| Study | Approach to reduce the number of initially available connectivities | atlas-based parcellation | data-driven parcellation | theory-based selection | model allocation | dimensionality reduction | filter feature selection | wrapper feature selection |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Drysdale, 2017 | 1. atlas-based brain parcellation (258 nodes: 33.153 connectivities),  2. feature selection: wilcoxon rank sum test | y | - | - | - | - | y | - |
| Harris, 2022 | 1. atlas-based brain parcellation (5 different atlases),  2. dimensionality reduction or feature selection in inner loop (4 different approaches: PCA, ANOVA, agglomeration, None) | y | - | - | - | y | y | - |
| Hopman, 2021 | 1. theory-based seed selection (2 brain regions),  2. feature selection outside ML (data leakage): seed-based analysis comparing responders vs. nonresponders in whole data set -> use seed-cluster correlation of the 4 clusters that got significant (4 connectivities),  3. create 15 models with different combinations of these 4 connectivities | - | - | y | y | - | y | - |
| Kong, 2021 | 1. atlas-based brain parcellation,  2. threshold functional connectivities (proportional),  3. pooling layers within STCGN (first layer: 90 ROIs, last layer: 14 ROIs) | y | - | - | - | y | y | - |
| Moreno-Ortega, 2019 | 1. theory-based ROI selection: 9 brain regions (38 between- and within-ROI-connectivities),  2. feature selection outside ML (data leakage): use connectivities that correlate significantly with treatment response  3. create a 1-feature-model for each of the 4 connectivities, create three 2-features-models by adding the feature that performed best in the 1-feature models | - | - | y | y | - | y | - |
| Pei, 2020 | 1. atlas-based brain parcellation (90 ROIs),  2. theory-based ROI selection (14 ROIs),  3. create 1st-level model per ROI (input features: 89 connectivities to whole-brain ROIs, classifier: SVM-RFE),  4. 2nd-level model: SVM | y | - | y | y | - | - | y |
| Schultz, 2018 | 1. theory-based ROI selection: 13 ROIs,  2. create one model per ROI (input features: connectivities to the 12 other ROIs) | - | - | y | y | - | - | - |
| Sun, 2020 | 1. atlas-based brain parcellation (246 ROIs; 30.135 connectivities),  2. feature selection via correlation analysis (keep only correlations above specific threshold value)  3. aggregate features by summing correlations | y | - | - | - | y | y | - |
| Tian, 2020 | 1. brain parcellation (95 ROIs),  2. feature extraction: extract time-dependent communities via a multilayer detection algorithm; create module allegiance matrices (show whether two nodes are assigned to the same community); calculate node flexibilities for 95 ROIs,  3. feature selection: minimum redundancy maximum relevance (mRMR) (potential data leakage: It is not clear whether this process is applied on each training set or on the whole data set) | y | - | - | - | - | y | - |
| van Waarde, 2015 | 1. data-based parcellation: MELODIC (Group-ICA, data leakage) -> result: 25 non-noise related independent components (ICs),  2. feature extraction: create subject-specific maps of group-based components via dual regression,  3. create a model for each IC,  4. feature selection within ML: Group comparison per voxel; voxels whose average values differ most between groups are kept (z-threshold) | - | y | - | y | - | y | - |
| Wu, 2022 | 1. theory-based ROI selection (36 ROIs: 630 connectivities),  2. feature selection in inner loop: SVM-RFE | - | - | y |  | - | - | y |
| Zhutovsky, 2019 | 1. data-driven parcellation: meta-ICA (based on combat controls) -> result: 48 non-noise-related independent components (ICs),  2. feature extraction: create subject-specific maps of group-based components via dual regression,  3. create a model for each IC,  4. feature selection within ML: group comparison per voxel; voxels whose values differ most between groups are kept (z-threshold) | - | y | - | y | - | y | - |
| Zhutovsky, 2021 | 1. data-driven parcellation: meta-ICA (based on trauma-exposed subjects) -> result: 48 non-noise-related independent components (ICs),  2. feature extraction: create subject-specific maps of group-based components via GIG-ICA,  3. create a model for each IC and for each measure of between-IC-connectivity | - | y | - | y | - | - | - |