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Predicting Adolescent Response to School-Based Mindfulness: A Machine Learning Analysis in the MYRIAD trial

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Key Points

Question: Can machine learning identify which adolescents will benefit more from school-based mindfulness training versus standard social-emotional education?

Findings: In this analysis of 8,376 adolescents from 84 UK schools, machine learning identified a subgroup with statistically significant but clinically trivial differences in depressive symptom change. Specifically, adolescents predicted to benefit from mindfulness training based on their baseline characteristics did show significantly better outcomes if they received mindfulness, but the effect was negligible across comparisons (d = 0.07 - 0.08).

Meaning: Despite the use of two complementary machine learning approaches in a large sample of adolescents, personalization indicated negligible clinical benefit. These findings underscore the challenges of achieving clinically impactful personalization in universal school-based prevention.

Abstract

Importance: Depression most commonly first emerges during adolescence, making early prevention critical. While school-based mindfulness training (SBMT) offers a scalable prevention approach with broad reach, evidence of its effectiveness is mixed, and there is a compelling case for a more personalized approach to prevention.

Objective: To develop a data-driven algorithm from baseline characteristics to predict which adolescents are most likely to benefit from SBMT.

Design: Secondary analysis of the My Resilience in Adolescence (MYRIAD) cluster randomized controlled trial conducted between 2016-2018. School-level nested cross-validation was used to train and evaluate machine learning models for predicting individualized benefit from SBMT.

Setting: Eighty-four broadly representative UK secondary schools across England, Scotland, Wales, and Northern Ireland.

Participants: A total of 8,376 adolescents aged 11-13 years at baseline were included. Students had to be enrolled in participating schools with parental consent and student assent. The sample was 55% female, 76% White ethnicity, with mean age 12.2 years.

Interventions: SBMT teaching core mindfulness skills through psychoeducation, class discussion, and practices, compared to standard social-emotional learning (teaching-as-usual; TAU).

Main Outcomes and Measures: Change in depressive symptoms from pre- to post-intervention measured by the Center for Epidemiologic Studies Depression Scale. Causal forest (CF) and elastic net regression (ENR) models computed Personalized Advantage Index scores quantifying individual expected benefit from SBMT vs. TAU.

Results: CF showed acceptable calibration (mean Best Linear Predictor slope = 0.78, SE = 0.15), while ENR demonstrated modest predictive performance (*r* = 0.29; R^2 = 0.09; RMSE = 10.3). Both the CF and ENR models identified a subset of adolescents predicted to benefit from SBMT, but group differences in outcomes were negligible (CF: d = 0.07, p = .007; ENR: d = 0.08, p = .004). Top predictive features from the CF model were symptom severity (e.g., low-to-moderate depression and anxiety predicted greater SBMT benefit) and several school factors with non-linear patterns. ENR emphasized school-level characteristics with minimal differentiation.

Conclusions and Relevance: Machine learning identified a subgroup with statistically detectable but clinically trivial differential intervention response. These findings highlight the substantial challenges in achieving clinically useful personalization in universal school-based prevention programs.

Trial Registration: ISRCTN86619085

Introduction

Many mental disorders have their first onset during adolescence, with depression contributing the greatest burden of disease in terms of years lost due to disability.[1–5] Rates of depression rise sharply during the adolescent years and have increased substantially over the past 15 years.[6] Given its recurrence and long-term consequences, preventing adolescent depression is a critical public health priority.[7–10]

Depression prevention research has grown considerably since early trials in the 1980s and 1990s, with momentum accelerating in recent years.[11–19] Schools have emerged as a particularly promising venue for scalable delivery of depression prevention programs, as they provide access to nearly all children, across socioeconomic, racial, and ethnic backgrounds, offering a unique opportunity for broad-reaching interventions.[12] A recent systematic review[12] of school-based depression prevention programs concluded that, although these interventions may produce modest average benefits, the literature is marked by substantial heterogeneity, inconsistent findings, and concerns about methodological rigor and publication bias. These limitations underscore the need for well-designed, large-scale trials that can more clearly delineate which programs work, for whom, and under what conditions.

One approach that has garnered considerable attention within this broader effort is school-based mindfulness training (SBMT).[20,21] SBMT teaches core mindfulness skills which are thought to buffer against the development of depression and related problems. To rigorously evaluate its effectiveness in real-world settings, the My Resilience in Adolescence (MYRIAD) trial was conducted—a cluster-randomized controlled trial involving 84 UK secondary schools and more than 8,000 students, comparing SBMT to teaching standard social-emotional education (teaching-as-usual; TAU). Primary results showed no overall benefit of SBMT in reducing depression risk or enhancing social-emotional-behavioural functioning or well-being.[20] However, a secondary exploratory analysis revealed individual differences in response, with some subgroups—particularly students with elevated baseline mental health difficulties—experiencing poorer outcomes following SBMT.[21]

This prior analysis focused on a small number of theory-driven baseline variables, which were not well-equipped to detect complex, multivariable, or non-linear patterns of treatment response. Machine learning methods are uniquely suited to modeling high-dimensional data, where many predictors may each contribute small effects that, in combination, meaningfully influence outcomes. Machine learning provides a data-driven alternative to conventional moderation approaches, enabling estimation of individualized treatment effects.[22–27]

In this study, we apply two machine learning approaches—causal forests and regularized regression—to predict differential responses to SBMT versus TAU within the MYRIAD sample. Models were evaluated using nested (as opposed to regular, non-nested) 10-fold cross-validation to provide out-of-fold estimates of generalizability. Using baseline student, teacher, and school-level characteristics, we aim to identify which adolescents are most likely to benefit from SBMT, which may fare better with TAU, and which may experience little or even negative impact from either approach. By uncovering these individual differences in treatment response, we hope to advance more personalized, data-driven guidance that could translate into more targeted recommendations for school-based mindfulness programmes.

Methods

Participants and Procedure

We performed secondary analyses using data from the MYRIAD trial, a cluster-randomized controlled trial (ISRCTN86619085; registered 03/06/2016). The trial included 8,376 adolescents aged 11 to 13 at baseline, drawn from 84 schools across the UK (See **Table 1).** Both schools and students were broadly representative of UK secondary schools and their populations. The two arms included SBMT, which teaches mindfulness skills via psychoeducation, class discussion, and practices, compared to TAU covering standard social-emotional learning (SEL) topics.[28] We analyzed data collected at baseline and post-intervention. See Supplement and prior MYRIAD publications[20,21,28,29] for trial details. This study followed the EQUATOR guidelines. The University of Oxford Central University Research Ethics Committee granted ethical approval for this research (R45358/RE001). All participants provided informed consent prior to enrollment.

Measures

Outcomes. Given our focus on depression prevention, we predicted change in depressive symptoms from pre- to post-intervention, as measured by the Center for Epidemiologic Studies Depression Scale[30] (i.e., CESD_post − CESD_pre).

We also examined social–emotional-behavioural functioning (Strengths and Difficulties Questionnaire; SDQ Youth Self-Report Version[31]) and well-being (Warwick-Edinburgh Mental Well-being Scale; WEMBS[32]), which were co-primary outcomes in the main trial.[20] Missingness was relatively low (10% for each outcome).

Predictors. Predictor variables were 76 student-rated, teacher-rated, and school-level characteristics (see **Supplemental Table 1**). These predictors were selected based on a theoretical framework derived from a scoping review,[33] prior pilot work,[34] earlier MYRIAD analyses of candidate moderators,[21] and consultation with MYRIAD investigators. The median and mean levels of missingness were 3.9% and 11.5% across all predictor variables (SD = 16.7%; Range 0% -79%). Four variables had greater than 50% missingness and were removed from the imputation and analyses.

Analytic Approach

To estimate which individuals were likely to benefit more from SBMT versus TAU, we computed Personalized Advantage Index (PAI)[22–26,35] scores using two complementary machine learning approaches: (1) Elastic Net Regression (ENR) implemented via the glmnet package (version 4.1-8)[36] and (2) Causal Forests (CF) implemented via the grf package (version 2.3.2).[37] Analyses were implemented in R and our code is available on OSF (https://osf.io/4ftq7/files).

Nested Cross-Validation. We implemented nested 10-fold cross-validation at the school level to obtain unbiased estimates of model performance while preserving school clustering. Schools were randomly assigned to outer folds stratified by mean baseline depression severity to ensure balanced severity distribution across folds. Within each outer fold, the inner loop tuned model hyperparameters for both causal forest and elastic net. Once optimal hyperparameters were identified, the model was re-fit on the full outer training fold and evaluated on the held-out outer test fold. This process was repeated across all outer folds so that every student received out-of-fold predictions.

Missing Data and Preprocessing. Missing values among predictor variables were imputed using multiple imputation by chained equations (MICE), performed separately for the training and test sets (within each fold) to avoid information leakage, using the mice package in R.[38] Consistent with best practices[39,40], both predictors and outcomes (at each timepoint) were included in imputations. For prediction analyses, binary variables were coded as -0.5 and 0.5, and categorical variables with more than two levels were one-hot encoded (i.e., converted into separate binary indicators).[see 41]

Elastic Net Regression (ENR). ENR combines L1 and L2 penalties to enhance predictive accuracy while accounting for multicollinearity. The model included all main effects of baseline variables, a binary intervention group indicator (SBMT vs. TAU), and all group × predictor interactions. See Supplement.

Causal Forest (CF). CF directly estimates heterogeneous treatment effects (HTEs) by modeling treatment effect variation as a function of baseline covariates.[37] Unlike ENR, CF is capable of automatically detecting non-linear relationships and higher-order interactions. Within each training set, nuisance functions were estimated using a SuperLearner ensemble for the outcome regression and a probability forest for intervention assignment, with school ID entered as a clustering variable. The details of the base learners in the ensemble can be found in the supplement. We employed a two-stage approach: first, a preliminary CF was fit with all baseline covariates to identify important features, selecting variables with relative importance >0.2 (or the top 10 if fewer variables met this threshold).[42] Second, a final CF was fit using only the selected variables. CF hyperparameters (including the number of trees, minimum node size, and sample fractions) were tuned within the training data.[42] See Supplement for details.

General Predictive Performance. We evaluated the predictive performance of both models using methods appropriate to their architectures. For CF, calibration was assessed using the Best Linear Predictor (BLP) test across cross-validation folds, while ENR performance was evaluated using R^2, RMSE, and MAE on held-out data. See Supplement for details. Critically, the ultimate test of predictive performance for intervention selection models is whether the algorithms successfully identify which individuals benefit from which intervention condition—this is directly assessed via the PAI analyses described below.

PAI Computation. For each individual, we generated predicted depression outcomes (change in CESD from pre- to post-intervention) under both SBMT and TAU conditions using out-of-fold predictions from the nested cross-validation procedure. PAI scores were calculated as the difference between predicted outcomes (TAU - SBMT), where positive values indicate greater expected benefit from SBMT. For ENR, this was achieved by varying the binary intervention indicator while holding covariates constant. CF directly outputs expected group differences for each individual.

Evaluation. We tested whether PAI scores moderated intervention group differences in depression outcome (i.e., Intervention Group x PAI interaction), providing a formal statistical test of whether individuals who were assigned to their algorithm-indicated intervention (as identified by the model) had better outcomes. We also examined binary subgroups (PAI > 0 vs. PAI < 0) to assess clinical utility.

See Supplement for decision curve analysis.

Results

Holdout Sample Results

General Prediction Performance. Models demonstrated modest predictive performance (ENR r = 0.29; R^2 = 0.09; RMSE = 10.3, MAE = 7.6) and acceptable calibration for intervention effect estimation (CF: BLP slope = 0.78, SE = 0.15).

Predicted Benefit of SBMT vs. TAU. The Causal Forest model predicted that 78.1% of participants in the holdout sample would have better depression outcomes if they received SBMT compared to TAU, whereas 21.9% were predicted to benefit more from TAU than SBMT. The Elastic Net model identified 61.1% of the holdout sample as more likely to achieve better depression outcomes from SBMT relative to TAU, while the remaining 38.8% were predicted to benefit more from TAU. There was a statistically significant, modest positive correlation between the Causal Forest and Elastic Net PAI scores (Spearman's rank correlation $\rho = 0.20$, $p < .001$).

Baseline Characteristics Predicting Better Outcomes to SBMT vs. TAU. The top 10 baseline moderators from the Causal Forest and Elastic Net models are presented in **Figures 1 and 2**, respectively. Only two variables overlapped between models: CHU9D health-related quality of life and pupil-teacher ratio. The Causal Forest moderators included student-level symptom severity (e.g., low-to-moderate depression and anxiety predicted greater SBMT benefit) and school-level factors (e.g., larger schools and higher pupil-teacher ratios also predicted greater SBMT benefit). These predictors exhibited non-linear relationships (**Figure**

1). The Elastic Net model emphasized school-level structural characteristics but showed minimal intervention differentiation overall. The differences in predictors between the models may be due to the fact that Causal Forest captures interactions and non-linear effects, including curvilinear relationships between predictors and treatment benefit.

Observed Outcomes Align with Model-Predicted Benefit. Group × PAI interactions reached the level of a nonsignificant trend for both models (CF: b = -1.56, $t(8372) = -1.92$, p = .05; **Figure 3, left panel**; ENR: b = -0.33, $t(8372) = -1.92$, p = .05; **Figure 3, right panel**), with weak patterns in the expected direction: higher PAI scores (predicting greater SBMT benefit) were associated with modestly better outcomes when assigned to SBMT.

Outcomes Among Model-Identified Subgroups. For the Causal Forest model, individuals predicted to benefit more from SBMT (i.e., those with PAI scores > 0) demonstrated significantly better depression outcomes when randomly assigned to SBMT compared to TAU, but the effect size was negligible (d = 0.07, p = .007; **Figure 4, left panel**). In contrast, there were no between-group differencs for the subgroup of individuals predicted by Causal Forest to benefit more from TAU (d = -0.01, p = .82). Similarly, the Elastic Net model showed a negligible effect for the SBMT-indicated subgroup (d = 0.08, p = .004) and no effect for the TAU-indicated subgroup (d = 0.00, p = .99)(**Figure 4, right panel)**. Additional details are provided in Supplement.

Additional Outcomes. We re-ran both the Elastic Net and Causal Forest models using the SDQ and WEMWBS outcomes (i.e., recomputing PAI scores reflecting predicted outcomes for the latter two measures). Of the four Group × PAI interaction tests conducted (2 models × 2 outcomes), none were significant.

Discussion

A number of large-scale trials have failed to demonstrate the benefits of universal depression prevention programs for youth.[20,43] The large MYRIAD trial is a prominent example: it found no average benefit of universal school-based mindfulness training (SBMT) over teaching-as-usual (TAU) in reducing adolescent depressive symptoms.[20] Rather than suggesting prevention efforts should be abandoned, these findings highlight the need for more targeted or personalized strategies—particularly given the complex, multifactorial nature of adolescent depression risk. One explanation for these findings is that "one-size-fits-all" universal interventions may obscure meaningful individual differences in response, with null average effects masking benefits (or harms) for specific subgroups.

Our analyses revealed minimal heterogeneity in intervention response, despite the very large sample and complementary (Causal Forest and Elastic Net) machine learning analyses applied to a relatively rich set of student-rated, teacher-rated, and school-level characteristics. Two statistically significant effect emerged: adolescents predicted (using nested cross-validation) by either Causal Forest or Elastic Net to benefit from SBMT showed marginally better outcomes when randomized to SBMT versus TAU (CF: $d = 0.07$, $p = .007$; ENR: $d = 0.08$, $p = .004$). However, these effects were clinically negligible—far below thresholds typically considered meaningful for guiding treatment decisions. These findings suggest that, at least within the context of a universal school-based prevention trial, baseline characteristics may not provide sufficiently strong or stable signals to guide individualized intervention assignment. This highlights the substantial challenges of precision prevention in real-world, heterogeneous school populations.

The modest correlation between models ($\rho = 0.20$) and differences in top moderating variables identified reflect their different approaches—Causal Forest captures non-linear relationships and complex interactions while Elastic Net models linear effects. If strong non-linear or interactive intervention response patterns existed, we would expect Causal Forest to identify larger differential intervention effects than Elastic Net. However, both methods yielded negligible clinical effects, suggesting that the minimal heterogeneity we observed reflects limited differential response signals in this universal prevention context rather than limitations of either modeling approach.

Several explanations may account for these findings. First, the predictors available in this dataset–primarely self-report and teacher-report questionnaires, along with school-level characteristics–may not capture the underlying mechanisms driving individual differences in response. In other words, there may be heterogeneity in response to SBMT vs. TAU, but our dataset lacked the necessary measures or precision to detect it. The integration of other measures (e.g., relevant cognitive tasks, ecological momentary assessments, biological markers, passively-collected data from smartphones or wearables) may improve predictive accuracy and clinical relevance.[24,44–46] Second, universal, classroom-based delivery of SBMT by schoolteachers may limit potency, such that even algorithm-indicated subgroups could not derive substantial benefit. More intensive or targetted mindfulness (or non-mindfulness) interventions may be needed to produce clinically meaningful effects. To summarize, both methodological limitations and intervention potency could explain the absence of stronger personalization signals.

From a broader perspective, we must recognize the limitations of an overly individual-level intervention focus. Although our models included both student- and school-level predictors (e.g., school climate, deprivation indices), the MYRIAD intervention itself was delivered at the individual student level rather than targeting systemic change. Yet systemic factors—including school climate, socioeconomic deprivation, and structural inequities—substantially shape youth mental health outcomes.[47,48] Focusing exclusively on individual-level interventions risks overlooking these broader influences. Future precision-prevention efforts should not only integrate multilevel measures assessing relevant individual and contextual influences, but also develop and test interventions that directly target contextual and structural factors—such as improving school climate, addressing family dynamics and strengthening social supports, and reducing social inequities—that shape adolescents' mental health.[49]

Strengths and Limitations. This study drew upon a very large and broadly representative sample of UK secondary schools and students. School-level nested cross-validation strengthened ecological validity by testing generalizability to new schools. Using two complementary machine learning approaches enabled the modeling of both linear and non-linear effects, as well as higher-order interactions among predictors, which may underlie differential intervention response.

Important limitations include modest predictive performance, which may reflect inherent challenges in predicting future outcomes from pre-intervention characteristics and/or limitations in input data relying largely on self-report measures. Second, trial exclusion criteria eliminated schools that had been deemed inadequate in their most recent official inspection, potentially limiting generalizability to the most disadvantaged settings. Third, because TAU in the MYRIAD trial reflected the UK's existing and variable SEL provision, findings may not generalize to countries where SEL curricula differ. Fourth, some school characteristics were unbalanced (e.g., most schools were in England and mixed-gender), and although nested cross-validation ensured all schools contributed across folds, generalizability to other school contexts (e.g., single-gender or non-English schools) is uncertain. Fifth, although planned analyses were described in a pre-publication form submitted to and approved by the MYRIAD publications committee (with devaitions noted in the supplement), they were not formally preregistered on a public platform (e.g., OSF). Finally, machine learning models pose interpretability challenges. Elastic Net regression is relatively transparent, whereas Causal Forests, though more flexible, function as black-box models that are harder to interpret. We sought to mitigate this limitation by reporting variable importance rankings and partial dependence plots to illustrate non-linear effects, though higher-order interactions remain difficult to visualize. These interpretability constraints, along with the large number of predictors included, highlight practical challenges in implementing such models for decision-making in school settings.

Future Directions. Our findings underscore the substantial challenges of using machine learning to personalize universal school-based mental health prevention. Several directions may advance this field. First, richer predictor sets may better capture mechanisms underlying differential response. Second, more intensive or targeted interventions may be necessary, as universal teacher-delivered programs may be too weak to produce detectable subgroup differences. Third, multilevel approaches targeting both individual characteristics and contextual factors (school or local community climate, family dynamics, socioeconomic supports) may prove more effective than individual-level personalization alone.

Future work should prioritize prospective trials directly testing whether algorithm-guided assignment improves outcomes, using streamlined variable sets to reduce measurement burden and enhance scalability. Moreover, even if stronger personalization signals emerged, implementation in school settings presents challenges: if individual characteristics predominate, personalized recommendations would need to be communicated to individual families for elective programming decisions; if school-level characteristics predominate, algorithm-guided assignment could occur at the school level. However, realistic expectations are warranted. The absence of strong heterogeneity signals—despite arguably optimal conditions—raises the possibility that universal school-based mindfulness may not produce sufficiently differentiated effects to enable useful personalization. A hybrid approach combining targeted prevention for high-risk youth with structural interventions addressing systemic determinants of adolescent mental health may ultimately prove more promising.

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Competing interests. WK is the director of the Oxford Mindfulness Centre and receives royalties for several books on mindfulness. CAW has received consulting fees from King & Spalding law firm. JM-M. is associated with the University of Oxford Mindfulness Research Centre. No other conflicts of interests were reported from the other co-authors.

Data Sharing. Data are available upon reasonable request. The baseline data and codebook from the MYRIAD Trial are available from Prof Kuyken (willem. kuyken@ psych.ox.ac.uk) upon request (release of data is subject to an approved proposal and a signed data access agreement).[20]

CAW had full access to all the data in the study and takes responsibility for the integrity of the data and the accuracy of the data analysis.

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Table 1. Baseline characteristics of schools and students by trial arm status and overall

School (Cluster) Characteristics	SBMT	TAU	Total
Country, n (%)			
England	38 (88%)	36 (88%)	74 (88%)
Scotland	2 (5%)	1 (2%)	3 (4%)
Wales	1 (2%)	2 (5%)	3 (4%)
Northern Ireland	2 (5%)	2 (5%)	4 (5%)
Urbanity—urban, n (%)	36 (84%)	35 (85%)	71 (85%)
School size ≥1000 students, n (%)	20 (47%)	22 (54%)	42 (50%)
Type of school			
Mixed	36 (84%)	37 (90%)	73 (87%)
Girls	7 (16%)	4 (10%)	11 (13%)
School quality rating, n (%)			
Requires improvement	6 (14%)	5 (12%)	11 (13%)
No improvement required	37 (86%)	36 (88%)	73 (87%)
% eligible for free school meals, mean (SD)	13.2% (8.1)	11.8% (10.7)	12.5% (9.4)
Provision of PSHE education, mean (SD)	12 (2.5)	12 (2.6)	12 (2.6)
SEL ethos, mean (SD)	50.0 (9.7)	49.9 (10.5)	50.0 (10.1)
Gender, n (%)			
Female	2350 (56.5%)	2159 (53.1%)	4509 (54.9%)
Male	1724 (41.5%)	1823 (44.9%)	3547 (43.2%)
Age, mean (SD)	12.2 (0.6)	12.2 (0.6)	12.2 (0.6)
Ethnicity—White, n (%)	3237 (78.1%)	2965 (73.2%)	6202 (75.7%)
Year group, n (%)			
Year 7	2082 (49.2%)	2142 (51.7%)	4224 (50.4%)
Year 8	1878 (44.4%)	1827 (44.1%)	3705 (44.2%)
Year 9	79 (1.9%)	64 (1.5%)	143 (1.7%)
Year S1	193 (4.6%)	111 (2.7%)	304 (3.6%)
Depression (CES-D), mean (SD)	13.6 (10.0)	13.3 (9.8)	13.5 (9.9)
Social-emotional-behavioral functioning (SDQ), mean (SD)	11.8 (6.5)	11.7 (6.4)	11.8 (6.5)
Well-being (WEMWBS), mean (SD)	49.7 (9.7)	49.6 (9.7)	49.7 (9.7)

Notes. CES-D, Center for Epidemiological Studies for Depression Scale; PSHE, personal, social, health and economic; SDQ, Strengths and Difficulties Questionnaire; SEL ethos, school social–emotional learning ethos; WEMWBS, Warwick-Edinburgh Mental Well- Being Scale. See previously published results from parent trial for additional details.[20,21]

Fig. 1. Feature Importance (Partial Dependence Plots) for Top 10 Moderating Variables from Causal Forest

Note. Panels show estimated conditional treatment effects (CATE) for the top 10 moderators (selected by mean causal-forest variable importance across outer folds). For each moderator, we varied its value over an evenly spaced grid between the 1st and 99th percentiles of its observed distribution while holding all other moderators at typical values (continuous = sample mean; categorical = most frequent level; binary variables coded −0.5/0.5 were fixed at +0.5). At each grid point, we used the fitted causal forest to predict the treatment effect (SBMT/Mindfulness − TAU). A LOESS smoother is overlaid to aid visualization of potential non-linear relations. Values > 0 indicate greater predicted benefit from SBMT. See Supplementary Table 1 for moderator definitions

Fig. 2. Feature Importance for Top 10 Moderating Variables from Elastic Net

Note. Plot of interaction between a baseline predictor variable and condition (SBMT vs. TAU). See supplemental Table 1 for variable descriptions.

Fig. 3. Group x PAI interaction for Causal Forest (left panel) and Elastic Net (right panel) models.

Fig. 4. Nested cross-validated out-of-fold change in CESD by model-indicated vs. actual assignment

Note. Bars show nested cross-validated, out-of-fold mean change in CES-D (post − pre) within outer-fold holdout sets, grouped by the model-indicated treatment (SBMT vs. TAU; PAI > 0 = SBMT, PAI < 0 = TAU) and colored by the actual randomized assignment. Error bars indicate ±1 SE. Positive values reflect increases (worsening) in depressive symptoms.