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Examining attentional functioning in depression using a personalized network approach: A proof-of-principle study

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ABSTRACT

Reduced attentional functioning has been identified as an important factor in depression etiology and maintenance. However, current research does not fully take into account the large heterogeneity of depression, for example identifying for whom and how reduced attentional functioning plays a role. In this proof-of-principle study, we demonstrate how a personalized network approach can provide more nuanced insight into the role of attentional functioning in depression. To this end, we estimated person-specific symptom networks in a depression sample, and explored associations between reduced attentional functioning (alerting, orienting, executive control) and symptom centrality (expected influence). Participants with ongoing and remitted depression were enrolled to 14 days of intensive assessment of depression symptoms in their daily life using a smartphone app. Based on these data, person-specific network models were estimated using vector autoregression modelling. Orienting, alerting and executive control were assessed using the Attentional Network Test in the laboratory. Person-specific networks showed large variability in symptom dynamics. Higher centrality of fatigue was associated with reduced orienting efficiency, and higher centrality of passivity was associated with reduced executive control. This study highlights the potential of assessing individual symptom dynamics when considering cognitive functioning in depression.

Author note

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1. Introduction

Attentional impairments are frequently demonstrated in patients with depression (Gotlib and Joormann, 2010; Hammar and Årdal, 2009; Keller et al., 2019; LeMoult and Gotlib, 2019). Indeed, inability to think and concentrate is a diagnostic criterion for Major Depressive Disorder (MDD; American Psychiatric Association, 2013). Reduced attentional functioning negatively impacts daily functioning (Keller et al., 2019), emotion regulation (Koster et al., 2011), has been implicated in the etiology and maintenance of depression (De Raedt et al., 2010), and is increasingly targeted in psychotherapy (Papageorgiou and Wells, 2000) and computerized training interventions (Koster et al., 2017). Although meta-analyses indicate evidence for impaired attentional functioning in depression (e.g., Quigley et al., 2022; Snyder, 2013) studies are divergent with regards to the magnitude and impact of such impairments (for example, see Ottowitz et al., 2002). Not all individuals with depression demonstrate attentional impairments, suggesting that there are individual differences in the presence and functional role of attentional

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impairments in explaining depressive symptomatology.

Depression is a remarkably heterogeneous disorder (Goldberg, 2011) and involves many plausible aetiological and maintaining pathways (e.g., Charney and Manji, 2004; Harrington et al., 1996; Hasler, 2010; Wittenborn et al., 2016). Studies that account for depression heterogeneity can therefore provide new knowledge on how and for whom attentional impairments are relevant. One way forward is to zoom in on the individual depression symptoms and examine the associations (i.e., dynamics) between them (Fried, 2017). This idea is in line with current network approaches to psychopathology defining depression as a complex dynamic network of interacting symptoms, and not as a latent disease entity (Borsboom, 2017). Using network analysis, one can model depression as a network of symptoms, and identify which symptoms are the most strongly connected to other symptoms, that is, which symptoms are the most "central" (Borsboom and Cramer, 2013). A recent meta-analysis of network analyses by Malgaroli et al. (2021) found that fatigue and depressed mood were the two symptoms that were most central in the context of depression. In contrast, weight change emerged as the least central symptom in the models. Interestingly, symptom centrality seems to provide clinically useful information. For example, high symptom centrality of fatigue has been associated with treatment non-response, whereas treatment responders were characterized by high centrality of negative mood (McElroy et al., 2019). In patients experiencing recurrence of depression, difficulty concentrating was among the most central symptoms (Lorimer et al., 2020).

Based on a network approach, one could examine whether attentional impairments are associated with the centrality of specific symptoms. However, no studies have examined this directly, although some studies have used network analysis to examine the role of other cognitive functions. For example, in a sample of remitted depressed patients, Hoorelbeke et al. (2016) examined links between performance on a cognitive control task (the Paced Auditory Serial Addition task) and a composite measure of depression symptoms and related risk factors using network analysis. Results showed that although self-reported executive impairments were linked to depressive symptomatology (via resilience), the contribution of the objective measure for cognitive control in the network models was negligible. Following up on this, Hoorelbeke et al. (2019) found associations between level of cognitive complaints (subjective experience of executive- and working memory impairments), co-occurrence of depressive symptomatology, as well as other risk factors for depression (e.g., rumination) following remission from depression using time-series data. Our research group has recently examined the link between executive functioning and depression symptoms in a mixed sample of depressed, previously depressed, and healthy individuals. Results showed that reduced executive functioning was primarily associated with fatigue (Kraft et al., 2023).

The aforementioned studies focused on symptom networks at the group level. However, given depression heterogeneity, symptom networks are likely to differ between individuals. For example, in some individuals, negative mood might be the most central symptom, while lack of positive mood may be the most central symptom in others. In a dynamic network perspective it is assumed that central symptoms are responsible for activating other depression symptoms, while peripheral symptoms are less relevant because they have little influence on the network (Fried et al., 2016). Individual differences in symptom centrality may therefore reflect heterogeneity in symptom dynamics. Symptom centrality have recently been proposed as an important source of variability to investigate in understanding psychopathological processes, and studies investigating whether such dynamics may be related to cognitive and affective outcomes have been called for (Ebrahimi et al., 2023).

Symptom centrality at the individual level can be calculated from person-specific networks which are estimated from temporally ordered data (Epskamp et al., 2018). This type of data can be gathered through experience sampling methods (ESM), where participants answer questions several times a day, often by the means of a smartphone app (Trull and Ebner-Priemer, 2009). With multilevel vector auto regressive (VAR) modelling, researchers can model the temporal order by which symptoms affect one another over time, as well as explore patterns of co-occurring activity within a symptom model capturing rapid processes often found in psychopathology (Epskamp et al., 2018). This provides a window into symptom dynamics at the individual level and an opportunity to identify which symptoms are most central for each person. Studies employing this personalized network approach demonstrate a large variability in symptom dynamics between individuals, and show that central symptoms predict clinically relevant outcomes (see for example Fisher et al., 2017; Levinson et al., 2020; Reeves and Fisher, 2020).

Attentional functioning is considered a clinically relevant phenomenon in depression, although, probably not for everyone. Network theory posits that symptoms that are central are more important than peripheral symptoms, and whether specific symptoms are central or peripheral may vary between individuals. Examining this could provide insights in how and for whom attentional impairments play a role in symptom dynamics.

In the present study, we aim to demonstrate how a personalized network approach can provide more nuanced insight into the role of attention in depression. As a proof of principle, we explore whether symptom centrality is associated with attentional functioning in a depression sample. We hypothesized that reduced attentional functioning is associated with individual differences in symptom centrality. Beyond this hypothesis, the literature gives little clues as to which results we could expect when using a personalized network approach. Thus, we explored the pattern of results without any specific hypothesis as to which symptoms might be involved. In this way, we hope to identify new directions for research to explore the interplay between depression and laboratory measures of attentional functioning.

First, we estimated person-specific networks based on ESM data using an idiographic network analytical approach. This allows us to identify which symptoms are most central in each individual's symptom network. Secondly, we measured attentional functioning in line with the seminal work by Posner and Petersen (1990) on attentional networks in the brain, where attention can be decomposed into three main functions. *Orienting* selects information from the sensory input; *alerting* maintains an alert state; *executive control* resolves conflict among possible responses (Fan et al., 2002). Findings regarding these attentional functions in depression are mixed (Sinha et al., 2022). For instance, Lyche et al. (2011) reported reduced alerting in patients suffering from ongoing major depression disorder. Impairments in all three functions have been reported in remitted depression (Paelecke-Habermann et al., 2005). However, other studies have shown no association between orienting, alerting, and executive control in remitted and subclinical depression (Preiss et al., 2010; Yang and Xiang, 2019). Finally, we examined associations between attentional functioning and symptom centrality.

2. Methods

2.1. Sample and procedure

The present study analyzed baseline data from a randomized controlled trial of attentional bias modification (ClinicalTrials.gov #NCT 04137367). Individuals reporting depressive complaints were recruited by advertisement in the community and on social media. Inclusion criteria were previous or current Major Depression Disorder, age 18–65 years, and fluency in Norwegian. Exclusion criteria were manic episodes, psychosis, and neurological disorders. Diagnostic status was assessed using the *MINI International Neuropsychiatric Interview* (Sheehan et al., 1998). All participants provided written informed consent in accordance with the Declaration of Helsinki, and the study was carried out in accordance with the recommendations of the Regional Committee for Medical and Health Research Ethics in Norway (2019/330) and the Norwegian Social Science Data Services.

After diagnostic assessment and inclusion in the study, participants were enrolled to 14 days of ESM assessment of depression symptoms and carried out their daily life as normal (for details, see below). Immediately after, participants returned to the lab for assessment of attentional functioning and depression symptoms (*Beck's Depression Inventory II* [BDI]; Beck et al., 1996). Data collection was performed from February 5, 2020 to August 31, 2021. Administrators were clinical psychologists and psychology students.

2.2. ESM

ESM data was collected using an app (PsyMate) installed on participants' smartphones. The app notified participants to report depression symptoms five times per day at random intervals between 8.30 a.m. and 10.30 p.m. (total number of measurements = 70). At each measurement participants were asked to complete a short questionnaire introduced by the sentence: "How have you been the last hour?". The questionnaire had to be completed within 30 minutes, or else a non-response was recorded.

The questionnaire consisted of items measuring depression symptoms using a slider scale with values going from 0 (nothing) to 100 (very much). When notified, participants were instructed to use approximately 1 minute to answer the questionnaire. Participants received an in-person demonstration of the app and received information on how to understand the items of the questionnaire.

Items were generated by B. Kraft and R. Bø based on the *Diagnostic and Statistical Manual of Mental Disorders 5*th *edition* (DSM-5; American Psychiatric Association, 2013). The items reported in this study cover five depression criteria, as well as rumination and activity level (which are often highlighted in research and targeted in clinical interventions). The items were as follows: sadness ("How sad have you been?"), fatigue ("How tired have you been?"), interest ("How interested have you been in what you have been doing?"), positive affect ("How happy have you been?"), concentration problems ("How great difficulties have you had concentrating?"), ruminating ("How much have you been ruminating?"), and activity ("How active have you been (physically/mentally/socially)?" Several DSM-5 criteria were not assessed to reduce load on participants and keep well below the recommended number of nodes in the network analysis (Epskamp, 2015). These were depression symptoms which are less common and involve both increased or decreased symptom quality (e.g., decreased or increased appetite). We did not assess suicidal thoughts, as it might be disturbing for participants to answer this item repeatedly throughout the day.

2.3. Attentional functioning

The Attentional Network Test (ANT; Fan et al., 2002) is a computerized task which measures the efficiency of the attentional networks involved in alerting, orienting, and executive control. In each trial, five arrows pointing left or right are presented either above or below a fixation cross. The target is the arrow at the center. By using two buttons on the keyboard, participants are asked to respond as quickly and accurate as possible to which direction the target arrow points. The target can be flanked by distractors which are either congruent (pointing in the same direction as the target) or incongruent, or by no distractors (neutral). Before each trial, one of four cues is presented: a spatial cue which indicates where the arrows will appear, and three cues which do not provide information about the location of the arrows (no-cue, center-cue, and double-cue). See Fan et al. (2002) for further details.

Calculation of attentional functioning measures are based on mean reaction time (RT) on correct trials (excluding RTs above and below 3 *SD)*. Three estimates of attentional functioning are computed as follows: Alerting = mean $RT_{no\text{-}cue}$ – mean $RT_{double\text{-}cue}$; Orienting = mean $RT_{center\text{-}cue}$ – mean $RT_{spatial\text{-}cue}$; Executive = mean $RT_{incongruent}$ – mean $RT_{congruent}$. Note that lower alerting and orienting scores indicate poorer performance, while higher executive scores indicate poorer conflict resolution.

2.4. Statistical analyses

Analyses involved four steps: 1) pre-processing of ESM-data, 2) estimation of person-specific networks, 3) calculation of centrality indices, and 4) examination of correlations between centrality indices and attentional functioning measures.

Interest, positive affect, and activity items were reverse coded, and are therefore hereby referred to as "interest loss", "low positive affect", and "passivity", respectively. Pre-processing of ESM-data started by excluding participants who responded to less than 30 measurements (Epskamp, 2015). Person-specific networks were estimated using the var1-function in the *R* package *psychonetrics*, with full-information maximum likelihood estimator. First, we removed the linear trend of time per subject (Fisher et al., 2017). Then, for each participant, we modeled a contemporaneous network in which symptoms predict one another in the same measurement window. We focused on contemporaneous networks as these are considered to better capture rapid processes often found in psychopathology (Epskamp et al., 2018), and because a recent simulation study shows that estimation of contemporaneous networks needs less observations than for example temporal networks (Mansueto et al., 2022). Contemporaneous networks are estimated from the residuals of a lag-1 vector autoregression model (where one variable predicts another in the next window of measurement; Epskamp et al., 2018). Thus, associations represent partial correlations controlled for temporal effects and all other variables in the same window of measurement. Networks thus reflect co-occurring symptom dynamics. We used *qgraph* to plot two sample participant's symptom networks for illustration, where symptoms are depicted as nodes, and associations between symptoms are depicted as edges.

For each individual we calculated the node's expected influence centrality. Expected influence centrality reflects a node's cumulative influence in the model, focusing on the level of association with its immediate neighbors (i.e., the nodes with which it shares an edge) while taking into account negative edges (Robinaugh et al., 2016). Centralities were calculated using qgraph (Epskamp et al., 2012) and were standardized.

Finally, bivariate correlations between symptom centrality indices and attentional functions were calculated.

3. Results

A total of 92 participants were recruited to the study. Four participants were excluded from further analyses because they did not return for assessment of attentional functioning, and 43 participants were excluded because they responded to fewer than 30 ESM measurements (most because of technical problems with the ESM app).

3.1. Sample characteristics

The final sample (n = 45) consisted of 32 (71%) women and 13 (29%) men. Mean age was 44.7 years (SD = 11.2). Thirty-five (77%) had an educational level comparable to bachelor's level or above. Twenty-two (47%) met criteria for ongoing MDD, and the remainder were in remission from MDD. Mean BDI score was 23.2 (range = 3–53; SD = 11.0). Thirty-three (73%) had co-morbid anxiety, obsessive-compulsive, or post-traumatic stress disorder. Twenty-seven participants (60%) used psychotropic medication. Means for attentional control measures were as follows: alerting = 30.6 (SD = 29.0); orienting = 63.3 (SD = 42.5); executive control = 138.3 (SD = 65.5). There were no statistical differences ($p > .05$) between included and excluded subjects on any of the demographic variables, nor the attentional measures.

The sample answered in total 2072 of 3150 ESM measurements (66%). Mean time lag between measurements (within days) was 213.2 min (SD = 113.9). Intraclass correlations ranged from 0.22 to 0.55.

Mean scores on ESM items were as follows: sadness = 29.2 (*SD* = 25.6); fatigue = 42.7 (*SD* = 28.8); interest loss = 41.2 (*SD* = 23.1); low positive affect = 29.82 (*SD* = 19.8); concentration problems = 37.5 (*SD* = 25.6); ruminating = 36.0 (*SD* = 26.2); passivity = 42.6 (*SD* = 28.4).

Correlations between attentional functioning and within-person means for each symptom showed no statistical significant associations.

3.2. Person-specific networks

Visual inspection of person-specific networks showed large variability in symptom networks. The networks for two sample participants are presented in Fig. 1. Edge thickness corresponds to the association strength. Blue edges represent positive associations between two given nodes, whereas red/dashed edges represent negative associations.

In sample participant #1's network we see that sadness is strongly connected with both fatigue and rumination. That is, when this participant reported being sad, higher levels of fatigue and rumination were also reported during the same window of measurement. The most influential symptoms were sadness (expected influence = 1.2) and fatigue (1.3).

On the other hand, sample participant #2's network showed strong associations between interest loss, concentration problems, and low positive affect. Note that compared to participant #1's network, edges from sadness and rumination were weaker. The most influential symptoms in participant #2's network were low positive affect (expected influence = 1.8) and interest loss (0.9).

3.3. Associations between symptom centrality and attentional functioning

Correlations between symptom centralities and attentional functioning are presented in Table 1. There were substantial correlations between level of centrality of fatigue and orienting ($r = -0.32$), and between passivity and executive control ($r = 0.34$).

Due to the high-dimensional nature of the data, analysis involved 21 comparisons, increasing the risk of false positive findings. Taking this into account, correlations were not statistically significant after Bonferroni-correction (α corrected = 0.002).

4. Discussion

Theoretical models have postulated that attentional impairments play an important role in depression vulnerability. Unfortunately, most research has been done at the group level and has mainly considered depression as a singular disease entity. In this proof-of-principle study, we set out to examine the association between individuals' symptom networks, meaning the extent to which specific symptoms appear to play a more central role in individual symptom dynamics in daily life (i.e., depressive symptom "profiles"), and objective indicators of attentional functioning. This study is among the first to model associations between centrality of specific depressive symptoms and cognitive risk factors for depression. Although results are tentative, our study points to the role of fatigue and passivity in explaining reduced attentional functioning.

Table 1
Correlations between symptom centrality and attentional functioning with P-values in parentheses.

	Alerting	Orienting	Executive
Sadness	−0.04 (.79)	0.03 (.87)	−0.13 (.39)
Fatigue	0.04 (.80)	**−0.32 (.03)**	0.02 (.92)
Loss of Interest	−0.10 (.53)	0.22 (.14)	−0.14 (.36)
Low positive affect	−0.14 (.36)	−0.07 (.67)	0.00 (.98)
Concentration problems	0.17 (.27)	−0.11 (.47)	−0.09 (.56)
Ruminating	−0.11 (.47)	0.19 (.20)	−0.05 (.74)
Passivity	0.19 (.21)	0.05 (.74)	**0.34 (.02)**

Note. P-values <.05 are denoted in boldface. Bonferroni-corrected significance level = 0.002.

Results suggested that the ability to efficiently orient one's attention is reduced when fatigue is a central symptom in the depression symptom network. Previous studies have shown that orienting efficiency is associated with fatigue levels (Feltmate et al., 2020). Fatigue is known to reduce the ability to allocate attention efficiently (Boksem et al., 2005), possibly through increased distractibility and decreased flexibility (Müller and Apps, 2019).

Results also suggested that individuals whose symptom network is more influenced by passivity tend to demonstrate reduced executive control. Previous studies have shown that attentional functioning and executive control is associated with physical activity levels (e.g., Erickson et al., 2019; Haverkamp et al., 2020) and social interactions levels (e.g., Ybarra et al., 2011). Depression is characterized by less physical activity and more sedentary behaviors (Schuch et al., 2017), and reduced social activity (Ryu et al., 2021). Unfortunately, however, the present study measured activity using only one item, collapsing both the physical and social domain. The present study therefore cannot point to whether the results are specific to passivity in one or more domains.

Several cognitive theories of depression emphasize attentional deficits in the processing of negative material and the maintenance of negative affect (for a review, see LeMoult and Gotlib, 2019). For

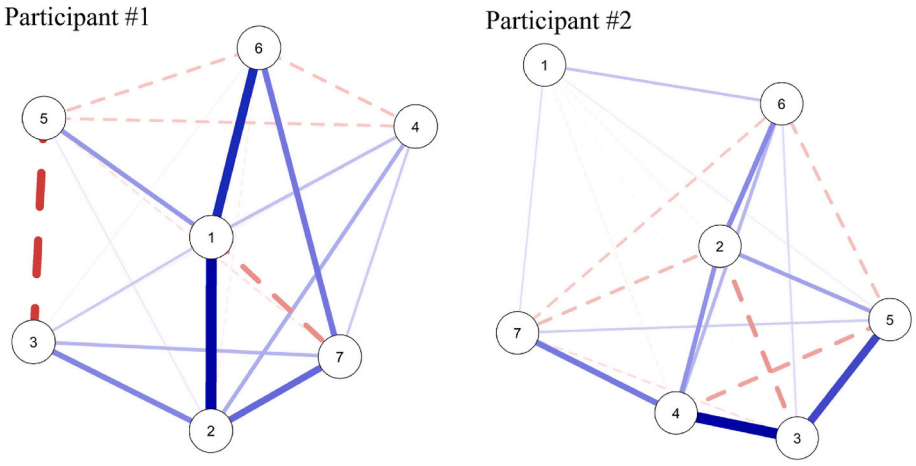

Fig. 1. Symptom networks for two sample participants.
Note. Edge thickness reflects the magnitude of the association (blue = positive, red dashed = negative).1 = Sadness; 2 = Fatigue; 3 = Interest loss; 4 = Low positive affect; 5 = Concentration problems; 6 = Ruminating; 7 = Passivity.

example, it has been proposed that reduced attentional functioning acts as a gateway to increased negative material in working memory, which maintains negative thoughts, and in turn sustained negative affect (De Raedt and Koster, 2010). However, results from the present study suggests that there is no association between reduced attentional functioning and centrality of negative affect symptom (sadness). Note that we cannot exclude the possibility that this is due to a false negative, as the sample size in the present study was small.

Likewise, there was no association between concentration problems and attentional functioning. This could be explained by the fact that self-reports of cognitive functioning and objective test performance are largely distinct phenomena (Buchanan, 2016; Snyder et al., 2020).

The personalized network models estimated in this study reflect co-occurring symptom dynamics (i.e., "fast-paced" symptom dynamics). Although the edges between symptoms reflect associations within the same time-window, the resulting edges still depends on the lag interval used. Some associations might be captured when intervals are short (i.e., rumination – sadness), and other associations might be captured when intervals are longer (i.e., fatigue – passivity). The optimal lag interval is unknown, and can also differ between individuals. In the present study, intervals varied randomly, and were thus unpredictable to participants. This increases ecological validity and reduces reactivity to the ESM (Piasecki et al., 2007). However, unequally spaced ESM data may lead to overestimation in VAR models when the true autocorrelation is very small (de Haan-Rietdijk et al., 2017). An alternative to handle unequally spaced ESM data better is by estimating a continuous-time model (de Haan-Rietdijk et al., 2017), but this is not implemented in psychonetrics. Future studies should examine the potential impact of different time-lags and alternative estimation methods.

This study has some important limitations. The present study analyzes high-dimensional data, involving many statistical comparisons. Our findings did not survive conservative corrections for multiple comparisons. There is therefore an increased risk that the observed associations are due to chance. Unfortunately, many of the participants had to be excluded due to low ESM response rates, resulting in a small sample size and reduced statistical power. A substantially larger sample size is required to reliably detect associations between centrality measures and attentional measures in future studies. Results must therefore be regarded as tentative until replication. Items were selected based on DSM-5 and clinical experience, but were not formally validated. Moreover, our analyses rely on a rather minimal set of depressive symptoms which do not fully capture the wide variety of depressive symptoms. There has been debate regarding the nature, reliability and clinical relevance of centrality measures derived from VAR models (Bringmann et al., 2019; Piccirillo et al., 2019). For example, there has been no study (yet) examining whether targeting central symptoms leads to better clinical outcomes than targeting non-central symptoms. However, a recent study examining eating disorder symptoms has shown that symptoms that were identified as central using group-level VAR models predicted eating disorder severity at one and six months (Levinson et al., 2021).

Despite these limitations, this study demonstrate that estimation of individual's symptom models has the potential to provide nuanced insight on the role of attentional functioning in depression. Future studies should aim to replicate findings, and establish whether the associations reflect causal relationships. For example, by examining whether interventions which improve cognition (e.g., Koster et al., 2017; Thérond et al., 2021) reduces the influence of fatigue and passivity, or whether interventions which aim to reduce the impact of fatigue (e.g., exercise) or passivity (e.g., behavioral activation) lead to improvements in attention. Future studies could also examine if attention training for depression is more effective when fatigue and passivity are central symptoms, and less effective when for example negative affect is central.

4.1. Conclusion

We set-out to model the associations between depression symptom centrality and attentional functioning in a mixed sample of patients with ongoing and remitted major depression. We estimated person-specific VAR network models and examined the associations between level of symptom centrality and measures of alerting, orienting, and executive control. Although tentative, results suggested that centrality of fatigue and passivity was associated with reduced attentional functioning. In sum, this study demonstrates a new approach in how to examine attentional functioning in depression.

CRediT author statement

Brage Kraft: Conceptualization, investigation, data curation, formal analysis, and writing – original draft. Ragnhild Bø;: Investigation, data curation, and writing – review & editing. Kristof Hoorelbeke: Writing – review & editing. Ernst Koster: Writing – review & editing. Rune Jonassen: Writing – review & editing. Catherine Harmer: Supervision, and writing – review & editing. Nils Inge Landrø;: Funding acquisition, supervision, and writing – review & editing.

Declaration of competing interest

CJH has received consultancy fees from P1vital, Lundbeck, Sage Therapeutics, Compass Pathways, Zogenix outside of this work. NIL has received consultancy fees and travel expenses from Lundbeck. The remaining author(s) declared that there were no conflicts of interest with respect to the authorship or the publication of this article.

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