A network analysis of borderline personality disorder symptoms: a real-world data (RWD), electronic health record (EHR) study

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BACKGROUND

Borderline Personality Disorder (BPD) is a heterogeneous disorder.[1] The current study used network analysis of electronic health record (EHR) data to explore associations between symptom groupings in patients diagnosed with BPD.

METHOD

- Patients with a diagnosis of BPD (ICD-9: 301.83, ICD-10: F60.3) and symptom data recorded within 1 month of diagnosis were included in the study.
- Symptom data recorded by healthcare professionals as part of clinical assessment were extracted from the NeuroBlu database (Figure 1 and 2).
- Symptoms were mapped into 9 BPD-specific constructs (affect instability, problems with relationships, impulsivity, emptiness, problems with anger control/irritability, identity disturbance, (para)suicide, fear of abandonment, dissociation). Pairwise associations were quantified using an average of the symptoms regression coefficient and visualised using a network graph.
- Analysis was conducted using R version 4.1.2 & Isingfit package v0.3.1
- The network of symptoms was estimated using Enhanced Least Absolute Shrinkage and Selection Operator (eLASSO).[2]
- Model selection was based on the Extended Bayesian Information Criterion (EBIC). Centrality measures of betweenness, closeness and strength were calculated.
- Fruchterman-Reingold[3] (spring-type) network structure was used, which places the most central nodes visually centre in the network graph.

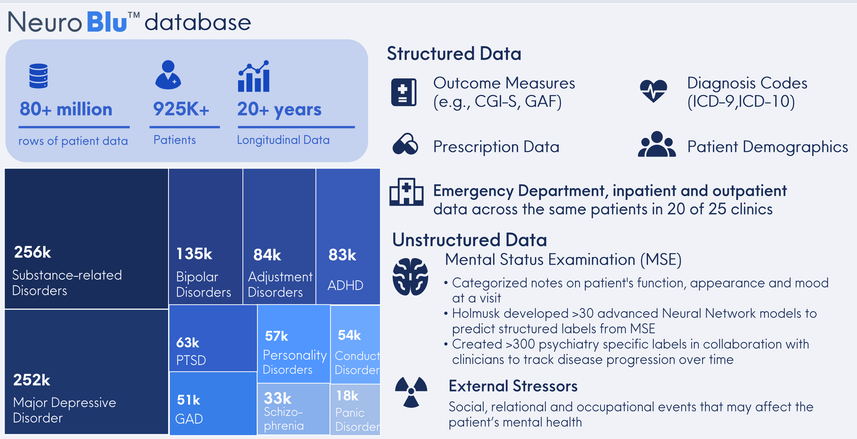

Figure 1. NeuroBlu Database overview

Data Source of US Health Facilities

De-identified EHR data were obtained from U.S. mental health services that use the MindLinc EHR system. The data were analysed in NeuroBlu, a secure Trusted Research Environment (TRE) that enables data assembly and analysis using an R/Python code engine.[4]

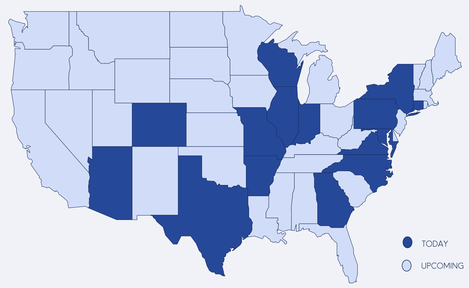

Figure 2. State specific data source for NeuroBlu

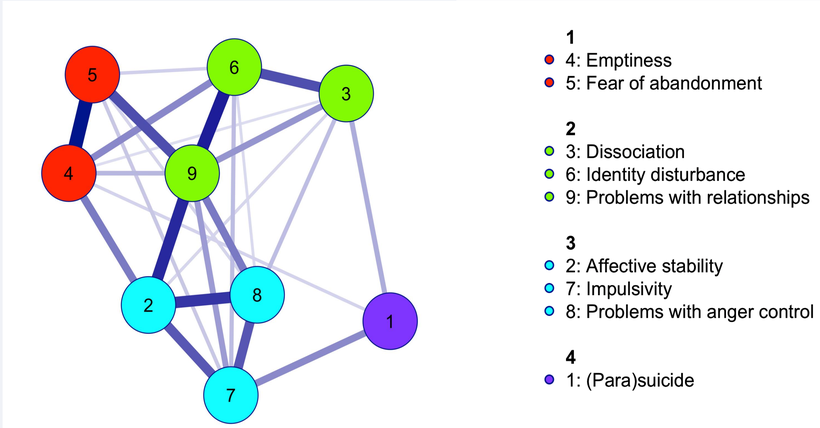

Figure 3. Network of BPD symptoms from data recorded from n=2,287 patients recorded within a month of diagnosis. BPD symptom constructs are represented as numbered nodes, the lines between each node indicates a partial correlation between two symptoms (correlation between two symptoms after controlling for all other symptoms within the network) The thickness of the line indicates the strength of association. The color of each node represents a cluster of symptoms listed on the right.

RESULTS

Data from 2,287 patients (Mean(SD) age=32.7(11.8) years; 85.1% female) with a diagnosis of BPD were used in the current analysis. 301 unique symptoms were recorded and mapped into 9 BPD specific constructs. Affective instability (n=1889, 82.8%), problems with relationships (n=1721, 75.3%) and impulsivity (n=1712, 74.9%) were the most frequently reported symptoms. The network of BPD symptoms is shown in Figure 3, and centrality indices are illustrated in Figure 4. Relationship problems were the most central node in the network. Affect instability was also important to the network, as indicated by the centrality indices. The edges of emptiness – fear of abandonment, identity disturbance – problems with relationships and problems with relationships - affective stability showed strong associations.

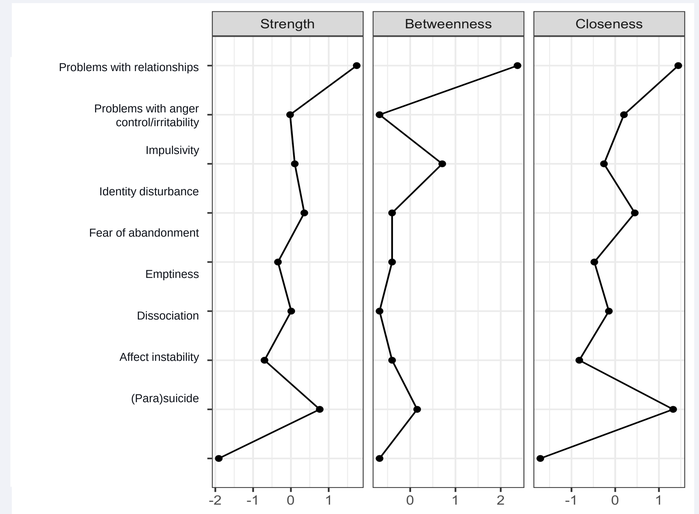

Figure 4. Centrality indices of BPD symptom network. Strength indicates the level of direct connection between one node and another. Betweenness quantifies the importance of a node in the average path between two other nodes. Closeness indicates how well a node is indirectly connected each other.

CONCLUSION

Affective instability, problems with relationships and impulsivity are key constructs in BPD. This finding is in-line with a previous cross-sectional analysis of BPD symptoms from semi structured diagnostic interviews assessing symptom stability by age.[5] Further exploration into the association between BPD symptom clusters could identify patient subtypes and provide insight into the heterogeneity of BPD[6] and help to personalise treatment pathways.

Conflicts of Interest: All authors report current employment with Holmusk Technologies, Inc. RP reports equity ownership in Holmusk Technologies, Inc

References:
1. Garland J, Miller S. Borderline personality disorder: part 1–assessment and diagnosis. BJPsych Advances. 2020;26(3):159-172.
2. van Borkulo CD, Borsboom D, Epskamp S, et al. A new method for constructing networks from binary data. Scientific Reports. 2014/08/01 2014;4(1):5918. doi:10.1038/srep05918
3. Fruchterman T. M. J., Reingold E. M. (1991). Graph drawing by force-directed placement. Software Pract. Exp. 21, 1129–1164. 10.1002/spe.4380211102
4. Patel R, Wee SN, Ramaswamy R, et al. NeuroBlu, an electronic health record (EHR) trusted research environment (TRE) to support mental healthcare analytics with real-world data BMJ Open 2022;12:e057227. doi: 10.1136/bmjopen-2021-057227
5. Peters JR, Crowe ML, Morgan T, Zimmerman M, Sharp C, Grilo CM, Sanislow CA, Shea MT, Zanarini MC, McGlashan TH, Morey LC, Skodol AE, Yen S. Borderline personality disorder symptom networks across adolescent and adult clinical samples: examining symptom centrality and replicability. Psychol Med. 2022 Jan 31:1-8. doi: 10.1017/S0033291721004931. Epub ahead of print. PMID: 35094733
6. Oladottir K, Wolf-Arehult M, Ramklint M, Isaksson M. Cluster analysis of personality traits in psychiatric patients with borderline personality disorder. Borderline Personality Disorder and Emotion Dysregulation. 2022/02/08 2022;9(1):7. doi:10.1186/s40479-022-00178-

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