	Interpretability	Inference	Captures non-linear effects	Captures (but does not test!) interactions	Can deal with (very) many possible predictors	Can account for multilevel structures	Valid uncertainty quantification for predictions	R package(s)
Elastic net (ridge / lasso)	+	-	-	-	+	-	-	**glmnet**
Generalized additive model	+	+	+	- (unless specified by researcher)	+ (through use of select argument of function gam())	+	+	**mgcv**
Support vector machines	- -	-	+ (depending on kernel used, but does not test)	+ (depending on kernel used)	+	-	-	**e1071**
Single decision trees	+	-	+ (but does not test)	+	+	+	-	**partykit; glmertree** (for multilevel data)
Random forest	-	-	+ (but does not test)	+	+	-	-	**randomForest; ranger**
Gradient boosting	-	-	+ (but does not test)	+	+	-	-	**gbm; xgboost**
Bayesian additive tree ensembles	-	-	+ (but does not test)	+	+	+	+	**dbarts** (function bart for 'standard' analyses, for multilevel data use function rbart_vi()); **bartMachine**

Gradient boosting (and random forest) win prediction competitions, but needs careful tuning. SVMs can also perform very well, but are notorious for being black boxes, and their tuning is a bit more tricky, as it can be difficult to choose a good tuning grid.

Conditional inference trees, glmertrees, generalized additive models, BART do not require tuning to perform well. So we can fit the model in one step.

In practice, I would compare the performance of simpler (e.g., (penalized) linear model, single tree, GAM) models with performance of more complex (SVM, random forest, gradient boosting, BART), to see what is gained in terms of predictive accuracy at the cost of interpretability or inference.