Research Synthesis & Big Data Conference, online, May 2021

Universität Trier

Using complex network analysis based on intensive longitudinal data to predict treatment dropout in patients with mood and anxiety disorders

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Treatment Dropout

mean dropout rate = 19.7 % (range = 0 – 74.2)

Swift & Greenberg (2012). J Consult Clin Psych, 80(4), 547–599.

Individual‘s perspective

- poor treatment outcomes
- higher hospitalization rates
- continuing psychological disorders
- strain for patients‘ relatives

Society‘s perspective

- inefficient use of clinical personnel
- strains the health system
- reduced productivity of patients
- increasing mental health costs

Predicting dropout based on a single measurement

- *N* = 707 patients treated by 66 therapists (*M* = 10.71 patients per therapist, range = 3 – 30)
- Impairment, interpersonal problems, treatment expectations, personality style, socio-demographics
- Multilevel logistic regression model

$R^2_{\text{GLMM(marginal)}}$ = .105

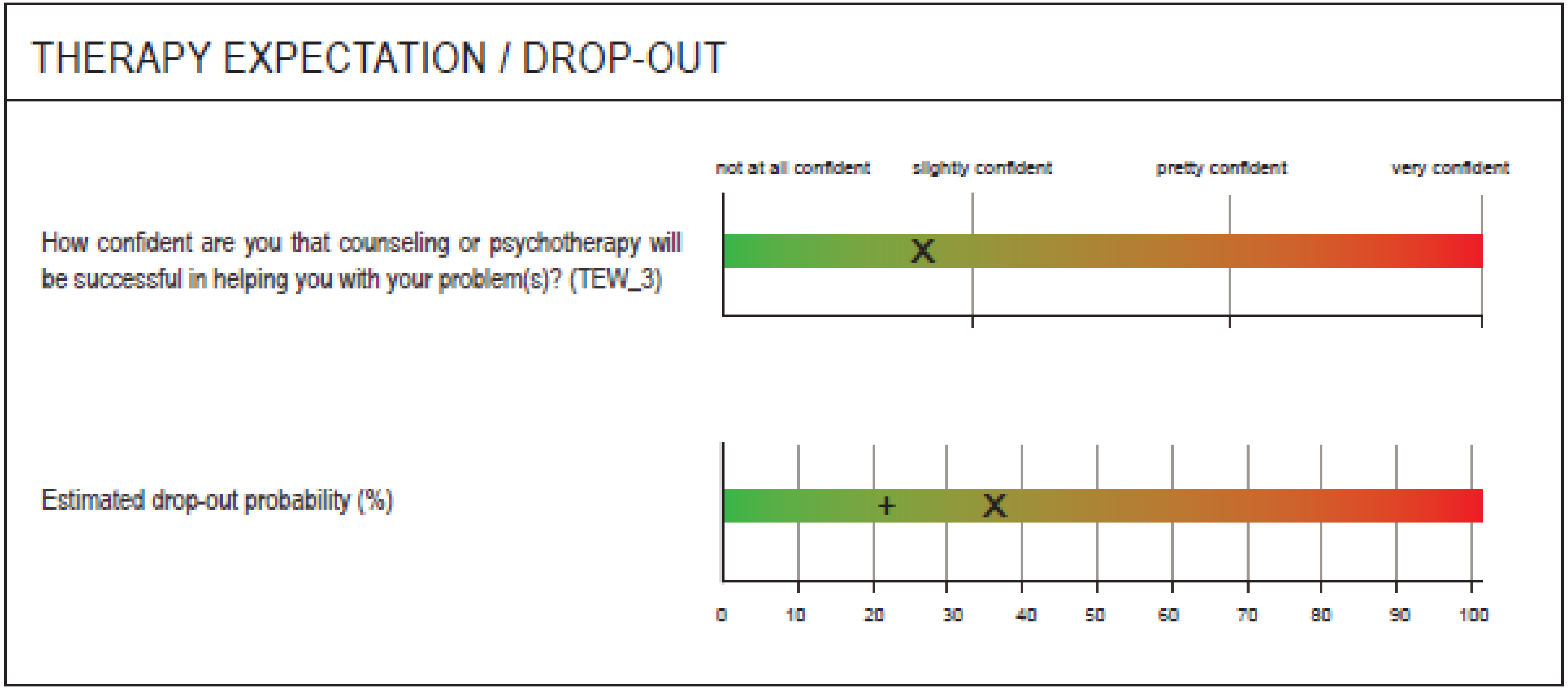
AUC = .686

Fixed effects on final model

	estimate	*P*-value
BSI – global severity index	0.396	.007
Age	–0.005	.549
Sex	0.458	.029
Education middle	–0.102	.691
Education high	-0.590	.022
PSSI-K – obsessive-compulsive	-0.390	.010
PSSI-K – histrionic	-0.395	.011
Treatment expectation 1	–0.254	.016
Treatment expectation 2	–0.457	.001

Zimmermann et al. (2017). Clin Psychol Psychot, 24(2), 312–321.

Dropout prediction in the Trier Treatment Navigator



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Dropout prediction in the Trier Treatment Navigator

Trier Treatment Navigator
Decision Support System
Trier University

- Archival data (*N* = 1234), 22.6% dropout

Variable selection

78 pre-therapy variables

Bivariate correlation with dropout

30 variables

Bootstrap ranking LASSO

7 variables

Model: Generalized linear model

Final prediction model for dropout

	BRLasso	GLM	p-value
FEP-2	-0.230	–0.697	.001
HSCL-11	0.261	0.609	.001
PSSI-K – histrionic	0.322	0.359	.001
OQ-30 – interpersonal relationships	0.411	0.530	<.001
PSSI-K – obsessive-compulsive	-0.416	–0.320	.004
Treatment expectation (therapist)	-0.509	–0.513	<.001
High school education	-0.586	–0.610	<.001

$R^2_{McFadden}$ = .120

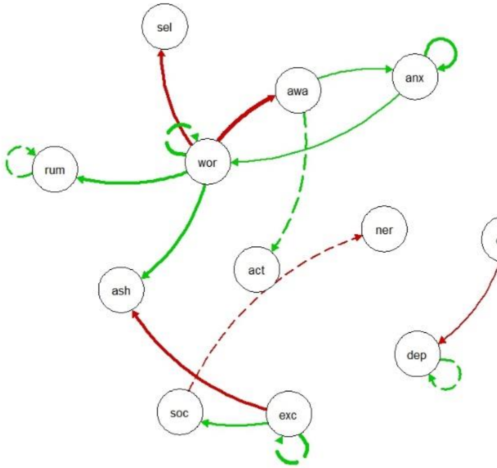
AUC = .698

Intensive longitudinal data and network analysis

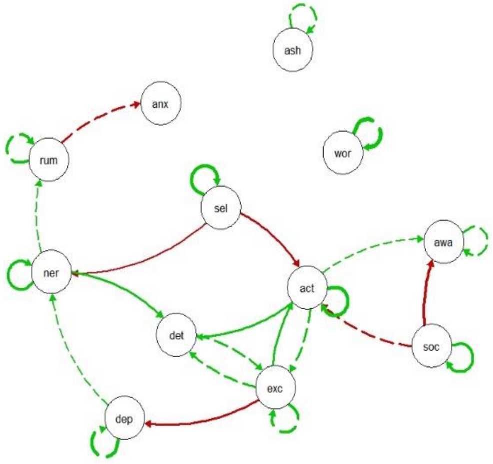
- Pre-therapy ambulatory assessments (4 times/day * 14 days)
- *N* = 3248 observations nested within *n* = 58 patients
- Positive and negative affect, rumination, worry, self-efficacy, social support (16 items)

- **Longitudinal Network analysis**:
  - Multilevel vector autoregressive (mlVAR) models
  - Each variable regressed on lagged versions of all variables (lag 1)

dropouts



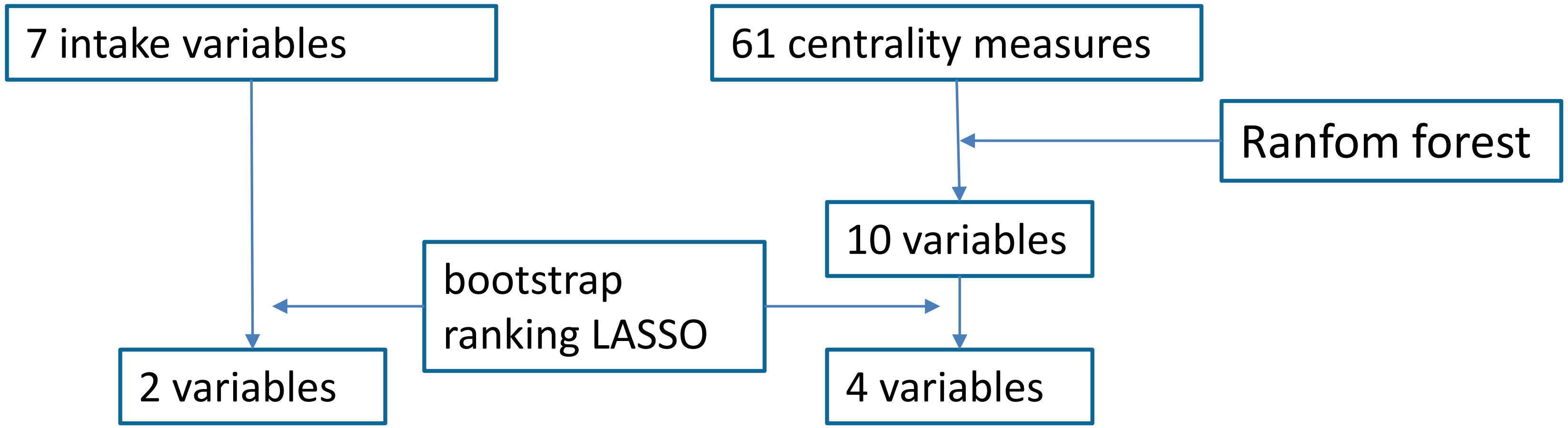
completers



Combining ML and statistical inference

- Network centrality measures: betweenness, closeness, instrength, outstrength, expected force
- 7 intake variables (e.g., impairment, sex, personality style)

Variable selection



Model: Hierarchical generalized linear model

Prediction based on centrality measures

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Hierarchical prediction model for dropout

	GLM			
	Block 1		Block 2	
	estimate	*p*-value	estimate	*p*-value
BSI – global severity index	0.87†	.066	0.62	.324
sex	– 0.79	.195	– 1.27	.101
nervous – betweenness			– 1.00*	.018
excited – expected force			– 0.90*	.035
active – instrength			– 1.02*	.035
social support – outstrength			– 1.00*	.029

Only cross-sectional variables (block 1)

$R^2_{\text{McFadden}} = .06$

$AUC = .64$

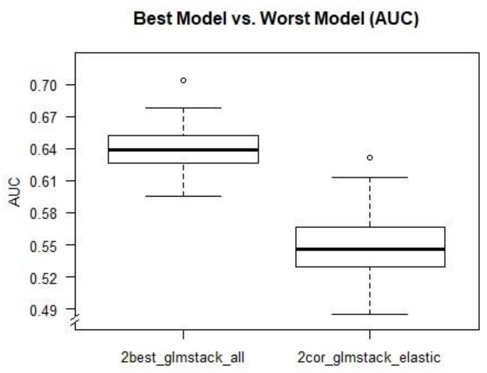
$R^2_{\text{McFadden}} = .32$

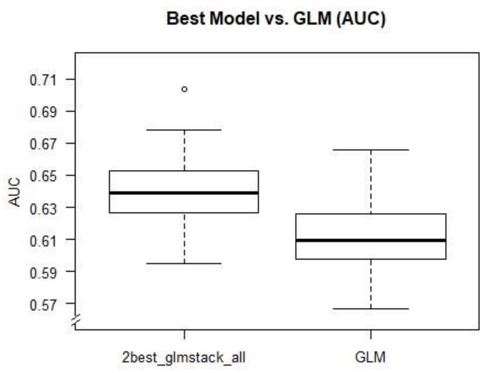
$AUC = .83$

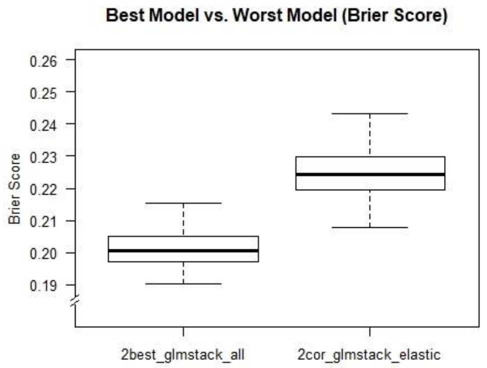
With centrality measures (block 2)

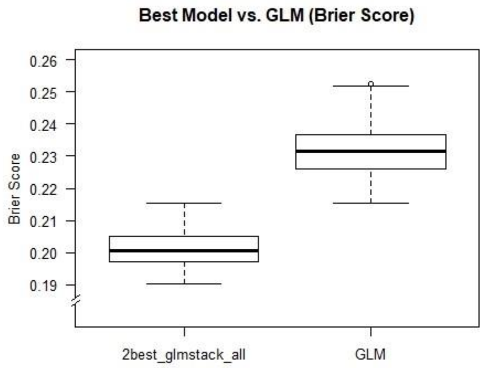
Selection of machine learning algorithms

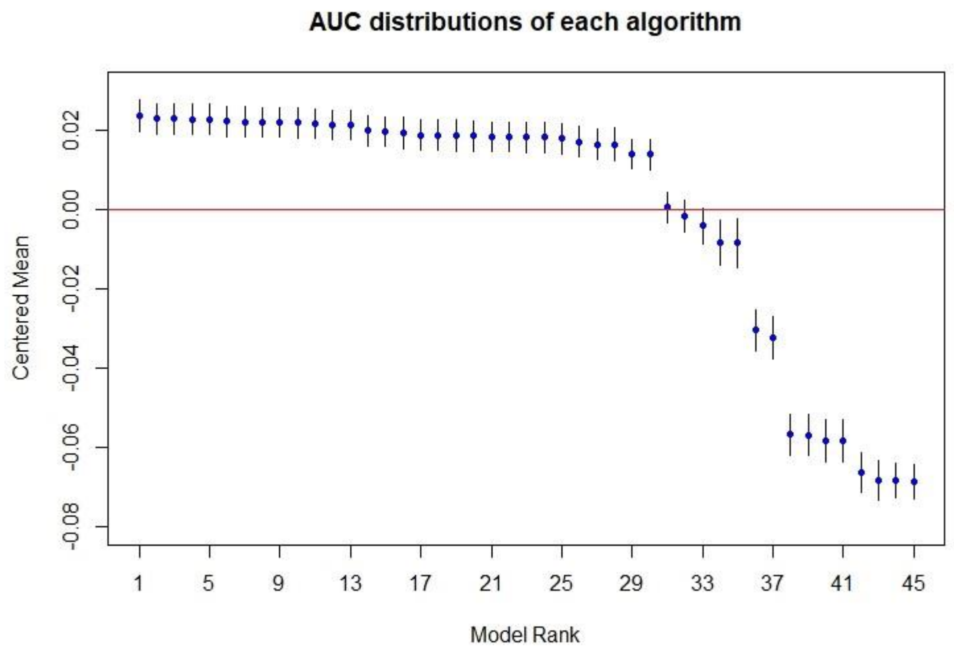
- *N* = 2043 outpatients, 22 algorithms and ensembles
- Best model: Ensemble of elasticnet and glmboost











Best model

$R^2_{McFadden}$ = .060

AUC = .640

Worst model

$R^2_{McFadden}$ = .007

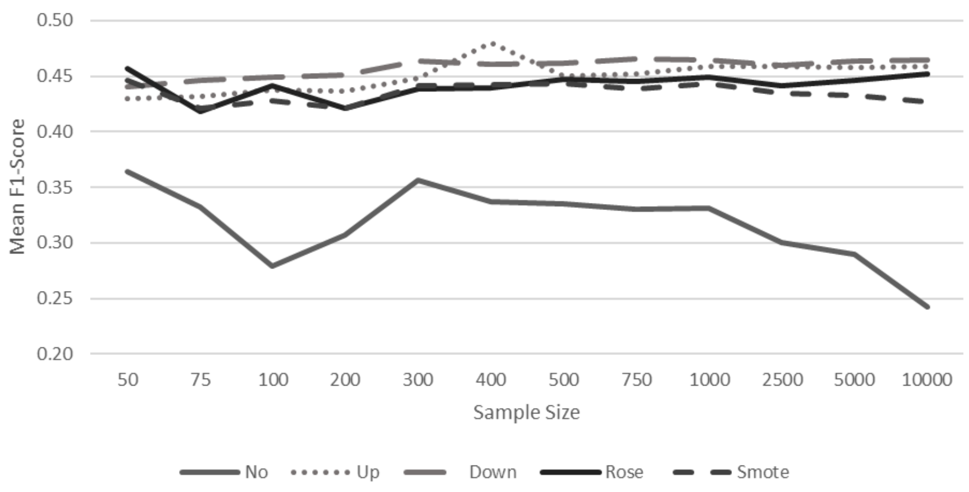
AUC = .548

Bennemann, Schwartz, Giesemann, & Lutz (submitted).

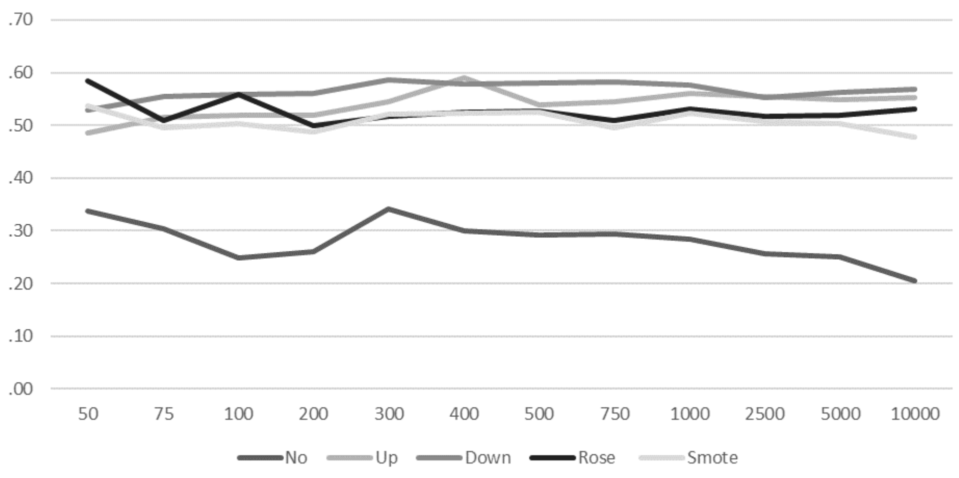
Resampling methods for imbalanced data

- *N* = 49,602 outpatients
- 5 resampling methods: no resampling, up-sampling, down-sampling, SMOTE, and ROSE
- F_1-score: accuracy of binary classifier by weighting precision and recall

Mean F_1-score across algorithms and sample sizes



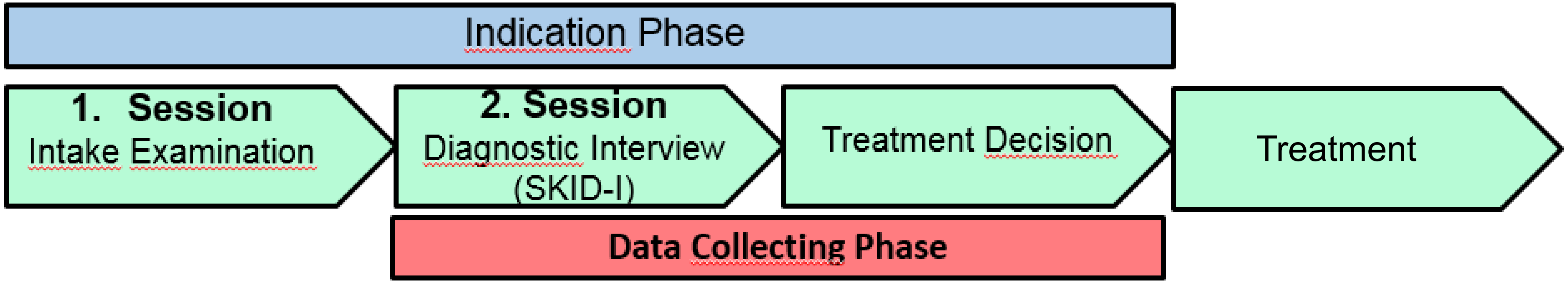
Mean sensitivity across algorithms and sample sizes



Giesemann, Delgadillo, Schwartz, Bennemann, & Lutz (submitted).

Additional data sources

- Assessing passive data from personal digital devices
- Fitness tracker: Garmin vivo smart 4
  - Stress levels (heart rate variability)
  - Sleep quality and duration
  - Activity (steps)
  - Pulse
  - …



Discussion

- Improving dropout prediction to support clinical desicion-making by scientifically trained therapists
- Longitudinal data seem to improve predictions, but implementation is challenging and psychometric training important
- Further investigation of longitudinal networks as well as ML before implementation into TTN/practice (larger data, crossvalidation, prospective evaluation)
- Unclear if centrality measures (as a summary of a network) can be meaningful predictors
  Bringmann et al. (2019). J Abnorm Psychol, 128(8), 892–903
- Limitations: Early implementation, new territory, methodological heterogenity

Thank you!

Follow this QR code to the network analysis paper

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