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Predicting barriers to treatment for depression in a US national sample: a cross-sectional, proof-of-concept study.

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Abstract

Objective. Despite the availability of safe and effective treatments for depression, many people who are diagnosed with depression do not return for treatment after the diagnosis is made. It could be helpful to identify patients who may not initiate treatment, and avert potential barriers to that individual initiating treatment.

Method. Data were aggregated from the U.S. National Survey on Drug Use and Health series between 2008-2014 (N=391,753), including 20,829 adults diagnosed with depression by a health care provider in the 12 months prior to the survey. Machine learning was applied to self-report survey items to develop strategies for identifying individuals that might not get the treatment that they need.

Results. Using a derivation cohort aggregated between 2008-2013, a model was developed to identify the 30.6% of depressed individuals that reported needing but not getting treatment. When applied to independent responses from the 2014 cohort, the model identified 72% of patients that did not engage in treatment ($p < 0.01$), with a balanced accuracy that was also significantly above chance (71%, $p < 0.01$). For individuals who did not get treatment, it was possible to predict ten of the different reasons that they endorsed as barriers to treatment, with balanced accuracies between 53% and 65% (all p 's < 0.05).

Conclusions. Considerable work needs to be done to improve follow up and retention rates after the critical initial meeting in which a patient is diagnosed with depression. Routinely-collected information about depressed patients could identify patients at risk for not obtaining needed treatment, which may inform the development and implementation of interventions to reduce the prevalence of untreated depression.

Introduction

The U.S. Substance Abuse and Mental Health Services Administration (SAMHSA) estimated that in 2014 less than half of the 43.6 million adults with a mental illness received mental health services (1). National guidelines recommend universal depression screening along with adequate systems for accurate diagnosis, treatment, and follow-up (2). However, many adults diagnosed with depression do not receive treatment for their symptoms (3–5), despite the availability of safe and effective psychological (6) and pharmacological (7) treatments. The financial cost of non-engagement is high (8,9), and the use of antidepressants amongst patients with mental illness is associated with reduced mortality and rate of completed suicide (10). Taken together, recent data from the World Health Organization (WHO) suggest that only 16.5% of all individuals with major depressive disorder each year receive minimally adequate treatment (11).

Thornicroft et al (2017) described the broad flow of depressed patients through the acute care pathway. After a diagnosis: only 56.7% of patients report needing treatment; 71.1% of these made at least one visit (i.e. initiated treatment); and 41.0% of those who receive treatment received treatment that meets at least minimal standards (11). Previous ethnographic and experimental research into the second step has revealed a number of barriers that patients face when initiating treatment (9,12–17). Practical barriers include perceived or real inability to pay for treatment (or lacking insurance coverage), lacking childcare, and lacking transport or not knowing where to go for treatment (9,16–18). Psychological barriers include stigmatization of depression, doubts that treatment is effective, or concerns that others may find out (14,16,17,19–21), and may be particularly prevalent amongst women and people of colour (5,16,17,19,20). Culture-specific nuances, such as the somatization of depressive symptoms in women of colour (17,22), can also complicate the detection and management of obstacles and have led groups to emphasize the need for tailoring interventions to specific patient strata (16,17,20,21,23,24). Of course, some of the lack of treatment uptake could be due to clinical inertia or a lack of provider recognition of depression (2,25).

What could be done to continue to develop this line of research? Other areas of medicine have highlighted the importance of “real-time” pre-emptive efforts to avoid unwanted outcomes, such as engaging high readmission risk patients with care plans before they are discharged(26).

Behavioral economic research has illustrated the utility of “nudges” — aspects of choice architectures that alter behavior in a desired way without restricting any options or altering economic incentives. Given previous findings that patients fall into statistically reliable groups based on their reasons for not initiating treatment (15), and that certain groups of patients may benefit from tailored interventions to improve the uptake of treatment (16,17), one application of this concept could be to pre-empt who is at risk of not initiating treatment (and why they might not). This would require analytic strategies that can identify barriers at an individual patient level rather than a group level. In situations like this, an analytic approach known as machine learning has proven useful for extracting complex or non-linear patterns from a wide range of characteristics that statistically relate to an outcome of interest(27,28).

With this in mind, this study set out to develop a case finding strategy for individual patients that might not initiate treatment amongst those who acknowledge needing treatment. Since to our knowledge, no study has ever attempted to pre-empt an individual’s reason for not initiating treatment, this study set out to develop a proof of concept that might form the basis for future experimental research and identify variables of potential utility. First, we apply machine learning to a large volume of retrospective patient-related information to develop a case identification algorithm that could be applied in the waiting room before the patient sees the physician. Second, amongst patients who endorsed needing treatment but not getting it, we explore multivariate associations between self-reportable variables and specific reasons that they endorsed for not getting treatment. Thirdly, to make machine learning results more interpretable for clinicians and less of a “black box”, we develop an open-source software library for calculating and illustrating exactly how each individual participant’s characteristics contributed to each prediction by the algorithm. Real-time methods for identifying patients at risk for not commencing treatment may help focus available resources for systems to intervene and improve the uptake of treatment, before the patient has made the decision not to engage in behavioral health care.

Methods

We used data from the National Surveys on Drug Use and Health (NSDUH), which are conducted by the U.S. Substance Abuse and Mental Health Services Administration (SAMHSA) every year. These surveys provide nationally representative data relating to substance abuse and mental illness among the civilian, noninstitutionalized population aged 12 years or older in the United States. In brief, participants completed the survey using a computer provided by the interviewer, largely without any assistance in their own home, and were compensated \$30 for approximately one hour of their time. The survey used a state-based design, with an independent, multistage area probability sample within each state and the District of Columbia. There was no planned overlap of sample dwelling units or residents. Weighted response rates for the survey ranged between 71.20% (2014) and 75.68% (2009). Institutional review board approval and informed consent were not needed because this was a secondary analysis of public use data.

Sample selection and outcome definition

We combined individual participant data from 2008-2014 public use files (N=391,753). We excluded individuals less than 18 years old (N=121,526) and retained adults who self-reported a doctor had told them that they had depression in the past year (N=20,829).

The primary outcome of interest was a participant's self-reported (binary) response to the question: "During the past 12 months, was there any time when you needed mental health treatment or counseling for yourself but didn't get it?". We excluded 44 participants who did not respond to this. Of these 20,785 participants, 6,271 indicated that they did not get the treatment or counseling that they needed. These participants were then asked, "Which of these statements explains why you did not get the mental health treatment or counseling you needed?" with 14 specific options and one option for "other" reasons (see supplementary CONSORT diagram). Participants were allowed to choose more than one option, and 46.2% of individuals did so. We excluded 61 participants (0.98%) who did not give any reason at all.

Predictor selection

We pre-selected a small number of participant-level characteristics that were surveyed consistently from 2008-2014, have been identified as relevant to depression in prior epidemiological studies (25), and could be self-reported via web-based assessment. These included sociodemographics, information about current behavioral health and suicidal thoughts, and a brief medical history (appendix). We used categorical single imputation whenever participants were missing a value for a predictor variable (< 1% for most variables), and conducted sensitivity analyses to ensure that including these participants did not unduly influence the results (appendix).

Statistical Modeling

Machine Learning. Machine learning methods identify patterns of information in data that are useful in predicting outcomes at the single-participant level (27,29,30). We used a tree-based machine learning algorithm (extreme gradient boosting, or XGBoost) that is fast, accurate, and has free open-source implementations (<https://github.com/dmlc/xgboost>). This algorithm works by fitting an ensemble of small decision trees, and iteratively focusing each new tree on predicting misclassified observations from previous trees (31,32). The algorithm also includes a number of explicit procedures to avoid “overfitting”, i.e. when the algorithm attempts to fit the noise instead of the underlying systematic relationship (see appendix for details). Algorithm hyperparameters were selected by cross-validation (appendix). Statistical significance was examined using label permutation testing (appendix). Particular care was taken to address issues of imbalanced class proportions when predicting the response variables, including a bootstrapped upsampling process and adjusted probability thresholds (appendix). Additionally, given these class imbalances, we focused on a metric known as balanced accuracy $[(\text{sensitivity} + \text{specificity})/2]$ whose null distribution is centered on 50%, unlike traditional accuracy (33,34) (appendix).

Individual participant variable importance. Machine learning have been characterized as a “black box” approach with limited interpretability since the rationale behind individual predictions is obscured by the complexity of the model. Researchers typically examine variable importance across the whole sample to determine the how much each predictor variable contributes to the overall model. Although this gives some insight into which variables are the

most influential across all predictions, there is no guarantee that they are also the most influential for a specific prediction for a particular individual. With this in mind, we have developed and introduced an open-source software library for deriving individual participant-level variable importance measures from xgboost ensembles (appendix, and <https://github.com/AppliedDataSciencePartners/xgboostExplainer>). Briefly, the library breaks down the (directional) impact of each predictor variable for a single participant, and illustrates these impacts so that a clinician can see exactly how the model weighted each variable when making the prediction for that individual (appendix). Critically, this means that these “impacts” are not static coefficients as in a logistic regression—the impact of a feature is dependent on the specific path that the observation took through the ensemble of trees (appendix).

Training and Testing. We developed the case finding model using data from 2008-2013. Models were constructed and examined with repeated five-fold cross-validation (3 repeats), which partitioned the 2008-2013 data into five distinct subsets, used four of those subsets in the training process, and then made predictions on the remaining subset. Relevant descriptions of model discrimination were determined at each stage, including positive predictive values (i.e. the probability that a participant did not get treatment, given that the model predicted that they would not) and the Area under the Receiver Operating Curve (AUC). To avoid opportune data splits, model performance metrics were averaged across the test folds and repeats.

Independent Validation. Models that show significant performance in test-folds during cross-validation may still not generalize to an independent sample (29,30,35). Therefore we applied our case finding models to the 2014 cohort that was not used in model development. Participant characteristics were similarly distributed across training and testing data sets, although noticeably smoking was less common and anxiety disorders were more common in 2014.

Analyses were conducted using the R statistical language (Version 3.2.2; <http://cran.r-project.org/>), and code is available upon request from the corresponding author.

Results

Getting treatment amongst those with a perceived need for treatment.

We focused on adults who stated that they were diagnosed with depression by a clinician in the last year ($n = 20,785$). The gender and racial breakdown of the cohort was as follows: 72% female, 28% male; 77% white, 10% Hispanic, 7% black, 4% multi-racial, 1% Asian, 1% Native American, 1% Native Hawaiian/Pacific Islander. The cohort was mostly 18-49 years old: 42% 18-25, 16% 26-34, 26% 35-49: 13% 50-64, 4% 65+. At the time of responding, 54.7% of the sample endorsed 5 of the 9 DSM criteria for a current major depressive episode. In terms of insurance coverage, 54% report having private health insurance, 22% had Medicaid/CHIP, and 11% had Medicare (13% unknown). Of these participants, 30.2% endorsed needing treatment but not receiving it. This is consistent with recent global estimates that used formal criteria for 12-month major depression(11). Breakdowns by age, sex, and gender are included in the supplementary materials.

We developed a case finding model to identify depressed patients who failed to receive mental health treatment amongst those with a perceived need for treatment. In the training cohort (2008-2013), 30.6% of patients needed but did not get treatment. During cross-validation, the model performed significantly above chance in predicting that a participant would not receive treatment that they need: balanced accuracy = $71 \pm 0.9\%$, $p < 0.001$, AUC = 0.79 (95% CI=0.78-0.80), with a PPV of $50 \pm 1.1\%$ and a sensitivity of $73 \pm 1.6\%$ (Table 1). To understand which variables are most influential at a group level, we include a variable importance plot (Figure 1A) illustrating the average improvement in accuracy (i.e. Gain) brought by a particular variable when it is used. As an example of how these predictions can be interpreted on an individual participant basis, we also derived and illustrated the change in log-odds attributable to each variable for an individual. Figure 1B shows an Explainer plot for an individual that was predicted not to get treatment they need, and Figure 1C shows one for an individual with a high predicted probability that they will engage.

[Figure 1]

The case finding model successfully identified individuals who needed but did not get treatment in the independent 2014 cohort, where 28.2% of patients did not get treatment (Table 1). Model performance was again significantly above chance (balanced accuracy 71%, permutation-based $p < 0.01$; AUC = 0.78 95% CI=0.76-0.79), with a PPV of 48% (95% CI=46-49) and a sensitivity of 72% (95% CI=71-74). Therefore, in an independent sample, this model identified over 70% of those who did not engage in treatment, and when the model predicts that a patient will engage in treatment, there is an 86% chance that they will (NPV of 86.3%). Conclusions remained the same and performance metrics were comparable in analyses where participants were excluded for missing data, rather than imputing missing data, and in analyses with more restrictive inclusion criteria (appendix). Models that include sociodemographic information alone had much worse performance (Supplementary Analysis 1, appendix).

Reasons for not getting needed treatment

Most individuals (2008-2014) endorsed one (53.8%), two (18.2%) or three (12.3%) reasons for not getting treatment (median = 1, mean = 2.10). The most common reason was being unable to afford the cost (47.7% endorsed), and the least common reason was lack of transport or treatment too far (5.8% endorsed, see Table 2). Breakdowns of endorsement by age, sex, and gender are included in the supplementary materials. For each possible reason, we trained a classifier to predict whether patients who did not get treatment would (or would not) endorse that particular reason for not getting treatment. Ten of the fifteen self-reported reasons were predictable with a balanced accuracy (range: 53% to 65%), and sensitivity (range: 14% to 63%) all above chance (all p 's < 0.05 , Table 2, Supplementary Table 7). For the models with the three highest balanced accuracies, we examined variable importance plots to understand which variables were most influential at a group (Figure 2). For “thinking you might be committed or forced to take medications” the model relied on suicide-related features. For “not being able to afford the cost” the model relied on information about health insurance and household income (Native American or black/African American). Detailed performance metrics and group-level variable importance plots for all models are reported in the appendix.

[Figure 2]

Discussion

These data indicate that in the USA between 2008 and 2014 approximately 30% of individuals with 12-month MDD self-identify as needing mental health treatment but not getting it. We set out to use a small number of patient-reportable items to develop a case finding algorithm that might identify these individuals who fail to initiate treatment after receiving a diagnosis and acknowledging a need for treatment. The balanced accuracy, sensitivity, and positive predictive value of this model was significantly better than chance even in a large external validation cohort. Amongst patients who endorsed needing but not getting treatment, we explored the percentage of patients who selected each of 15 possible reasons for not getting treatment. We were able to predict above chance whether patients would endorse a specific reason for 10 of the 15 available reasons. This combination of large data sets and machine learning tools provides an empirical platform for future experimental research and highlights the potential for improving overall treatment outcomes by minimizing the number of people who fail to initiate treatment after endorsing a need for it.

U.S. PSTF guidelines (2016) noted that, “research is needed to assess barriers to establishing adequate systems of care and how these barriers can be addressed”(2). Corroborating recent WHO findings (11), these data suggest that around 30% of patients who are diagnosed with depression and acknowledge a need for treatment do not get mental health treatment. This study makes an important step toward a broader discussion of the reasons why people do not get treatment, and what can be done to improve it (9,18,36,37). In the U.S., cost or cost-related reasons are perceived as a barrier to mental health treatment for over half of patients with depression, despite the availability of generic antidepressants costing >\$10 per month (free under Medicare Part D and Medicaid/CHIP). Two other primary reasons for not getting treatment were not knowing where to go for the service (16.7%), and fear of being committed or forced to take medications (15.2%). Many of the identified reasons for not receiving care may of course reflect

symptoms of the depression itself. Pessimistic statements like thinking that treatment will not help, for example, may reflect negative thoughts associated with depression.

As such, it is clear that uptake of treatment is (and remains) a substantial barrier for efforts towards universal screening reaching their full potential for improving population mental health. The utility of treatments for depression depends on the first step of getting patients to engage in treatment. We developed a case finding tool that might help to identify individuals who do not engage in treatment. The most influential variable in the model pertained to suicidal ideation, which is consistent with previous associations between suicidal ideation and deterrents to mental health treatment(38). Other variables included those relating to insurance status, demographics, and medical comorbidities that have been reported in previous studies, but are not currently used for predictive purposes (9,18,38–44). An ultimate goal for this approach would be to anticipate which individuals will not initiate treatment (for more concerted outreach), and try to estimate how likely they are to accept various treatment options. The levels of risk can then be relayed to the clinician or case manager to help foster shared decision making and minimize barriers to initiating treatment from the very outset.

The natural next step for this line of research is to explore prospectively whether statistical models like this could help to develop and tailor engagement interventions, such as motivational interviewing, psychoeducation, or care management (16,45–47). For example, if an individual is predicted to be concerned about cost, is it effective to subsidize their care or highlight cheaper options? Although the NSDUH survey was not designed explicitly for this, it offered an opportunity to develop hypotheses and tools for future study to determine if the approach can improve treatment uptake. Since low motivation, hypersomnia, and low energy are cardinal symptoms of depression, aggressive outreach may be required to encourage some individuals to begin and remain in care (45,48), and so better targeting of the patients in need of this encouragement may help this outreach remain cost effective.

Limitations

The study relied on self-reported survey data rather than data from clinical practice, which must be considered when interpreting the present findings. Although we focused on adults diagnosed with depression in the last 12 months, from this survey it cannot be guaranteed that a patient was specifically responding about their experiences of depression (vs. another mental health issue, since the survey did not examine comorbid mental disorders), and patients may also have had multiple mental health episodes within that time period. Our exclusion based on individuals being told by a clinician that they have depression may also bias the sample toward those with more easily recognizable depressive symptoms or those with better access to providers. In addition, it is known that at least some patients with major depression experience sudden therapeutic gains and may have recovered without treatment(14,49), although long-term outcomes are generally not favorable for untreated patients(18).

While our anticipation of specific concerns for not getting treatment was statistically robust it may best be considered as a helpful warning sign rather than requiring urgent action. It is an advantage of these models to require only a brief and readily available data source, but they may be improved by the inclusion of more training data, or by integrating other sources of predictor variables (e.g., electronic medical records, feedback from caregivers/family members), and this would help improve the sensitivity of the model. The performance nonetheless compares favorably to other predictive models in psychiatry that included large validation samples(30,35,50). Unfortunately, in these survey data there was no option for a patient to indicate a lack of treatment availability (or unacceptable wait time), and so our analyses focused on patient-perceived barriers rather than structural system-level barriers. In addition, causal associations cannot be drawn from this retrospective, cross-sectional analysis, especially since NSDUH does not sequence the symptoms, perceived need, and decision not to receive mental health treatment. Finally, it is not clear to what extent the context of health and mental healthcare in the US influenced both the predictor variables (e.g., public insurance), the reasons (e.g., cost), and the outcomes, and so it will be important to examine similar data in countries with universal healthcare or other healthcare models.

Conclusion

It is clear that more work needs to be done to improve follow up and retention rates after the critical initial meeting in which a patient is diagnosed with depression. We developed a brief model based on self-report data that makes individual level predictions about who will get treatment amongst patients who endorse needing treatment. If validated in clinical care settings, predictive tools could be used to focus health system resources on patients that are at high risk of not engaging in treatment, and ultimately inform efforts toward universal treatment and follow-up for depression.

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Authors' contributions

A.M. Chekroud had access to all data in the study and takes overall responsibility for the integrity of the data and the accuracy of the data analysis.

Study concept and design: Chekroud

Acquisition, analysis, or interpretation of data: All authors

Drafting of the manuscript: Chekroud, Krystal, Zheutlin

Critical revision of the manuscript for important intellectual content: All authors

Statistical Analysis: Chekroud, Foster, Zheutlin, Gueorguieva

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Study supervision: Krystal, Paulus

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Figure Captions

Figure 1. Factors influencing whether an individual will fail to engage in needed mental health treatment. Group-level variable importance plot (A) illustrates the amount that the model accuracy improves when each variable is included (on average). Explainer plots (B, C) decompose the model prediction as a function of each characteristic for an individual participant. The x-axis reflects predicted probability of the response, such that values to the right indicate a patient is predicted not to initiate treatment (e.g. B), and values to the left reflect high likelihood of initiating treatment (e.g. C). Green bars indicate that a characteristic contributed toward initiation, while red bars indicate that a characteristic contributed toward non-initiation. Black bars reflect the overall model prediction. Values inside the bars indicate the change in log-odds attributable to that characteristic.

Figure 2. Predicting the self-reported reasons why an individual patient would not get needed treatment for mental health. We inspected group-level variable importance for the three most predictable self-reported barriers to obtaining mental health treatment amongst individuals diagnosed with depression in the past year. Variable importance (x-axis) reflects the average

improvement in predictive accuracy when a variable is included in the model (i.e. Gain improvement). BAC = Balanced Accuracy. Sens = Sensitivity. Spec = Specificity.

Tables

Balanced Acc. = Balanced Accuracy, PPV = Positive Predictive Value, NPV = Negative Predictive Value, AUC = Area under the Receiver Operating Curve. Chance performance reflects Mean (SD) of that metric during permutation testing. ‘Positive’ outcome refers to non-engagement, since this is the outcome of interest. During training (2008-2013), test-fold AUC was 0.792 95% CI= 0.78-0.80. During validation (2014), the AUC was 0.777 95% CI= 0.76-0.79

Table 1. Performance in predicting the failure to engage in needed mental health treatment.				
Metric	Training Cohort (2008-2013)		Validation Cohort (2014)	
	Test-fold Performance	Chance Performance	Observed Performance	Chance Performance
Accuracy	69.5±1.0%	51.1±1.1%	69.7%	51.4±4.6%
Balanced Acc.	70.6±0.9%	50.3±0.4%	70.5%	50.5±4.8%
PPV	50.1±1.1%	30.9±0.4%	47.5%	28.7±4.1%
NPV	85.3±0.7%	69.7±0.4%	86.4%	72.1±3.8%
Sensitivity	73.4±1.6%	48.4±2.8%	72.4%	48.5±7.2%
Specificity	67.8±1.4%	52.3±2.7%	68.6%	52.5±5.2%

Table 2. Self-reported reasons for not engaging in needed treatment for mental illness.

Reason	Endorsement Rates			External Validation Performance			
	2008-2014	2008-2013	2014	BAC	Sens	PPV	PLR
Couldn't afford cost	47.7%	47.9%	46.4%	64.2*	62.9*	61.2	1.81
Thought they could handle without treatment	22.2%	22.2%	22.4%	55.8*	31.0*	31.5	1.59
Didn't know where to go for service	16.7%	16.0%	20.6%	52.9*	20.6*	26.6	1.40
Some other reason	15.3%	15.0%	16.8%	51.8	17.9	20.1	1.25
Thought might be committed or forced to take meds	15.2%	15.3%	14.8%	64.9*	40.6*	39.5	3.75
Didn't have time/too busy	14.2%	14.3%	13.8%	56.2*	24.8*	24.1	1.99
Not enough health insurance coverage	11.7%	11.5%	13.1%	55.3*	20.6*	23.6	2.06
Concerned about opinion of neighbors	11.0%	10.9%	11.8%	56.3*	21.9*	24.0	2.36
Didn't think treatment would help	10.9%	10.9%	11.0%	53.0*	16.1*	16.3	1.58
Concern about confidentiality	9.7%	9.7%	9.8%	54.1*	16.8*	17.4	1.93
Don't think they needed it at that time	8.6%	8.6%	8.6%	53.3*	14.5*	14.6	1.82
Concern about effect on job	8.1%	8.0%	8.4%	51.8	11.1	11.8	1.47
Health insurance didn't cover it	6.5%	6.6%	6.1%	48.6	3.4	3.4	0.55
Didn't want others to find out	6.5%	6.4%	6.8%	52.3	10.6	11.5	1.77
Had no transportation or treatment too far	5.8%	5.6%	7.2%	52.5	10.1	13.2	1.98

BAC = Balanced Accuracy (%), Sens = Sensitivity (%), PPV = Positive Predictive Value (%), PLR = Positive Likelihood Ratio. Asterisks indicate where BAC and Sens external validation metrics were significantly greater than chance during permutation testing (* $p < .05$), with full permutation-based performance metrics reported in the appendix.