct	No	No	No	No
54	Multirelational graph attention network and depth wise separable convolutional neural network	Static	No	Direct	Yes	Yes	No	No
55	convolutional neural network and gated recurrent unit	N/A	No	Direct	No	No	No	No
56	Gaussian process	N/A	Yes	Direct	No	No	No	No
57	LSTM + GCN	Static	No	Direct	No	No	No	No
58	GCN + sequence to sequence model	Static	No	Direct	No	No	No	No
59	Hybrid LSTM with differential equations	Static	Yes	Direct	No	No	No	No
60	Graph neural network	Static	No	Direct	No	No	No	No
61	ResNet + LSTM	N/A	No	Direct	No	No	No	No
62	Recurrent self-attention	Dynamic	No	Direct	Yes	No	No	No
63	LSTM	N/A	No	Direct	No	No	No	No
64	GCN and self-attention	Dynamic	No	Direct	Yes	No	No	No
65	LSTM and self-attention	N/A	No	Direct	Yes	No	No	No
66	LSTM	N/A	No	Direct	No	No	No	No
67	Gradient boosting, random forest, ARIMA, INLA	N/A	No	Direct	No	No	No	No
68	SARIMA, XGBoost, RNN, LSTM, BiLSTM, CNN-LSTM, Bayesian spatiotemporal	N/A	No	Direct	No	No	No	No

69	SVM, RF, EML, MLP, ESM, DeepESM, LR	N/A	No	Direct	No	No	No	No
70	Graph attention network	Static	No	Direct	Yes	No	No	No
71	Extreme gradient boosting but five different ML models were tested to see which was the best	N/A	No	Direct	No	No	No	No
72	Gaussian process regression	N/A	No	Bayesian	No	No	No	No
73	GCN + CNN + GRU	Static	No	Direct	No	No	No	No
74	GCN + LSTM + CNN	Static	No	Direct	No	No	No	No
75	LSTM, GRU, attention mechanism	Dynamic	No	Direct	Yes	Yes	No	No
76	LSTM	N/A	No	Inferred	No	No	No	No
77	GLM and ensemble regressor	N/A	No	Direct	No	No	No	No
78	Naïve bayes classification prediction model	N/A	No	Direct	No	No	No	No
79	Physics informed graph attention network	Dynamic	Yes	Direct	No	No	No	No
80	Physics informed graph neural network	Static	Yes	Direct	Yes	No	No	No
81	MPNN + LSTM and MPNN + transfer learning	Dynamic	No	Direct	No	No	No	No
82	Physics informed graph neural network	Static	Yes	Direct	No	No	No	No

83	Hybrid metapopulation model and graph neural network model. Temporal convolutional network and graph convolutional module for learning spatial dependencies	Dynamic	Yes	Direct	No	No	No	No
84	Graph neural network with SIR model embedded	Dynamic	Yes	Direct	No	No	No	No
85	GNN	Static	No	Direct	No	No	No	No
86	GNN + CNN	Static	No	Direct	No	No	No	No
87	LSTM	N/A	No	Direct	No	No	No	No
88	physics informed GNN , GAT. Encoder-decoder module	Static	Yes	Direct	Yes	No	No	No
89	Hybrid metapopulation model and graph transformer neural network	Dynamic	Yes	Direct	Yes	no	No	No
90	EpiCNNRNN-Res and Epi-Cola-GNN	Static	Yes	Direct	No	No	No	No
91	Dynamic adaptive spatiotemporal graphic neural network	Dynamic	No	Direct	Yes	No	No	No
92	GCN, GRU, MLP	Static	No	Direct	Yes	No	No	No
93	GAT, GRU	Static	No	Direct	No	No	No	No

D4. Covariates used in the included studies.

ID	Case counts	Mobility	Climate	Pollution	Socioeconomic	Policy	Variant frequency	Satellite data	Remote sensing	Demographics	Other
1	1	1	0	0	1	0	0	0	0	0	Urban, shapefiles
2	1	1	1	1	0	0	0	1	0	0	
3	1	0	0	0	0	0	0	0	0	0	0
4	1	0	1	1	0	0	0	1	0	1	Urban
5	1	1	0	0	0	1	0	0	0	0	0
6	1	0	0	0	0	0	0	0	0	0	0
7	1	0	1	0	0	0	0	0	0	0	Google flu trends, spatial proximity to neighboring regions
8	1	0	0	0	0	0	0	0	0	0	Latitude and longitude data
9	1	0	0	0	0	0	0	0	0	0	0
10	1	0	1	0	0	0	0	0	1	0	Latitude, longitude, settlements, area sown, buildings, households, land use
11	1	0	1	0	1	0	0	1	1	1	0
12	1	1	1	0	0	0	0	0	0	0	0
13	1	0	0	0	0	0	0	0	0	0	Incidence in neighboring regions
14	1	1	0	0	0	0	0	0	0	1	Population density, health conditions
15	1	1	1	0	1	0	1	0	0	1	Vegetation index
16	1	0	1	1	1	0	0	0	0	1	0
17	1	0	0	0	0	0	0	0	0	0	Population, longitude and latitude
18	1	0	1	0	0	0	0	0	1	1	Longitude and latitude
19	1	1	0	0	0	0	0	0	0	1	Population size
20	1	1	1	0	1	1	0	1	0	0	
21	1	1	0	0	0	0	0	0	0	1	0
22	1	1	0	0	0	0	0	0	0	0	
23	0	0	0	0	0	0	0	0	0	0	0
24	1	1	0	0	0	0	0	0	0	0	0
25	1	1	0	0	0	0	0	0	0	0	Mobile phone signal
26	1	0	0	0	0	0	0	0	0	1	Incidence in neighboring regions, distance to nearby cities
27	1	0	0	0	1	0	0	0	0	0	Hospital information
28	1	0	0	0	0	0	0	0	0	0	Geolocated case counts
29	1	1	0	0	0	0	0	0	0	0	0
30	1	0	0	0	0	0	0	0	0	0	0
31	1	1	0	0	0	0	0	0	0	0	Hospitalizations, deaths, vaccinations
32	1	1	0	0	0	0	0	0	0	0	0
33	1	0	1	0	0	0	0	0	0	0	0
34	1	0	0	0	0	0	0	0	0	0	0
35	1	0	0	0	0	0	0	0	0	0	Recovery and deaths
36	1	1	0	0	1	0	0	0	0	1	Vaccination, medical claim statistics, medical resource usage
37	1	0	0	0	0	0	0	0	0	0	Surveillance, testing positivity
38	1	1	0	0	0	0	0	0	0	0	0
39	1	1	0	0	0	0	0	0	0	1	Mask usage, ICU bed capacity, vaccination
40	1	1	0	0	0	1	0	0	0	0	
41	1	1	0	0	0	0	0	0	0	0	0
42	1	0	0	0	0	0	0	0	0	0	Latitude and longitude, population size
43	1	0	1	0	0	0	0	0	0	0	0
44	1	1	0	0	0	0	0	0	0	1	0
45	1	0	0	0	0	0	0	0	0	1	Distances of states/counties to target

46	1	0	0	0	0	0	0	0	0	0	Adjacency between regions
47	1	0	0	0	0	0	0	0	0	0	0
48	1	1	1	0	0	1	1	0	0	1	COVID symptom survey
49	1	0	0	0	0	0	0	0	0	0	0
50	1	0	0	0	0	0	0	0	0	0	Social media data and meteorological data
51	1	1	0	0	0	0	0	0	0	1	Shapefiles
52	1	0	0	0	0	0	0	0	0	1	food surveillance data
53	1	0	0	0	0	0	0	0	0	1	Land use - urban, crops, wetland
54	1	0	0	0	0	0	0	0	0	1	geographic proximity
55	1	0	0	0	0	0	0	0	0	0	deaths
56	1	0	0	0	0	0	0	0	0	0	buildings the individual visited within 14 days before positive test
57	1	1	1	0	1	0	0	0	0	1	0
58	1	1	0	0	0	0	0	0	0	0	0
59	1	0	0	0	0	0	0	0	0	0	Infection rates of nearby neighbors
60	1	1	0	0	0	0	0	0	0	0	Mask wearing survey, daily deaths
61	1	1	0	0	0	0	0	0	0	1	0
62	1	0	0	0	0	0	0	0	0	0	0
63	1	1	0	0	0	0	0	0	0	0	0
64	1	0	0	0	0	0	0	0	0	0	Physical distances between states
65	1	1	0	0	0	0	0	0	0	0	Hospitalizations
66	1	1	0	0	0	0	0	0	0	0	0
67	1	0	0	0	0	0	0	0	0	1	Hospitalizations, ICU beds, calls to healthcare advice line, vaccine coverage, social contacts
68	1	0	0	0	0	0	0	0	0	0	0
69	1	0	1	0	0	0	0	0	0	0	Environment, meteorologic al
70	1	0	0	0	0	0	0	0	0	0	0
71	1	1	1	0	1	0	0	0	0	1	Social connectedness data
72	1	0	0	0	0	0	0	0	0	0	geographic coordinates, seasonality
73	1	1	0	0	0	0	0	0	0	1	latitude and longitude
74	1	1	0	0	0	0	0	0	0	1	distance of the geographic centre of mass
75	1	1	0	0	0	0	0	0	0	1	
76	1	1	1	0	0	0	0	0	0	1	Google search data
77	1	0	0	0	0	0	0	0	0	1	0
78	1	0	1	0	1	0	0	0	0	1	Altitude, total population
79	1	1	0	0	0	0	0	0	0	0	0
80	1	0	0	0	0	0	0	0	0	0	Medical claims data, hospitalizations
81	1	1	0	0	0	0	0	0	0	0	0
82	1	1	0	0	0	0	0	0	0	0	0
83	1	1	0	0	0	0	0	0	0	0	0
84	1	0	0	0	0	0	0	0	0	0	0
85	1	0	0	0	1	0	0	0	0	1	Emergency department visits
86	1	1	0	0	0	0	0	0	0	0	Proximity between regions

87	1	0	1	0	0	0	0	0	0	0	Spatial influence from neighboring states
88	1	0	0	0	0	0	0	0	0	0	Deaths, claim data from IQVIA
89	1	1	0	0	0	0	0	0	0	1	Birth rate, death rate
90	1	1	0	0	0	0	0	0	0	0	0
91	1	1	0	0	0	1	0	0	0	0	Recovered, deaths, influence of neighboring regions
92	1	1	1	0	1	0	0	0	0	1	0
93	1	1	0	0	0	0	0	0	0	1	Interactions between Regions

D5. Evaluation metrics used in the included studies.

ID	Baselines compared	RMSE/NRMSE	MAE	MAPE	AUC	Cross-validation?	External validation?	Uncertainty interval reported?	MOV	R2	F-score	RMSPE	Pearsons	Watanabe Akaike information criterion	Deviance information criterion	Precision	Recall	Accuracy	Relative error	MSE	Other
1	1	1	1	0	0	0	0	1	0	0	0	0	0	1	1	0	0	0	0	0	
2	0	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	
3	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
4	1	1	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	
5	1	1	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	
6	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
7	1	1	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	
8	1	1	1	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	
9	1	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	
10	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	
11	0	1	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	
12	1	0	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	
13	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	
14	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	
15	1	1	1	1	1	0	0	0	0	1	1	0	0	0	0	0	1	1	0	1	
16	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	
17	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	
19	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	
20	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	1	0	0	
21	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	
22	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
24	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
25	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	Normalized deviation
26	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
28	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	Explained variance
29	1	1	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	
30	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	RSE, relative prediction error
31	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
32	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
33	0	1	1	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	
34	0	1	1	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	SMAPE
35	1	1	1	0	0	0	1	1	0	0	0	0	1	0	0	0	0	0	1	0	CCC
36	1	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	CCC
37	1	1	0	1	0	1	0	1	0	0	0	0	1	0	0	0	0	0	0	0	
38	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	

39	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
40	1	1	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	
41	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	"Error"
42	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	Freeman Tukey, CRPS, Bayesian P-value
43	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
44	1	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
45	1	1	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
46	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	Mean relative prediction error
47	1	1	1	1	0	0	On data from different domain	0	0	0	1	0	0	0	0	0	0	0	0	0	0	Regression demographic parity ratio
48	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	weighted interval scores
49	1	1	1	0	0	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
50	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	MSLE
51	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
52	0	0	0	1	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0
53	1	1	1	0	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	Log scores, Bayesian GLM
54	1	1	1	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	CCC
55	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
56	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	Simulation outcome comparison
57	1	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
58	1	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
59	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
60	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	RMSLE
61	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
62	1	1	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	MASE
63	1	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
64	1	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	RMSLE
65	0	1	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
66	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
67	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
68	0	1	1	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	SMAPE

69	0	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	R, Kendall's, Spearman's
70	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
71	1	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
72	1	1	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0
73	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
74	1	0	1	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	1	0
75	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	1	1	0	0	0
76	1	1	0	1	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0
77	1	0	1	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0
78	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0
79	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
80	1	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
81	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
82	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
83	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
84	1	1	1	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	CCC
85	1	1	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
86	1	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
87	1	0	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	CRPS
88	1	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
89	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
90	0	1	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
91	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
92	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
93	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0

D6. Interpretability methods used in the included studies.

ID	SHAP	Sensitivity analysis	Rt estimation	Causal modeling	Early warning system	Resource allocation	Real-time deployment	Federated learning	Fairness analysis	Ablation study
1	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0
4	1	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	1
6	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	1
12	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	1	0	0	0	0	0
14	0	0	1	0	0	0	0	0	0	0
15	0	1	0	0	0	0	0	0	0	1
16	0	1	0	1	0	0	0	0	0	1
17	0	0	0	1	0	0	0	0	0	1
18	0	1	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0
20	0	0	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0
22	0	0	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0	0	1
25	0	0	0	0	0	0	0	0	0	1
26	1	1	0	0	0	0	0	0	0	0
27	0	0	0	0	1	0	0	0	0	0
28	0	0	0	0	0	0	0	0	0	0
29	0	0	1	1	0	0	0	0	0	1
30	0	1	0	0	0	0	0	0	0	0
31	0	0	0	0	0	0	0	0	0	0
32	0	0	0	0	0	0	0	0	0	0
33	0	0	0	0	0	0	0	0	0	0
34	0	1	0	0	0	0	0	0	0	0
35	1	0	1	0	0	0	0	0	0	1
36	0	0	0	0	0	0	0	0	0	1
37	0	1	0	0	0	0	0	0	0	0
38	0	0	0	0	0	0	0	0	0	0
39	0	0	0	0	0	0	0	0	0	1
40	1	0	0	0	0	0	0	0	0	0
41	0	0	0	0	0	0	0	0	0	0
42	0	0	0	0	0	0	0	0	0	0
43	0	0	0	0	0	0	0	0	0	0
44	0	0	0	0	1	0	0	0	0	0
45	0	0	0	0	0	0	0	0	0	1
46	0	0	0	0	0	0	0	0	0	0
47	0	0	0	0	0	1	0	0	1	1
48	0	1	0	0	0	0	0	0	0	0
49	1	0	0	0	0	0	0	0	0	0
50	0	0	0	0	0	0	0	0	0	0
51	0	0	0	0	0	0	0	0	0	0
52	0	0	0	0	0	0	0	0	0	0
53	0	1	0	0	0	0	0	0	0	0
54	0	0	0	0	0	0	0	0	0	0
55	0	0	0	0	0	0	0	0	0	0
56	0	0	0	0	0	1	0	0	0	0
57	0	0	0	0	0	0	0	0	0	0
58	0	0	0	0	0	0	0	0	0	0
59	0	0	0	0	0	0	0	0	0	0
60	0	0	0	0	0	0	0	0	0	0
61	0	0	0	0	0	0	0	0	0	0
62	0	1	0	0	0	0	0	0	0	0
63	0	0	0	0	0	0	0	0	0	1
64	0	0	0	0	0	0	0	0	0	0

65	0	0	0	0	0	0	0	0	0	1
66	0	0	0	0	0	0	0	0	0	0
67	0	0	0	0	0	0	0	0	0	0
68	0	0	0	0	0	0	0	0	0	0
69	0	0	0	0	0	0	0	0	0	0
70	0	0	0	0	0	0	0	0	0	0
71	0	0	0	0	0	0	0	0	0	0
72	0	0	0	0	0	0	0	0	0	0
73	0	0	0	0	0	0	0	0	0	1
74	0	0	0	0	0	0	0	0	0	1
75	0	0	0	0	0	0	0	0	0	1
76	0	1	0	0	0	0	0	0	0	0
77	0	0	0	0	0	0	0	0	0	0
78	0	0	0	1	0	0	0	0	0	0
79	0	0	0	0	0	0	0	0	0	1
80	0	0	0	0	0	0	0	0	0	1
81	0	0	0	0	0	0	0	0	0	0
82	0	0	0	0	0	0	0	0	0	0
83	0	0	0	0	0	0	0	0	0	1
84	0	0	0	0	0	0	0	0	0	1
85	0	0	0	0	0	0	0	0	0	1
86	0	1	0	0	0	0	0	0	0	1
87	1	0	0	0	0	0	0	0	0	0
88	0	0	0	0	0	0	0	0	0	1
89	0	0	1	0	0	0	0	0	0	1
90	0	0	0	0	0	0	0	0	0	0
91	0	0	0	0	0	0	0	0	0	1
92	0	0	0	0	0	0	0	0	0	1
93	0	0	0	0	0	0	0	0	0	0

Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) Checklist

SECTION	ITEM	PRISMA-ScR CHECKLIST ITEM	REPORTED ON PAGE #
TITLE			
Title	1	Identify the report as a scoping review.	1
ABSTRACT			
Structured summary	2	Provide a structured summary that includes (as applicable): background, objectives, eligibility criteria, sources of evidence, charting methods, results, and conclusions that relate to the review questions and objectives.	1
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of what is already known. Explain why the review questions/objectives lend themselves to a scoping review approach.	2
Objectives	4	Provide an explicit statement of the questions and objectives being addressed with reference to their key elements (e.g., population or participants, concepts, and context) or other relevant key elements used to conceptualize the review questions and/or objectives.	2 - 3
METHODS			
Protocol and registration	5	Indicate whether a review protocol exists; state if and where it can be accessed (e.g., a Web address); and if available, provide registration information, including the registration number.	n/a
Eligibility criteria	6	Specify characteristics of the sources of evidence used as eligibility criteria (e.g., years considered, language, and publication status), and provide a rationale.	4
Information sources*	7	Describe all information sources in the search (e.g., databases with dates of coverage and contact with authors to identify additional sources), as well as the date the most recent search was executed.	3
Search	8	Present the full electronic search strategy for at least 1 database, including any limits used, such that it could be repeated.	Appendix
Selection of sources of evidence†	9	State the process for selecting sources of evidence (i.e., screening and eligibility) included in the scoping review.	4
Data charting process‡	10	Describe the methods of charting data from the included sources of evidence (e.g., calibrated forms or forms that have been tested by the team before their use, and whether data charting was done independently or in duplicate) and any processes for obtaining and confirming data from investigators.	4
Data items	11	List and define all variables for which data were sought and any assumptions and simplifications made.	4
Critical appraisal of individual sources of evidence§	12	If done, provide a rationale for conducting a critical appraisal of included sources of evidence; describe the methods used and how this information was used in any data synthesis (if appropriate).	n/a

SECTION	ITEM	PRISMA-ScR CHECKLIST ITEM	REPORTED ON PAGE #
Synthesis of results	13	Describe the methods of handling and summarizing the data that were charted.	4
RESULTS			
Selection of sources of evidence	14	Give numbers of sources of evidence screened, assessed for eligibility, and included in the review, with reasons for exclusions at each stage, ideally using a flow diagram.	5
Characteristics of sources of evidence	15	For each source of evidence, present characteristics for which data were charted and provide the citations.	5 - 7
Critical appraisal within sources of evidence	16	If done, present data on critical appraisal of included sources of evidence (see item 12).	n/a
Results of individual sources of evidence	17	For each included source of evidence, present the relevant data that were charted that relate to the review questions and objectives.	5 - 14
Synthesis of results	18	Summarize and/or present the charting results as they relate to the review questions and objectives.	5 - 14
DISCUSSION			
Summary of evidence	19	Summarize the main results (including an overview of concepts, themes, and types of evidence available), link to the review questions and objectives, and consider the relevance to key groups.	14 - 19
Limitations	20	Discuss the limitations of the scoping review process.	18
Conclusions	21	Provide a general interpretation of the results with respect to the review questions and objectives, as well as potential implications and/or next steps.	18
FUNDING			
Funding	22	Describe sources of funding for the included sources of evidence, as well as sources of funding for the scoping review. Describe the role of the funders of the scoping review.	1

JBI = Joanna Briggs Institute; PRISMA-ScR = Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews.

* Where *sources of evidence* (see second footnote) are compiled from, such as bibliographic databases, social media platforms, and Web sites.

† A more inclusive/heterogeneous term used to account for the different types of evidence or data sources (e.g., quantitative and/or qualitative research, expert opinion, and policy documents) that may be eligible in a scoping review as opposed to only studies. This is not to be confused with *information sources* (see first footnote).

‡ The frameworks by Arksey and O'Malley (6) and Levac and colleagues (7) and the JBI guidance (4, 5) refer to the process of data extraction in a scoping review as data charting.

§ The process of systematically examining research evidence to assess its validity, results, and relevance before using it to inform a decision. This term is used for items 12 and 19 instead of "risk of bias" (which is more applicable to systematic reviews of interventions) to include and acknowledge the various sources of evidence that may be used in a scoping review (e.g., quantitative and/or qualitative research, expert opinion, and policy document).

From: Tricco AC, Lillie E, Zarin W, O'Brien KK, Colquhoun H, Levac D, et al. PRISMA Extension for Scoping Reviews (PRISMAScR): Checklist and Explanation. Ann Intern Med. 2018;169:467–473. doi: 10.7326/M18-0850.