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Research paper

Differentiation of bipolar disorder versus borderline personality disorder: A machine learning approach

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ABSTRACT

Background: Differentiation of bipolar disorder (BP) from borderline personality disorder (BPD) is a common diagnostic dilemma. We undertook a machine learning (ML) approach to distinguish the conditions.
Methods: Participants meeting DSM criteria for BP or BPD were compared on measures examining cognitive and behavioral BPD constructs, emotion regulation strategies, and parental behaviors during childhood. Two analyses used continuous and dichotomised data, with ML-allocated diagnoses compared to DSM.
Results: 82 participants met DSM criteria for BP and 52 for BPD. Accuracy of ML classification was 84.1% - 87.8% for BP, 50% - 57.7% for BPD, with overall accuracy of 73.1% - 73.9%. Importance of items differed between the analyses with the overall most important items including identity difficulties, relationship problems, female gender, feeling suicidal after a relationship breakdown and age.
Limitations: Participants were volunteers, preponderance of bipolar II (BP II) participants, comorbidity of BP and BPD not examined, and small BPD sample contributed to the relatively low classification accuracies for this group
Conclusions: Study findings may assist distinguishing BP and BPD based on differences in cognitive and behavioral domains, emotion regulation strategies and parental behaviors. Future studies using larger datasets could further improve predictive accuracy and assist in differential diagnosis.

1. Introduction

Differentiating the bipolar disorders (BPs) from borderline personality disorder (BPD) is a frequent diagnostic dilemma (Bassett, 2012) and which has been the subject of previous reviews (e.g. Paris and Black, 2015; Bayes and Parker, 2019). Differentiation problems emerge principally from overlapping symptoms and behaviors such as dysphoric mood states, suicidality and deliberate self-harm (DSH), as well as impulsivity (especially in relation to spending and sexual disinhibition), and alcohol and other substance misuse (Ghaemi et al., 2014; Paris and Bayes, 2019). The transdiagnostic features of impulsivity and emotional dysregulation (ED) in particular risk misdiagnosis. For example, trait-based impulsivity intrinsic to BPD may, on cross-sectional assessment, resemble manic or hypomanic disinhibition, leading to an incorrect BP diagnosis. Conversely, mood elevation integral to BP, in particular irritable 'highs' or mixed states, may be mistaken as ED and lead to an incorrect misdiagnosis of BPD (Kernberg and Yeomans, 2013).

Differentiating bipolar I disorder (BP I) from BPD is generally more straightforward owing to the frequent presence of psychotic symptoms in manic BP I states. Differentiating bipolar II disorder (BP II) from BPD is the more common dilemma, due to hypomanic mood states lacking psychotic features (by definition) and generally being of lesser severity.

The symptom overlap has led to multiple interpretations arguing for interdependence and independence of the two conditions. Two interdependence models are noted. Firstly, at the symptom level, oscillating mood symptoms observed in BPD have led some to consider it as being on the 'bipolar spectrum' as an 'ultrarapid cycling' variant of BP (MacKinnon and Pies, 2006). Secondly, a shared aetiology between the conditions was suggested by a genome-wide association study (Witt et al., 2017) which found genetic overlap of BP with BPD – though there was also an overlap with schizophrenia and major depressive disorder.

Other researchers have argued for independence of the conditions. As reviewed by Paris and Black (2015), certain BPD features, such as interpersonal difficulties and micro-psychotic symptoms, are not readily explainable as mood fluctuations. Empirical studies also favour independence. For example, a latent class analysis of BP and BPD symptoms in a large sample of individuals generated a three-factor solution (i.e. capturing BPD, depression, and mania), with pairwise correlations

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between the factors being consistent with a model suggesting two separate syndromes (BP and BPD) but allowing comorbidity (de la Rosa et al., 2017) or co-occurrence. Their co-occurrence is not rare. In one study (Zimmerman and Morgan, 2013), 10% of those with BPD had a BP I condition, a further 10% had a BP II condition; and 10% of those with BP I and 20% of those with BP II had a BPD.

In prior studies by our group, we have sought to differentiate BP from BPD across multiple domains, including family history, developmental antecedents, clinical symptoms and illness correlates (Bayes et al., 2016a); as well as using a self-report measure of cognitive and behavioral borderline features (Bayes and Parker, 2019). Further studies utilising validated scales compared BP vs. BPD vs. co-occurring BP/BPD on emotion regulation strategies (Bayes et al., 2016b); and remembered parental behaviors during childhood (Parker et al., 2016). Strong differentiation was achieved in distinguishing BP vs. BPD with an accuracy of 92-95%, with history of childhood sexual abuse (CSA), childhood depersonalisation, personality variables capturing sensitivity to criticism and relationship difficulties, as well as an absence of a BP family history being the strongest predictors (Bayes et al., 2016a). All these studies used standard statistical methods which largely assumed a parametric model and normal distributions.

There is growing interest in machine learning (ML) methods to examine datasets, which seek to optimise predictive performance on observations not used in training the model (Fokkema and Strobl, 2020). ML may have advantages over traditional explanatory statistical methods that often assume a parametric model but which may not be realistic in the real world, or where the number of predictor variables exceeds the number of participants (Fokkema and Strobl, 2020). We therefore elected to employ a ML approach to differentiating BP from BPD.

The current study seeks to use a machine learning approach for participants in our previously reported samples (Bayes et al., 2016a; 2016b; Bayes and Parker, 2019; Parker et al., 2016) to determine variables (both as part of rules or individually) that best distinguish those individuals with BP as against BPD, excluding those comorbid for both conditions.

2. Methods

2.1. Participants

The study design has previously been reported (Bayes et al., 2016a), so we therefore only describe key aspects. We recruited participants aged 18 years and above who had a previous diagnosis of BP (I or II) disorder, BPD, or both conditions. Recruitment was primarily from clinical sources: two public psychiatric hospital in-patient services, a tertiary referral depression clinic, a public hospital outpatient psychotherapy clinic, three dialectical behavior therapy outpatient clinics, and three private psychiatric clinics. Advertisements were also placed in newspapers and on our clinical institute's website, while an invitation was also placed on the institute's volunteer research register. Ethics approval was granted across sites by regional ethics committees with ratification by the University of New South Wales Human Research Ethics Committee. Exclusion criteria included English language difficulties, psychotic features, current substance dependence, or significant medical comorbidities. Participants provided informed written consent and were remunerated for travel expenses.

2.2. Instruments

Participants completed a booklet assessing sociodemographic data, current and past mood history, family history and treatment data. It also included a 113-item self-report measure of personality items developed by Ruiz, Fletcher and Parker (see Appendix 1) to assess behavioral and cognitive BPD constructs, a set of items addressing mood, interpersonal functioning, self-harm and suicidality, as well as childhood experiences. Items were derived from a detailed review of the BPD literature as well as clinical experience and captured a broad range of cognitive and behavioral features. Participants were required to answer these questions based on their general functioning over time (not just during mood swings). Questions were coded on either a 5-point Likert scale (1 = 'not at all characteristic'; 5 = 'very characteristic') or dichotomously ('yes' or 'no').

Three self-report questionnaires were completed: the Cognitive Emotion Regulation Questionnaire (CERQ; Garnefski et al., 2001), the Difficulties in Emotion Regulation Scale (DERS; Gratz and Roemer, 2004) and the Measure of Parental Style (MOPS) (Parker et al., 1997). The CERQ is a 36-item measure which assesses nine cognitive strategies - adaptive and maladaptive - regulating emotions in response to stressful life events. The four maladaptive strategies are (i) self-blame for what has been experienced (CERQ_Self-blame), (ii) rumination (CERQ_Rumination), (iii) catastrophizing (CERQ_Catastrophize), and (iv) blaming others (CERQ_Blame). The five adaptive strategies are (i) acceptance of the experience (CERQ_Accept), (ii) positively refocusing on pleasant ideas (CERQ_PosRefocus), (iii) planning on how to manage negative events (CERQ_Planning), (iv) positive reappraisal of the event (CERQ_PosReapp), (v) putting things into perspective (CERQ_Perspective). Each strategy is rated on a 5-point scale (1 - 'Almost never'; 5 - 'Almost always'), with more frequent use indicated by higher scores.

The DERS is a 36-item tool examining emotional regulation strategies. The measure relates to both the understanding and awareness of emotional responses, as well as capturing the ability to act in desired ways and refrain from acting in undesired ways if experiencing negative emotions (Gratz and Roemer, 2004). The assessed strategies are (i) non-acceptance of emotional responses (DERS_NonAccept), (ii) difficulties engaging in goal-directed behaviors (DERS_Goals), (iii) difficulties in controlling impulsive behaviors (DERS_Impulse), (iv) lack of emotional awareness (DERS_Aware), (v) limited access to emotion regulation strategies (DERS_Strategy), (vi) lack of emotional identification or clarity (DERS_Clarity). Each strategy is rated on a 5-point scale (1 - 'Almost never'; 5 - 'Almost always'), with higher scores indicating more frequent use.

The Measure of Parental Style (MOPS) is a 30-item tool (the same 15 items for each parent) examining parental behaviors as remembered by the individual over the first 16 years of their life. Maternal and paternal indifference (MOPS_Mother_Indiff, MOPS_Father_Indiff), overcontrol (MOPS_Mother_OverControl, MOPS_Father_OverControl) and abuse (MOPS_Mother_Abuse, MOPS_Father_Abuse) scale scores are generated. Each statement is rated on a 4-point scale from (0 – 'Not true at all'; 3 – 'Extremely true'), with higher scores indicating the degree to which that parental style was experienced by an individual.

2.3. Diagnostic assessment

We generated both DSM-based and clinician diagnoses. DSM-IV Axis I diagnoses were generated by administering the following subsections of the Mini International Neuropsychiatric Interview (MINI) (Sheehan et al., 1997): A - major depressive episode; B - dysthymia; D - hypomanic/manic episode; and M - psychotic disorders. A DSM-IV diagnosis of BP I or BP II disorder was then determined using the MINI's diagnostic algorithm. A DSM-IV diagnosis of BPD was generated by administering the Diagnostic Interview for Personality Disorders IV – BPD section (Zanarini et al., 1996), which includes the nine DSM-IV BPD criteria. Participants who scored two for five or more criteria received a BPD DSM-IV diagnosis.

2.4. Analyses

Analyses used prediction rule ensembles or PREs (Fokkema and Strobl, 2020), which amongst machine learning techniques have been shown to strike an acceptable balance between easily interpretable techniques like single decision trees, and more accurate but complex techniques like random forests. However, the *pre* R package has the capability to mimic random forest algorithms whilst computing the ensembles (Fokkema, 2020). Random forest algorithms were applied to our analysis.

For the 113 items in the self-report questionnaire, chi square tests comparing prevalence rates in the BP and BPD groups were first undertaken, with the top 10 most differentiating items in included in the PREs. Two separate analyses were completed, the first set of analyses used the raw data for each measure without any transformations (referred to as 'DSM'). A second set of analyses was also undertaken with dichotomisation (DSM-dichot) as 'yes' or 'no' of as many variables as possible in order to generate a set of rules that would be more clinically practical. For the personality items, Likert scores were dichotomised, with those nominating a 1 or 2 score assigned as answering 'no' and those scoring 3, 4 or 5 assigned as answering 'yes'. Dichotomisations for the DERS were based off whether or not an individual's score differed by at least one standard deviation (in whichever direction was considered more maladaptive) from the mean of a normative data set provided by Gratz and Roemer (2004). A similar approach was used for the CERQ, using a normative data set (Garnefski and Kraaij, 2007). For the MOPS, dichotomisations were based off the presence of individual items that were judged to best reflect the construct measured by the subscale (i.e. indifference items: ignored me, uncaring of me, rejecting of me, was uninterested in me; abuse items: verbally abusive of me, physically violent or abusive of me; overcontrol items: overcontrolling of me, overprotective of me).

PRE output is similar to a logistic regression, in which each variable takes the form of a logical rule (e.g. "Age > 30 and Suicide Attempt = Yes", and which might have a regression coefficient of 0.5. If an individual was both older than 30 and had attempted suicide, that rule would be included in the regression model, with 0.5 being added to the log-odds. Coefficients represent the log-odds of belonging to the target class for a unit increase in the predictor variable, while keeping all of the other predictors constant. In the present study, a B weight of > 0 indicates a greater probability of a BPD diagnosis, while a B weight < 0 indicates a greater probability of a BP diagnosis. In accordance with previous analyses of this kind (Fokkema and Strobl, 2020), the predictive accuracy of the ensembles were tested using 10 repetitions of 10-fold cross validation.

Variable 'importance' measures aim to quantify the influence of variables on the predictions of the ensemble. The importance of a rule or linear term is the absolute value of the regression coefficient, multiplied by the standard deviation (Friedman and Popescu, 2008). Therefore, the importance of a rule increases with the absolute value of the estimated coefficient and the extent to which the rule membership varies across the training observations. Total importance (Friedman and Popescu, 2008) is defined as the sum of the importance of the linear term and the importance of every rule in which the variable appears divided by the number of conditions in the rule, with larger importance values having a greater effect on the model.

3. Results

DSM criteria allocated 82 patients as having a BP disorder (four with BP I, 78 with BP II), and 52 as having BPD. There was no significant difference in age between groups. Females were over-represented in the BPD vs. the BP group (chi-square = 12.6; $p < 0.001$).

3.1. Prediction accuracy

The analyses compared BP vs. BPD groups through a binary regression model. PRE-allocated diagnoses were compared to DSM diagnoses (see Table 1). PRE-derived diagnoses offered overall high accuracy in classifying BP, ranging from 84.1% - 87.8%. Compared to BP allocation, accuracy of BPD classification was substantially lower, ranging from 50% to 57.7% for DSM. There was a moderate level of overall classification accuracies ranging from 73.1%, to 73.9%.

Table 1
Accuracy of PRE-allocated diagnoses compared to DSM.

Analysis	No. of rules	Prediction accuracy BP	BPD	Overall
DSM	20	84.1%	57.7%	73.9%
DSM-dichot	14	87.8%	50%	73.1%

BP = bipolar disorder; BPD = borderline personality disorder; DSM = raw scores used for analysis; DSM-dichot = dichotomisation of raw scores.

3.2. Variable importance

Individual variable importance values for the two analyses are detailed in Figures 1 and 2. The importance of variables differed between the two analyses, though with substantive overlap. The DSM analysis using raw data found the CERQ item putting things into perspective to be the most important item followed by "I believe I have more difficulties with relationships than the average person my age", "I do not know who I am in terms of my identity", female gender and "suicidal thoughts during and after a break-up or being rejected by someone". The next most important items were age, planning to manage negative emotions, lack of emotional awareness, "during times of stress, I often feel that others are deliberately mean to me" and "if others knew the real me, they would not like me".

The DSM-dichot analysis shared four of the same items in the top five most important items, though with the rank order differing and the most important item being "I do not know who I am in terms of my identity". DSH was included as the fifth most important item (and CERQ_Perspective not included in top five). The next most important items were age, self-blame, a history of CSA, BP family history and childhood depersonalisation.

3.3. Rules

The rules with associated B values for the DSM analysis are detailed in Table 2, with a total of 20 rules generated. Table 3 details the 14 rules generated in the DSM-dichot analysis.

4. Discussion

We first detail a number of study limitations, including participants being volunteers and likely to have less severe conditions. there was a preponderance of bipolar participants having a BP II condition (and thus results may not be representative of bipolar disorder in general or BP I in particular), and individuals with both BP and BPD being excluded, thus disallowing analysis of a comorbid group. Further, using the PRE approach (which may improve predictive capacity) generates a large number of rules that can be difficult to interpret. The data set was relatively small for using an ML analysis with a larger data set preferable. In particular, the small BPD sample likely contributed to the relatively low classification accuracies for this group. The study is reliant on the validity of DSM-based diagnoses – which are largely symptom-based and syndromal - and therefore machine learning approaches still remain a preliminary step in separating the disorders until objective biomarkers are identified.

Strengths include use of DSM criteria to assign diagnoses. Further we undertook two sets of analyses - one which examined all data derived from the included scales, and another with dichotomised data. The latter analysis demonstrated comparable overall accuracy to the former analysis, and would be more easily ascertainable by a clinician in practice.

Study findings revealed a distinct set of rules generated for each of the analyses. While the rules themselves may be difficult to interpret, analysis of the importance of individual variables revealed key items

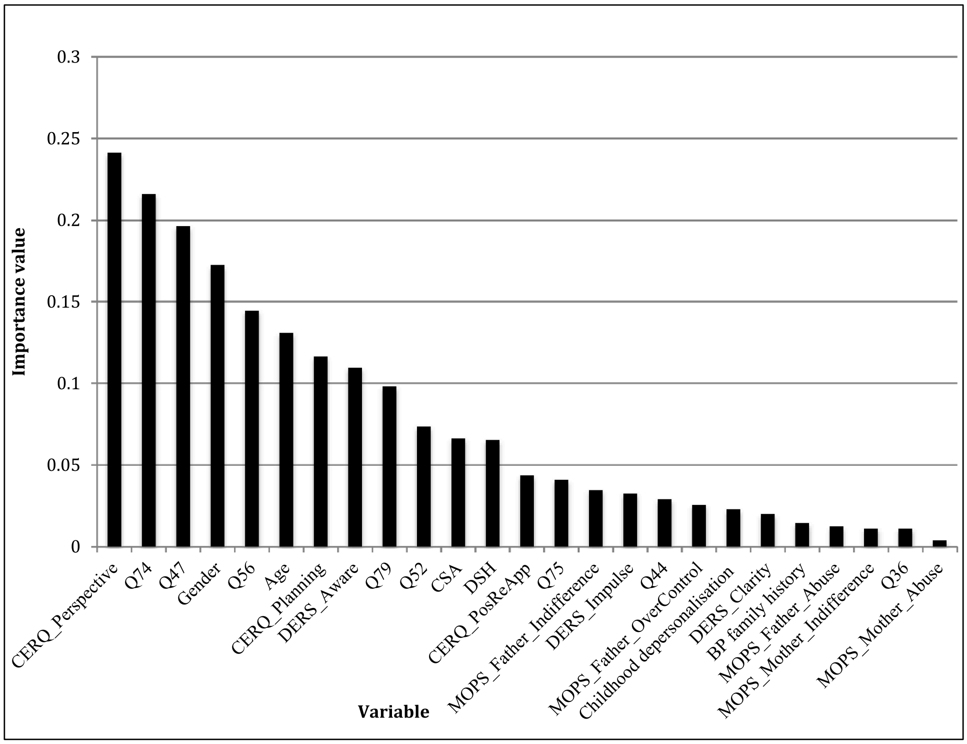

Fig. 1. Importance values for DSM analysis.

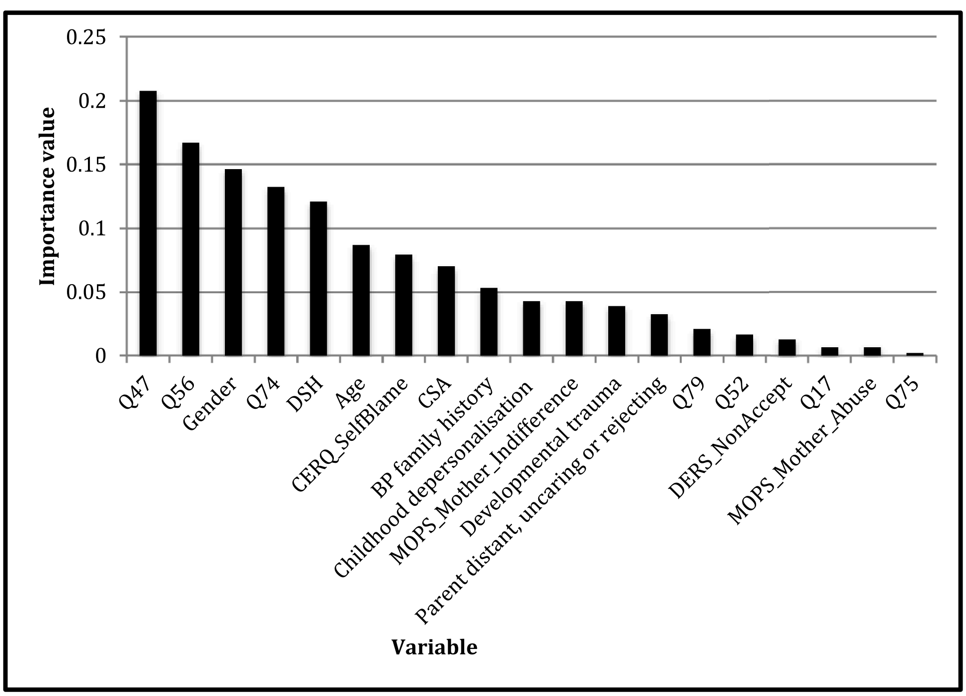

Fig. 2. Importance values for DSM-dichot analysis.
DSH = deliberate self-harm; CSA = childhood sexual abuse; DERS = Difficulties in Emotion Regulation Scale; CERQ = Cognitive Emotion Regulation Questionnaire; MOPS = Measure of Parental Style; CSA = childhood sexual abuse, BP = bipolar disorder.
Scale items: DERS_Impulse = difficulties in controlling impulsive behaviors; DERS_Aware = lack of emotional awareness; DERS_NonAccept = non acceptance emotional responses; DERS_Clarity = lack of emotional identification or clarity; CERQ-SelfBlame = blaming self; CERQ_Perspective = putting things into perspective; CERQ_Planning = planning on how to manage negative events; CERQ_PosReApp = positive reappraisal of the event; MOPS_Mother_Indiff = maternal indifference; MOPS_Mother_Abuse = maternal abuse; MOPS_Father_Indiff = paternal indifference; MOPS_Father_OverControl = paternal overcontrol; MOPS_Father_Abuse = paternal abuse.
Candidate cognitive and personality items: Q17 = *'I tend to idealise others (i.e. put them on a pedestal) but then often seek to hurt them back if I judge them as hurtful to me'*; Q36 = *'My value as a person depends enormously on what others think of me'*; Q44 = *'I have a big fear of rejection of any kind'*; Q47 = *'I do not know who I am really in terms of my identity'*; Q52 = *'If others knew the real me, they would not like me'*; Q56 = *'I tend to have suicidal thoughts during and after a break-up or being rejected by someone'*; Q74 = *'I believe I have more difficulties with relationships than the average person my age'*; Q75 = *'I've felt empty inside for as long as I can remember'*; Q79 = *'During times of stress, I often feel that others are deliberately mean to me'*.

Table 2
Rules generated for DSM analysis.

Rule	B	SD
Intercept	-1.155	
Q47 >= 2.5 & CERQ_Perspective < 13.5 & Age < 51 & CERQ_Planning >= 4.5	0.973	0.479
Q79 >= 1.5 & CERQ_Perspective < 13.5 & Female	0.501	0.479
Q74 >= 3.5 & DERS_Aware >= 15.5 & Female	0.532	0.441
Q74 >= 3.5 & CERQ_PosReapp < 13.5 & Q56 >= 2.5	0.289	0.452
Q47 >= 2.5 & DSH = No & Q56 >= 1.5	0.238	0.485
Q52 < 4.5 & CSA = Yes	-0.229	0.481
Q47 >= 2.5 & DSH = No & Q56 >= 2.5	0.173	0.466
Q74 < 4.5 & MOPS_Father_Indiff < 6.2	-0.138	0.500
Q74 >= 3.5 & CERQ_Perspective < 13.5 & DERS_Clarity < 20.5	0.130	0.463
DERS_Impulse >= 14.5 & Age < 51 & BP family history = Yes & MOPS_Father_OverControl < 7.5	0.130	0.445
DERS_Impulse < 21.5 & Q75 < 4.5 & Q79 < 2.5	-0.108	0.500
Childhood depersonalisation = Yes & Q75 < 4.5	-0.092	0.497
Q56 < 4.5 & Q52 < 4.5 & Q47 < 4.5	-0.088	0.497
Q44 >= 3.5 & Female & DERS_Aware >= 12.5	0.089	0.483
Q74 >= 3.5 & CERQ_Perspective < 13.5 & MOPS_Father_Abuse < 13.5	0.080	0.469
Q56 < 4.5 & DERS_Aware < 22.5	-0.070	0.485
Q74 >= 3.5 & Q44 >= 3.5	0.060	0.491
Q74 >= 3.5 & CERQ_Perspective < 13.5	0.051	0.487
CSA = Yes & MOPS_Father_OverControl < 3.5	-0.045	0.497
MOPS_Mother_Indiff < 5.5 & Q36 < 3.5	-0.045	0.491

DSH = deliberate self-harm; CSA = childhood sexual abuse; DERS = Difficulties in Emotion Regulation Scale; CERQ = Cognitive Emotion Regulation Questionnaire; MOPS = Measure of Parental Style; CSA = childhood sexual abuse; BP = bipolar disorder.
Scale items: DERS_Impulse = difficulties in controlling impulsive behaviors; DERS_Aware = lack of emotional awareness; DERS_Clarity = lack of emotional identification or clarity; CERQ_Perspective = putting things into perspective; CERQ_Planning = planning on how to manage negative events; CERQ_PosReapp = positive reappraisal of the event; MOPS_Mother_Indiff = maternal indifference; MOPS_Father_Indiff = paternal indifference; MOPS_Father_OverControl = paternal overcontrol; MOPS_Father_Abuse = paternal abuse.
Candidate cognitive and personality items: Q36 = '*My value as a person depends enormously on what others think of me*'; Q44 = '*I have a big fear of rejection of any kind*'; Q47 = '*I do not know who I am really in terms of my identity*'; Q52 = '*If others knew the real me, they would not like me*'; Q56 = '*I tend to have suicidal thoughts during and after a break-up or being rejected by someone*'; Q74 = '*I believe I have more difficulties with relationships than the average person my age*'; Q75 = '*I've felt empty inside for as long as I can remember*'; Q79 = '*During times of stress, I often feel that others are deliberately mean to me*'.

Table 3
Rules generated for DSM-dichot analysis.

Rule	B	SD
Intercept	-1.081	
Q56 = Yes & Q47 = Yes & DSH = No	0.684	0.466
Q74 = Yes & Gender = Female & CERQ_SelfBlame = Yes	0.410	0.479
Q47 = Yes & Age < 51 & BP family hitsory = Yes	0.330	0.483
Childhood depersonalisation = Yes & MOPS_Mother_Indiff = No & CSA = Yes	-0.259	0.495
Q74 = Yes & Developmental trauma = No & Gender = Female	0.262	0.445
Q47 = Yes & Q56 = Yes & Age < 51	0.205	0.474
CSA = Yes & Q79 = No & Parent distant, uncaring or rejecting = Yes	-0.138	0.456
Q47 = Yes & DERS_NonAccept = Yes & DSH = No & Q56 = Yes	0.116	0.441
Q74 = Yes & Gender = Female & Q52 = Yes	0.108	0.459
Q56 = Yes & Gender = Female & CERQ_SelfBlame = Yes	0.092	0.452
Q74 = Yes & Parent distant, uncaring or rejecting = No & Gender = Female	0.081	0.428
CSA = Yes & MOPS_Mother_Abuse = No & Q17 = No	-0.039	0.498
Q56 = Yes & DSH = No & Q47 = Yes & Q75 = Yes	0.019	0.437
Q47 = Yes & Age < 52.5	0.005	0.502

DSH = deliberate self-harm; CSA = childhood sexual abuse; DERS = Difficulties in Emotion Regulation Scale; CERQ = Cognitive Emotion Regulation Questionnaire; MOPS = Measure of Parental Style; BP = bipolar disorder
Scale items: DERS_NonAccept = non-acceptance of emotional responses; CERQ_SelfBlame = self-blame for what has been experienced; MOPS_Mother_Abuse = maternal abuse; MOPS_Mother_Indiff = maternal indifference.
Candidate cognitive and personality items: Q17 = '*I tend to idealise others (i.e. put them on a pedestal) but then often seek to hurt them back if I judge them as hurtful to me*'; Q47 = '*I do not know who I am really in terms of my identity*'; Q52 = '*If others knew the real me, they would not like me*'; Q56 = '*I tend to have suicidal thoughts during and after a break-up or being rejected by someone*'; Q74 = '*I believe I have more difficulties with relationships than the average person my age*'; Q75 = '*I've felt empty inside for as long as I can remember*'; Q79 = '*During times of stress, I often feel that others are deliberately mean to me*'.

pertinent to distinguishing BP from BPD. Across both analyses, identity disturbance was a highly ranked item, a core component of those with BPD who report a 'noxious' sense of self and 'painful incoherence' (Meares et al., 2011). BP patients tend to have a more coherent sense of self, though this is modulated by mood state e.g. perceived self-deficits when depressed, and grandiose self when elevated (Renaud, 2012). Other items found to be of high importance were relationship difficulties and suicidal thoughts after a break-up or rejection - both core features of BPD. Female gender was found to be an important variable which is in keeping with higher prevalence rates in most BPD clinical samples (Widiger and Trull, 1993), with more equal prevalence rates found in BP, though a female preponderance has been found in BP II clinical samples (Goodwin and Jamieson, 2007).

Following the top five most highly ranked items, there was less consistency in the importance values between analyses. Overall, a history of childhood sexual abuse was an important differentiator - and though it can occur in both disorders - is more prevalent in BPD (Bassett, 2012; Coulston et al., 2012). Other important differentiating items included stress-related paranoid ideation and childhood depersonalisation – which are established BPD features (Meares et al., 2011). A family history of bipolar disorder also showed overall importance, with such a history over-represented in patients with bipolar disorder (Bassett, 2012).

Few prior studies have applied an ML approach in distinguishing BP from BPD with most delineating each condition separately from healthy controls (HCs). For example, using ML, BP has been distinguished from schizophrenia and HCs with an accuracy of 79% using functional magnetic resonance imaging (fMRI) responses to a verbal fluency task (Costfreda et al., 2011) and Schnack et al. (2014) using structural MRI data, achieved 61% accuracy in classifying BP vs. HCs. For BPD, Sato et al. (2012) used ML with structural neuroimaging data comparing BPD with HCs, with classification accuracy of 80%; and Xu et al. (2014) distinguished BPD from HCs using resting state fMRI with an accuracy of 93%. Only one study (Arribas et al., 2018) has used an ML approach to distinguish BP (non-subtyped), BPD and HCs. This study used sequential data gathered via smartphone mood ratings and demonstrated an overall accuracy of 75%. Our results offer comparable accuracy.

The classificatory accuracy of the ML approach (compared to DSM criteria) was relatively strong for BP however only marginally above chance for BPD, with moderate overall classificatory accuracy when both diagnoses were considered. When the continuous data obtained from the various included scales was dichotomised, diagnostic accuracy reduced only marginally, suggesting information obtained from clinical assessment could be used to enter variables into the PRE and determine diagnosis (this could be done by development of a simple app).

The current study identified key variables distinguishing BP from BPD, demonstrating moderate accuracy of classification when applied using a machine learning framework and which may assist in clarifying the differential diagnosis. Future studies could apply this strategy using larger numbers of participants or larger datasets to improve the accuracy of predictions. Additionally, studies could consider applying a similar approach to distinguishing comorbid BP/BPD patients from those who have each condition separately. Future studies building on our approach might also be developed into a computer program whereby rules are coded in such a way that a clinician or patient enters study variables and, based on the results of the rule-based program, the output classifies the patient as having BP or BPD.

Author statement

AB designed study, recruited participants and prepared manuscript; MS performed analyses; DHP contributed to analysis plan; GP assisted with overall study design and manuscript. All authors have approved the final article.

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Declaration of interest

None.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jad.2021.03.082.

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