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Machine learning approaches to distinguish bipolar disorder from borderline personality disorder: a scoping review

Aroldo Dargél[1,2,3,4,5*], Tanya Tanya[2,3], Sara Mahdiabadi[1,2], Risa Shorr[3] and Kathleen Pajer[1,5]

Abstract

Background Borderline personality disorder (BPD) and bipolar disorder (BD) are debilitating psychiatric illnesses with significant rates of misdiagnosis. This scoping review explores the potential of machine learning (ML) approaches in distinguishing individuals diagnosed with BD from those with BPD, reporting the performance metrics of various predictive models.

Methods We searched Ovid MEDLINE, PubMed, Scopus, and Web of Science from inception to March 2025 for studies involving the terms "bipolar disorder," "borderline personality disorder," "machine learning", and "artificial intelligence." Peer-reviewed research was included without restriction on publication date or language. Of 60 studies screened, 5 met the inclusion criteria. The review followed the PCC framework, JBI Reviewer's Manual, and PRISMA guidelines.

Results This study identified five studies that applied predictive models to data from 591 participants to differentiate individuals with BD and BPD. Classification accuracy ranged from 61.7% to 89%. While ML models outperformed DSM-based categorical approaches overall, accuracy differed markedly by diagnosis: correctly 87.8% for BD compared with 57.7% for BPD, illustrating the persistent diagnostic challenges for BPD. Models were more accurate in distinguishing patients with both BD and BPD from those with BD alone (79.6%) than from those with BPD alone (61.7%). ML techniques based on brain imaging features achieved 80% accuracy, while mood ratings collected via smartphone enabled the differentiation of BD, BPD, and controls with 75% accuracy.

Conclusion Currently, few predictive models have been developed to distinguish between BD and BPD. The findings of this review suggest that ML algorithms show moderate to good performance in clinical differentiation of BD and BPD. Further research is warranted to refine and validate predictive tools that aim to improve diagnostic precision in BD and BPD clinical practice.

Keywords Bipolar disorder, Borderline personality disorder, Artificial intelligence, Machine learning, Predictive tools

*Correspondence:
Aroldo Dargél
adargel@toh.ca
[1]Department of Psychiatry, Faculty of Medicine, University of Ottawa, Ottawa, ON, Canada
[2]Precision Psychiatry and Artificial Intelligence for Early Intervention and System Innovation in Affective Disorders (PRECISAI lab), Department of Psychiatry, University of Ottawa, Ottawa, ON, Canada
[3]Department of Mental Health, The Ottawa Hospital, Ottawa, ON, Canada
[4]Ottawa Hospital Research Institute, Ottawa, ON, Canada
[5]Children Hospital Eastern Ontario-CHEO Research Institute, Ottawa, ON, Canada

Introduction

Borderline personality disorder (BPD) and bipolar disorder (BD) are debilitating psychiatric illnesses with significant rates of misdiagnosis [1–4]. Although they are thought to develop through distinct mechanisms, differentiation is challenging due to shared transdiagnostic features, such as affective disturbances and impulsivity, as well as overlapping behaviors, including sexual disinhibition, substance misuse, self-harm, and suicidality [5–7]. Neuropsychological profiles appear more similar than different [8, 9], and screening instruments for BD have proven ineffective at distinguishing between the two [10]. Additionally, similar neurobiological abnormalities, including changes in the amygdala and reduced volume of the right medial orbitofrontal cortex (OFC), have been observed in both disorders [11].

Clinicians often struggle to distinguish between BD and BPD, particularly without a detailed longitudinal history [3, 12]. Trait-based impulsivity in BPD can resemble (hypo)manic disinhibition during cross-sectional assessments, potentially leading to a misdiagnosis of BD. Conversely, impulsivity in manic episodes is often misinterpreted as a core feature of BPD [5, 13, 14]. Mood elevation in BD—particularly irritable "highs" or mixed states—may be mistaken for emotional dysregulation, resulting in a BPD misdiagnosis [12, 15]. Studies indicate that up to 40% of individuals with BD exhibit mixed features, further complicating differentiation [16]. Moreover, misdiagnosing individuals with BD—who face a suicide risk 15 times higher than the general population— can divert clinical focus from managing BD's symptoms, resulting in worsening conditions, delayed diagnosis, treatment failure, and potentially fatal outcomes [17, 18].

These disorders differ significantly in terms of neurobiology, epidemiology, illness course, and therapeutic targets, making accurate diagnosis essential as treatment approaches vary widely [1, 5, 6]. While psychopharmacological treatment is recommended for BD [18], BPD patients typically respond better to psychotherapeutic modalities, such as Dialectical Behavioral Therapy (DBT) [19] and Mentalization-Based Treatment, due to lower response rates to medication [20]. Misdiagnosis and inappropriate treatment delay mood stabilization, prolong illness, and may lead to behavioral (e.g., chronic mood instability, emotional dysregulation), systemic (e.g., cardiometabolic disturbances), and functional consequences (e.g., cognitive decline) [13, 15, 21], exacerbating emotional distress and further impairment.

Evidence indicates a high co-occurrence of BD and BPD [22–24]. Comparisons of BD, BPD, and their co-occurrence (BD-BPD) reveal distinct patterns in emotion regulation strategies and recalled parental behaviors across these groups [22, 25]. Euthymic bipolar patients assessed by a structured interview had comorbid personality disorders in around 30%, including BPD [26], aligning with the growing focus on personality functioning in mental disorders, as reflected in DSM-5 [27] and ICD-11 [28]. Conversely, latent class analysis on a large sample of US adults identified three distinct factors (BPD, depression, and mania), with correlations supporting two distinct syndromes (BP and BPD) with potential comorbidity [29]. Differentiation between BP and BPD achieved 92–95% accuracy, with childhood sexual abuse, depersonalization, sensitivity to criticism, relationship difficulties, and absence of BP family history as key predictors [30]. Neuroimaging studies have identified brain abnormalities that distinguish the two conditions; however, their diagnostic precision is limited by high inter-individual variability in brain functional parameters and a reliance on traditional parametric or univariate statistical methods, which assume normal distributions [11, 31].

Machine learning (ML) techniques, a subset of Artificial Intelligence (AI) methods, utilise large numbers of predictor variables to uncover underlying patterns without relying on strict parametric assumptions, and are gaining interest in mental health research [32, 33]. Emerging research highlights the potential of ML techniques in distinguishing between mental disorders, offering promise for improved diagnostic accuracy and treatment outcomes. Unlike traditional statistical methods, which often assume fixed models and struggle with datasets where predictors outnumber participants, ML allows data to "speak for themselves" and may provide more realistic insights [32, 34]. To date, only a limited number of studies have applied ML techniques specifically to the differentiation of BD and BPD, with the earliest of these published in 2018 [22, 35, 36]. To address this gap, we conducted a scoping review to map the existing literature on the potential of machine learning techniques in distinguishing individuals diagnosed with BD from those with BPD, identifying the most relevant variables for differentiation and summarising the performance of reported predictive models.

Materials and methods

Search strategy

The search was carried out in four electronic databases: Ovid MEDLINE, PubMed, Web of Science, and Scopus, from their inception to March 2025 by applying a combination of the following search terms bipolar disorder (e.g., mania, bipolar); borderline personality disorder (e.g., BPD, emotional intensity disorder), and Artificial Intelligence (e.g., Machine Learning). The research strategy was developed in collaboration with a librarian (RS), and the reference lists from identified studies were also hand searched for any additional studies. The protocol

for this study was published on OSF in January 2025 [37]. See Additional file 1 for the detailed search strategy.

All the articles selected were peer-reviewed primary research publications. No restrictions were applied to the publication date. After conducting the search and importing articles into Covidence, we used the inclusion and exclusion criteria to select studies for the review. The process followed the PCC (Population, Concept, Context) [38, 39] and adhered to PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews) guidelines [40].

Inclusion/exclusion criteria

The inclusion and exclusion criteria were developed based on the PCC framework [39]. Inclusion criteria: Individuals diagnosed with BD, BPD, or both (BD-BPD), according to DSM criteria, with the concept of distinguishing between the two disorders. Exclusion criteria: individuals with primary diagnosis of psychotic or current substance use disorders, with intellectual disabilities or those with a history of head trauma, brain injury, or neurosurgery; studies that did not apply ML approaches for differentiating between BD and borderline personality disorders. Eligible contexts include ML techniques that predict the distinction between BD and BPD. Eligible study designs included prospective/retrospective cohorts, and cross-sectional studies reporting ML performance metrics. Case reports, reviews, abstracts, editorials, opinion pieces, and animal studies were excluded from the screening process.

Study selection and data extraction

A total of 60 studies were imported into Covidence and screened by two raters (TT, SM, AA, MI) using article title, abstract, and full-text screening. A third rater, AD, resolved all conflicts. The articles whose titles and abstracts were relevant underwent full-text screening. Then, articles that met the exclusion and inclusion criteria and parameters were included ($n = 5$, Fig. 1). Table 1 summarizes the study characteristics, including study design, study setting, sample size, patient characteristics (e.g., age, sex, primary diagnosis), and type of ML approach used. Table 2 summarizes the performance of the selected model in each study.

Results

Study selection

The PRISMA review selection process for the articles included in the review is shown in the diagram in Fig. 1.

A total of 60 articles were generated from the search strategy from four databases after Covidence removed 32 duplicates. Using Covidence to screen for relevant articles from the title and abstract, 28 articles were selected. Finally, after the full-text screening phase, five articles met the inclusion criteria and were eligible for inclusion in this review.

Study characteristics

The five studies included in this review involved a total of 591 participants, with individual study sample sizes ranging from 45 to 187, and participants' ages ranged from 18 to 59 years. All included studies were cross-sectional and collected patient sex data, with predominantly female (51.7%) subjects. Patients included in the studies were adults with a preexisting psychiatric diagnosis of BD ($n = 262$), BPD ($n = 180$) or comorbid BD/BPD ($n = 53$) in outpatient settings. Two studies also included healthy controls (HC) ($n = 96$). Geographically, the studies spanned multiple countries, including the United Kingdom, Iran, Italy, and Australia.

Outcomes: predictive models

The included studies investigated the potential of ML techniques for differentiating between individuals with BD or with BPD, including ML algorithms [e.g., random forest (RF), prediction rules ensemble (PRE), neural networks (NN), multiple learning kernel (MLK), and support vector machines (SVM)].

All included studies reported overall accuracy, while only two studies assessed performance by measuring the area under the ROC curve (AUC) [14, 31]. A higher AUC indicates high performance and greater accuracy in distinguishing between categories, and thus, a higher predictive value. AUC is beneficial for imbalanced datasets, as it considers performance across all possible thresholds, whereas accuracy focuses on the overall proportion of correct predictions [34].

Bayes et al., 2021 compared BP vs. BPD groups using continuous and dichotomized data, with ML-allocated diagnoses compared to DSM diagnoses [35]. Overall, classificatory accuracy ranged from 73.1 to 73.9%. PRE-derived diagnoses achieved higher accuracy in classifying BD (84.1% – 87.8%). Compared to BD allocation, the accuracy of BPD classification was substantially lower, ranging from 50% to 57.7% for DSM. Feature importance differed between the analyses, with the top five important items including identity difficulties, relationship problems, female gender, feeling suicidal after a relationship breakdown and age, which suggests a substantive overlap between the two analyses [35]. A data re-analysis by Bayes et al. (2021) applied the PRE technique to identify key variables distinguishing comorbid BP and BPD from each condition individually. Compared to DSM-assigned diagnoses, PRE-derived diagnoses offered a high accuracy of 79.6% in classifying comorbid BD-BPD vs. BD but a lower accuracy rate of 61.7% in distinguishing comorbid BD-BPD vs. BPD [22]. Nazari et al., 2024 employed 24 different ML approaches to differentiate between BD type II

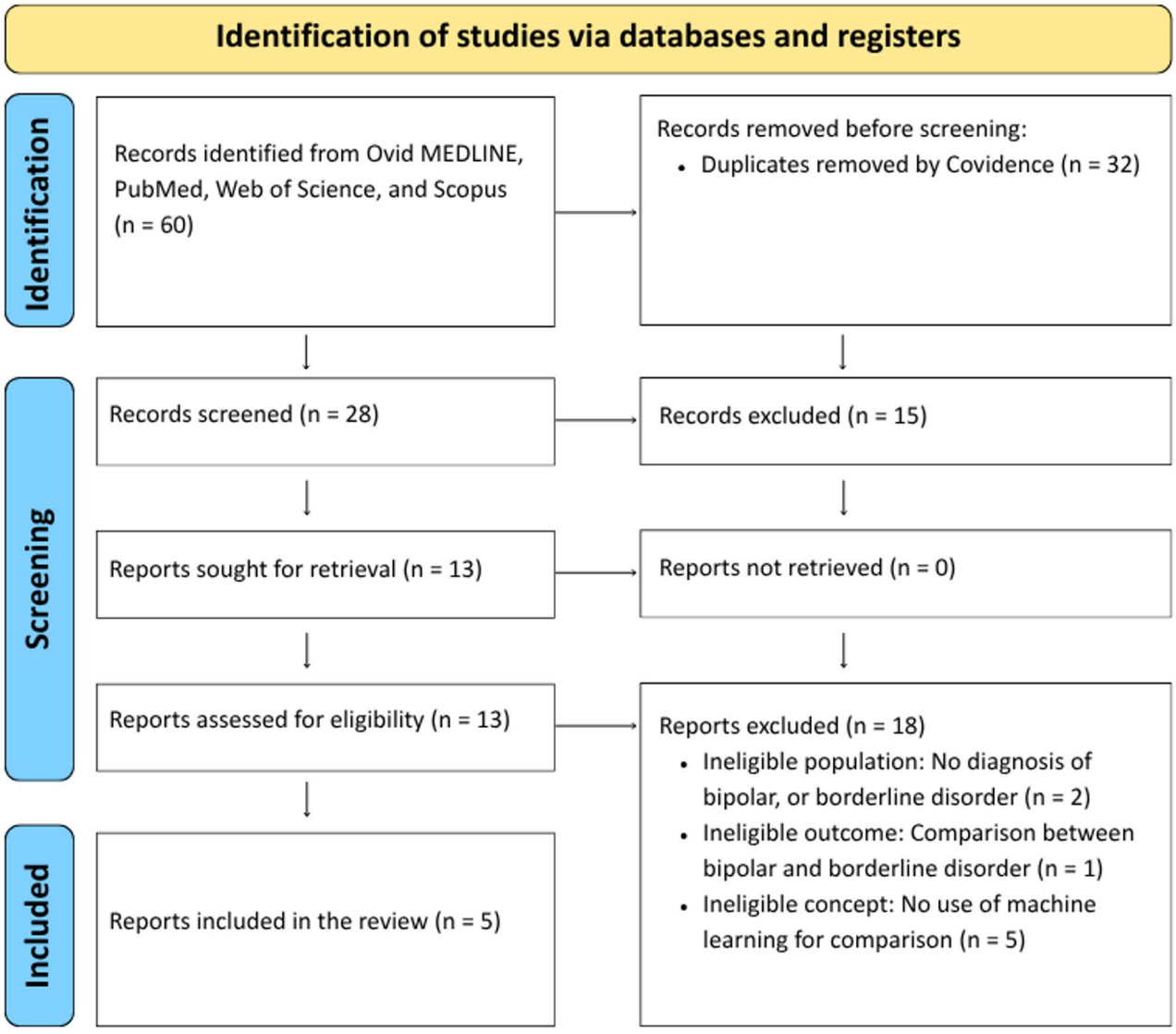

Fig. 1 PRISMA search strategy diagram

and BPD, using both electroencephalography (EEG) and cognitive test data (i.e., Wisconsin Card Sorting Test and Integrated Cognitive Assessment) [36]. Among diverse ML techniques applied in this study, the KNN algorithm demonstrated the highest performance (89% accuracy), suggesting that EEG features have a higher contribution than cognitive test data in differentiating between BD II and BPD [36]. By using a supervised ML method, Grecucci et al. 2022 classified individuals with BPD, BD, or HCs based on structural brain features [31], showing that patients with BPD were correctly and reliably classified against those with BD (AUC = 0.83; Accuracy = 80%) and HC (AUC = 0.88; Accuracy = 84.62%). The top three brain regions with larger contributions to the model (weight > 1%) were the right pallidum, the right inferior frontal cortex, and the right amygdala [31]. Prez-Arribas et al., 2018 have demonstrated an overall accuracy of 75% to distinguish BD, BPD, and HCs using a ML approach based on sequential mood rating data gathered via smartphone [14].

Discussion

Accurately distinguishing BD from BPD remains a clinical challenge, with significant treatment implications—mood stabilizers are key for managing BD, while psychotherapy is the foundation of BPD care. Although the clinical implications are substantial, no biomarkers currently provide reliable diagnostic differentiation. This review highlights how ML approaches are being applied to enhance diagnostic precision, offering insights into their methodology, performance, and potential utility in real-world clinical practice.

Table 1 Study characteristics

Author, Year, Country	Study Design	Sample Size, n (%)					Age, Mean (SD)				Females, *n* (%)				Setting (OP, IP)	Data Source	Machine learning technique
		N	BD	BPD	BD-BPD	HC	BD	BPD	BD-BPD	HC	BD	BPD	BD-BPD	HC			
Nazari et al., 2024 Iran [36]	Cross- sectional	45	20 (44.4)	25 (55.6)	-	-	31.9 (9.8)	30.64 (11.4)	-	-	7 (35.0)	21 (84.0)	-	-	OP	Socio-demographic and clinical data from surveys/ clinical questionnaires; neuroimaging data	Support Vector Machines, K-Nearest Neighbors, Random Forests, Neural Networks
Grecucci et al., 2022 Italy [31]	Cross- sectional	95	30 (31.6)	20 (21.1)	-	45 (47.3)	37.1 (8.6)	35.7 (8.6)	-	36.8 (8.4)	21 (70.0)	17 (85.0)	-	34 (75.5)	OP, IP	Socio-demographic and clinical data from surveys/ questionnaires; neuroimaging data	Multiple kernel learning
Bayes et al., 2022 Australia [22]	Cross- sectional	187	82 (43.8)	52 (27.9)	53 (28.3)	-	33 (-)	30 (-)	32 (-)	-	18 (53.7)	25 (84.6)	26 (80.8)	-	OP, IP	Socio-demographic and clinical data from surveys/ questionnaires	Prediction rule ensembles
Bayes et al., 2021 Australia [35]	Cross- sectional	134	82 (61.2)	52 (38.8)	-	-	33 (-)	30 (-)	-	-	18 (53.7)	25 (84.6)	-	-	OP, IP	Socio-demographic and clinical data from surveys/ questionnaires	Prediction rule ensembles
Perez Arribas et al., 2018 United Kingdom [14]	Cross- sectional	130	48 (36.9)	31 (28.8)	-	51 (39.3)	38 (21.0)	34 (15.0)	-	37 (20.0)	32 (66.6)	29 (93.5)	-	33 (64.7)	OP	Socio-demographic and clinical data from surveys/ questionnaires	Random Forest

BD = bipolar disorder; BPD = borderline personality disorder; BD-BPD = patients with both conditions; HC = healthy control; OP = Outpatient; IP = Inpatient

Table 2 Performance for different models in different studies

Study	BPD vs. BD		BD vs. BD-BPD		BPD vs. BD-BPD	
	AUC	Accuracy	AUC	Accuracy	AUC	Accuracy
Nazari et al., 2024 [36]	-	89%	-	-	-	-
Grecucci et al., 2022 [31]	83%	80%	-	-	-	-
Bayes et al., 2022 [22]	-	-	-	79.6%	-	61.7%
Bayes et al., 2021 [35]	-	73.9%[a] 73.1%[b]	-	-	-	-
Perez Arribas et al., 2018 [14]	86%	80%	-	-	-	-

[a] DSM raw scores used for analysis, [b] DSM dichotomization of raw scores

AUC = area under the curve; BD = bipolar disorder; BPD = borderline personality disorder; BD-BPD = patients with both conditions

Predictive models' performance

Using previously published datasets [9, 23, 30], Bayes et al. (2021) applied the PRE approach to classify BD and BPD based on emotion regulation strategies, childhood parenting experiences, and personality traits. Although the PRE model outperformed DSM criteria in classifying BD (87.8% accuracy), its accuracy (57.7%) for BPD was only slightly above chance [35], reflecting the challenge of diagnosing BPD via symptom-based criteria. The PRE method generated numerous rules, some of which were difficult to interpret, though variable importance analysis provided clinically meaningful insights. BD was associated with a more coherent sense of self (modulated by mood state, perceived self-deficits when depressed and grandiose self when elevated), while BPD was linked to relationship instability, suicidal thoughts following rejection, and higher rates of childhood sexual abuse [3, 41]. Other important BPD features included stress-related paranoid ideation, childhood depersonalization, and female gender, consistent with epidemiological trends [4, 17]. A family history of BD was more common in the BD group [40], further aiding differentiation. However, the study overrepresented BD II, excluded comorbid BD-BPD cases, and participants were volunteers who were likely to have milder symptoms; it also included relatively few BPD participants, contributing to the lower classification accuracy for BPD [35].

Bayes et al. (2022) identified distinct rule sets for classifying comorbid BD-BPD versus BD or BPD alone. Paranoid ideation under stress was most predictive of BD-BPD vs. BD, reflecting core BPD features [26]. Impulsivity emerged as a transdiagnostic marker, though its expression varies—state- and trait-dependent in BD [16] and more maladaptive behavior in BPD [1, 2]. Compared to BPD alone, those with BD-BPD reported greater difficulties with emotion regulation, reduced impulse control, and more adverse childhood experiences, suggesting additive effects that complicate diagnosis. Classification was less accurate for BD-BPD vs. BPD, highlighting diagnostic overlap. However, findings were limited by DSM-based diagnoses (which may lack validity), small datasets, and a lack of model validation [22].

Two studies have integrated neurobiological markers into ML models for distinguishing BPD from BD [31, 36]. By using a whole-brain supervised ML technique, Grecucci et al. (2022) identified alterations in the putamen–amygdala–OFC circuit as specific to BPD [31], consistent with known roles in affective instability and emotion dysregulation [42]. However, the findings were limited by small sample sizes for BPD, which may affect prediction cross-validation. MRI-based models have achieved up to 93.6% accuracy in distinguishing between BPD and healthy controls, and 59% accuracy in distinguishing between BD and healthy controls [43, 44]. Nazari et al. (2024) used EEG and cognitive features to classify BD II and BPD, with EEG offering greater discriminative power [36]. However, prior work found no significant EEG differences between these groups [45], suggesting possible biological overlap. Despite heterogeneity in datasets, these studies highlight the value of combining neurobiological features with diverse ML methods (e.g., KNN, SVM, Decision Trees, XGBoost) to improve diagnostic precision and understanding of underlying pathophysiology [32, 33, 46].

A Random Forest model using daily mood data classified 75% of participants correctly, outperforming traditional metrics such as mean mood scores (54%; [14]). It also predicted next-day mood with high accuracy (89–98% in HC; 82–90% in BD, and 70–78% in BPD), highlighting distinct mood dynamics across groups [14]. The overlap between BD and HC suggests partial mood normalization in BD, which is consistent with clinical observations; while BPD showed clear separation from both, supporting its status as a distinct disorder. Despite limitations such as a stable sample (excluding acute subjects or those with significant comorbidities) mostly on psychotropic medications, these findings underscore the diagnostic value of mood-based ML models [14]. Incorporating daily mood and behavior data into AI-driven algorithms may further enhance prediction accuracy and reduce overreliance on traditional diagnostic frameworks for BD or BPD.

Limitations and strengths

A key strength of this review lies in its use of multiple databases to identify studies for inclusion, without restriction on publication date or language. This approach enhanced the diversity and representativeness of the analyzed sample. Additionally, the study provides a comprehensive review of existing predictive models that differentiate between BD and BPD, highlighting emerging trends and clinical implications.

However, several limitations should be noted. The scoping review design, while well-suited to capturing the breadth and heterogeneity of the existing literature, inherently limits the depth of analysis. A quantitative synthesis and formal quality appraisal were not conducted, as these procedures fell outside the scope of this review. As such, the findings serve primarily as a broad and informative overview, intended to support future systematic reviews and meta-analyses that focus on more narrowly defined research questions and apply rigorous evaluation criteria. A notable methodological constraint was the inclusion of many studies with small sample sizes, which reduced statistical power and limited the generalizability of results. Furthermore, the predominance of cross-sectional designs, along with the relative scarcity of prospective studies, restricted the ability to draw robust causal inferences.

Beyond methodological limitations, domain-specific gaps were also evident. A significant shortfall in the literature is the limited application of ML to distinguish BD from BPD or to address their frequent comorbidity, which constrains the scope of available evidence. Most included studies disproportionately represented individuals with BD II [22, 35, 36], limiting generalizability of the findings across the full bipolar spectrum, particularly BD I populations. Moreover, participants with comorbid BD and BPD were often excluded from the analyses [14, 31, 36], precluding insights into diagnostic overlap. This limitation is especially relevant given the symptom overlap—such as emotional dysregulation and impulsivity—between BD II and BPD, which complicates accurate diagnosis and may contribute to reduced responsiveness to mood stabilizers [4, 6, 26]. Indeed, over half of BD patients may exhibit traits commonly associated with BPD [5], increasing the risk of misdiagnosis and suboptimal treatment outcomes.

Accurately identifying comorbid BD-BPD is critical, as treatment priorities differ: mood stabilizers remain the first-line treatment for BD, whereas structured psychotherapy is essential for managing BPD. Although few studies have evaluated treatments targeting both conditions [47, 48] preliminary evidence suggests that mood stabilizers like lamotrigine and valproate may alleviate BPD-related symptoms in BD patients, including anger and interpersonal sensitivity [47]. Asenapine has shown some reduction in aggression in BD I patients, potentially offering greater benefits in those with comorbid BPD [49], though these effects may be partly attributed to sedation. Further research is needed to inform integrated pharmacological and psychotherapeutic strategies.

Another limitation in the reviewed literature is the lack of reporting on depressive symptom variation in BD and BPD, especially in comorbid cases. Subclinical depressive symptoms in BPD may reflect stress reactivity, while comorbid cases likely require more sustained, multidimensional care [26, 50]. Ecological momentary assessment studies underscore the dynamic, context-sensitive nature of mood fluctuations in both disorders, reinforcing the need for predictive tools that support proactive self-management and relapse prevention [51].

Finally, considerable heterogeneity in study design limited comparability across predictive models. Most studies relied on small and single-model approaches, heightening the risk of overfitting and reducing external validity. No investigations reported internal or external validation, limiting clinical applicability [14, 22, 31, 35, 36]. While initial findings suggest potential for predictive models, their utility remains constrained without validation in real-world settings. Future research should prioritize large-scale implementation studies, employ diverse model comparisons, and incorporate rigorous validation techniques. Transparency in model development and reporting will be essential for clinical integration- ensuring trust, safety, privacy, and ethical standards are upheld.

Conclusions

This scoping review reports that ML approaches for distinguishing BD from BPD remain in an early stage of development, with preliminary evidence suggesting moderate discriminative performance that varies substantially by diagnosis. Accurately distinguishing BD from BPD remains clinically challenging, and diagnosis continues to depend mainly on the patient's reports and the clinician's observation. Future studies leveraging longitudinal data, larger and more diverse cohorts, and a range of AI-driven approaches, integrating diverse ML algorithms, may enhance diagnostic accuracy and risk stratification—particularly considering the overlapping symptoms and fluid diagnostic boundaries between these conditions. With advances in digital and computational phenotyping [32, 33, 52], leveraging multimodal patient data through AI-driven systems can support clinicians in delivering more accurate diagnoses and timely interventions, ultimately improving patient outcomes and long-term prognosis.

Supplementary Information

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Supplementary Material 1

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Author contributions
A.D. and T.T. contributed to the conceptualization of the study. A.D., T.T., S.M. and R.S. collaborated throughout the review process. A.D., T.T., and K.P. collaborated throughout manuscript writing. AD supervised the review, and all authors reviewed the final draft of the manuscript.

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Data availability
No, I do not have any research data outside the submitted manuscript file.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
I confirm that I understand BMC Psychiatry is an open-access journal that levies an article processing charge per article accepted for publication. By submitting my article, I agree to pay this charge in full if my article is accepted for publication.

Competing interests
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