Journal Pre-proof

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PII: S0022-3956(22)00192-3

DOI: <https://doi.org/10.1016/j.jpsychires.2022.03.063>

Reference: PIAT 5053

To appear in: *Journal of Psychiatric Research*

Received Date: 15 July 2021

Revised Date: 8 December 2021

Accepted Date: 31 March 2022

Please cite this article as: Jiménez S, Angeles-Valdez D, Rodríguez-Delgado André., Fresán A, Miranda E, Alcalá-Lozano R, Duque-Alarcón Xó., Arango de Montis Ivá., Garza-Villarreal EA, Machine learning detects predictors of symptom severity and impulsivity after dialectical behavior therapy skills training group in borderline personality disorder, *Journal of Psychiatric Research* (2022), doi: <https://doi.org/10.1016/j.jpsychires.2022.03.063>.

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Machine learning detects predictors of symptom severity and impulsivity after Dialectical Behavior Therapy skills training group in Borderline Personality Disorder

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Abstract

Only 50% of the patients with Borderline Personality Disorder (BPD) respond to psychotherapies, such as Dialectical Behavioral Therapy (DBT), this might be increased by identifying baseline predictors of clinical change. We use machine learning to detect clinical features that could predict improvement/worsening for severity and impulsivity of BPD after DBT skills training group. To predict illness severity, we analyzed data from 125 patients with BPD divided into 17 DBT psychotherapy groups, and for impulsiveness we analyzed 89 patients distributed into 12 DBT groups. All patients were evaluated at baseline using widely self-report tests; ~70% of the sample were randomly selected and two machine learning models (*lasso* and *Random forest* [*Rf*]) were trained using 10-fold cross-validation and compared to predict the post-treatment response. Models' generalization was assessed in ~30% of the remaining sample. Relevant variables for DBT (i.e. the mindfulness ability "non-judging", or "non-planning" impulsiveness) measured at baseline, were robust predictors of clinical change after six months of weekly DBT sessions. Using 10-fold cross-validation, the *Rf* model had significantly lower prediction error than *lasso* for the BPD severity variable, Mean Absolute Error (MAE) *lasso* - *Rf* = 1.55 (95% CI, 0.63-2.48) as well as for impulsivity, MAE *lasso* - *Rf* = 1.97 (95% CI, 0.57 - 3.35). According to *Rf* and the permutations method, 34/613 significant predictors for severity and 17/613 for impulsivity were identified. Using machine learning to identify the most important variables before starting DBT could be fundamental for personalized treatment and disease prognosis.

Keywords

machine learning, random forest, lasso, impulsivity, borderline personality disorder, dialectical behavioral therapy

Highlights

- Two machine learning models (Random forest [*Rf*] and *lasso*) allowed us to mine a complex data matrix and identify the most important baseline clinical variables that predicted outcome in Dialectical Behavioral Therapy, among the many sources of measures frequently available to a practitioner.
- The predictive precision of the *Rf* learner was significantly better than *lasso* during cross-validation training. Both models had an acceptable performance in a sample *a priori* selected for validation.
- The *Rf* learner identified relevant clinical predictors for DBT, such as "non-judging" ability, related to mindfulness practice, or "non-planning" impulsivity.

Introduction

Psychotherapy is considered the main treatment for Borderline Personality Disorder (BPD) (Stoffers et al., 2010; Storebø et al., 2020) and although multiple psychological therapies have been proposed, one of the most studied interventions is Dialectical Behavioral Therapy (DBT), which has shown positive outcomes compared to control interventions in meta-analyses (Cristea et al., 2017). However, only 50% of the patients respond to therapy, and the features or variables that predict the clinical response are still unknown (Schmitgen et al., 2019). We propose that the identification of these predictors can improve disease outcome prognosis and potentially increase the number of patients who may benefit from psychological treatments such as DBT.

Even though the clinical interview can provide valuable information regarding relevant predictors of treatment response, professionals often face the challenge of distinguishing between numerous sources of information that could contribute to the understanding of a clinical case. Examples are genetic or brain imaging measurements, which, although have gained popularity in research (Poldrack et al., 2020; Varoquaux, 2018), their high cost and/or complexity make their use for daily clinical practice unfeasible, especially in developing countries; not to mention that reported accuracies may be too optimistic due to methodological problems (Janssen et al., 2018). A very large source of possible information may come from self and clinician report instruments, which, despite their widespread use, their predictive value has been poorly exploited (Chekroud et al., 2016).

Machine learning is a tool that could potentially help facilitate the understanding of the information from self-report instruments and make accurate predictions regarding treatment outcomes. Probably due to the advantages that machine learning tools represent over traditional statistical methods, many studies have implemented these techniques to predict treatment response in other psychiatric diseases, for example, in patients with depression (Lee et al., 2018), or with first-episode psychosis (Koutsouleris et al., 2016) and even for BPD (Beeney et al., 2021; Schmitgen et al., 2019). However, specifically for BPD, some studies have limitations associated with their sample size, the lack of cross-validation, or their analyses reflect correlations among variables instead of predictions (Bellino et al., 2015; Landes et al., 2016).

Hence, in the present study we aimed to determine the clinical variables from self-report questionnaires that predict treatment outcomes, severity and impulsivity, in BPD, after 6 months of DBT skills training group, using multivariate machine learning methods.

Methods

Participants

This was a retrospective study that included demographic and clinical information in the clinical database from all patients who received DBT psychotherapy from October 2015 to July 2019, as part of their treatment at the Borderline Personality Disorder (BPD) clinic at the Ramón de la Fuente Muñiz National Institute of Psychiatry (INPRFM). This is a specialized public psychiatric facility in Mexico City. All patients were diagnosed with BPD according to the DSM-IV criteria and confirmed on consensus by the consultant psychiatrists at the BPD clinic. The patients did not have a comorbid psychotic disorder, bipolar disorder, active

eating disorder, or substance dependence (except for nicotine). All clinical procedures of assessment and psychotherapeutic interventions were approved by the Ethics Committee of the INPRFM (INPDSCEC-02-20.01) in accordance with the Declaration of Helsinki. We obtained full informed consent from patients regarding their anonymity and the value of the clinical research. We took a *complete cases* approach, including only patients without missing observations at baseline and treatment outcomes. The most important outcomes for our study were BPD symptoms severity and impulsiveness, therefore, we considered the selection of cases that had the complete Borderline Evaluation of Severity over Time (BEST) scale and Barratt Impulsivity Scale, version 11 (BIS) tests, both in the pre-treatment and post-treatment timepoints. For BPD severity, 125 BDP patients (111F/14M) had the complete application of the BEST, while for impulsivity, only 89 patients (81F/8M) met this criterion (Table 1).

DBT Skills training group

The Dialectical Behavioral Therapy-Informed brief intervention included group sessions designed to focus on enhancing patients' competences by teaching them DBT skills (Linehan, 2015). The group therapist teaches brief interventions for BPD in their everyday lives (skills) during the session and assigns homework for patients to practice. The structure skills are divided into four modules that included: 1) Mindfulness, 2) Emotional Regulation, 3) Distress Tolerance, and 4) Interpersonal Effectiveness. The intervention model also includes a one-hour weekly consulting team meeting, as well as telephone assistance for patients.

Clinical assessment

Before patients were enrolled (baseline) and at the end of the DBT intervention, a full clinical assessment that included the following instruments was performed (see supplementary Methods for a full description of instruments and predictors): 1) The Clinical Interview for DSM-IV Axis II Personality Disorders self-report screening questionnaire (SCID-II-PQ) (First et al., 1997); 2) Borderline Evaluation of Severity over Time (BEST) (Pfohl et al., 2009); 3) Barratt Impulsivity Scale, version 11 (BIS-11) (Patton et al. 1995; Oquendo et al. 2001); 4) Experiencing of Self Scale (EOSS) (Kanter et al., 2001); 5) Adult Attachment Questionnaire (AAQ) (Melero and Cantero, 2008); 6) the Five-Facet Mindfulness Questionnaire (FFMQ) (Baer et al., 2006); 7) the Spanish version of 24 self-reported items of the Difficulties in Emotion Regulation Scale (DERS) (Tejeda et al., 2012); 8) Inventory of Personality Organization (IPO) (Smits et al., 2009); 9) the Reflective Functioning Questionnaire (RFQ) (Fonagy et al., 2016) ; 10) Beck Depression Inventory (BDI-II) (González et al. 2015); and 11) The World Health Organization - Quality of Life (WHO-QoL BREF) (Harper et al., 1998).

Machine learning Analysis

In order to predict the clinical response to the DBT treatment in the post-evaluation, our outcomes variables were: 1) BDP severity, measured by the BEST and 2) impulsiveness, measured by the BIS-11 total score. For the prediction of BPD severity, the full sample was included, divided into 17 DBT psychotherapy groups (with a median of 8 patients per group). Of those 17, 12 groups were randomly selected to make up the subset of data for model *training* with ~70% of the sample available, and the remaining ~30% of the data (5 groups) was used for model *validation* (Table 1). For the prediction of impulsiveness scores, the sample consisted of 89 subjects, corresponding to 12 DBT psychotherapy groups. In the same way, 8 groups were randomly selected to train the models, ~70% for model *training* and ~30% (4 groups) for model *validation* (Table 1). All data and scripts to reproduce the

analysis and results are available in the GitHub repository:
https://github.com/saidejp/machine_learning_BPD.

Table 1. Demographic characteristics of the training and testing datasets in the severity (BEST) and impulsiveness (BIS) scales

[Insert Table 1]

We trained models using information from 613 features, which included sociodemographic, clinical, and pharmacological variables, associated with a specific score for the variables of BPD severity and impulsivity. We use two widely used machine learning models: the *lasso* and *Rf* (Breiman, 2001; Zou & Hastie, 2005). In addition to making very accurate predictions, these models have the advantage that they allow identifying and ordering the importance that the features studied have in predicting new observations. Therefore these models were selected for their simplicity, their interpretability, and their power of generalization. The phases of the machine learning analysis were programmed in R with the *caret* (Kuhn, 2008) and *tidyverse* packages. The *Rf* method proposed by Breiman (2001) was implemented, using the *ranger* package. The values of the *mtry* and *splitrule* parameters were selected by means of Cross-Validation (CV) depending on the combination with the lowest prediction error. On the other hand, the *lasso* method was implemented through the *glmnet* package which performs the regularization of the regression coefficients through the L1 penalty, the size of the penalty was selected by CV, depending on the value that the prediction error decreased the most.

Cross-Validation (training set)

Both the *lasso* and *Rf* models were trained under identical conditions to predict BPD severity and impulsivity. The ~70% of the entire available sample was used to train the models, as well as to identify the combination of hyperparameters that could mostly decrease the prediction error (tuning models). We used two training strategies, one was *k-folds* cross validation (10-folds CV), and to consider the natural grouping of the observations we also used Leave One Group Out cross validation (LOGOCV). The training with 10-folds CV divides the total sample of data into 10 subsets of approximately the same size (~9 subjects per set), and iteratively uses 9 of the folds to train the model and one to evaluate it (testing), until each fold played the role of training and testing set. In this iterative process, 12 hyperparameter combinations were used for the *Rf* and 10 combinations for the *lasso*, in order to select the two models from each that showed the least prediction error in training and then evaluate their generalizability in the ~30% remaining sample. The LOGOCV randomly excludes one of the treatment groups, then performs training in the remaining and subsequently evaluates performance in the excluded set. The previous operation is repeated until all the groups have been in the training and the evaluation set (test).

Model prediction errors were quantified using two metrics: the Root Mean Square Error (RMSE) and the Mean Absolute Error (MAE). We implement the prediction error metrics most used in the literature (Poldrack et al., 2020). Both the RMSE and the MAE are measures of the prediction error for each individual, which do not weigh differently the direction of the errors, that is, they do not consider whether they underestimate or overestimate. In the case of RMSE, the residuals are squared so that it no longer analyzes whether they are overestimations or underestimations, and in the case of MAE, the residuals

are taken in their absolute dimension, that is, regardless of the sign. The interpretation of these indices is similar to that of a standard deviation, which, although it is a positive quantity, is considered a measure of dispersion both above and below the mean.

Model comparison (training set)

Since the models were trained with the same training set and folds, after a benchmark experiment we perform statistical inference regarding the differences in performance during the training of the best *lasso* and *Rf* models. The RMSE and MAE metrics of each of the 10 folds were taken during training, the difference between the prediction error for *lasso* and *Rf* was calculated, and finally, the hypothesis was evaluated as to whether these differences were different from zero by means of a one sample t-test (Hothorn et al., 2005; Jiménez et al., 2019).

Validation (test set)

In addition to the comparison described in the previous section, ~30% of the remaining sample, which was not seen by the models in any step of the training, was used to evaluate the generalization that our models had. Each model made its prediction of the new observations and the prediction error was obtained using the RMSE and MAE metrics. To show the superiority of machine learning over traditional approaches, we created a baseline model, which was a multiple linear regression that only included the sociodemographic variables and the pre-treatment score in the severity and impulsivity tests to explain the BEST and BIS after treatment. This baseline model (*B*) was fitted in the same training set as the other two learners (*lasso* and *Rf*), and its performance in the prediction of the subjects included in the testing set was subsequently evaluated.

Variable importance

Once the best *Rf* model was selected, we calculated the importance and p-value of each predictor using the permutations method (Altmann et al., 2010), subsequently, for visualization purpose, the 9 most important predictors were selected for the BEST and BIS prediction, and Partial Dependence Plots (PDP) and Individual Conditional Expectation curves (ICE) were constructed to visualize their predictive value (Goldstein et al., 2015). Although both models allow selecting the best predictors, we decided to show only those of *Rf*, because they have the advantage of capturing non-linear relationships between predictors and outcomes.

Results

The DBT skills training group reduced BPD severity and impulsivity, comparing the pre and post-treatment measurements of the BEST and BIS total scales. A paired t-test estimated a significant reduction in the BEST scale in the post-treatment of 18 points on average (95% CI 15.6-22.4), while for impulsivity, a reduction in post-treatment of 13.9 points was estimated on average (95% CI 10.9-16.9).

Differences between models

During the training of the two models for the prediction of BDP severity and impulsiveness, *Rf* had significantly less prediction error (RMSE and MAE) than *lasso* (Figure 1). In the case of BPD severity, the difference in RMSE and MAE was on average 1.96 (95% CI 0.85 - 3.07), and 1.55 (95% CI 0.63-2.48) respectively. For the BIS, *Rf* also was a better model

than *lasso* during training, the estimate of the difference in RMSE was on average 2.40 (95% CI 0.90-3.88) and for the MAE = 1.97 (95% CI 0.57 - 3.35). However, the two models performed very similarly in the testing set; for the BEST variable, the *Rf* had a lower score in MAE, and slightly higher in RMSE; while in the BIS, the *Rf* had slightly greater prediction error than *lasso* for the two metrics used (Table 2). Although both learners had a similar performance in the testing dataset, the multiple regression model that we fitted as a baseline (*Bl*), allowed us to have a reference of how adequate were the test predictions using *lasso* and *Rf*. The experiment revealed very serious prediction errors for the *Bl* model compared to *lasso* and *Rf*; for example: with the *Bl* model, post-test prediction errors on the BEST scale were 9.7 - 21.2 points (RMSE 95% CI), while with *lasso* and *Rf*, we estimated errors between 7.2 - 13.2, and 7.9 - 12.7 points on the BEST scale (RMSE 95% CI), respectively (Table 2). To get an idea of the prediction at the individual level, we constructed Figures 2 and 3, which show the performance in the prediction of the post-treatment scores for *Bl*, *Rf*, and *lasso* models. Figures 2 and 3 show respectively the performance of the models to predict the BPD severity and impulsivity score of each patient, on the x-axis the BEST or BIS scoring scale is included, while on the y-axis each patient is displayed, the orange circles indicate the patient's actual post-test score and the yellow circles indicate the prediction, the line between the dots represents the distance or prediction error. The magnitude of the errors of the baseline model can be noted, for example in patient number 9 or 35 of the BEST, and in patient number 9 or 22 of the BIS. This contrasts with the performance of the *lasso* and *Rf* models, which although they also have errors, are much smaller.

[Insert Figure 1]

Figure 1 caption. The prediction error (measured by MAE and RMSE) during the 10 folds of the Cross-Validation training is shown for each model. Each circle represents the prediction error of one of the 10 cycles of the k-fold Cross-Validation. Lower scores represent better model predictions. The RMSE is obtained by averaging the differences between the predictions for each subject and their actual squared score, and then the square root of this average is taken. The MAE refers to the average of the absolute value of the differences between the predictions and the actual observations. RMSE: Root Mean Square Error; MAE: Mean Absolute Error; BEST: Borderline Evaluation of Severity Over Time; BIS: Barratt Impulsivity Scale.

[Insert Table 2]

Note. MAE: mean absolute error, RMSE: residual mean square error, *Rf*: random forest, BEST: BPD severity scale, BIS: Barratt Impulsiveness scale. CV: cross-validation training, *Bl*: Baseline model (simple multiple regression), LOGO: Leave One Group Out cross-validation. The RMSE is obtained by averaging the differences between the predictions for each subject and their actual squared score. The MAE refers to the average of the absolute value of the differences between the predictions and the actual observations. Bootstrapped 95% Confidence Intervals with 10,000 repetitions are shown in parenthesis.

[Insert Figure 2]

Figure 2 caption. Individual predictions in the severity of BPD symptoms measured with the BEST scale. Each panel shows the performance in the individual prediction of the baseline model *Bl*, the random forest *Rf* and the *lasso* regression. In the x-axis the post-treatment

BEST score is included, while on the y-axis each patient is displayed, the orange circles indicate the patient's actual post-test score and the yellow circles indicate the prediction, the line between the dots represents the distance or prediction error.

[Insert Figure 3]

Figure 3 caption. Individual predictions in the impulsivity of BPD patients measured with the BIS scale. Each panel shows the performance in the individual prediction of the baseline model *Bl*, the random forest *Rf* and the *lasso* regression. In the x-axis the post-treatment BIS score is included, while on the y-axis each patient is displayed, the orange circles indicate the patient's actual post-test score and the yellow circles indicate the prediction, the line between the dots represents the distance or prediction error.

Clinical Predictors

Using the permutations method, the *Rf* model detected 34 important and statistically significant predictors, out of 613 variables, for the severity of BPD after psychotherapy (see Supplementary Table 1 and Table 2 for detailed information). The three most important features to predict a reduction of the BEST score were: the total score of the "non-judging" subscale from the FFMQ and two individual items of the WHOQOL test ("How well are you able to get around?" and "Support you get from your friends"). Specifically, for individuals who scored more than 30 points on the "non-judging" subscale at baseline, a reduction of 0.7 points on average in the BEST score was predicted during the post-test. Likewise, the two items mentioned from the WHOQOL scale, predicted an improvement of 0.7 and 0.5 on average, for the patients who gave a higher response to the option "very dissatisfied". While the three most important predictors of worsening of the BEST in post-treatment were: 1) the "General self scale" from the EOSS instrument, scores greater than 35 on this scale during the baseline, predicted a worsening of 0.6 to 0.8 points on average. 2) The AAQ item "I never get seriously compromised in my relationships" predicted increases in the BEST from 0.6 - 0.7, for individuals who responded that they were from "somewhat agree" to "completely agree" with the statement of this item. And, 3) the "Paranoia" subscale of the SCIID predicted increases of up to 1 point in the post-treatment BEST for individuals who had 8 points or more of paranoia during the pre-test (Figure 4).

[Insert Figure 4]

Figure 4 caption: Each graph represents the change in BEST prediction, related to the range of values in the predictors. The faint lines represent individual predictions and the yellow line indicates the average of the individual curves. The x-axis of each panel begins its scale at the minimum value recorded in the sample for that particular predictor, while the y-axis shows changes with respect to the BEST test average in the post-treatment. When the yellow line exceeds zero, it means that increases in post-treatment severity are predicted, while values below zero indicate improvement. EOSS: Experiencing of Self Scale; AAQ: Adult Attachment Questionnaire; SCIID: The Clinical Interview for DSM-IV Axis II Personality Disorders self-report screening questionnaire; FFMQ: Five-Facet Mindfulness Questionnaire; IPO: Inventory of Personality Organization; WHOQOL: The World Health Organization - Quality of Life; DERS: Difficulties in Emotion Regulation Scale.

From the 17 statistically significant features that predict changes in BPD impulsivity after treatment, the three most important features for predicting post-treatment improvement according to the R^2 were: the individual item on “Crying” in the BDI and two items on mentalization skills of the RFQ test (“I pay attention to the impact of my actions on the other’s feelings” and “I keep the other person’s point of view in my mind”). The prediction with the BDI was that the individuals who selected the option “Before I could cry but I can no longer” would have reductions of 0.3 points on average in the BIS during the post-test. While for the people who gave answers to the option of “agree” in the aforementioned items of the RFQ, the R^2 predicted reductions of up to 0.2 points in impulsivity. On the other hand, the three most important variables that predicted worsening of impulsivity after treatment were: the “Non-planning impulsiveness” subscale of the BIS, the total scale of the BIS, and the item “I would like to change many things about myself” from the AAQ test (Figure 5). It is important to note in Figures 4 and 5 that the prediction of reductions and/or increases is not uniform throughout the range of feature scores and that several individual items or subscales from different clinical instruments were better predictors of clinical outcome than full instruments.

[Insert Figure 5]

Figure 5 caption: Each graph represents the change in the BIS prediction, related to the range of values in the predictors. The faint lines represent individual predictions and the yellow line indicates the average of the individual curves. The x-axis of each panel begins its scale at the minimum value recorded in the sample for that particular predictor, while the y-axis shows changes with respect to the BIS test average in the post-treatment. When the yellow line exceeds zero, it means that increases in post-treatment impulsivity are predicted, while values below zero indicate improvement. BIS: Barratt Inventory of Impulsiveness; BDI: Beck Depression Inventory; AAQ: Adult Attachment Questionnaire; RFQ: Reflective Functioning Questionnaire; SCID: The Clinical Interview for DSM-IV Axis II Personality Disorders self-report screening questionnaire; BEST: Borderline Evaluation of Severity Over Time.

Discussion

In this study we wanted to identify the clinical characteristics of borderline personality disorder (BPD) patients that better predict the outcome after 6 months of dialectical behavior therapy (DBT). For this, we applied two machine learning models to predict BPD severity (BEST score) and total impulsivity (BIS score), using variables assessed before treatment (baseline). Overall, we found that different individual items or sections in questionnaires, and not complete tests, were predictive of the clinical outcome after DBT. From the 34 predictors found for BPD severity and the 17 predictors for BPD impulsivity, we will discuss the most relevant predictors in accordance with DBT (see Supplementary Materials for a discussion of other predictors that come from psychodynamic and attachment theory).

Predictors of severity

The most important negative predictor was the score in the Experiencing of Self Scale (EOSS) subscale related to the “*general experience of the self*”. This finding is consistent

with the idea that BPD patients may suffer from the excessive influence of other people on their experience of the self, and that the more influence others have, the worse self-esteem is predicted (Kanter et al., 2001). On the other hand, higher levels of “*non-judging*” (Linehan, 2015) (self or internal experience) from the Five-Facet Mindfulness Questionnaire (FFMQ), relevant in DBT patient skills training, predicted less severity of BPD. It consists of an acceptance strategy, which allows one to approach (cognitively or physically) negative emotions or distressing thoughts, and to be able to experience them as they are, without the individual seeking to escape or avoid. It is proposed that this favors emotional regulation, similar to what occurs in exposure treatments for phobias (Lynch et al., 2006). Also, it has been proposed that all effective psychotherapies for BPD patients may increase mentalization capacity (Fonagy et al., 2016) and the DBT technique could enhance mentalization through mindfulness practice, which could facilitate a cognitive and affective integration of mental states that through attention regulation, improves BPD symptoms (Byrne & Egan, 2018) .

Predictors of impulsiveness

A higher score on the *non-planning impulsiveness scale* from Barratt Impulsiveness Scale (BIS-11) at baseline was a negative predictor. It has been identified that patients with BPD report higher scores of non-planning impulsiveness than controls (Wilson et al., 2007) and that the above may be related to higher temporal discount rates (Lawrence et al., 2010). Rapid and unplanned decisions may interfere with goals to regulate emotional experience through mindfulness or other DBT’ skills. Conversely, a positive predictor of impulsiveness was the Beck Depression Inventory (BDI-II) item “*before, I could cry, but I can no longer*”. This item is related to severe depression, however our results predict a reduction in impulsivity. This result should be taken with caution as it may reflect maladaptive emotional restriction and severe depression prior to treatment. It could also suggest that these types of patients, those with an unavailability to a component of the emotional experience such as crying, may benefit more from DBT by allowing the identification and naming of emotions before acting. Finally, the Reflective Functioning Questionnaire (RFQ) items related with awareness and emotional understanding about the self and the others were also positive predictors of impulsivity improvement, these abilities may function as a behavior modulator and patients with this prior understanding may benefit more from DBT (Fonagy et al., 2016; Lynch et al., 2006).

The present study contributes to predicting the response to BPD treatment, with some methodological considerations that have not been carried out until now. The studies located to date fitted their predictive models in samples of less than 60 subjects (Bellino et al., 2015; Landes et al., 2016) or performed training by CV with 31 subjects (Schmitgen et al., 2019), although they are studies of great value for the difficulty and cost of obtaining samples with this diagnosis, not using CV does not allow estimating the generalization capacity of a model and the use of CV with small samples can lead to overestimations of predictive precision, which gives a misconception of its possibility of generalization (Varoquaux, 2018). Although, the present study is far from the recommendation of having several hundred subjects for training by CV (Poldrack et al., 2020), here we present more than twice the sample that previous studies have included, which increases the confidence in the estimates regarding the generalizability of our models. Another problem in research is that the studies carried out do not use model comparisons (Beeney et al., 2021; Bellino et al., 2015; Landes et al., 2016; Schmitgen et al., 2019). It is known that the predictive ability of the models may depend on

the characteristics of the sample (such as its size or homogeneity), the process that generates the data, or the type of problem they have to solve (e.g. classification or regression). Thus, the model comparison is a necessary empirical procedure, not only to evaluate the performance but to select the best model among several candidates (Hothorn et al., 2005). In this work, we show the comparison of two models trained under identical conditions, which strengthens the possibility of generalization of the predictors indicated by our best models.

Limitations

One limitation is that the sample is still below the recommended size, which is why the predictions of the models could be over-optimistic, however, the issue of sample size with machine learning models is still a pending research topic in the current literature, and there is no consensus regarding the number of individuals necessary to train or test a model, mainly because the models work under different assumptions and therefore they require rules sensitive to their specific nature. Taking as a reference the number of participants in similar studies with BPD patients (Beeney et al., 2021; Schmitgen et al., 2019; Bellino et al., 2015; Landes et al., 2016) we consider that our present estimates are still valid. Other limitation is the absence of a completely independent sample (for example, patients from another institution). We can argue that the performance of the models in the available test set is an approximation to the degree of transfer of the findings to a new context, since both models make predictions in patients completely unknown to them. Although the prediction is far from perfect, considering that the models were trained with information exclusively from self-reporting instruments, the level of prediction achieved in the present study is important and relevant. Finally, although the ICE plots seek to facilitate the detected predictors' interpretation, the technique is not immune to scenarios in which the predictors interact with each other or have heterogeneous effects, so the direction of predictions should be investigated further.

Conclusions

In this study, using machine learning we found individual items or sections from several clinical questionnaires that were strongly and reproducibly predictive of BPD severity and impulsivity after DBT skills training group. The detected variables are usually available in self-report measurements that are frequently applied to patients with BPD in routine psychiatric care, however, their use as predictors of treatment response is not commonly exploited. It is also worth mentioning that although we focused on self-report questionnaires in the present study, it would be useful to investigate the usefulness of other low-cost measures such as the assessment of neurological soft signs (Khoweiled et al. 2021). Overall, our resulting features may not only help predict treatment outcome, they could also help clinicians cluster patients prior to DBT to improve treatment efficacy and optimize resources based on personalized treatment (Iniesta et al., 2016; Poldrack et al., 2020). Identifying possible DBT non-responders beforehand may help clinicians find other beneficial treatment approaches for these patients, and reduce the burden of disease (American Psychiatric Association, 2001). All these are mandates that should be observed by healthcare providers according to the WHO guidelines (World Health Organization, 1996).

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Table 1. Demographic characteristics of the training and testing datasets in the severity (BEST) and impulsiveness (BIS) scales

	BEST (n = 125)		BIS (n = 89)	
	Training (n = 90)	Testing (n = 35)	Training (n = 61)	Testing (n = 28)
Age, mean (SD)	30.6 (9.13)	31.6 (9.82)	31.58 (9.27)	30.64 (9.44)
Education, mean (SD)	13.8 (2.8)	13.11 (3.45)	13.35(2.98)	13.96 (3.45)
Sex				
Women	80 (88.8%)	31 (88.6%)	56 (91.8%)	25 (89.3%)
Men	10 (11.2%)	4 (11.4%)	5 (8.2%)	3 (10.7%)
Marital status				
Single	60 (66.7%)	21 (60%)	37 (60.6%)	18 (64.3%)
Married	13 (14.4%)	5 (14.3%)	7 (11.4%)	4 (14.3%)
Cohabiting	7 (7.8%)	6 (17.2%)	8 (13.1%)	4 (14.3%)
Divorced	7 (7.8%)	3 (8.5%)	7 (11.4%)	2 (7.1%)
Widow	1 (1.1%)	0	0	0
Unknown	2 (2.2%)	0	0	0
Occupation				
Student	23 (25.5%)	6 (17.2%)	12 (19.7%)	6 (21.4%)
Employee	26 (28.9%)	17 (48.5)	25 (40.9%)	11 (39.4%)
Unemployed	22 (24.5%)	7 (20%)	12 (19.7%)	5 (17.8%)
Housework	17 (18.9%)	5 (14.3%)	10 (16.4%)	6 (21.4%)
Unknown	2 (2.2%)	0	2 (0.03%)	0

Table 2. Prediction errors for baseline (*Bl*), *lasso* and *Rf* models in the testing data set

CV	Model	Severity (BEST)		Impulsiveness (BIS)	
		MAE	RMSE	MAE	RMSE
One split	<i>Bl</i>	10.8 (7.4, 15.0)	15.4 (9.7, 21.2)	13.8 (9.2, 19.0)	18.8 (12.5, 25.0)
10-fold	<i>Lasso</i>	8.2 (6.3, 10.4)	10.2 (7.2, 13.2)	10.6 (7.7, 13.8)	13.2 (9.7, 16.8)
	<i>Rf</i>	7.8 (5.8, 10.2)	10.2 (7.9, 12.7)	11.5 (8.6, 14.7)	13.9 (10.6, 17.5)
LOGO	<i>Lasso</i>	8.6 (6.5, 10.9)	10.8 (8.4, 13.1)	10.7 (7.8, 13.7)	13.2 (9.7, 16.7)
	<i>Rf</i>	7.9 (6.0, 10.2)	10.0 (7.4, 12.8)	11.2 (8.4, 14.3)	13.6 (10.2, 17.1)

MAE: mean absolute error, RMSE: residual mean square error, Rf: random forest, BEST: BPD severity scale, BIS: Barratt Impulsiveness scale. CV: cross-validation training, Bl: Baseline model (simple multiple regression), LOGO: Leave One Group Out cross-validation. The RMSE is obtained by averaging the differences between the predictions for each subject and their actual squared score. The MAE refers to the average of the absolute value of the differences between the predictions and the actual observations. Bootstrapped 95% Confidence Intervals with 10,000 repetitions are shown in parenthesis.

Conflict of interest

All authors declare that they have no conflicts of interest.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors

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