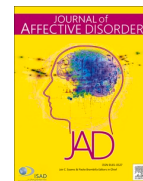




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Research paper

## An exploration of the relationship between ineffective modes of mentalization and difficulties related to borderline personality disorder: A network approach

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## ABSTRACT

**Background:** The mentalization-based perspective of Borderline Personality Disorder (BPD) underscores fluctuating interpersonal functionality, believed to arise from suboptimal mentalization modes, including hyper- and hypomentalizing. The connection between ineffective mentalizing and specific BPD challenges remains ambiguous. Network theory offers a unique means to investigate the hypothesis that distinct yet interconnected mental challenges ('symptoms') construct 'disorders' through their continuous mutual interactions. This study aimed to probe the pairwise interrelations between ineffective mentalizing and BPD challenges and to distinguish these relations between individuals with (clinical group) and without (community group) a BPD diagnosis using a network analysis approach.

**Methods:** Through a cross-sectional secondary data analysis, a moderated Mixed Graphical Model was employed on data from 575 individuals (350 clinical, 225 community). The study evaluated associations between ineffective mentalization modes (hypermentalizing, hypomentalizing, and no mentalization) gauged by the MASC and self-reported BPD-associated challenges, using BPD diagnosis as the moderating variable.

**Results:** The analysis confirmed the presence of significant links between ineffective mentalizing and specific interpersonal BPD challenges, which were moderated by BPD diagnosis. It implied that hypermentalizing and hypomentalizing might simultaneously shape BPD-associated challenges.

**Conclusions:** The results offer fresh insights into the interplay between hypermentalizing, hypomentalizing, and BPD-related difficulties.

## 1. Introduction

Borderline Personality Disorder (BPD) represents a significant psychiatric disorder that disrupts various facets of daily functioning,

impacting an individual's emotional experiences, cognitive processes, and behavioural patterns (American Psychiatric Association, 2013). A central etiological perspective of BPD lies in the mentalization-based developmental model (Fonagy and Bateman, 2007). Mentalizing is

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understood as a capacity gained over development, an internal imaginative facility, enabling an individual to comprehend and interpret their own and others' explicit actions and behaviours as manifestations of underlying mental states (Fonagy et al., 2002). A substantial volume of empirical studies substantiates the association between borderline symptomatology and ineffective mentalizing in both adults and adolescents (Akca et al., 2021; Badoud et al., 2018; Berenson et al., 2018; Euler et al., 2021; Fossati et al., 2018; Kvarstein et al., 2020; Normann-Eide et al., 2020; Sharp et al., 2013, 2011; Somma et al., 2019). Although overall associations have been ascertained, the intricate bi-directional dynamics between individual BPD-related symptoms and the diverse ineffective forms of mentalizing largely remain uncharted.

The network approach, which prioritizes individual symptoms over the dichotomous categorization of disorder presence or absence, aids in the exploration of specific BPD symptoms' unique contributions to the persistence of the disorder (Bringmann and Eronen, 2018). Instead of viewing mental disorders as isolated latent entities formed by clusters of covarying symptoms, the network model assumes that complex network of symptoms directly affect and influence each other, leading to the emergence of disorders (Borsboom, 2017b; Borsboom and Cramer, 2013; Cramer and Borsboom, 2015). Interlinked difficulties are examined as they are suspected to provide the very essence and source of mental problems due to the meaningful interactions found between them.

According to this approach, symptoms reinforce and feed back to each other, creating loops and vicious cycles until the symptoms' activation becomes persistent in the network, which is when a harmful equilibrium state or in other words a mental health problem emerges clinically (Borsboom, 2017b). Individual symptoms may be triggered by external events and depending on the network's state, the activation spreads and interconnected difficulties are stimulated. Highly connected networks facilitate and accelerate the activation of nodes to a greater extent than less connected networks (Borsboom, 2017a). Once a network is induced, it can turn into an independent, self-sustaining entity over time, preserving its internal activation in the absence of the original external trigger (Borsboom, 2017b). Weakly connected networks might respond to adverse environmental impacts by gradually and continuously increasing their connectivity (Fried et al., 2017; van de Leemput et al., 2013). In contrast, strongly connected networks, may be characterised by a prolonged period of recovery from additional external triggers due to the already high level of coactivation between the difficulties (Fried et al., 2017). In this sense, the theory of epistemic mistrust, that is closely linked with mentalization as it represents the inability to acquire and accommodate new knowledge for the purpose of adequate social communication (Fonagy et al., 2015), may overlap with the network theory, which captures the self-sustaining aspect of highly connected systems that are difficult to de-activate due to their existing patterns of connectivity (Borsboom, 2017b). Both would suggest that people's level of psychopathology depends on the level of rigidity that they exhibit in the face of new experiences and information, particularly in emotionally stressful social situations (Fonagy and Allison, 2014).

Given that network structures likely differ among individuals with varying severity of difficulties, integrating ineffective modes of mentalization into network models of BPD-related complications could provide an avenue for examining and comparing unique connections among these features across different levels of system activation. Furthermore, this model's ability to incorporate additional external or internal variables offers a robust tool to disentangle the fundamental dynamics related to ineffective mentalizing. This exploration could yield a more profound understanding of the implications of impaired mentalizing across a spectrum of BPD-related issues, potentially informing therapeutic strategies aimed at enhancing mentalization.

In summary, this study aims to illuminate how ineffective modes of mentalization are associated with BPD-related complications in both BPD-diagnosed and undiagnosed individuals. To achieve this, we will examine the complex interaction between mentalizing deficits

(specifically hypermentalization, hypomentalization, and no mentalization) and the BPD symptom network in two distinct groups, BPD-diagnosed and undiagnosed individuals. In line with the mentalization-based model, we anticipate identifying connections between various mentalization deficits and BPD-related characteristics, with these network patterns expected to differ between the two participant samples.

## 2. Method

### 2.1. Design

The present study utilized data gathered within the expansive research project, "Probing Social Exchanges," which seeks to comprehend Borderline and Antisocial Personality Disorders (ASPD) through behavioural and neuroimaging techniques (Michael et al., 2021; Wendt et al., 2019, 2023, Kumpasoglu et al., 2024; Lahnakoski et al., 2024; Schwarzer et al., 2024). This study employs a cross-sectional correlational design, wherein a network incorporating BPD-related symptoms and three forms of ineffective mentalizing is created as a mathematical representation of conditional associations among these issues. To dissect the structure of this network and comprehend the intricate interactions between symptoms, network analysis was adopted (Borsboom, 2017b). For clarity and succinctness, individuals without a BPD diagnosis are labelled as the "community group," while those with a BPD diagnosis are termed the "clinical group."

### 2.2. Participants

The clinical sample was recruited using a non-probabilistic consecutive sampling technique from personality disorder services in London. Conversely, the community control group was sourced through posters and online platforms using a non-probabilistic purposive sampling approach, ensuring a closer demographic alignment between the groups.

Eligible participants were individuals aged between 18 and 60, possessing proficiency in understanding and writing in English. For the clinical sample, a suspected or confirmed primary diagnosis of BPD or ASPD was an essential inclusion criterion. Individuals with severe learning disabilities, with current or past neurological disorders or trauma were excluded from participation, alongside people with psychotic or mood disorders or substance use disorders. Within the community control group, individuals with any current or past psychiatric or personality disorder diagnosis were excluded.

In the clinical sample, the presence of a BPD or ASPD diagnosis was affirmed using the Structured Clinical Interview for Diagnostic and Statistical Manual-Fourth Edition Axis II Disorders (First and Gibbon, 2004), as this was the most recent diagnostic system at the time the data was collected (the DSM-5 and the ICD-11 had not yet been released). For the community sample, the absence of any personality disorder was ascertained through the Standardised Assessment of Personality-Abbreviated Scale questionnaire (Fok et al., 2015). Any participant scoring above a threshold of four was further evaluated using SCID-II. Individuals meeting the criteria for BPD were reclassified into the group with a clinical diagnosis.

The recruitment process continued until March 2020. In total, the study enrolled 971 participants. For the current study's purposes, individuals primarily diagnosed with ASPD were omitted from the analysis, culminating in a final participant count of 658. Nine individuals withdrew from the study, and three cases were discarded due to data entry errors, resulting in a final sample size of 646.

### 2.3. Materials

#### 2.3.1. BPD-related difficulties

The Personality Assessment Inventory - Borderline Personality

Feature Scale (PAI-BOR) was utilized to quantify BPD-related characteristics (Morey, 1991). The PAI-BOR is a 24-item self-report instrument designed to gauge BPD-related psychopathological features using a 4-point Likert scale. The items were developed to assess specific BPD characteristics (e.g., “My mood can shift quite suddenly”) and align directly with the DSM-4 and DSM-5 criteria of the construct (American Psychiatric Association, 2013; Morey, 1991). The PAI-BOR has been effectively utilized across various settings and populations, both clinical and non-clinical, and exhibits satisfactory psychometric properties (Bell-Pringle et al., 1997; Morey, 1991; Trull, 1995). The statistical analysis detailed below employs the questionnaire items and the raw values that respondents indicated for them (0–3). Before conducting the relevant analyses, reverse score transformation was implemented on the respective items.

### 2.3.2. Ineffective mentalizing

The Movie for the Assessment of Social Cognition (MASC) was employed to measure self-related mentalizing and various ineffective modes of mentalization (Dziobek et al., 2006). The MASC is a video-based behavioural assessment that gauges participants’ subtle mentalizing abilities while they watch a 15-min movie about four individuals at a social gathering (Dziobek et al., 2006). The movie includes 45 pauses during which participants answer a multiple-choice question concerning the mental states of the individuals depicted in the movie. The responses include four options: 1) correct answer (appropriate mentalizing), 2) hypermentalizing/over-mentalizing (excessive attribution of mental states without observable data to justify it; MASCcorr), 3) hypomentalizing/under-mentalizing (misattribution of mental states due to reduced mentalizing; MASCless), and 4) no mentalizing (total absence of inferring mental states in social situations, with inferences being drawn based on physical causations; MASCno). Four sum scores are computed based on the frequency of each answer selected, with one score for correct responses and three scores for different types of errors. In this study, the three subscales of ineffective mentalization modes were employed. The MASC has demonstrated satisfactory psychometric properties on numerous occasions (Dziobek et al., 2006; Fossati et al. (2018); Preißler et al. (2010). Convergent and discriminant validity of the measurement has been demonstrated by Dziobek et al. (2006); Fossati et al. (2018); Preißler et al. (2010) and test-retest reliability was also found to be high ( $r = 0.97$ ; Dziobek et al., 2006). Adequate and high internal consistency of the MASC was demonstrated in both clinical ( $\alpha = 0.78$ ) and non-clinical samples respectively ( $\alpha = 0.80$ ; Fossati et al., 2018).

## 2.4. Data analysis

All statistical computations were conducted using R, version 4.0.5 (R Core Team, 2021), and IBM SPSS Statistics, version 18.0.

### 2.4.1. Missing data analysis

Initially, participants who did not complete either the PAI-BOR questionnaire or the MASC task were removed from the analyses, reducing the participant count to 575. To address any potential selection bias, a chi-square test of association and Mann-Whitney  $U$  tests were executed in SPSS. Results of these analyses can be found in the supplementary material. Subsequently, missing data was managed using the R “mice” package, which performs multivariate imputation by chained equation (van Buuren and Groothuis-Oudshoorn, 2011).

### 2.4.2. Non-paranormal transformation

Given that the pertinent variables were not normally distributed, the R “huge” package was employed to apply a nonparanormal transformation to the dataset. This transformation ameliorated normality and ensured that the assumption of a normal distribution of residuals was satisfied for all regression models (Epskamp and Fried, 2018; Zhao et al., 2012).

### 2.4.3. Item redundancy

Network analysis presumes that the nodes of the network represent unique entities measuring distinct constructs (Peckham et al., 2020). Failure to meet this assumption, where the examined items (PAI-BOR items and MASC error subscales) load onto the same underlying construct or a smaller latent variable, would render these items redundant. Such redundancy could lead to suboptimal model fit and increased risk of false positive correlations (Christensen et al., 2020; Santiago et al., 2021). To statistically identify potential redundant variables in the data and minimize inaccurate estimates of dimensional structures, Unique Variable Analysis (UVA) was utilized (Christensen et al., 2020). This analysis was performed in R using the “EGAnet” package. Adhering to the guidelines of Christensen et al. (2020), weighted topological overlap statistics (wTO) were estimated with an adaptive alpha (Pérez and Pericchi, 2014; Zhang and Horvath, 2005). When redundancies were identified between a set of items, these items were consolidated into a new minor latent factor rather than being eliminated, thereby preventing the loss of substantial information. Decisions regarding the combination of potential redundancies into a new variable were informed by theoretical knowledge about the topological overlap between the variables in question. Full results of the UVA are reported in the supplementary material.

### 2.4.4. Mixed Graphical Model analysis

Given that the data encompassed a mix of ordinal (PAI-BOR), continuous (MASC), and binary data (BPD diagnosis), a Mixed Graphical Model (MGM) was employed to investigate potential differences in the network connectivity patterns among the two groups (Haslbeck and Waldorp, 2020). This method hinges on multivariate Gaussian distribution and deploys an L1-regularized [LASSO] regression term to estimate regression coefficients signifying edge weights (Haslbeck et al., 2018). L1-regularization is utilized to avert model overfitting, predicated on the assumption that most parameters in the true model equate to zero (Haslbeck et al., 2018). Each node-wise regression calculation also includes a tuning parameter ( $\lambda_s$ ), employed to govern the penalty strength. The optimal  $\lambda_s$  value is selected through a 10-fold cross-validation scheme (Haslbeck et al., 2018). The OR-rule was used as the default to combine the mean of the edge weight for three-way interactions, aligning with the study’s exploratory nature (Haslbeck et al., 2018).

The computation of conditional pairwise effects utilizes regularized node-wise regression, in which each variable is regressed on all others, and the results are consolidated to produce the network. The regression coefficients represent conditional dependence relationships between nodes, once the influences of all other nodes have been accounted for (Haslbeck et al., 2018). The thickness of edges symbolizes the association strength, and weak edges are shrunk to zero (Epskamp et al., 2012). The pairwise effects can be interpreted as partial correlations, with a value range from  $-1$  to  $1$  (Burger et al., 2020; Haslbeck et al., 2018). The partial correlation values were evaluated according to the guidelines by Doucouliagos (2011), wherein an effect size below  $\pm 0.07$  is considered small, between  $0.07$  and  $0.33$  is moderate, and above  $\pm 0.33$  is large.

MGM examines group differences in network structure through three-way interactions, where a BPD diagnosis can moderate pairwise associations between network variables (Haslbeck et al., 2018). Such moderation effects are anticipated to be subtle and less consistent due to the power prerequisites (Haslbeck et al., 2018).

To verify the reliability and stability of the parameters, the network underwent 1000 resamples, producing a bootstrapped sampling distribution of edge weights—indicative of variable dependency strength—and moderation effects. Parameters were derived from both the 5% and 95% quantiles of this distribution, establishing 95% confidence intervals.

For enhanced result assurance, a sensitivity analysis was performed using the AND-rule for amalgamating estimates across proximal regressions. Given the noted conservatism of the AND-rule (Haslbeck and

Waldorp, 2020), this analysis fortifies the credibility of the primary findings.

The networks were computed in R using the “mgm” package and visualized with the “qgraph” package (Epskamp et al., 2012; Haslbeck and Waldorp, 2020). Predictability and expected influence of the nodes were also determined and are reported in the supplementary material.

### 2.5. Ethical considerations

The larger research project, which provided the dataset for the present study, was thoroughly reviewed and approved by the Research Ethics Committee (REC) of Wales, under the reference number: 12/WA/0283, and IRAS project ID: 103075. Further approval for the use of this data for the current secondary data analysis was also granted by the Ethics Sub Committee of the University of Essex, with the application numbers ETH1920–1420 and ETH2021–0857. The procedures followed were in accordance with the Helsinki Declaration as revised in 2013. The participants provided their written informed consent to participate in this study.

### 2.6. Open data and transparency

We fully support open data and transparency in scientific research. The raw data supporting our findings will be made accessible upon request. For those interested in the codes used for the analysis, as well as the supplementary materials, these can be accessed at the OSF open repository via the following link: [https://osf.io/nd28j/?view\\_only=f1eb20d22bf84b079278d725f64fd93e](https://osf.io/nd28j/?view_only=f1eb20d22bf84b079278d725f64fd93e).

## 3. Results

### 3.1. Descriptive statistics

Table 1 presents the demographic profiles of the community and clinical cohorts. The clinical group had a notably greater proportion of females, White participants, and older individuals than the community group. Additionally, the clinical group exhibited increased unemployment rates and a larger segment without formal education, yet also had a greater percentage of individuals with higher education qualifications compared to the community group. While no significant disparities in socioeconomic status were observed between the groups, the community cohort reported significantly elevated earnings relative to the clinical group.

### 3.2. Unique Variable Analysis (UVA)

In the Unique Variable Analysis (UVA), eight target variables were identified as having high topological overlap with other items. However, in the interest of preserving the specificity of Borderline Personality Disorder (BPD)-related traits and to maintain a good model fit, only two of these target variables were considered redundant and combined into new minor latent variables. The remaining five target variables from the Personality Assessment Inventory-Borderline (PAI-BOR) scale were deemed to capture significantly different difficulties than the proposed items and were therefore kept separate in the analysis. Additionally, the Movie for the Assessment of Social Cognition (MASC) hypomentalization subscale was kept separate from the proposed MASC no mentalization subscale.

Two new minor latent variables were created by combining target and redundant items. The first one, titled “Impulsivity and recklessness,” included items such as “I’m a reckless person,” “I sometimes do things so impulsively that I get into trouble,” “I’m too impulsive for my own good,” “I spend money too easily,” and “I’m careful about how I spend my money.” The second new variable, “Intense mood shifts,” was formed from items like “My mood can shift quite suddenly,” and “My mood gets quite intense.” Consequently, the network analyses

**Table 1**

Sociodemographic characteristics of participants within the two groups.

Demographic variable	Clinical group (n = 350)	Community group (n = 225)	Value of relevant comparative statistic <sup>d</sup>	p-Value
	n (%) or median	n (%) or median		
Gender			$\chi^2(1) = 24.427^a$	<0.001
Male	69 (20 %)	87 (39 %)		
Female	277 (79 %)	137 (61 %)		
Transgender	2 (0.5 %)	1 (0 %)		
Other	2 (0.5 %)	–		
Age	29 (40)	26 (44)	U = 350.50	0.030
Ethnicity <sup>b</sup>			$\chi^2(3) = 12.192$	0.007
White	261 (75 %)	138 (61.5 %)		
Black/Black British	27 (8 %)	26 (11.5 %)		
Asian/British Asian	21 (6 %)	25 (11 %)		
Mixed/other	39 (11 %)	35 (16 %)		
Employment			$\chi^2(3) = 82.76$	<0.001
Employed	100 (29 %)	123 (55 %)		
Unemployed	194 (56 %)	40 (18 %)		
Student/apprentice	47 (14 %)	57 (25 %)		
Retired/carer	5 (1 %)	5 (2 %)		
Education			$\chi^2(6) = 14.651$	0.023
No formal education	24 (7 %)	7 (3 %)		
Other qualification (e.g. certificate)	10 (3 %)	6 (3 %)		
Vocational level 1 (e.g. NVQ), GCSE (<5 A*-C), or equivalent	29 (8 %)	16 (7 %)		
GCSE (5 or more A*-C), level 2 (e.g. NVQ), or equivalent	65 (19 %)	46 (20 %)		
A level, vocational level 3 (e.g. NVQ), or equivalent	99 (28 %)	90 (40 %)		
Higher education or professional/vocational equivalent	97 (28 %)	42 (19 %)		
Post graduate education or professional/vocational equivalent (e.g. Masters, PhD)	24 (7 %)	18 (8 %)		
Household income			$\chi^2(2) = 35.288$	<0.001
<£10k	161 (48 %)	52 (24 %)		
£10k–35k	128 (38 %)	106 (48.5 %)		
>£35k	48 (14 %)	60 (27.5 %)		
SES <sup>c</sup>	10,562 (31252)	10,802 (31166)	U = 35,795	0.635

Note. N = 575. BPD = borderline personality disorder.

<sup>a</sup> People who identify as transgender or other had to be excluded from comparative analysis to meet assumptions of the relevant test.

<sup>b</sup> White = White British, White Irish, Any other white; Black/Black British = Caribbean, African, Any other black; Asian/British Asian = Indian, Pakistani, Bangladeshi, Chinese, any other Asian; Mixed/other = White and Black Caribbean, White and Black African, White and Asian, any other mixed, any other background not stated.

<sup>c</sup> SES = socioeconomic status indicated by the social deprivation rank according to post code.

<sup>d</sup>  $\chi^2$  for chi-square test of independence, U for Mann-Whitney U test (data was not normally distributed).



encompassed a total of 19 BPD-related features. For more detailed results, please refer to the supplementary materials.

### 3.3. Moderated Network Analysis

In the Moderated Network Analysis, the network consisted of 23 nodes which included 19 Borderline Personality Disorder (BPD)-related features, three types of ineffective mentalization modes (hypermentalization, hypomentalization, and no mentalization), and a binary variable indicating the presence or absence of a BPD diagnosis (see Table 2). The total sample size for the estimated network was 575 individuals. To create a condition relating to BPD diagnosis and to compare the two groups (community group:  $N = 225$ ; clinical group:  $N = 350$ ), the condition() function from the “mgm” package was used (Haslbeck et al., 2018).

Fig. 1 presents visual representations of the estimated moderated network models. The network of the whole sample is depicted in Fig. 1/A, while Fig. 1/B and C depicts the network when conditioned on BPD diagnosis. Each edge in these models represents a unique undirected pairwise association between BPD- and mentalization-related difficulties, while controlling for all other variables in the networks.

The edge weights are not interpreted as partial correlation coefficients but can be understood in a similar way. The key values relevant to the research question are reported below (and summarized in Table 3), while all bootstrapped average edge weights, moderation effects, and corresponding confidence intervals of the network are included in the supplementary material.

### 3.4. Group differences moderated by BPD diagnosis

The moderation network analysis showed several pairwise associations for all participants, moderated by the presence of BPD to various degrees. Associations between ineffective modes of mentalization and BPD-related difficulties were reported if they reached an edge weight of  $\pm 0.05$  and appeared in at least 45 % of the bootstrapped samples (any smaller or less stable correlations were considered too weak or unstable). For all such associations, moderation effects were reported. The estimated means of the edge weights are reported with low (5 %) and high (95 %) quantiles of the bootstrapped sample distribution, resulting in 95 % confidence intervals. Narrower confidence intervals suggest less variance in pairwise interaction effects, indicating higher stability of the estimated parameters.

**Table 2**  
Nodes included in final MGM analysis.

Node number	Item description
1	Intense mood shifts
2	Attitude about self changes a lot
3	Stormy relationships
4	Chronic emptiness
5	Want to let people know they hurt me
6	Unsteady mood
7	Worry about people leaving
8	Feeling that people let one down
9	Little control over anger
10	Wonder about what to do with life
11	Feeling lonely
12	Feeling unhappy
13	Cannot handle separation
14	Making mistakes in picking friends
15	Hurt self when upset
16	Cannot express all of anger
17	Getting bored easily
18	Difficulty to stay friends for long time
19	Impulsivity and recklessness
20	Hypermentalization
21	Hypomentalization
22	Lack of mentalization
23	BPD diagnosis

#### 3.4.1. Hypermentalization

Hypermentalization was found to have a moderate positive pairwise association with the feature ‘having stormy relationships’ (weight = 0.14; bootstrapped 95 % CI [0–0.25]). This association was negatively moderated by the presence of a BPD diagnosis ( $-0.15$ ; bootstrapped 95 % CI [ $-0.15$  to  $-0.26$ ]). This indicates that, in the clinical sample, the probability of hypermentalization leading to stormy relationships, and vice versa, is less likely. This association was confirmed in 90 % of the 1000 bootstrap samples, with the moderation effect confirmed in 89 % of the samples.

Further, a moderate positive pairwise cross-sectional association was found between hypermentalization and the feature ‘worrying about people leaving’ (weight = 0.08; bootstrapped 95 % CI [0–0.19]). This association was confirmed in 67 % of the 1000 bootstrap samples. However, the moderation effect was very weak (0.01; bootstrapped 95 % CI [0–0.12]; found in 8 % of the samples), suggesting that the likelihood of hypermentalization increasing worry about people leaving, and vice versa, is similar in the two samples.

The moderated network analysis revealed a small positive pairwise cross-sectional association between hypermentalization and ‘mistakes in making friends’ (weight = 0.05; bootstrapped 95 % CI [0–0.17]). This association was negatively moderated by the presence of a BPD diagnosis ( $-0.03$ ; bootstrapped 95 % CI [ $-0.03$  to  $-0.14$ ]), indicating that the probability of hypermentalization increasing the feeling of making mistakes when choosing friends and vice versa might be less likely in the clinical sample. This association was confirmed in 48 % of the 1000 bootstrap samples, and the moderation effect was found in 30 % of the samples.

Finally, a moderate negative pairwise association was observed in the clinical group between hypermentalization and ‘feeling that people let one down’ (weight =  $-0.21$ ; bootstrapped 95 % CI [ $-0.32$  to  $-0$ ]). This association was positively moderated by the presence of a BPD diagnosis (0.16; bootstrapped 95 % CI [0–0.3]). This indicates that the likelihood of hypermentalization decreasing the feeling that people let one down and vice versa is less likely in the clinical group. This association was confirmed in 99 % of the 1000 bootstrap samples, and the moderation was confirmed in 92 % of the samples.

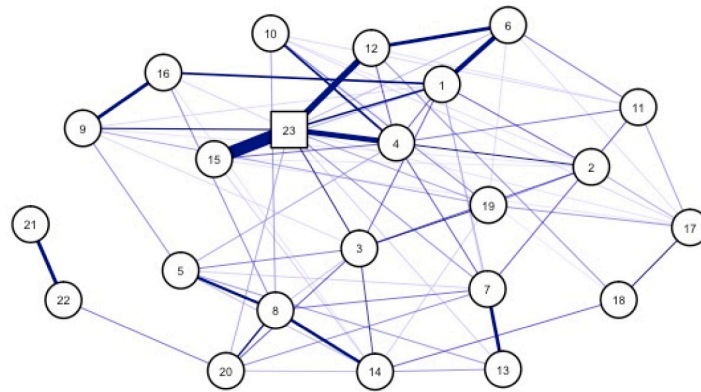
#### 3.4.2. Hypomentalization and no mentalization

In the representative network of the whole sample (Fig. 1/A), no associations involving hypomentalization or no mentalization scales were identified. However, across 1000 bootstrapped samples, a moderate positive pairwise association between hypomentalization and ‘struggling to handle separation’ was revealed (weight = 0.07; bootstrapped 95 % CI [0–0.18]). This association was confirmed in 69 % of the bootstrap samples. The moderation effect of diagnosis on this association was negligible (0.01; bootstrapped 95 % CI [0–0.12]; found in 10 % of the samples), suggesting a similar likelihood of hypomentalization influencing ‘struggling to handle separation’ and vice versa in both community and clinical samples.

Bootstrapping also unearthed a minor positive pairwise association between hypomentalization and ‘wanting to let people know how much they hurt one’ (weight = 0.06; bootstrapped 95 % CI [0–0.17]). This association was confirmed in 58 % of the bootstrap samples. The presence of a BPD diagnosis slightly negatively moderated this pairwise effect ( $-0.03$ ; bootstrapped 95 % CI [ $-0.03$  to  $-0.13$ ]), but this moderation effect was only validated in 30 % of the bootstrap samples. This implies that the likelihood of hypomentalization increasing the desire to communicate one’s hurt feelings to others, and vice versa, might be marginally lower in the clinical sample compared to the community sample.

**Sensitivity Analysis:** The findings from the sensitivity analysis closely mirrored the primary analysis over 1000 bootstrapped samples concerning pairwise associations observed in the network (refer to Table 3). Nonetheless, BPD diagnosis emerged as a moderator specifically between ‘having stormy relationships’ and hypermentalization, and

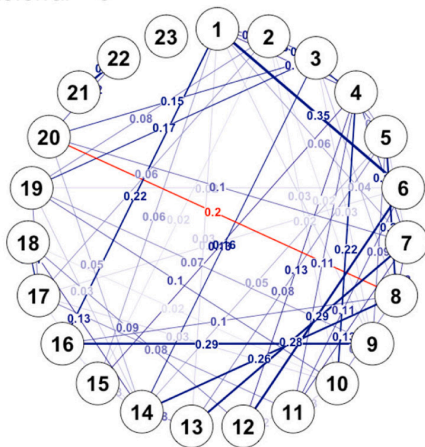
A. Whole Sample (N=575)



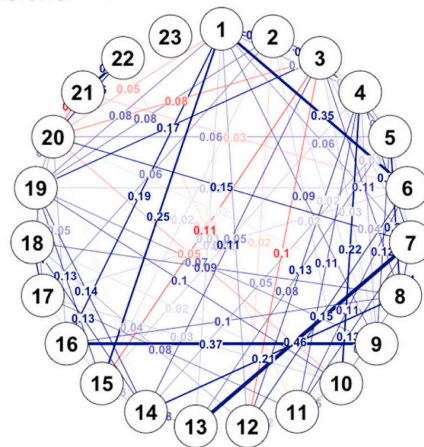
B. Community Sample (n=225)

C. Clinical Sample (n=350)

Referral = 0



Referral = 1



**Fig. 1.** Moderated network models for the whole sample and conditioned on the absence and presence of BPD diagnosis.

Note. BPD = borderline personality disorder.

Legend. node 1 = intense mood shifts, node 2 = attitude about self changes, node 3 = stormy relationships, node 4 = chronic emptiness, node 5 = let people know they hurt me, node 6 = unsteady mood, node 7 = worry about people leaving, node 8 = ‘people let me down’, node 9 = little control over anger, node 10 = wonder about life, node 11 = feeling lonely, node 12 = feeling unhappy, node 13 = cannot handle separation, node 14 = mistakes in picking friends, node 15 = hurt self when upset, node 16 = cannot express all of anger, node 17 = gets bored easily, node 18 = difficulty with staying friends with people, node 19 = impulsivity and recklessness, node 20 = hypermentalizing, node 21 = hypomentalizing, node 22 = no mentalizing, node 23 = BPD diagnosis. Values along the edges represent average absolute value of edge weights (pairwise partial correlation values), with thicker edges visualizing stronger relationships. Blue and red edges indicate positive or negative linear relationships between the variables when moderated. Absent edges do not suggest an absence of marginal connections between variables, but rather that the relationship vanishes when controlled for all other variables in the network. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

between ‘feeling that people let one down’ and hypermentalizing.

**4. Discussion**

The primary aim of this research was to elucidate the complex relationship between ineffective mentalizing strategies and Borderline Personality Disorder (BPD) symptomatology. This was achieved by contrasting these dynamics between individuals diagnosed with BPD and those without. A network analysis approach was utilized to generate

a comprehensive representation of how mentalizing difficulties intertwine with BPD and to emphasize any differences in these interactions at various system activation levels. Consistent with the mentalization-based theoretical model, we hypothesized the existence of connections between diverse mentalizing deficits and BPD-related features, and postulated that the configuration of these networks would diverge between the two participant groups.

In alignment with our hypothesis, the findings of this study elucidated consistent relationships between ineffective mentalizing modes

**Table 3**  
Pairwise and moderation effects found in the moderation and sensitivity analyses.

Node in the network	Hypermentalization		Hypomentalization		No mentalization		Moderation effect of BPD diagnosis		
	Primary analysis	Sensitivity analysis	Primary analysis	Sensitivity analysis	Primary analysis	Sensitivity analysis	Primary analysis	Sensitivity analysis	
N3: Stormy relationships	0,14	0,13					-0,15	-0,01	0,3
N5: Let people know they've hurt me			0,06	0,04			-0,03	0	0,2
N7: Worry about people leaving	0,08	0,07					0,01	0	0,1
N8: People let me down	-0,21	-0,21					0,16	0,02	0
N13: Can't handle separation			0,07	0,05			0,01	0	-0,1
N14: Mistakes in picking friends	0,05	0,05					-0,03	0	-0,2
MASCless					0,3	0,3	0,02	0	-0,3
MASCno	0,11	0,09					0,02	0	

Note. BPD = Borderline personality disorder. Blue values represent positive, red values represent negative partial correlations. Small effect size:  $\leq \pm 0.07$ ; moderate effect size:  $\pm 0.07$ – $\pm 0.33$ .

and distinct BPD-related challenges. In accordance with the mentalization model, all the BPD-related difficulties identified to engage with ineffective mentalizing modes were intrinsically interpersonal, meaning they emerge in the context of negotiating relationships. Furthermore, the results lend support to the notion that hypermentalization and hypomentalization may concurrently influence BPD-related difficulties, and conversely, within a network of BPD-related difficulties. This builds upon existing literature that underscores the significance of either hypermentalization (Kvarstein et al., 2020; Sharp et al., 2013, 2011; Sharp and Vanwoerden, 2015; Somma et al., 2019) or hypomentalization (Brüne et al., 2016; Euler et al., 2021; Goueli et al., 2020; Vahidi et al., 2021) in relation to BPD symptomatology and proposes that these ineffective modes of mentalization might both induce and maintain BPD-related interpersonal difficulties depending on the type of relational problem encountered. Our findings are also consistent with a recent meta-analysis highlighting that implicit and explicit mentalizing is correlated with lower levels of psychopathology (including personality pathology), more adaptive personality, and greater attachment security (Kivity et al., 2024).

Despite these findings, the outcomes of the moderation analysis were not always immediately comprehensible based on the existing theoretical framework and empirical evidence. Notably, aside from two pairwise associations ('worry about people leaving' and hypermentalization; 'struggling to handle separation' and hypomentalization) where the moderating effect of the diagnosis was virtually absent, almost all of the most robust interactions between ineffective mentalizing modes and BPD-related difficulties ('stormy relationships' and hypermentalization; 'feeling that people let one down' and hypermentalization; 'desire to let people know they hurt one' and hypomentalization; 'making mistakes in selecting friends' and hypermentalization) were more likely to manifest in the community sample than in the clinical sample. This surprising observation warrants further exploration and implies that our comprehension of the complex interplay between mentalizing difficulties and BPD may necessitate revision or expansion. On the other hand, these results align with a more recent hypothesis by Luyten et al. (2012), which suggested that mentalization abilities fluctuate, even in people without mental health difficulties. For instance, it may be more difficult to accurately mentalize about people outside of one's intimate social circle, particularly if an individual is experiencing attachment-related stress (Bartz et al., 2011; Nolte et al., 2013). Fossati et al. (2018) also suggested people without mental health difficulties may at times struggle to mentalize. They found that non-clinical adolescents and adults mistakenly inferred mental states on nearly half of the MASC

questions. Together, this research supports the notion that mentalizing is not static, and that automatic, non-mentalizing states are present even in people with predominantly secure attachment styles (Bartz et al., 2011).

Another salient consideration for the difference in the unique associations between the two groups is that individuals in the clinical group might experience interpersonal difficulties and heightened stress in relation to them so chronically and frequently that these struggles become their norm, rendering mentalizing attempts to understand the reasons and impacts of these difficulties neither activated nor inhibited. Instead, individuals may exist in a constant state of epistemic mistrust (Fonagy et al., 2017), where expectations of a hostile world lead to a general reduction in openness and interest toward new information, different perspectives, and engagement in interactive exchanges and exploration of internal states to shield against anticipated psychological pain (Fonagy and Allison, 2014; Haslanger, 2014; Stubbley, 2021). As such, ineffective mentalization modes would neither activate nor sustain interpersonal problems and vice versa, as the interest in understanding one's own and others' minds is generally low, and personal beliefs are held rigidly. By withdrawing from social communication individuals also limit their ability to receive benevolent and transformative inputs from the environment, which may prevent their network connectivity to change. This could perpetuate a harmful equilibrium, reducing opportunities for recovery and hindering the reactivation of mentalizing.

It is crucial to reflect upon how the psychometric attributes of the MASC could have impacted our findings. Firstly, it is possible that the no mentalization scale of the MASC does not capture the whole domain of total lack of mentalization and may instead represent the lower end of a spectrum of hypomentalization. Other instruments such as the Reflective Functioning Scale (Fonagy et al., 1998) might capture no mentalization better. Another important issue is the degree of relational stress incurred during the MASC measurement which remains ambiguous. This is noteworthy because intricate patterns of mentalizing difficulties can fluctuate depending on individuals' attachment history and the emotional and attachment-related stress imposed by a specific task (Bateman and Fonagy, 2016). As emotional arousal within a relational context escalates, a tipping point is eventually reached beyond which mentalizing capacities become overwhelmed, resulting in a defensive inhibition of interest in others' mental states (Fonagy and Luyten, 2009). This tipping point is highly individual, largely contingent on the presence of developmental trauma and insecure attachment style, typically prevalent in individuals with a BPD diagnosis (Luyten et al., 2020). Considering the substantial topological overlap between the hypomentalization and no mentalization subscales found in the UVA analysis, it is

plausible that the MASC may not capture the full spectrum of reduced mentalization if the attachment-related stress elicited by the task overwhelms the mentalizing system of individuals with a BPD diagnosis. The subscales might instead represent a spectrum of ‘reduced’ mentalization, whereby each subscale refers to a different severity of hypomentalization without encapsulating the complete shutdown of mentalization (representing the extreme end of the ‘reduced mentalization’ continuum).

If, conversely, the attachment-related stress during the MASC is low, individuals with BPD might not default to ineffective mentalizing modes during the test or may even display surprisingly proficient mindreading capabilities (Carter and Rinsley, 1977; Dinsdale and Crespi, 2013). Related to this is the fact that the MASC does not assess self-related mentalizing in participants, thereby leaving an important domain of mentalizing unexplored. Adaptive forms of self-mentalizing often become obscured in interpersonal situations among individuals with a BPD diagnosis, resulting in heightened sensitivity to others’ mental states and an emotional merging with them (Luyten et al., 2020). It has been argued that individuals with BPD are often well-able and over-focused on perceiving and interpreting others’ emotional states as long as attachment-related stress of the situation remains low, while avoiding or distorting their own emotional experiences (Bateman and Fonagy, 2004; Luyten and Fonagy, 2015). Consequently, the impaired self-aspect of mentalizing may directly relate to ineffective mentalizing modes in people with a diagnosis of BPD and the MASC could distort or overlook their measurement and representation. To investigate these hypotheses, future network studies should contemplate employing alternative, more sensitive methods of measuring mentalization-related difficulties.

Several limitations warrant caution in interpreting this study’s results. First, the bootstrapped sampling distribution exhibited significant variability in network parameters. Second, the sample size was somewhat limited, given the statistical demands of network analysis (Fried and Cramer, 2017). Third, although a sensitivity analysis was performed for robustness, our primary analysis leaned toward an exploratory stance, using lenient statistical penalties in the regularization techniques. These aspects hint at the potential suboptimal reliability and stability of the estimates. Hence, particularly for more marginal results, interpretation should be made with prudence. Future studies should aim to validate these conclusions using more stringent criteria. Another limitation of this study is its cross-sectional design, which leaves the temporal directionality of these relationships unclear, and the extent of bidirectional causal inferences that can be drawn from them uncertain (von Klipstein et al., 2021). It is also possible that some of the relationships identified in the networks are the result of common causes or indirect causal links that were not accounted for (von Klipstein et al., 2021). The overall sociodemographic diversity within our sample was low, and significant sociodemographic differences existed among participants, which were not controlled for. Furthermore, the measurement used to capture ineffective mentalization lacked sensitivity to assess all domains of mentalization (particularly self-mentalization) and the hypomentalization and no mentalization subscales may have too much topological overlap, meaning they do not measure independent constructs. Regarding the diagnostic criteria, although the SCID version adopted in the current study (SCID-II) is still regarded as a valid diagnostic tool, there is an updated version of the instrument based on a more recent version of the DSM (DSM 5). The adoption of DSM 5 could potentially have helped to capture the complexity and non-linearity of the psychopathological features. Finally, decisions regarding the combination of potential redundant items into new latent variables were made based on statistical parameters and clinical judgement, so there might have been some sort of bias related to researcher/clinician’s prior theoretical assumptions.

## CRediT authorship contribution statement

**Lilla Asztalos:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Hugo Senra:** Writing – review & editing, Validation, Supervision, Methodology, Investigation, Data curation, Conceptualization. **Ciarán O’Driscoll:** Writing – review & editing, Validation, Supervision, Project administration, Methodology, Investigation. **Janet Feigenbaum:** Writing – review & editing, Validation, Supervision, Methodology, Investigation. **Julia Griem:** Writing – review & editing, Validation, Supervision, Methodology, Investigation. **Brooks King-Casas:** Writing – review & editing, Validation, Methodology, Investigation. **Tobias Nolte:** Writing – review & editing, Validation, Supervision, Methodology, Investigation. **Richard Pratt:** Writing – review & editing, Validation, Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Farzad Vaziri:** Writing – review & editing, Methodology, Investigation. **Read Montague:** Writing – review & editing, Validation, Resources, Project administration, Methodology, Investigation, Funding acquisition. **Peter Fonagy:** Writing – review & editing, Validation, Supervision, Resources, Methodology, Investigation, Funding acquisition, Conceptualization.

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## Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Peter Fonagy reports financial support was provided by National Institute for Health and Care Excellence Research ARC North Thames. Read Montague reports financial support was provided by Wellcome Trust. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.jad.2025.01.031>.

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