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Table S1. Abridged Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis (TRIPOD) guideline checklist used for assessment of methodological quality.

Section/Topic	Question Number	Checklist Item
Methods		
Source of data	4a	Describe the study design or source of data (e.g., randomized trial, cohort, or registry data), separately for the development and validation data set, if applicable
	4b	Specify the key study dates, including start of accrual; end of accrual; and, if applicable, end of follow-up
Participants	5a	Specify key elements of the study setting (e.g., primary care, secondary care, general population) including number and location of centers
	5b	Describe eligibility criteria for participants
	5c	Give details of treatments received, if relevant
Outcome	6a	Clearly define the outcome that is predicted by the prediction model, including how and when assessed
	6b	Report any actions to blind assessment of the outcome to be predicted
Predictors	7a*	Clearly define all predictors used in developing the machine learning model, including how and when they were measured
	7b	Report any actions to blind assessment of predictors for the outcome and other predictors
Missing data	9	Describe how missing data were handled (e.g., complete-case analysis, single imputation, multiple imputation) with details of any imputation method
Statistical analysis methods	10a	Describe how predictors were handled in the analyses
	10b*	Specify type of model, all model-building procedures (including any predictor selection or hyperparameter selection if applicable), and method for internal validation
	10d	Specify all measures used to assess model performance and, if relevant, to compare multiple models
Risk groups	11	Provide details on how risk groups were created, if done
Results		
Participants	13a	Describe the flow of participants through the study, including the number of participants with and without the outcome and, if applicable, a summary of the follow-up time. A diagram may be helpful
	13b	Describe the characteristics of the participants (basic demographics, clinical features, available predictors), including the number of participants with missing data for predictors and outcome
Model development	14a	Specify the number of participants and outcome events in each analysis
	14b	If done, report the unadjusted association between each candidate predictor and outcome
Model specification	15a*	Present the full prediction model to allow predictions for individuals (i.e., links to the final model online, code, and final parameters/coefficients), with the architecture described in full in the article
	15b	Explain how to use the prediction model
Model performance	16	Report performance measures (with CIs) for the prediction model

*Adjustments to guideline verbiage as described by Wang et al.[37]

Table S2. Conceptual overview of common machine learning algorithms currently applied to TJA predictive tasks.

	Algorithm Description	**Common Applications†**
Supervised (training data labeled) learning		
Decision tree	Principle component of random forest algorithms. Sequential series of nodes, edges, and terminal nodes. Nodes represent a decision point based on the value of a given predictive factor. Splitting at the decision point generates sub-nodes, which coalesce into terminal nodes (i.e., final prediction) after a pre-specified number of iterations.	Classification, regression, multi-output
Artificial Neural Network*	Model architecture analogous in certain ways to biological neurons in the brain. Briefly, input nodes are created from the data and form the input layer. The input layer is connected to a variable number of hidden layers using weights, which are optimized through backpropagation of the networks' predictive errors. ANNs with many hidden layers are referred to as deep neural networks.	Regression, classification, multi-output, computer vision, natural language processing
Support Vector Machine	Kernel-based model used to compute a decision boundary that optimally differentiates outcome classes in *N*-dimensional space.	Classification, regression, outlier detection
Gradient Boosting algorithms	Form of ensemble learning that sequentially trains models that iteratively correct predictive errors made by the predecessor model.	Classification, regression
Random forest	Form of ensemble learning that incorporates many individual decision trees into an aggregate "forest". A random subset of the predictive features is used for each individual decision tree to encode greater diversity and increase accuracy.	Classification, regression
Lasso regression	Version of linear regression that adds a regularization term (ℓ_1) to the cost function. Automatically sets the weights of least important features to zero.	Classification, regression

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Ridge regression	Version of linear regression that adds a regularization term to the cost function to constrain model weights and prevent overfitting.	Classification, regression
Elastic Net	Regression model that is a combination of lasso and ridge regression techniques.	Classification, regression
Unsupervised (training data unlabeled) learning		
Clustering	Identification of similar instances among a data set and subsequent assignment of these instances to clusters.	Dimensionality reduction, outlier detection, data and image segmentation

*Of note, there are other neural network architectures besides supervised learning not covered in this review, including unsupervised (e.g., autoencoders) or semisupervised (e.g., unsupervised pretraining) training. A comprehensive description of these architectures is out of scope of the current review.
†Classification and regression refer to tasks involving the prediction of discrete (i.e., binary, multi-level) and continuous outcomes, respectively. Outlier detection refers to the identification of rare instances that differ substantially from the rest of the data.
Abbreviations: Lasso, least absolute shrinkage and selection operator; ANN, artificial neural network

Table S3. Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis (TRIPOD) ratings for all included studies.

Study	Q 4a	Q 4b	Q 5a	Q 5b	Q 6a	Q 6b	Q 7a	Q 7b	Q 9	Q 10a	Q 10b	Q 10d	Q 11	Q 13a	Q 13b	Q 14a	Q 14b	Q 15a	Q 15b	Q 16
Bini 2019[70]	Yes	Yes	No	Yes	Yes	No	Yes	NA	No	No	No	Yes	Yes	Yes	Yes	No	Yes	No	No	No
Bloomfield 2019[64]	Yes	No	No	Yes	Yes	NA	Yes	Yes	No	Yes	No	Yes	Yes	Yes	Yes	Yes	NA	No	No	Yes
Borjali 2020[22]	Yes	Yes	No	Yes	Yes	NA	Yes	NA	Yes	Yes	Yes	No	NA	Yes	Yes	Yes	NA	No	No	No
Bovonratwet 2020[28]	Yes	Yes	Yes	Yes	Yes	NA	Yes	NA	No	No	No	Yes	NA	Yes	Yes	Yes	Yes	No	No	Yes
Cafri 2019[48]	Yes	Yes	Yes	Yes	Yes	NA	Yes	NA	Yes	Yes	Yes	Yes	NA	Yes	Yes	Yes	Yes	No	No	No
Dindorf 2020[68]	Yes	Yes	Yes	No	Yes	NA	Yes	No	No	Yes	Yes	Yes	NA	Yes	Yes	Yes	NA	No	No	Yes
El-Galaly 2020[31]	Yes	Yes	Yes	Yes	Yes	NA	Yes	NA	Yes	Yes	Yes	Yes	NA	Yes	Yes	Yes	NA	No	No	Yes
Farooq 2020[38]	No	Yes	No	No	Yes	No	Yes	No	No	No	Yes	Yes	NA	Yes	No	Yes	Yes	No	No	No
Fontana 2019[54]	Yes	Yes	Yes	Yes	Yes	No	Yes	No	Yes	No	Yes	Yes	NA	Yes	Yes	No	NA	Yes	No	Yes
Gabriel 2019[50]	Yes	Yes	Yes	Yes	Yes	NA	Yes	NA	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Gram 2017[52]	Yes	Yes	Yes	Yes	Yes	NA	Yes	NA	No	No	Yes	Yes	NA	Yes	Yes	Yes	Yes	No	No	No
Greenstein 2020[55]	Yes	Yes	Yes	Yes	Yes	NA	Yes	NA	Yes	No	Yes	Yes	NA	No	Yes	Yes	NA	No	Yes	No
Harris 2019[57]	Yes	Yes	Yes	Yes	Yes	NA	Yes	NA	Yes	No	Yes	Yes	NA	Yes	Yes	No	NA	No	Yes	Yes
Harris 2021[41]	Yes	No	Yes	Yes	Yes	No	Yes	NA	No	Yes	Yes	Yes	NA	Yes	Yes	Yes	NA	No	No	Yes
Hsieh 2020[26]	Yes	No	No	No	Yes	NA	Yes	NA	No	Yes	Yes	Yes	NA	No	Yes	Yes	NA	No	No	No
Huber 2019[53]	Yes	Yes	No	No	Yes	NA	No	NA	Yes	No	No	Yes	NA	Yes	Yes	Yes	NA	No	No	No
Hyer 2020[19]	Yes	Yes	Yes	Yes	Yes	NA	No	NA	No	No	Yes	Yes	Yes	Yes	No	Yes	NA	No	No	Yes
Jo 2020[39]	Yes	Yes	No	Yes	Yes	NA	Yes	NA	No	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Jones 2016[66]	Yes	No	No	Yes	Yes	NA	Yes	Yes	No	Yes	No	No	NA	Yes	Yes	No	NA	No	No	Yes
Kang 2020[61]	Yes	No	No	No	Yes	NA	No	NA	Yes	No	Yes	No	NA	Yes	No	No	NA	No	No	No
Karhade 2019[29]	Yes	Yes	Yes	Yes	Yes	NA	Yes	NA	Yes	No	Yes	Yes	NA	Yes	Yes	No	NA	Yes	No	Yes
Karnuta 2019[16]	Yes	Yes	Yes	Yes	Yes	NA	Yes	NA	No	No	Yes	Yes	NA	No	Yes	No	NA	No	No	Yes
Karnuta 2020[12]	Yes	Yes	Yes	No	Yes	Yes	Yes	NA	Yes	Yes	Yes	Yes	NA	Yes	No	Yes	NA	No	No	No
Karnuta 2021[58]	Yes	Yes	Yes	No	Yes	Yes	Yes	NA	Yes	Yes	Yes	Yes	NA	Yes	No	Yes	NA	No	No	No
Kluge 2018[65]	Yes	No	Yes	Yes	Yes	No	Yes	NA	No	No	Yes	Yes	NA	No	Yes	No	NA	No	No	Yes
Ko 2020[42]	Yes	Yes	No	Yes	Yes	NA	Yes	NA	No	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kuntze 2015[67]	Yes	No	No	Yes	Yes	NA	Yes	NA	No	Yes	Yes	Yes	NA	No	Yes	Yes	NA	No	No	No
Kunze 2020[5]	Yes	Yes	No	Yes	Yes	NA	Yes	NA	Yes	Yes	Yes	Yes	NA	Yes	Yes	No	NA	Yes	No	Yes
Kunze 2020[4]	Yes	Yes	Yes	Yes	Yes	No	Yes	NA	Yes	Yes	Yes	Yes	NA	Yes	Yes	No	NA	No	No	Yes
Leung 2020[59]	Yes	Yes	No	Yes	Yes	Yes	No	NA	No	No	Yes	Yes	NA	Yes	Yes	Yes	Yes	Yes	No	Yes
Li 2020[44]	Yes	Yes	No	Yes	Yes	NA	Yes	NA	Yes	No	No	No	NA	Yes	Yes	Yes	Yes	Yes	No	Yes
Lu 2020[43]	Yes	Yes	Yes	Yes	Yes	NA	Yes	NA	Yes	Yes	Yes	Yes	NA	Yes	Yes	No	NA	Yes	Yes	Yes
Magneli 2020[47]	Yes	Yes	Yes	Yes	Yes	NA	No	NA	No	No	Yes	Yes	NA	Yes	Yes	Yes	NA	Yes	No	No
Milimonfared 2018[62]	Yes	No	No	No	Yes	No	Yes	NA	Yes	Yes	Yes	Yes	NA	No	No	No	NA	No	No	No
Mohammadi 2020[56]	Yes	Yes	Yes	Yes	Yes	NA	Yes	NA	No	No	Yes	Yes	No	Yes	No	Yes	NA	No	No	Yes
Murphy 2021[23]	Yes	Yes	No	Yes	Yes	NA	No	NA	Yes	No	Yes	No	NA	No	No	No	NA	No	Yes	No
Navarro 2018[11]	Yes	Yes	No	Yes	Yes	NA	Yes	NA	Yes	Yes	Yes	Yes	Yes	No	No	No	NA	No	No	No
Pareek 2020[45]	Yes	Yes	Yes	Yes	Yes	NA	Yes	No	No	No	Yes	Yes	No	Yes	Yes	Yes	NA	Yes	No	No
Polus 2021[69]	Yes	No	No	Yes	Yes	Yes	Yes	NA	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	Yes
Pua 2020[30]	Yes	Yes	Yes	Yes	Yes	NA	Yes	NA	Yes	No	Yes	Yes	NA	Yes	Yes	Yes	NA	Yes	No	Yes
Ramkumar 2019[10]	Yes	Yes	No	Yes	Yes	NA	Yes	NA	Yes	Yes	Yes	Yes	Yes	No	No	No	NA	No	No	No
Ramkumar 2019[49]	Yes	Yes	Yes	Yes	Yes	NA	Yes	NA	Yes	No	Yes	Yes	Yes	Yes	Yes	No	NA	Yes	No	No
Ramkumar 2019[9]	Yes	Yes	Yes	Yes	Yes	NA	Yes	NA	No	Yes	No	Yes	NA	Yes	Yes	Yes	NA	No	No	Yes
Ramkumar 2019[46]	Yes	Yes	Yes	Yes	Yes	NA	Yes	NA	Yes	No	Yes	Yes	Yes	Yes	Yes	No	NA	Yes	No	No
Ranti 2020[20]	Yes	Yes	Yes	Yes	Yes	NA	Yes	NA	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	NA	No	No	Yes
Ricciardi 2020[51]	Yes	No	Yes	Yes	Yes	NA	Yes	NA	Yes	No	Yes	Yes	NA	No	Yes	No	NA	No	No	No
Shah 2019[71]	Yes	No	No	No	Yes	NA	No	NA	Yes	No	Yes	Yes	NA	Yes	Yes	Yes	Yes	No	No	No
Shah 2020[63]	Yes	Yes	Yes	Yes	Yes	NA	Yes	NA	Yes	No	Yes	Yes	NA	Yes	No	Yes	NA	No	No	No
Shah 2020[72]	Yes	Yes	Yes	Yes	Yes	NA	Yes	NA	No	Yes	Yes	Yes	NA	Yes	No	Yes	NA	No	No	No
Shohat 2020[18]	Yes	Yes	Yes	Yes	Yes	NA	Yes	NA	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	No	No	No	No
Teufl 2019[25]	Yes	No	Yes	Yes	Yes	No	Yes	NA	No	Yes	Yes	Yes	NA	Yes	No	Yes	NA	No	No	No
Tibbo 2019[27]	Yes	Yes	Yes	Yes	Yes	NA	Yes	NA	No	Yes	Yes	Yes	NA	Yes	Yes	Yes	NA	No	No	No
Tolpadi 2020[60]	Yes	Yes	Yes	Yes	Yes	NA	Yes	NA	Yes	Yes	Yes	Yes	NA	Yes	Yes	Yes	NA	Yes	No	Yes
Verstraete 2020[40]	Yes	Yes	No	Yes	Yes	NA	Yes	NA	Yes	Yes	Yes	Yes	NA	Yes	No	Yes	NA	No	No	No
Yi 2020[24]	Yes	No	No	No	Yes	NA	Yes	NA	No	Yes	Yes	Yes	NA	Yes	No	No	NA	No	No	No

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