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Predicting Outcomes from Cognitive Behavioural Therapy for Social Anxiety Disorder: A Bayesian Network Analysis

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ABSTRACT

Better understanding of predictors of treatment response to cognitive behavioural therapy (CBT) for social anxiety disorder (SAD) holds potential for improving outcomes. This study sought to identify which specific social anxiety symptoms measured pretreatment were associated with post-treatment outcomes. A pre-registered retrospective cohort study was used in a sample of N=1315 patients treated with CBT for SAD in routine clinical practice. The outcome was a reliable and clinically significant improvement (RCSI) on the Generalized Anxiety Disorder-7 outcome measure. A Bayesian network symptom model of the Social Phobia Inventory (SPIN) was trained using Bayesian network analysis with 10- fold cross-validation (n=658). Predictive accuracy was evaluated in an external test sample (n=657). The performance of the network model generalised to an external test sample (AUC = 0.59; PPV = 0.53; NPV = 0.59) with moderate prediction shrinkage relative to performance in the test sample (AUC = 0.67). A network of four interrelated SAD symptoms were found to be reliable outcome predictors: fear of embarrassment, avoiding talking, avoiding criticism and fear of being observed. Identifying important SAD symptoms at assessment could enable these to be targeted during CBT to help maximize treatment efficiency and effectiveness.

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Introduction

Social anxiety disorder (SAD) is a common form of anxiety that tends to emerge during early adolescence that can then create lifelong problems with social interactions without an evidence-based intervention [1-3]. SAD in adults also often co- occurs with other mental disorders and it is a risk factor for greater suicidality even after controlling for depression [4,5]. The core feature of SAD is a fear of humiliation and embarrassment experienced before, during and after social interactions, with this fear maintained by hypervigilant attentional bias and negative processing of social cues [6,7]. Patients with SAD therefore report an enhanced and acutely painful sense of self-consciousness which has both a private and public dimension [8,9]. When there is an associated avoidance of interpersonal interactions this creates a vicious circle which increases social isolation, fear of future socializing and the slow atrophy of social skills [10-12].

The National Institute for Health and Care Excellence recommends cognitive behavioural therapy (CBT) as a first-line treatment for SAD [1]. In England in the National Health Service's Talking Therapies (NHS-TT) programme, patients with SAD are only offered CBT, as there is no efficacious psychoeducational intervention currently available [13]. Because social interactions are difficult for patients with SAD and CBT requires social interaction, attrition rates during treatment are concerning. NICE guidelines (2013) try to ameliorate this by recommending that services offer individual as opposed to group CBT [14]. Disorder specific CBT for SAD focusses on reducing avoidance of social interactions and then changing the way self and others are processed during social interactions. Two widely applied CBT approaches are the Heimberg and Becker 16-session treatment (i.e., cognitive restructuring, education, exposure, examining core believe and relapse prevention) and the Clark and Wells 16-session treatment (i.e., video feedback, in and out of session behavioural experiments and imagery work) [15,16].

In NHS-TT services, patients with clinically significant symptoms of SAD are offered evidence-based and protocol-driven CBT. According to a study by Robinson et al. in which treatment outcomes were examined across several diagnostic groups, SAD had the poorest outcomes among all of the anxiety disorders treated in the NHS-TT services that participated in the study [17]. Identifying reliable prognostic indicators for SAD is important to improve outcomes for this clinical population, and predictors of response to CBT for this condition are currently poorly understood. Any predictors are likely interrelated and so a better understand of possible interactions is logical. For example, elevated scores on specific symptoms of SAD could be more important predictors of treatment response, and it is theoretically plausible that symptoms interact in a network of interrelations.

A recent scoping review of the network structure of SAD contained ten studies of SAD patients; the central symptoms were difficulties with group interactions, engaging with strangers, social events and feeling the centre of attention. When patients with SAD have been compared to controls, they have much more densely interconnected network of social fear and avoidance of social situations [18]. Networks with tightly interconnected interactions

are likely more pathogenic [19-21]. There is also evidence that SAD networks change over time. Miers et al. found that four social anxiety components interlinked over time to suggest that the social-emotional traits moderated cognitive and behavioural symptoms [22]. More evaluations of how SAD changes over time and in response to intervention have been recommended as has the need for more SAD-specific network research [23,24]. Although such emerging findings imply that attending to symptom networks could be a fruitful research direction, conventional network analysis of partial correlations has come under criticism in recent years. Some known problems include the lack of replicability of network structures in different samples, the unclear clinical and predictive value of centrality indices [25]. Alternative methods, such as Bayesian network analysis, which examine relationships between network variables and an outcome of interest, could potentially shed light onto the symptoms that may be most important predictors of treatment response.

This is the first study to complete a Bayesian network analysis of the SPIN during CBT in routine practice. This study had two aims: (1) to produce a network model of the SPIN to model the central and important features of SAD and (2) to then identify which specific SAD symptoms/nodes successfully predicted recovery during treatment with CBT.

Method

Ethics and Context

The study was pre-registered (AsPredicted ref: 71256) and ethical approval for the fully anonymized archival dataset analysis was obtained (North East-Newcastle & North Tyneside NHS research ethics committee and Health Research Authority ref; 15/NE/0062). Routine clinical outcomes and demographics for patients that accessed an NHS-TT service in Northern England were accessed and analyzed. Patients with SAD were offered high intensity CBT, following national clinical guidelines [13]. The inclusion criteria were for a patient to: (1) have a diagnosis of SAD, (2) received individual CBT using the Clark and Wells 16-session protocol, (3) completed a SPIN at assessment, (4) had clinical case-level symptoms assessed by the GAD-7 anxiety measure (i.e., a score >=8) before CBT started and (5) had available post-treatment GAD-7 outcome measures [26].

Outcomes from N=2133 patients were screened, and the inclusion criteria created a research sample of N=1315 patients (see Figure 1 for a flowchart of this sample selection process).

Demographics (i.e., age, gender, job status, medication usage and employment status) for the research sample are presented in Table 1.

Table 1: Socio-Demographic Characteristics of the Research Sample (n=1315)

Age (Years)	
Mean	29.35 (SD = 10.50)
Range	17-82
Gender	
Females	727 (55.3%)
Males	584 (44.4)
Ethnicity	
British	1080 (82.1%)
White Other	40 (3.0%)
White and Black Caribbean	24 (1.8%)
Pakistani	20 (1.5%)
Other	151 (11.4%)
Employment Type	
Employed	575 (43.7)
Student	187 (14.2)
Homemaker / carer	113 (8.6%)
Unemployed, not seeking work	110 (8.4)
Other	330 (25.0%)
Medication Usage	
Prescribed and Taking	596 (45.3)
Not Prescribed	559 (42.5%)
Other	160 (12%)

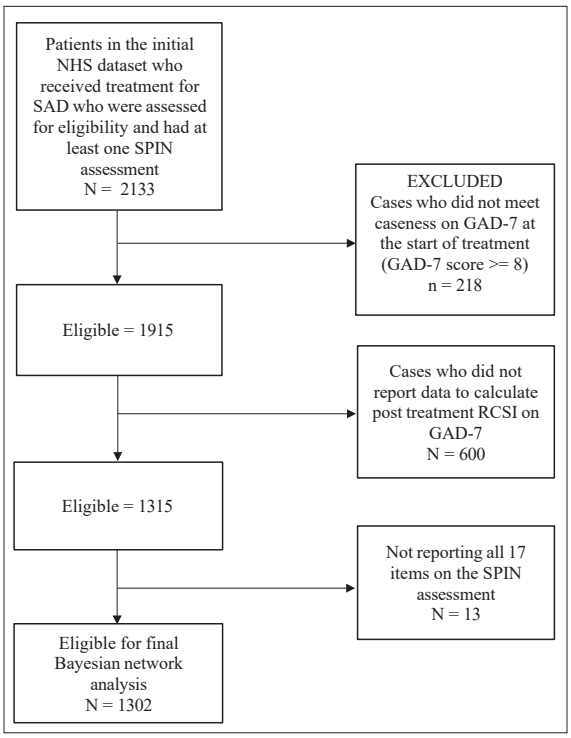

Figure 1: Flow Chart of Participant Selection

Measures and Analysis

General Anxiety Disorder-7 (GAD-7: Spitzer). The General Anxiety Disorder assessment (GAD-7) is used as part of a battery of routine outcome monitoring measures in NHS-TT services. Rates of pre- and post-CBT reliable and clinically significant improvement (RCSI) were calculated using the method proposed by Jacobson and Truax applying criteria of pre-post change >=5 and post-score <8. The GAD-7 has adequate psychometric properties as a case-finding measure for a wide range of anxiety disorders, including SAD [27]. Since this measure is administered in NHS-TT services on a session-by-session basis, it is an a psychometrically adequate measure to monitor treatment response for patients with a variety of anxiety disorders.

Social Phobia Inventory [28]. The Social Phobia Inventory (SPIN) has been psychometrically validated for assessing severity of SAD and has good test-retest reliability, internal consistency, convergent and divergent validity. SPIN scores of 19+ identifies SAD caseness, the scale has five factors and is responsive to both

pharmacological and psychotherapeutic intervention [28,29]. The SPIN is used in NHS-TT services as a case-finding measure to identify patients with SAD, in order to appropriately refer to an empirically-supported treatment. After initial assessments, the SPIN is used infrequently to monitor treatment response, and hence the GAD-7 which is completed at every session is the default option to measure post-treatment outcomes if the SPIN is missing at a final treatment session. As the baseline GAD-7 and SPIN measures were significantly correlated (r=.30, p<.001), use of the GAD-7 as the recovery outcome measure was justified to maximize the sample size.

Data Analysis and Statistical Methods

All data was analyzed using IBM SPSS Modeler version 18.2. A three-phase machine learning pipeline (i.e., pre-processing, training and variable selection, external cross- validation and evaluation) was applied. The original dataset was randomly partitioned into two halves using a 50:50 ratio (i.e., n=658 training sample, n=657 external validation sample). A Bayesian network analysis of the SPIN was performed in a training sample. The training sample developed the algorithm to predict recovery after CBT, using 10-fold internal cross-validation and the hold-out sample was used to perform an external cross-validation.

1. **Pre-Processing:** The training dataset was partitioned into 10 equally sized folds, to support cross-validation. A random noise variable was created replicating the distribution of SPIN item values, but containing no meaningful signal information. The noise variable aided variable selection, as described below. The dataset contained the following variables: case ID, 17 SPIN questionnaire items, the noise variable, GAD-7 recovery outcome (RCSI = yes or no), partition (for cross-validation).
2. **Training and Variable Selection:** Variable selection was performed via 10-fold cross- validation. Each of the 10 iterations of the analysis (loops) produced a Bayesian network model, where SPIN items formed a network of interrelated predictors of post-treatment recovery (as a binary outcome). Each of the ten models output a variable importance plot, which ranked all predictors according to their contribution to variance in treatment outcomes. The variable selection approach involved selecting only those predictors that were consistently ranked as more important than the noise variable in more than half of the 10 iterations. A final model was trained using the full training sample and only entering the selected variables as predictors.
3. **External Cross-Validation and Evaluation:** The Bayesian network model developed in the training sample was then used to make predictions using data from the hold-out (test) sample. The area under the curve (AUC), positive predictive values (PPV) and negative predictive values (NPV) were used to assess classification accuracy in both the training and test samples, to assess generalisability (to new cases) and prediction shrinkage (relative to the training cases).

Results

The Bayesian network model is displayed in Figure 2. After variable selection, the final model consisted of four SPIN items: SPIN6 '*I avoid doing things or speaking to people for fear of embarrassment*', SPIN11 '*I avoid having to give speeches', SPIN12 'I would do anything to avoid being criticized*' and SPIN14 '*I am afraid of doing things when people might be watching*'. All of these items had relatively similar indices of variable importance (i.e., predictive value): SPIN11 was the most important predictor, while SPIN14 was the least. All selected SPIN items interacted with each other, SPIN6 was a central node, interacting with SPIN12 and SPIN14. SPIN 14 interacted with SPIN11.

Overall, the network model correctly classified 62.77% of recovery cases in the training sample, with prediction error being 0.34. The model's classification accuracy for recovery was high (AUC = 0.67; PPV = 0.68; NPV = 0.60).

The model's classification accuracy generalised to an external test sample, albeit with modest prediction accuracy (AUC = 0.59; PPV = 0.53; NPV = 0.59). There was evidence of moderate prediction shrinkage by a value of 6.76% (with 10% being considered high), so that the model could then only predict 56.01% of patients correctly, but the measure of error reduced significantly by a value of 0.16 to 0.18.

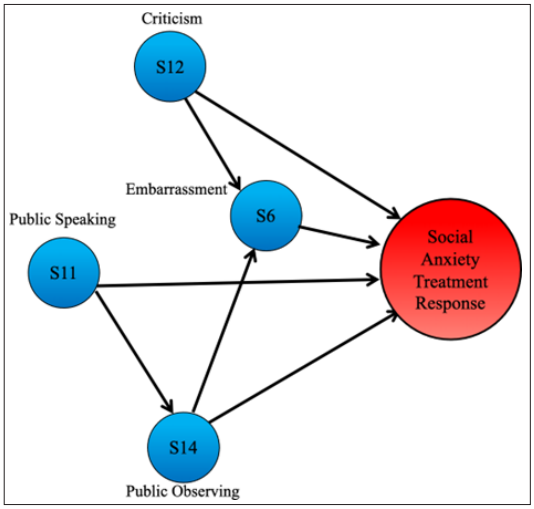

Figure 2: Bayesian Network Model of the Inter-Relationship of Social Anxiety Items Can Recovery.

Discussion

The present study sought to identify important SAD symptoms that may be prognostic indicators for patients who access CBT. Classification accuracy was good in the training sample (AUC = 0.67) but lower in the hold-out test sample (AUC = 0.59). Prediction shrinkage was higher for the positive predictive values compared to the negative predictive values. This suggests that the model would retain higher accuracy when predicting patients who do not recover during CBT as compared to those that do. Four key SPIN items predicted the probability of recovery during CBT. These SAD items were levels of severity in *fear of embarrassment* (SPIN6), *avoidance of speaking* (SPIN11), avoidance of criticism (SPIN12) and *fear of being observed* (SPIN14). Therefore, there were two key related aspects of SAD which predicted recovery and these were social fears (i.e., embarrassment and observation) and social avoidance (i.e., of speaking and criticism). None of the physiological symptoms of SAD included in the SPIN were selected as predictors (i.e., SPIN2, SPIN7, SPIN13 and SPIN 17). It is interesting that the SPIN9 (centre of attention) item was not selected, as that is the closest item to the self-consciousness of the Clark and Wells model [16].

These findings suggest that different aspects of SAD (i.e., the nodes in the network) do not operate in isolation, but rather these differing behavioural and emotional aspects interrelated to create and maintain SAD. The Bayesian network model illustrated

interactions between nodes and therefore suggested which nodes acted as moderators. The predictive value of *fear of embarrassment* (SPIN6) was moderated by severity of *avoidance of criticism* (SPIN12) and the *fear of being observed* (SPIN14). The predictive value of *fear of being observed* (SPIN14) was moderated by *avoidance of speaking* (SPIN11). The most frequent fear for SAD patients is the fear of speaking in public or having to perform in front of an audience and so the network produced here mirrors that evidence [28].

Heeren and McNally have also previously illustrated that those with SAD have tightly connected nodes focusing on both the fear and associated avoidance of social situations. The current findings are that the four nodes of SAD network all relate to avoidance of social situations (i.e., speaking and being observed) to avoid the anticipated embarrassment and criticism. Li et al., recently conducted a network analysis in a large community sample (N=3294) to also find that the central symptom was fear of negative evaluation and the current results also support the Noda et al., scoping review results. Previously, negative perceptual bias during social interactions has been strongly implicated in the onset and maintenance of SAD, but the SPIN concentrates on fear of social situations, social avoidance and physiological arousal symptoms in social settings [7,9,28]. There have been calls to expand the scope of the SPIN. Kerriche et al. carried out a network analysis of the SPIN in a community sample (N=1530), finding items 5, 6, 9, 14, 15 and 17 had the highest strength centrality index; the SPIN6 (fear of embarrassment) and SPIN14 (fear of being observed) were replicated in the current study. Although there are some interesting similarities in findings across these studies, results from traditional network analyses of partial correlations are not directly analogous to those of Bayesian network analysis. The latter is a form of supervised machine learning that plots network graphs on the basis of their associations with an outcome of interest, and moderator relationships with respect to that outcome. Furthermore, variable importance indices in Bayesian networks bear no direct parallel to centrality indices in conventional network analyses.

Clinical Implications

Findings suggests that during CBT, patients need to receive support to reduce their levels of social avoidance as action tendencies, as they are obstacles to recovery and moderate the heightened fear that patients experience in social settings (i.e., SPIN6 and SPIN14). Facilitating behavioural exposure to perceived criticism and/or speaking with and to people are therefore important to consider in treatment planning and as homework and in-session behavioural experiments. The focus of the behavioural experiments for SAD should target the cognitive aspects of behavioural avoidance and social fear to enable recovery, and so therefore place less emphasis on the physiological reactivity experienced in social settings (e.g., blushing, trembling, palpitations, sweating and shaking). The sessional use of the SPIN is recommended, as this will be able to track change and also to index when a reliable and clinically significant change has occurred on this disorder-specific outcome measure.

Strengths, Limitations and Recommendations for Future Research

A major strength of the current study is the inclusion of a representative clinical sample; while many of the network studies of SAD are based on community samples. Few exclusion criteria were applied, and this increases the clinical generalisability of the results. The internal validity of the study would have been improved through use of both diagnostic interviewing and assessment of the clinical competency and treatment differentiation of the CBT delivered. The context of an NHS-TT service may limit the international generalisability of the results. The role of medication was not explored, and all the outcomes were self-report. The difference in recovery the model could predict between the training and test samples reduced significantly, so further research should use the same methods but in different samples (i.e., clinical settings, community and cultural) to assess if this is a stable effect. There was no follow-up and so the predictive value of the SPIN over longer time frames is currently unknown [23]. Large samples will be required in future studies to enable more reliable and accurate models to be produced and these studies should also compare mild, moderate and severe forms of SAD [30].

Conclusions

Four key symptoms of SAD were interrelated and significantly predicted the probability of recovery in patients receiving CBT in routine practice. Social fears and social avoidance have emerged as important predictors of SAD outcomes. These SAD symptoms could be targeted in CBT to maximize treatment response, and this should now be tested in well designed and suitably powered studies [31-44].

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