Predicting treatment outcome based on baseline restingstate fMRI functional connectivity? A realistic view

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BACKGROUND

- **Predicting treatment outcome prior to treatment** initiation could be a crucial step towards a more **personalized treatment selection**.
- Machine learning is particularly suitable for this endeavor as it enables the accurate prediction of new data on a single-subject level.
- One data modality that appeared promising is resting-state fMRI functional connectivity (rs FC), which describes the covariation of the BOLD (blood-ulletoxygenation level dependent) signal in voxels or brain regions over time.

Aim 1: Giving an estimate of the rs FC` predictive performance from prior machine-learning studies and highlighting current challenges.

METHODS & RESULTS

1. SYSTEMATIC REVIEW & META-ANALYSIS

- Search in Scopus, PubMed and PsycINFO (12th of December 2022) Result: 13 articles (n = 972 patients)
- Random effect meta-analysis for proportions

The mean estimated balanced accuracy was 77%, suggesting a good predictive ability of rs FC.

	_			Balanced			
Study	Events	Total		accuracy	95%-CI	Weight	
Harris, 2022	84	144		0.58	[0.50; 0.66]	9.5%	
Sun, 2020	82	122		0.67	[0.58; 0.75]	9.2%	
Tian, 2020	72	106		0.68	[0.58; 0.77]	9.0%	
Schultz, 2018	15	21		0.71	[0.48; 0.89]	4.9%	
Zhutovsky, 2021	30	40		0.75	[0.59; 0.87]	6.7%	
Drysdale, 2017	97	124		0.78	[0.70; 0.85]	9.3%	
Wu, 2022	54	67	,	0.81	[0.69; 0.89]	8.0%	
Pei, 2020	79	98	,	0.81	[0.71; 0.88]	8.8%	
Zhutovsky, 2019	36	44		0.82	[0.67; 0.92]	6.9%	
van Waarde, 2015	38	45		0.84	[0.71; 0.94]	7.0%	
Hopman, 2021	52	61		0.85	[0.74; 0.93]	7.8%	

2. EMPIRICAL ANALYSIS

COMBINED DATASET (larger than any of the studies included in our review)

	SPIDER PHOBIA ² (n = 196; 103 Responders)	DEPRESSION ³ (n = 77; 34 Responders)
Treatment	1 session virtual exposure	25 sessions CBT (+ exercise)
Response	↓30% Spider Phobia Questionnaire	BSI-GSI < 0.56 + reliable change

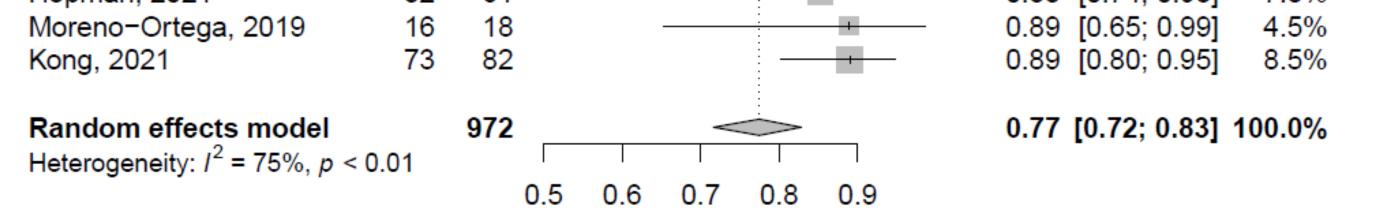
FEATURES EXTRACTED FROM RS FC 42 Graph metrics (AUC across several thresholds):

Local (for the anterior

LOW-BIAS MACHINE LEARNING PIPELINE

Preregistered:

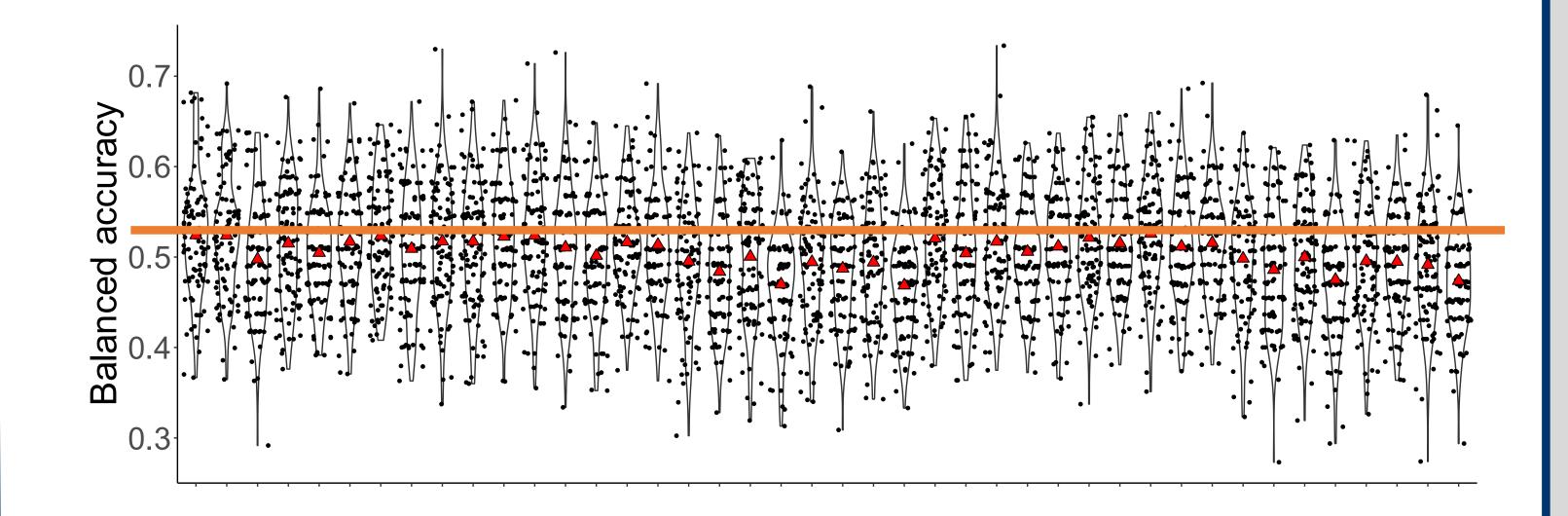
- 100 * random shuffle split (80/20)
- feature selection with elastic net
- Final classifier: random forest



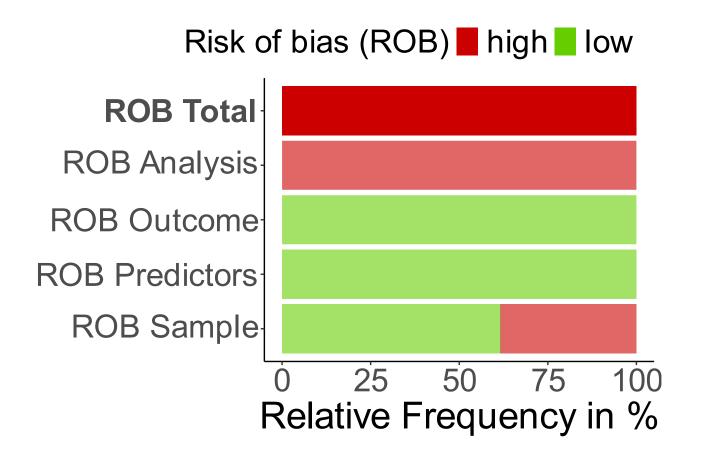
- cingulate cortex)
- Global
- Network-based

Exploratory: varying preprocessing of rs FC, graph metrics summary measure, stratification, hyperparameter tuning, classifier

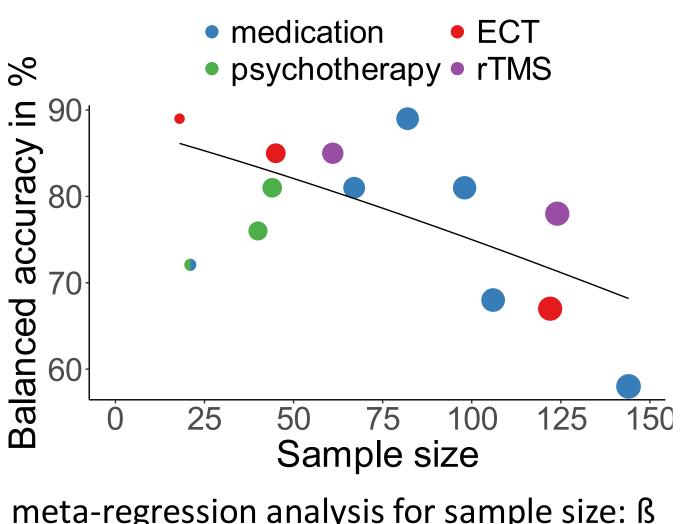
The maximal balanced accuracy reached by pipelines employed (preregistered + exploratory) was 0.52.



BUT... ... the risk of bias assessed with PROBAST¹ was high



... studies with small sample sizes did likely overestimate predictive performance



meta-regression analysis for sample size: ß based on transformed proportions = -0.0017, t(11) = -2.5, p = 0.0280

DISCUSSION

- > In regard of the studies' high risk of bias, the mean estimated balanced accuracy of 77% should be considered as an optimistic upper limit of potential predictive performance.
- > In our own empirical analysis, where we mitigated some of the biasing factors identified (e.g., sample) size), predictive performance was **not above chance**.
- > Other recent state-of-the machine-learning corroborate that the predictive ability of rs FC is still unclear^{4,5}.

References

[1] Moons, Karel G. M.; Wolff, Robert F.; Riley, Richard D.; Whiting, Penny F.; Westwood, Marie; Collins, Gary S. et al. (2019): PROBAST: A tool to assess the risk of bias and applicability of prediction model studies. In: Annals of Internal Medicine 170 (1), S. 51–58. DOI: 10.7326/M18-1376.

[2] Schwarzmeier, H., Leehr, E. J., Böhnlein, J., Seeger, F. R., Roesmann, K., Gathmann, B., Herrmann, M. J., Siminski, N., Junghöfer, M., Straube, T., Grotegerd, D., & Dannlowski, U. (2020). Theranostic markers for personalized therapy of spider phobia: Methods of a bicentric external cross-validation machine learning approach. International Journal of Methods in Psychiatric Research, 29(2), e1812. https://doi.org/10.1002/mpr.1812

[3] Heinzel, S., Rapp, M. A., Fydrich, T., Ströhle, A., Terán, C., Kallies, G., Schwefel, M., & Heissel, A. (2018). Neurobiological mechanisms of exercise and psychotherapy in depression: The SPeED study-Rationale, design, and methodological issues. Clinical Trials (London, England), 15(1), 53–64. https://doi.org/10.1177/1740774517729161

[4] Harris, J.K., Hassel, S., Davis, A.D., Zamyadi, M., Arnott, S.R., Milev, R., et al., 2022. Predicting escitalopram treatment response from pre-treatment and early response resting state fMRI in a multi-site sample: a CAN-BIND-1 report. Neuroimage Clin. 35, 103120.

[5] Hilbert, K., Böhnlein, J., Meinke, C., Chavanne, A. V., Langhammer, T., Stumpe, L., Winter, N., Leenings, R., Adolph, D., Arolt, V., Bischoff, S., Cwik, J. C., Deckert, J., Domschke, K., Fydrich, T., Gathmann, B., Hamm, A. O., Heinig, I., Herrmann, M. J., . . . Lueken, U. (2024). Lack of evidence for predictive utility from resting state fMRI data for individual exposure-based cognitive behavioral therapy outcomes: A machine learning study in two large multi-site samples in anxiety disorders. *NeuroImage*, 295, 120639. https://doi.org/10.1016/j.neuroimage.2024.120639



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