Predicting mental health treatment access in high-symptom adolescents:

Machine learning approaches

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Abstract

Purpose: A majority of adolescents experiencing depression never access treatment. To increase access to effective mental health care, it is critical to understand factors associated with increased versus decreased odds of adolescent treatment access. This study investigated the relative importance of individual depression symptoms and sociodemographic variables in predicting *whether* and *where* adolescents with depression accessed mental health treatments. **Methods:** We performed a pre-registered, secondary analysis of data from the 2017 National Survey of Drug Use and Health (NSDUH), a nationally representative sample of non-institutionalized civilians in the United States. Using four cross-validated random forest models, we predicted whether high-symptom adolescents (N = 1,671; ages 12-17 years) accessed specific mental health treatments in the previous 12 months (“yes/no” for inpatient, outpatient, school, any). **Results:** 53.38% of adolescents with elevated depressive symptoms accessed treatment of any kind. Even with depressive symptoms and sociodemographic factors included as predictors, pre-registered random forests explained < 0.00% of pseudo out-of-sample deviance in adolescent access to inpatient, outpatient, school, or overall treatments. Exploratory elastic net models explained 0.80 - 2.50% of pseudo out-of-sample deviance in adolescent treatment access across all four treatment types. **Conclusions:** Neither individual depressive symptoms nor any socioeconomic variables meaningfully predicted specific or overall mental health treatment access in high-symptom adolescents. This study highlights substantial limitations in our capacity to predict whether and where high-symptom adolescents access mental health treatment and underscores the broader need for more accessible, scalable adolescent depression treatments.

Keywords: Depression; adolescence; treatment access; predictive modeling

Depression risk increases dramatically as children transition to adolescence (Wilson et al., 2015). Nearly 20% of youths experience a depressive episode between ages 12 and 18, with adolescent-onset depression predicting interpersonal challenges, substance abuse, and a 20-fold increased risk for attempting suicide (Effinger & Stewart, 2012; Hammen et al., 2008). Despite depression's early onset and protracted course, overall effects for treatments have remained small across more than fifty years of research (Weisz et al., 2017) and have even declined in recent decades (Weisz et al., 2019). Better tailoring depression treatments to address youths' individual clinical needs is one of the many ways to improve treatment potency (Ng & Weisz, 2016). Given the variety of settings where youths may access depression treatment (e.g. outpatient, inpatient, and school settings; Weersing et al., 2017), one path towards this goal involves determining whether certain youth characteristics—such as depression symptom profiles or sociodemographic factors—predict *whether* and *where* an adolescent is most likely to access care. For instance, if adolescents with certain symptoms of depression (e.g., anhedonia; suicidal ideation; hopelessness), or those with specific demographic risk factors (e.g., those in low-income families), tend to access services in systematically different settings, tailoring the *focus* of setting-specific services (e.g., to target specific symptoms or specific risk factors) may be of great practical value. Treatments targeting specific symptoms of depression (e.g. anhedonia, insomnia) can improve depression overall (Carney et al., 2017; Craske et al., 2019). Knowing if certain symptoms are more predictive of treatment access overall, or within specific settings, could help improve quality of care. Moreover, identifying factors linked to *failure* to access services may highlight targets for dissemination efforts. To address both of these goals, we tested the relative importance of individual depressive symptoms, demographic variables, and socioeconomic variables in predicting *whether* and *where* adolescents with depression accessed

mental health treatment types (inpatient, outpatient, school, any) in the previous 12 months, using a large, nationally-representative sample.

Individual Depression Symptoms and Depression Treatment Access

There is reason to expect that individual depressive symptoms may differentially influence whether and where people access treatment. Depression is a multifarious diagnosis reflecting >1400 possible symptom combinations (Fried & Nesse, 2015), and different symptoms differentially relate to overall impairment (Fried & Nesse, 2014), personal and familial risk factors (Fried et al., 2014; Fried & Nesse, 2014), and treatment response (Bos et al., 2018). This complexity highlights the need to understand individual symptoms' possible links to accessing mental health services. For instance, tiredness, difficulties concentrating, and thoughts of death, but not other individual depression symptoms, were associated with outpatient mental health service access among 557 depressed Finnish adults—even after controlling for overall depression severity, duration, and impairment (Hämäläinen et al., 2004). Thus, certain symptoms might matter more than others with respect to seeking and accessing treatment.

Although research linking specific symptoms to whether and where youths access treatment is scarce, some evidence suggests its potential role. Certain symptoms (suicidality; irritability; cognitive and sleep disturbances) were significantly more common than others in a sample of adolescents referred for outpatient depression treatment in the UK (Orchard et al., 2017). Individual depressive symptoms may also be differentially related to treatment access in certain settings (e.g. inpatient and outpatient settings, which youths tend to access only when referred by a caregiver) due to differences in parents' recognition of youth symptoms. One large study of 3,461 youth-parent pairs found that agreement between youths' self-reported symptoms and parent reports of youths' symptoms was twice as strong among specific somatic symptoms

(e.g., disturbed sleep) versus affective symptoms (e.g., feeling guilty; Kröner-Herwig et al., 2009). As parents often initiate mental health treatment for adolescents (Boyd et al., 2018), some symptoms (e.g., those that parents can more easily observe, such as changes in their child's eating or sleeping patterns), but not others, could influence adolescents' odds of accessing treatment. Other work suggests overall functional impairment and symptom *severity* is associated with increased odds of adolescent treatment-access across school, outpatient, and inpatient settings; however, in these studies, individual depression symptoms were not examined as predictors of setting-specific service access relative to overall distress severity (Langer et al., 2015; Wu et al., 1999). Thus, while individual symptoms might differentially relate to treatment access across settings, research on links between *specific symptoms* and access to care remains scarce.

Lastly, substantial evidence suggests that researchers can predict important, multi-determined life outcomes more effectively by including both composite scores *and* individual items in statistical models—rather than relying on the composites alone. For example, individual items (i.e. “I often feel blue”) outperformed composite measures of personality (e.g. neuroticism) in predicting a broad range of 40 outcomes (e.g., general health, relationship satisfaction)—with individual items explaining an average of 30% more variance in outcomes than composite scores (Seeboth & Möttus, 2018). Another study found individual personality items (e.g. “I act forcefully and energetically”) incrementally predict interests (e.g. “civic obligations”) and BMI over and above composite personality domains in large samples of German twins (Möttus et al., 2017). Extending this statistical insight to clinical psychology research, including item-level predictors (i.e. individual symptoms of depression) may improve the ability to predict whether and where adolescents access mental health treatment.

Sociodemographic Factors and Depression Treatment Access

Several studies have suggested sociodemographic factors relate to rates of mental health treatment access. For instance, some studies suggest that individuals who are male, live in a single-parent household, and have lower family income are more likely to access mental health services—although the link between male sex and service use are likely attributable to externalizing problems rather than depression (Costello & Janiszewski, 1990; Wu et al., 1999; Zahner & Daskalakis, 1997). Consistent with this result, a systematic review of ethnicity's relation to mental health service use found that African American adolescents accessed fewer mental health services than their Caucasian counterparts in six of ten studies, regardless of setting (Elster et al., 2003). Additional work has corroborated the role of ethnic minority status on decreased odds of accessing depression treatment, even after accounting for family income and insurance status (Cummings et al., 2014; Cummings & Druss, 2011). Importantly, sociodemographic variables may have different relationships with rates of mental health service access in schools versus other settings (Garland et al., 2001). In a nationally-representative survey of middle and high school students, African American and American Indian adolescents were *more* likely than their Caucasian peers to have accessed school-based mental health treatments in the past 12 months—although individual problem types were not explored (Slade, 2002). Likewise, other work suggests that youths in low-income families are *more* likely to access school-based mental health services (Farmer et al., 1999), but youths with fewer socioeconomic advantages are *less* likely to access either inpatient or outpatient specialty mental health services after accounting for symptom severity (Amone-P'Olak et al., 2010). However, research on how various sociodemographic factors relate to treatment access for depressed

adolescents—while simultaneously examining the influence of the specific symptoms they experience—does not yet exist within the present authors’ knowledge.

Predictive Modeling and Treatment Access

Predictive modeling approaches are ideally suited to test how well individual depressive symptoms *and* various sociodemographic variables predict adolescents’ access to mental health care. Predictive modeling techniques are designed to (1) simultaneously evaluate the role of a large number of related factors in relation to the outcome of interest, and (2) use statistical algorithms to evaluate how well these variables *predict* future, new, or unobserved data—even when utilizing a cross-sectional sample (Yarkoni and Westfall 2017). In contrast, most adolescent treatment access research to date utilizes an *explanatory* modeling approach: researchers attempt to explain causal mechanisms underlying behavior by examining the strength of relationships between the variables and outcome of interest in a single, given sample. Importantly, while models with high explanatory power in a particular sample (e.g., high F-value, high R-squared) are often assumed to have high predictive power across new data, they often fail to do so (Shmueli, 2010; Yarkoni & Westfall, 2017); as such, the generalizability of a result merits explicit testing in its own right.

Random forest modeling is one statistical technique that exercises both benefits of predictive modeling: (1) by teasing apart the relative importance of a large number of highly correlated factors (e.g., relationship to national poverty threshold, income, and enrollment in government assistance programs) in predicting a multi-determined outcome (e.g., treatment access), and (2) by evaluating how well the model performs within cases/observations that were intentionally “held out” of the data used “train” or fit the model (i.e., “out of bag” observations; Grömping, 2009; James et al., 2013). Random forests therefore evaluate how well the selected

variables predict the outcome of interest for new, or “unobserved” data. Lastly, random forests can detect complex, non-linear interactions among predictors (Breiman, 2001). Taken together, random forests are a valuable statistical technique for the prediction of multi-determined outcomes, including adolescent treatment access.

Present Study

We evaluated the relative importance of individual depressive symptoms and sociodemographic factors in predicting access to specific mental health treatment types (inpatient, outpatient, school, any) across 12 months using a national adolescent sample (ages 12-17; $N=1,671$). All adolescents reported at least one two-week period of significant depressed mood or anhedonia in the past 12 months. To our knowledge, this study is the first to examine *both* specific symptoms and sociodemographic factors as predictors of treatment access among adolescents experiencing depression. This pre-registered (<https://osf.io/ag8ez>) secondary data analysis used data obtained from the 2017 National Survey on Drug Use and Health (NSDUH; Center for Behavioral Health Statistics, 2018). Given the scarcity of literature in comparing the relative importance of individual depression symptoms and socioeconomic factors, we did not propose specific hypotheses for study results.

Methods

The NSDUH is an annual survey of mental health, substance use, and treatment-seeking in U.S. individuals ages 12 and older. Sampling uses an independent, multistage area probability design including all U.S. states, using population-based weights to inform nationally representative estimates. The NSDUH assesses all sensitive variables (e.g., those linked to treatment and mental health) using audio computer-assisted self-interviewing, and less sensitive variables (e.g. demographics, education) using computer-assisted personal interviewing by a

field interviewer. The 2017 NSDUH survey (NSDUH-2017-DS0001) included skip-outs and consistency checks to promote complete responding. In 2017, the weighted screening response rate was 75.08%, and the weighted interview response rate was 67.12%. Details about the NSDUH, including psychometrics, is available elsewhere (Substance Abuse and Mental Health Services Administration, 2018).

Participants

This study included individuals aged 12-17, inclusive, in the 2017 public use file who reported experiencing depressive symptoms in the past year for at least two weeks. Due to internal branching logic within the 2017 NSDUH survey, only adolescents meeting certain severity thresholds completed survey items for the full range of individual depression symptoms. Thresholds were as follows (per NSDUH survey items):

1. Endorsed “Sadness/discouragement/boredom for at least one hour, during times where [they] felt problems with their mood had lasted for at least 2 weeks,” *and*
2. Did *not* endorse the following: “bad feelings during these times were mild,” “[they] never felt so bad that nothing could cheer [them] up,” and “[They] never felt so bad [they] could not carry out activities”, *and*
3. Endorsed “feeling sad/depressed/empty/discouraged/hopeless for several days or longer in lifetime” *or* endorsed “2+ weeks of losing interest or becoming really bored in lifetime,” *and*
4. Endorsed “lifetime presence of 2+ week timeframe for other symptoms (changes in sleeping, eating, energy, concentration, self-dislike).”

Among adolescents meeting these criteria, we included those who reported experiencing depressive symptoms “for two weeks or longer” during the previous 12 months; we excluded

those who were missing data on our treatment-access outcomes (whether and where they accessed services), individual depression symptoms, or sociodemographic variables of interest (total N excluded due to missing data = 183). This yielded a final sample of $N=1,671$, among whom 72.77% were female; 55.60% Non-Hispanic White; 9.22% Non-Hispanic Black/African-American; 1.56% Non-Hispanic Native American/Alaskan Native; 0.48% Non-Hispanic Native Hawaiian/Other Pacific Islander; 3.65% Non-Hispanic Asian; 7.90% Non-Hispanic more than one race; and 21.60%, Hispanic/Latino. For age, 5.21% were 12 years of age; 10.77% were 13; 15.56% were 14; 22.68% were 15; 22.62% were 16; and 23.16% were 17. 94.61% of the sample endorsed speaking English “very well”. 53.38% of these adolescents had accessed treatment of any type, and 41.17%, 29.62%, and 7.18%, accessed treatment in outpatient, school-based, and inpatient settings, respectively (see Supplements 1 and 2 for data processing code).

Survey

Adolescents who met the aforementioned depression severity thresholds were prompted to answer the full range of depression symptom items: sadness, anhedonia, weight/appetite changes, sleep problems, psychomotor changes, fatigue, worthlessness/guilt, concentration/indecisiveness, and suicidal ideation/behaviors. All symptom variables were evaluated as “yes” or “no” variables, with “yes” responses indicating the presence and “no” indicating the absence of that symptom. Depression severity was measured using a single binary variable indicating whether or not each responder had 5 symptoms or more.

The survey next evaluated whether adolescents accessed mental health care from a variety of sources in the past year for “problems with behaviors or emotions that were not caused by alcohol or drugs”. Responders indicated (“yes” or “no”) whether they had accessed various services. If responders indicated they had (a) stayed overnight in a hospital or (b) stayed in a

residential health facility, they were recorded as having accessed *inpatient* services in the past 12 months. If responders indicated they had (c) spent time in a day treatment facility, (d) accessed treatment at a mental health clinic, (e) accessed treatment from a private therapist, or (f) accessed treatment from an in-home therapist, they were recorded as having accessed *outpatient* services in the past 12 months. If responders indicated they had (g) talked to school social worker, school psychologists, or school counselors for problems, or (h) attended a special school or participated in a special program at a regular school for problems for problems with behavior or emotions, they were recorded as having accessed *school* services in the past 12 months. If a responder accessed any of the above listed forms of mental health services, they were recorded as having accessed *any* services in the past 12 months.

We included several demographic variables in our models: age, sex, race/ethnicity, and English-speaking ability (“very well”, “well”, “not well”, or “not well at all”). We also included the following socioeconomic variables, consistent with prior work exploring socioeconomic correlates of treatment access: education level (e.g. sixth grade completed), Medicaid/CHIP status, gaps in insurance coverage within the past 12 months, government programs status, total family income, and total family income relative to the federal poverty threshold. While we planned to include “current insurance status” as a predictor variable in each of our models, all adolescents in the present sample had insurance at the time of the survey. With < 2 levels (i.e. zero variance), this predictor variable was therefore omitted from all predictive models. Therefore, our final predictive models included a total of 20 predictors (10 depressive symptom-related predictors, 10 sociodemographic predictors). Additional variable descriptions can be found in our preregistration (<https://osf.io/ag8ez>) and in the NSDUH 2017 Analytic File Codebook (Center for Behavioral Health Statistics, 2017).

Data were statistically imputed by the NSDUH for the following variables in the current sample ($N = 1,671$): Medicaid/CHIP status (3 values imputed), total family income (119 values imputed), and four variables used to create the aggregate “government programs status” predictor variable (36 values imputed across four variables). In accordance with the official NSDUH recommendation, imputed variables were used in the present analyses wherever possible (see NSDUH 2017 Analytic File Codebook, p. i-15). Statistical imputation involved two imputation procedures: (1) predictive mean neighborhood (PMN), a “combination of model-assisted and nearest neighbor hot-deck imputation methods”, and (2) modified predictive mean neighborhood (modPMN), a technique which “uses the model-assisted imputation methodology of the PMN approach while also permitting the user to cycle through a set of related variables multiple times” (see NSDUH 2017 Analytic File Codebook, p. i-24). Additional information can be found in the 2017 NSDUH Methodological Summary and Definitions (Center for Behavioral Health Statistics and Quality, 2018). Table 1 outlines adolescent responses for symptom and socioeconomic predictors.

[Table 1]

Analytic Plan

We pre-registered our analytic plan on Open Science Framework before accessing the data (<https://osf.io/ag8ez>) and have provided our R code so our analyses can be fully reproduced (see Supplements 1 and 2). Our pre-registered analyses involved predicting whether an adolescent accessed inpatient, outpatient, school-based, or any mental health treatment in the past 12 months via complete-case analysis of four separate random forest models grown using classification trees. Many machine learning algorithms require extensive tuning of hyperparameters, or fitting hundreds to thousands of models and selecting the “best” predictive

model (Yogatama & Mann, 2014). However, extensive hyperparameter tuning can lead to an overly optimistic prediction due to fitting so many models (Ng, 1997).

Random forests. Random forests are an ensemble prediction method that can perform well without hyperparameter tuning—substantially reducing concerns of overfitting (Cawley & Talbot, 2010; James et al., 2013). Individual classification “trees” within a random forest are each fit using a random subset of the total observations. Each tree performs a series of recursive, binary “splits” to partition the data using the predictor variable and split-point that best increases “node purity”, or best ensures observations in the resulting group are of the same class (e.g. *all* individuals within a node have accessed treatment; (Hastie et al., 2009). When selecting the variable and split point for each split, only a random subset of the total predictors is considered each time—allowing variables of varying importance to potentially contribute to the model’s prediction. Trees stop growing, or only grow to a certain depth, once further splitting would result in too few observations in a particular “terminal” node. The majority class within each terminal node is a tree’s estimate for all observations within that node, and the final, ensemble prediction is composed of the majority vote prediction across all trees in the forest. Therefore, random forest models have 3 hyperparameters: (1) number of trees included in the random forest, (2) tree depth, and (3) m , number of predictors considered at each split.

We set our random forest models to contain the default value of 500 trees and confirmed this was sufficient for the error rate to have “settled down”, i.e. for the generalization error to plateau (James et al., 2013; see Supplement 1). We used the default tree depth setting, where tree growth would terminate once an additional split resulted in fewer than five observations. This default setting is encouraged, as tuning this tree depth hyperparameter often does not make a substantive difference in prediction (Hastie et al., 2005). We set m , number of predictors

considered at each split, to equal the square root of the total number of predictors—a common default setting in classification trees (Hastie et al., 2005). We included an if/then structure within our pre-registration, detailing how we would select alternative m settings if too few of our predictors were relevant, or non-zero (<https://osf.io/ag8ez>).

Each random forest evaluated how well the model could predict whether an adolescent accessed each type of treatment (inpatient, outpatient, school-based, and any treatment) using 10-fold cross-validation (Genuer et al., 2010). Observations are randomly divided into ten “folds” (i.e. subsets), and the model is trained using nine folds and tested on the tenth fold. This process is repeated ten times, each time using a different set of training and testing folds. This procedure allows us to calculate “pseudo out-of-sample deviance explained”, or how well we would expect the models to predict whether different types of treatment were accessed in a new, separate sample (Yarkoni & Westfall, 2017). Unlike traditional within-sample deviance explained, the pseudo out-of-sample deviance can have a negative value. There is the possibility that a model will have *worse* prediction out-of-sample than picking the majority class of the outcome in each instance. In these cases, the pseudo out-of-sample deviance explained will therefore be negative. For example, if a majority of adolescents in the sample accessed outpatient treatment, the model could perform worse than simply predicting that every adolescent accessed outpatient treatment.

Lastly, we evaluated variable importance. Given that each tree is grown using a bootstrapped sample of the original data, approximately $\frac{1}{3}$ of the data will naturally be “out of bag”, or not included, for each tree. The increase in classification error in “out of bag” samples when a variable is randomly permuted determines that variable’s relative importance within the model. The greater the increase in classification error when the variable is permuted, the more relatively important the variable is. These “out of bag” samples assess pseudo out-of-sample

prediction, serving as a natural hold out sample (Grömping, 2009). In this paper we focus on total model performance in terms of percentage deviance explained via cross-validation, but “out of bag” total model error rates were consistent with the cross-validation error rates and are reported in Supplement 1. All random forest and variable importance analyses were pre-registered (<https://osf.io/ag8ez>).

Elastic nets. To confirm our results were not model-specific (Munafò & Davey Smith, 2018), we fit 4 exploratory, cross-validated elastic net models, which (like the random forests) predicted whether an adolescent accessed inpatient, outpatient, school-based, or any mental health treatment. These models therefore served as an alternative prediction-focused modeling approach and included an identical set of predictors.

Elastic nets are a type of linear regression that penalizes predictors with: (1) a ridge penalty that shrinks useful but redundant predictor coefficients toward one another and zero (2) a lasso penalty that shrinks the coefficients of irrelevant predictors to zero (Zou & Hastie, 2005). The λ hyperparameter determines the *magnitude* of these shrinkage penalties and requires tuning with cross-validation. The α hyperparameter determines the *proportion* of ridge vs. lasso penalty in the model (0.01: favoring inclusion of most variables, 0.99: favoring sparsity, and 0.5: an equal mix of both ridge and lasso). For each outcome, we searched over 100 possible values of λ (auto-generated by the model-fitting program) and three possible values of α (0.01, 0.99, and 0.5). To account for the possibility of hyperparameter tuned estimates being overly optimistic, we employed nested cross-validation (Varma & Simon, 2006). Relative variable importance was quantified as the absolute value of the standardized regression coefficient for each predictor.

Comparing models. To compare the predictive performance of random forests versus elastic nets, we subtracted the percentage deviance explained between model types for each of

our four treatment outcomes. These difference scores indicated predictive gain between models (Δ deviance explained), with 95% CIs representing 0.25 and 0.75 quantiles of the Δ deviance explained distribution—calculated using 10,000 bootstraps.

Additional Sensitivity Analyses

We performed additional sensitivity analyses to assess whether overall random forest and elastic net prediction performance could be improved under varied circumstances: (1) only non-zero “relevant” predictors included, (2) altering the number of candidate predictors randomly sampled at each random forest split, and (3) using differing indices for depression severity (number of depressive symptoms endorsed) and suicidality (separate items for specific presentations of suicidality, i.e. “thoughts of death” and “thoughts of killing self”; see Supplements 1 and 2).

All analyses were conducted using the random forest and elastic net algorithms from the *randomForest* and *glmnet* packages in R—available on the Comprehensive R Archive Network (Liaw & Wiener, 2002; Friedman, Hastie, & Tibshirani R, 2010). A wrapper for the *randomForest* and *glmnet* packages was used to aid interpretation and to compare and plot cross-validated models (*beset*, R Core Team, 2019; <https://github.com/jashu>).

Results

Pre-registered Random Forest Analyses

In accordance with our preregistration plan (<https://osf.io/ag8ez>), we report results from our default *m* models—as >10% of our total number of predictors were “relevant” (i.e. had a positive relative importance score estimate with 95% CIs that do not overlap with zero) across all four pre-registered random forests.

Inpatient treatments. The first random forest model explained $< 0.00\%$ pseudo out-of-sample deviance (Mean = -0.147, SE = 0.030, Min = -0.187, Max = -0.120) in whether adolescents accessed inpatient mental health services in the past year. A negative value for cross-validation deviance explained indicates poor model performance (Beevers et al., 2019). The current model (including symptom, demographic, and socioeconomic predictors) predicts less out-of-sample deviance than an “intercept only” model, which is equivalent to predicting outcome class in the test sample using only the “majority class” of the train sample (i.e. whether most people had, or had not, accessed that treatment). The train sample majority class will not outperform test sample majority class when predicting outcomes in the test sample itself—resulting in negative deviance explained. Put simply, the model *adds* to uncertainty when making predictions about whether an adolescent will access inpatient treatment.

Outpatient treatments. The second random forest model predicted $< 0.00\%$ pseudo out-of-sample deviance (Mean = -0.063, SE = 0.020, Min = -0.074, Max = -0.051) in whether adolescents accessed outpatient mental health services in the past year.

School treatments. The third random forest model predicted $< 0.00\%$ pseudo out-of-sample deviance (Mean = -0.168, SE = 0.023, Min = -0.186, Max = -0.156) in whether adolescents accessed school-based mental health services in the past year.

Any treatment. The fourth random forest model predicted $< 0.00\%$ pseudo out-of-sample deviance (Mean = -0.104, SE = 0.021, Min = -0.108, Max = -0.098) in whether adolescents accessed any mental health services in the past year.

Relative importance of predictors. With very poor overall model performance (i.e. negative out-of-sample deviance explained) across all four treatment type outcomes

(Kenchington et al., 2016), relative importance scores for individual predictors should not be interpreted.

Exploratory Elastic Net Analyses

To ensure poor predictive ability was not model-specific, we predicted each of the four treatment type outcomes using a second, exploratory elastic net analysis. We formally compared model performance (indexed using pseudo out-of-sample deviance explained) between pre-registered random forests and exploratory elastic nets for each of the four outcomes.

Inpatient treatments. The first elastic net model explained 0.80% of pseudo out-of-sample deviance ($SE = 0.004$, $Min = 0.008$, $Max = 0.012$) in whether adolescents accessed inpatient mental health services in the past year. In a formal comparison, the elastic net explained greater out-of-sample deviance in inpatient treatment access than the random forest (95% CI: [0.081, 0.230]).

Outpatient treatments. The second elastic net model explained 1.90% of pseudo out-of-sample deviance ($SE = 0.004$, $Min = 0.016$, $Max = 0.021$) in whether adolescents accessed outpatient mental health services in the past year. In a formal comparison, the elastic net explained greater out-of-sample deviance in outpatient treatment access than the random forest (95% CI: [0.045, 0.120]).

School treatments. The third elastic net model explained 1.10% of pseudo out-of-sample deviance ($SE = 0.003$, $Min = 0.010$, $Max = 0.013$) in whether adolescents accessed school mental health services in the past year. In a formal comparison, the elastic net explained greater out-of-sample deviance in school treatment access than the random forest (95% CI: [0.130, 0.230]).

Any treatment. The fourth elastic net model explained 1.00% of pseudo out-of-sample deviance (SE = 0.003, Min = 0.008, Max = 0.012) in whether adolescents accessed any mental health services in the past year. In a formal comparison, the elastic net explained greater out-of-sample deviance in any treatment access than the random forest (95% CI: [0.075, 0.150]).

Relative importance of predictors. While all four elastic net models outperformed the random forest models, pseudo out-of-sample deviance explained ranged from 0.80 - 1.90%. With such minimal variance explained in the outcome (Kenchington et al., 2016), relative variable importance should not be substantively interpreted.

Additional Sensitivity Analyses

Across all additional sensitivity analyses (including only non-zero predictors, varying number of candidate predictors considered at tree splits, and using different indices of depression severity and suicidality), random forest and elastic net models explained very little pseudo-out-of-sample deviance (all models explaining $\leq 2.5\%$ pseudo out-of-sample deviance explained; see Supplement 1).

Discussion

This pre-registered study examined the relative importance of depressive symptoms and sociodemographic factors in predicting whether and where adolescents experiencing depression accessed treatment across a 12-month period, using a nationally representative U.S. sample. Based on random forest and elastic net predictive models, neither individual depressive symptoms (sadness, anhedonia, weight/appetite change, sleep problems, psychomotor change, fatigue, worthlessness/guilt, concentration/indecision, suicidal thoughts/behaviors), nor depression severity, nor any sociodemographic factors (including age, gender, race, education, receipt of government assistance, insurance status, and family income) meaningfully predicted

access to inpatient treatment, outpatient treatment, school-based services, or overall mental health treatment access. Together, these variables accounted for no more than 2.5% of total variance in treatment access. Each factor's exceptionally small overall importance precludes interpretation or practical application of variables' relative importance.

The results of this study stand in contrast to the findings of previous investigations indicating race (Elster et al., 2003), income (Farmer et al., 1999), and other socioeconomic factors (Amone-P'Olak et al., 2010) predict adolescents' mental health treatment access across settings. Also in contrast to prior studies, our results provided little evidence that individual depressive symptoms predicted depressed adolescents' treatment access patterns—including symptoms indexing higher immediate need (e.g., suicidality). However, previous investigations often found mixed results regarding each factor's predictive value (Elster et al., 2003), and no previous investigation of mental health treatment access known to these authors used pseudo out-of-sample prediction. Compared to prior research in this area (which has generally *not* used out-of-sample prediction), our use of cross-validation and subsequent pseudo out-of-sample prediction allows for greater confidence in results' generalizability (Yarkoni & Westfall, 2017)—including, as in the current case, when those results are null.

Random forests and elastic nets are also considerably more robust to the inclusion of highly correlated predictors (e.g., multiple indices of adolescent SES; co-occurring depressive symptoms; Breiman, 2001; Zou & Hastie, 2005) than more commonly-used linear regressions and ANOVAs (Goodhue et al., 2017). Indeed, including highly-correlated predictors in typical regressions and ANOVAs increases risk of false-positives (Kalnins, 2018). Because using 10-fold cross-validation with random forests and elastic nets guards against these false-positives (Jacobucci et al., n.d.), the current study's results are more likely to generalize across diverse,

high-symptom adolescent samples. Therefore, while pre-existing evidence indicates these factors influence adolescent treatment access (Cummings & Druss, 2011; Zimmerman, 2005), the present results imply these relationships do not collectively account for a substantial amount of the variation in access to care among high-symptom adolescents.

The inability of depression symptoms and sociodemographic factors to predict adolescent treatment access in this study raises a critical question: which factors, if any, *can* predict mental health treatment access in a generalizable way? Three potentially important factors not included in the NSDUH survey are stigma related to mental illness, experiences of discrimination, and perceived need for treatment by parents. Among adolescents of minority groups, stigma associated with experiencing and seeking support for mental illness may decrease willingness to seek out and receive psychiatric treatment (Brown et al., 2010). Separately, past experiences of discrimination are linked to the underutilization of mental health care (Burgess et al., 2008). Although race is often viewed as a proxy variable for experiences of discrimination and racism (Corbie-Smith et al., 2008), a direct measure of perceived discrimination may improve the prediction of treatment access across samples and contexts. For example, in large, community sample of women in San Francisco, adding self-reported discrimination in health care delivery as a predictor variable more than doubled the variance explained in health services utilization ($R^2 = 10.0\%$) when compared to accounting for demographic variables (e.g. income, education level, ethnic or racial group) and social desirability response bias alone ($R^2 = 4.4\%$; Facione & Facione, 2007). Parent perceptions of their child's need for service may also directly shape access to care. Indeed, parents have been termed the 'gatekeepers' for youths' mental health treatment, as they are primarily responsible for initiating and transporting their adolescent offspring to and from treatment (Boyd et al., 2018; Breland et al., 2014). Previous work suggests that adolescents

whose parents perceive a need for external support are more likely to access care (Zahner & Daskalakis, 1997).

However, it is important to note that the added value of these (and other) factors in predicting adolescent treatment access may well be small. Thus, it is critical to attend to our finding that, even among high-symptom adolescents, nearly 50% failed to access services of any kind. This finding corroborates other literature documenting the gap between rates of mental health treatment *need* and *access* in adolescents (Kataoka et al., 2002; Merikangas et al., 2011). Further, other recent work within the 2017 NSDUH sample indicates that, even among adolescents who *do* access outpatient care, a substantial portion (23.36%) terminate treatment after receiving only 1-2 sessions of psychotherapy (Abel et al., 2020). Regardless of our current or future capacity to predict which teens with depression will access care, this pattern of findings underscores the need to develop and disseminate interventions that can be accessed by youths *regardless* of symptom profiles, sociodemographic disadvantage, or access to traditional services (e.g., inpatient, outpatient, and school-based supports). Recent work has shown that brief, self-administered interventions can help reduce and prevent psychopathology of diverse types, including adolescent depression (Schleider et al., 2019; Schleider & Weisz, 2017). As we continue to refine our capacity to predict *whether* and *where* youths access treatment, an equally critical goal will be identifying, optimizing and scaling-up more accessible, cost-effective supports.

Certain limitations warrant mention and suggest directions for future research. As noted above, we were unable to include potentially relevant factors in our models (e.g. youths' and parents' perceived need for services; stigma towards treatment-seeking; experiences of discrimination) that were not included in the NSDUH survey. Additionally, while the present

study's outcomes indicate which adolescents accessed mental health treatment via different settings in the past year, they do not provide information about the *quality* or *effectiveness* of the care received. Future work should extend the present research to predict the quality of care accessed, as evidence suggests socioeconomic and demographic factors are associated with receiving poorer quality-of-care (Neighbors et al., 2007; Young et al., 2001). Further, while some adolescents in this sample had experienced gaps in health insurance coverage in the past 12 months, all had health insurance at the time of the survey. Replicating these analyses in a large sample containing adolescents with and without health insurance could help determine whether sociodemographic predictors are more relatively important when health insurance coverage is mixed. Responses were also self-reported and cross-sectional, introducing potential informant bias and precluding conclusions about directionality. Lastly, our findings are unable to capture if participants sought treatment from nontraditional sources—e.g., online support networks—which some consider to be an alternative help resource (Montagni et al., 2019).

Additionally, while one may argue a lack of variation among the symptom-level predictors may contribute to the present null result, we argue that: (1) substantial variation exists within many of our predictors, and (2) these data are generally representative among adolescents experiencing elevated depressive symptoms. First, many of the sociodemographic factors (e.g. sex, race, age, education, Medicaid/CHIP status, government programs, family income, poverty) and several of the symptom-level factors (e.g. weight/appetite change, psychomotor change, worthlessness/guilt, and suicidality) *do* vary considerably within the present sample. Second, less variation will inherently occur within certain symptoms when working selectively within an elevated-symptom sample. However, evaluating treatment access within a higher-severity sample is especially valuable—as it seeks to identify the minority of adolescents who do access

services among those in need of them. The present null result is not simply a feature of the present data, but rather a reflection of how difficult it is to predict access to care among adolescents in particular need of mental health supports. Overall, given the scarcity of work in this area, robustness of our analyses, and the large, nationally representative sample, our results may help guide future examinations of adolescent treatment access.

This study highlights substantial limitations in our capacity to predict whether and where high-symptom adolescents access mental health treatment. Future work is needed to understand whether factors beyond symptom types and sociodemographic risk (e.g. stigma, discrimination, and parents' perceived need for services) may help account for treatment-access patterns in adolescents experiencing depression. Simultaneously, it will be crucial to invest in testing briefer, targeted, and more accessible supports for adolescents with depressive symptoms, which may be easier to access for the many depressed adolescents who continue to go without care.

Declarations

Funding. There is no funding to report for the present work.

Conflicts of Interest/Competing Interests. The authors declare that they have no conflict of interest related to the present study.

Ethics Approval. The present study was conducted using publicly-available, de-identified data from the 2017 National Survey of Drug Use and Health (NSDUH):

<https://www.datafiles.samhsa.gov/study-dataset/national-survey-drug-use-and-health-2017-nsduh-2017-ds0001-nid17939>. No ethical approval was required for this study.

Informed Consent. All secondary data analyses were conducted using de-identified data that is publicly available on the Substance Abuse and Mental Health Services Administration website. As such, no additional informed consent was required for this study.

Availability of Data and Material. The data reported in this manuscript were obtained from publicly available data, the 2017 National Survey on Drug Use and Health (NSDUH): <https://www.datafiles.samhsa.gov/study-dataset/national-survey-drug-use-and-health-2017-nsduh-2017-ds0001-nid17939>.

Code Availability. All code used to conduct data analysis in the present study is available for review in Supplements 1 and 2.

References

- Amone-P'Olak, K., Ormel, J., Oldehinkel, A. J., Reijneveld, S. A., Verhulst, F. C., & Burger, H. (2010). Socioeconomic position predicts specialty mental health service use independent of clinical severity: the TRAILS study. *Journal of the American Academy of Child and Adolescent Psychiatry*, 49(7), 647–655.
- Beevers, C. G., Mullarkey, M. C., Dainer-Best, J., Stewart, R. A., Labrada, J., Allen, J. J. B., McGeary, J. E., & Shumake, J. (2019). Association between negative cognitive bias and depression: A symptom-level approach. *Journal of Abnormal Psychology*, 128(3), 212–227.
- Bos, F. M., Fried, E. I., Hollon, S. D., Bringmann, L. F., Dimidjian, S., DeRubeis, R. J., & Bockting, C. L. H. (2018). Cross-sectional networks of depressive symptoms before and after antidepressant medication treatment. *Social Psychiatry and Psychiatric Epidemiology*, 53(6), 617–627.
- Boyd, R. C., Butler, L., & Benton, T. D. (2018). Understanding Adolescents' Experiences with Depression and Behavioral Health Treatment. In *The Journal of Behavioral Health Services & Research* (Vol. 45, Issue 1, pp. 105–111). <https://doi.org/10.1007/s11414-017-9558-7>
- Breiman, L. (2001). Random Forests. *Machine Learning*, 45(1), 5–32.
- Breland, D. J., McCarty, C. A., Zhou, C., McCauley, E., Rockhill, C., Katon, W., & Richardson, L. P. (2014). Determinants of mental health service use among depressed adolescents. *General Hospital Psychiatry*, 36(3), 296–301.
- Brown, C., Conner, K. O., Copeland, V. C., Grote, N., Beach, S., Battista, D., & Reynolds, C. F. (2010). Depression stigma, race, and treatment seeking behavior and attitudes. In *Journal of Community Psychology* (Vol. 38, Issue 3, pp. 350–368). <https://doi.org/10.1002/jcop.20368>
- Burgess, D. J., Ding, Y., Hargreaves, M., van Ryn, M., & Phelan, S. (2008). The Association

- between Perceived Discrimination and Underutilization of Needed Medical and Mental Health Care in a Multi-Ethnic Community Sample. In *Journal of Health Care for the Poor and Underserved* (Vol. 19, Issue 3, pp. 894–911). <https://doi.org/10.1353/hpu.0.0063>
- Carney, C. E., Edinger, J. D., Kuchibhatla, M., Lachowski, A. M., Bogouslavsky, O., Krystal, A. D., & Shapiro, C. M. (2017). Cognitive Behavioral Insomnia Therapy for Those With Insomnia and Depression: A Randomized Controlled Clinical Trial. In *Sleep* (Vol. 40, Issue 4). <https://doi.org/10.1093/sleep/zsx019>
- Cawley, G. C., & Talbot, N. L. C. (2010). On Over-fitting in Model Selection and Subsequent Selection Bias in Performance Evaluation. *Journal of Machine Learning Research: JMLR*, 11(Jul), 2079–2107.
- Center for Behavioral Health Statistics and Quality. (2018). *2017 National Survey on Drug Use and Health: Methodological summary and definitions*. Rockville, MD: Substance Abuse and Mental Health Services Administration.
- Center for Behavioral Health Statistics. (2017). *2017 National Survey on Drug Use and Health Public Use File Codebook*. Substance Abuse and Mental Health Services Administration Rockville, MD. <http://samhda.s3-us-gov-west-1.amazonaws.com/s3fs-public/field-uploads-protected/studies/NSDUH-2017/NSDUH-2017-datasets/NSDUH-2017-DS0001/NSDUH-2017-DS0001-info/NSDUH-2017-DS0001-info-codebook.pdf>
- Center for Behavioral Health Statistics. (2018). Key substance use and mental health indicators in the United States: Results from the 2017 National Survey on Drug Use and Health (HHS Publication No. SMA 17-5044, NSDUH Series H-52). Rockville, MD: Center for Behavioral Health Statistics and Quality. *Substance Abuse and Mental Health Services Administration. Retrieved from <https://www.samhsa.gov/data>*.

- Corbie-Smith, G., Henderson, G., Blumenthal, C., Dorrance, J., & Estroff, S. (2008). Conceptualizing Race in Research. In *Journal of the National Medical Association* (Vol. 100, Issue 10, pp. 1235–1243). [https://doi.org/10.1016/s0027-9684\(15\)31470-x](https://doi.org/10.1016/s0027-9684(15)31470-x)
- Costello, E. J., & Janiszewski, S. (1990). Who gets treated? Factors associated with referral in children with psychiatric disorders. *Acta Psychiatrica Scandinavica*, 81(6), 523–529.
- Craske, M. G., Meuret, A. E., Ritz, T., Treanor, M., Dour, H., & Rosenfield, D. (2019). Positive affect treatment for depression and anxiety: A randomized clinical trial for a core feature of anhedonia. *Journal of Consulting and Clinical Psychology*, 87(5), 457–471.
- Cummings, J. R., & Druss, B. G. (2011). Racial/ethnic differences in mental health service use among adolescents with major depression. *Journal of the American Academy of Child and Adolescent Psychiatry*, 50(2), 160–170.
- Cummings, J. R., Wen, H., Ko, M., & Druss, B. G. (2014). Race/ethnicity and geographic access to Medicaid substance use disorder treatment facilities in the United States. *JAMA Psychiatry*, 71(2), 190–196.
- Effinger, J. M., & Stewart, D. G. (2012). Classification of Co-occurring Depression and Substance Abuse Symptoms Predicts Suicide Attempts in Adolescents. In *Suicide and Life-Threatening Behavior* (Vol. 42, Issue 4, pp. 353–358). <https://doi.org/10.1111/j.1943-278x.2012.00092.x>
- Elster, A., Jarosik, J., VanGeest, J., & Fleming, M. (2003). Racial and ethnic disparities in health care for adolescents: a systematic review of the literature. *Archives of Pediatrics & Adolescent Medicine*, 157(9), 867–874.
- Facione, N. C., & Facione, P. A. (2007). Perceived Prejudice in Healthcare and Women's Health Protective Behavior. In *Nursing Research* (Vol. 56, Issue 3, pp. 175–184).

<https://doi.org/10.1097/01.nnr.0000270026.90359.4c>

- Farmer, E. M., Stangl, D. K., Burns, B. J., Costello, E. J., & Angold, A. (1999). Use, persistence, and intensity: patterns of care for children's mental health across one year. *Community Mental Health Journal*, 35(1), 31–46.
- Fried, E. I., & Nesse, R. M. (2014). The impact of individual depressive symptoms on impairment of psychosocial functioning. *PloS One*, 9(2), e90311.
- Fried, E. I., & Nesse, R. M. (2015). Depression sum-scores don't add up: why analyzing specific depression symptoms is essential. In *BMC Medicine* (Vol. 13, Issue 1).
- <https://doi.org/10.1186/s12916-015-0325-4>
- Fried, E. I., Nesse, R. M., Zivin, K., Guille, C., & Sen, S. (2014). Depression is more than the sum score of its parts: individual DSM symptoms have different risk factors. *Psychological Medicine*, 44(10), 2067–2076.
- Friedman J, Hastie T, Tibshirani R (2010). "Regularization Paths for Generalized Linear Models via Coordinate Descent." *Journal of Statistical Software*, 33(1), 1–22.
- Garland, A. F., Hough, R. L., Landsverk, J. A., & Brown, S. A. (2001). Multi-Sector Complexity of Systems of Care for Youth With Mental Health Needs. In *Children's Services* (Vol. 4, Issue 3, pp. 123–140). https://doi.org/10.1207/s15326918cs0403_2
- Genuer, R., Poggi, J.-M., & Tuleau-Malot, C. (2010). Variable selection using random forests. *Pattern Recognition Letters*, 31(14), 2225–2236.
- Goodhue, D. L., University of Georgia, Lewis, W., Thompson, R., & Wake Forest University. (2017). A Multicollinearity and Measurement Error Statistical Blind Spot: Correcting for Excessive False Positives in Regression and PLS. In *MIS Quarterly* (Vol. 41, Issue 3, pp. 667–684). <https://doi.org/10.25300/misq/2017/41.3.01>

- Grömping, U. (2009). Variable Importance Assessment in Regression: Linear Regression versus Random Forest. In *The American Statistician* (Vol. 63, Issue 4, pp. 308–319).
<https://doi.org/10.1198/tast.2009.08199>
- Hämäläinen, J., Isometsä, E., Laukkala, T., Kaprio, J., Poikolainen, K., Heikkinen, M., Lindeman, S., & Aro, H. (2004). Use of health services for major depressive episode in Finland. In *Journal of Affective Disorders* (Vol. 79, Issues 1-3, pp. 105–112).
[https://doi.org/10.1016/s0165-0327\(02\)00342-7](https://doi.org/10.1016/s0165-0327(02)00342-7)
- Hammen, C., Brennan, P. A., & Keenan-Miller, D. (2008). Patterns of adolescent depression to age 20: the role of maternal depression and youth interpersonal dysfunction. *Journal of Abnormal Child Psychology*, 36(8), 1189–1198.
- Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The Elements of Statistical Learning: Data Mining, Inference, and Prediction, Second Edition*. Springer Science & Business Media.
- Hastie, T., Tibshirani, R., Friedman, J., & Franklin, J. (2005). The elements of statistical learning: data mining, inference and prediction. *The Mathematical Intelligencer*, 27(2), 83–85.
- Jacobucci, R., Littlefield, A. K., Millner, A. J., Kleiman, E. M., & Steinley, D. (n.d.). *Pairing Machine Learning and Clinical Psychology: How You Evaluate Predictive Performance Matters*. <https://doi.org/10.31234/osf.io/2yber>
- James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). *An Introduction to Statistical Learning: with Applications in R*. Springer, New York, NY.
- Kalnins, A. (2018). Multicollinearity: How common factors cause Type 1 errors in multivariate regression. In *Strategic Management Journal* (Vol. 39, Issue 8, pp. 2362–2385).
<https://doi.org/10.1002/smj.2783>

- Kenchington, E., Beazley, L., Lirette, C., Murillo, F. J., Guijarro, J., Wareham, V., Gilkinson, K., Koen-Alonso, M., Benoît, H., Bourdages, H., & Others. (2016). *Delineation of coral and sponge significant benthic areas in Eastern Canada using Kernel Density Analyses and Species Distribution Models*. Canadian Science Advisory Secretariat.
- Kröner-Herwig, B., Morris, L., Heinrich, M., Gassmann, J., & Vath, N. (2009). Agreement of Parents and Children on Characteristics of Pediatric Headache, Other Pains, Somatic Symptoms, and Depressive Symptoms in an Epidemiologic Study. In *The Clinical Journal of Pain* (Vol. 25, Issue 1, pp. 58–64). <https://doi.org/10.1097/ajp.0b013e31817fc62d>
- Langer, D. A., Wood, J. J., Wood, P. A., Garland, A. F., Landsverk, J., & Hough, R. L. (2015). Mental Health Service Use in Schools and Non-School-Based Outpatient Settings: Comparing Predictors of Service Use. *School Mental Health*, 7(3), 161–173.
- Liaw, A., & Wiener, M. (2002). Classification and Regression by randomForest. *R News* 2(3), 18–22.
- Montagni, I., Tzourio, C., Cousin, T., Sagara, J. A., Bada-Alonzi, J., & Horgan, A. (2019). Mental Health-Related Digital Use by University Students: A Systematic Review. In *Telemedicine and e-Health*. <https://doi.org/10.1089/tmj.2018.0316>
- Möttus, R., Kandler, C., Bleidorn, W., Riemann, R., & McCrae, R. R. (2017). Personality traits below facets: The consensual validity, longitudinal stability, heritability, and utility of personality nuances. *Journal of Personality and Social Psychology*, 112(3), 474–490.
- Munafò, M. R., & Davey Smith, G. (2018). Robust research needs many lines of evidence. *Nature*, 553(7689), 399–401.
- Neighbors, H. W., Caldwell, C., Williams, D. R., Nesse, R., Taylor, R. J., Bullard, K. M., Torres, M., & Jackson, J. S. (2007). Race, Ethnicity, and the Use of Services for Mental Disorders.

- In *Archives of General Psychiatry* (Vol. 64, Issue 4, p. 485).
<https://doi.org/10.1001/archpsyc.64.4.485>
- Ng, A. Y. (1997). Preventing“ overfitting” of cross-validation data. *ICML*, 97, 245–253.
- Ng, M. Y., & Weisz, J. R. (2016). Annual Research Review: Building a science of personalized intervention for youth mental health. *Journal of Child Psychology and Psychiatry, and Allied Disciplines*, 57(3), 216–236.
- Orchard, F., Pass, L., Marshall, T., & Reynolds, S. (2017). Clinical characteristics of adolescents referred for treatment of depressive disorders. In *Child and Adolescent Mental Health* (Vol. 22, Issue 2, pp. 61–68). <https://doi.org/10.1111/camh.12178>
- R Core Team. (2019). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing. <https://www.R-project.org/>
- Schleider, J. L., Mullarkey, M. C., & Chacko, A. (2019). Harnessing Wise Interventions to Advance the Potency and Reach of Youth Mental Health Services. *Clinical Child and Family Psychology Review*. <https://doi.org/10.31234/osf.io/jhuvr>
- Schleider, J. L., & Weisz, J. R. (2017). Little Treatments, Promising Effects? Meta-Analysis of Single-Session Interventions for Youth Psychiatric Problems. *Journal of the American Academy of Child and Adolescent Psychiatry*, 56(2), 107–115.
- Seeboth, A., & Möttus, R. (2018). Successful Explanations Start with Accurate Descriptions: Questionnaire Items as Personality Markers for More Accurate Predictions. In *European Journal of Personality* (Vol. 32, Issue 3, pp. 186–201). <https://doi.org/10.1002/per.2147>
- Shmueli, G. (2010). To Explain or to Predict? *Statistical Science*, 25(3), 289-310.
[doi:10.1214/10-sts330](https://doi.org/10.1214/10-sts330)
- Slade, E. P. (2002). *Mental Health Services Research* (Vol. 4, Issue 3, pp. 151–166).

<https://doi.org/10.1023/a:1019711113312>

- Substance Abuse and Mental Health Services Administration. (2018). *Reliability of Key Measures in the National Survey on Drug Use and Health*. Substance Abuse and Mental Health Services Administration (US).
- Varma, S., & Simon, R. (2006). Bias in error estimation when using cross-validation for model selection. *BMC Bioinformatics*, 7, 91.
- Weersing, V. R., Jeffreys, M., Do, M.-C. T., Schwartz, K. T. G., & Bolano, C. (2017). Evidence Base Update of Psychosocial Treatments for Child and Adolescent Depression. *Journal of Clinical Child and Adolescent Psychology: The Official Journal for the Society of Clinical Child and Adolescent Psychology, American Psychological Association, Division 53*, 46(1), 11–43.
- Weisz, J. R., Kuppens, S., Ng, M. Y., Eckshtain, D., Ugueto, A. M., Vaughn-Coaxum, R., Jensen-Doss, A., Hawley, K. M., Krumholz Marchette, L. S., Chu, B. C., Weersing, V. R., & Fordwood, S. R. (2017). What five decades of research tells us about the effects of youth psychological therapy: A multilevel meta-analysis and implications for science and practice. *The American Psychologist*, 72(2), 79–117.
- Weisz, J. R., Kuppens, S., Ng, M. Y., Vaughn-Coaxum, R. A., Ugueto, A. M., Eckshtain, D., & Corteselli, K. A. (2019). Are Psychotherapies for Young People Growing Stronger? Tracking Trends Over Time for Youth Anxiety, Depression, Attention-Deficit/Hyperactivity Disorder, and Conduct Problems. *Perspectives on Psychological Science: A Journal of the Association for Psychological Science*, 14(2), 216–237.
- Wilson, S., Hicks, B. M., Foster, K. T., McGue, M., & Iacono, W. G. (2015). Age of onset and course of major depressive disorder: associations with psychosocial functioning outcomes

- in adulthood. *Psychological Medicine*, 45(3), 505–514.
- Wu, P., Hoven, C. W., Bird, H. R., Moore, R. E., Cohen, P., Alegria, M., Dulcan, M. K., Goodman, S. H., Horwitz, S. M., Lichtman, J. H., Narrow, W. E., Rae, D. S., Regier, D. A., & Roper, M. T. (1999). Depressive and Disruptive Disorders and Mental Health Service Utilization in Children and Adolescents. In *Journal of the American Academy of Child & Adolescent Psychiatry* (Vol. 38, Issue 9, pp. 1081–1090). <https://doi.org/10.1097/00004583-199909000-00010>
- Yarkoni, T., & Westfall, J. (2017). Choosing Prediction Over Explanation in Psychology: Lessons From Machine Learning. *Perspectives on Psychological Science: A Journal of the Association for Psychological Science*, 12(6), 1100–1122.
- Yogatama, D., & Mann, G. (2014). Efficient Transfer Learning Method for Automatic Hyperparameter Tuning. *Artificial Intelligence and Statistics*, 1077–1085.
- Young, A. S., Klap, R., Sherbourne, C. D., & Wells, K. B. (2001). The Quality of Care for Depressive and Anxiety Disorders in the United States. In *Archives of General Psychiatry* (Vol. 58, Issue 1, p. 55). <https://doi.org/10.1001/archpsyc.58.1.55>
- Zahner, G. E., & Daskalakis, C. (1997). Factors associated with mental health, general health, and school-based service use for child psychopathology. *American Journal of Public Health*, 87(9), 1440–1448.
- Zimmerman, F. J. (2005). Social and economic determinants of disparities in professional help-seeking for child mental health problems: evidence from a national sample. *Health Services Research*, 40(5 Pt 1), 1514–1533.
- Zou, H., & Hastie, T. (2005). Regularization and variable selection via the elastic net. *Journal of the Royal Statistical Society. Series B, Statistical Methodology*, 67(2), 301–320.