Network approach to items and domains from the Toronto Alexithymia Scale

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Abstract

The aim of this paper is to explore network structures of the Toronto Alexithymia Scale (TAS) in a large sample of 1925 French-speaking Belgian university students and compare results with previous studies from different samples and tools to identify potential targets for clinical intervention. We estimated network models for the twenty items of the TAS and for its three domains *difficulty identifying feelings*, *difficulty describing feelings* and *externally-oriented thinking*. We explored item connectivity through node predictability (shared variance with other network components). We performed an Exploratory Graph Analysis (EGA) to explore the dimensionality of our dataset and compare results with the original three-factor model; because a different model was proposed, we estimated an additional network structure on the new structure. Items from the TAS connect both within and between domains. The three-domain network identifies *difficulty describing feelings* as the most connected domain. The EGA reported that three items from *externally-oriented thinking* form a new domain, distraction. In the new four-domain network, *difficulty describing feelings* remains the most interconnected domain; however, two negative connections are found.

Our findings support the relative importance of identifying and describing feelings as a meaningful target for intervention.

Keywords: community detection; psychometrics; students; connectivity

Introduction

The construct of alexithymia has been around for more than half a century: it was named from Greek meaning “lack of word for emotion” (Sifneos 1972). Alexithymia is understood as a personality construct with four main features: 1) difficulty identifying and distinguishing emotions from bodily sensations; 2) difficulty describing and verbalizing emotions; 3) poverty of fantasy life; and 4) externally-oriented thinking (Loas, Braun, Delhayé, & Linkowski, 2017). It is a subject of interest in psychiatric research so as to better understand the physiological basis of mental disorders associated with emotions, such as mania, addiction and depression. Extensive neuroimaging research has been conducted on alexithymia, reporting alterations in affective arousal to external stimuli, voluntary cognitive functioning; an impaired activation of the insula during cognitive processes has indicated a potential overlap between alexithymia and other psychiatric disorders presenting with impaired empathy such as psychopathy and autism (Moriguchi & Komaki, 2013). Because of such clinical implications, some researchers recommend to transpose the concept of alexithymia to that of “affective agnosia” (Lane, Weihs, Herring, Hishaw, & Smith, 2015).

The Toronto Alexithymia Scale (TAS) is the most commonly used measure of alexithymia in empirical research (Bagby, Parker, & Taylor, 1994) and is composed of twenty items designed to assess three domains: *difficulty identifying feelings* (e.g. item 1 “I am often confused about what emotion I am feeling”); *difficulty describing feelings* (e.g. item 4 “It is difficult for me to find the right words for my feelings”), and *externally-oriented thinking* (e.g. item 8 “I prefer to just let things happen rather than to understand why they turned out that way”). These three domains as originally described are to be interpreted as passive and interchangeable consequences of the construct itself, and therefore are not active contributors to alexithymia (Van Bork, Wijsen, & Rhemtulla, 2017).

In the last decade, network analysis has affirmed itself as new way of analyzing data in psychiatry and psychology, which allows to conceive constructs or mental disorders as a complex system of mutually influencing elements (Borsboom & Cramer, 2013). In this framework, the unobserved interactions between psychological components (for instance symptoms, or items from a questionnaire) are often computed as regularized partial correlations (Epskamp & Fried, 2018). Network analysis has been used to explore several mental disorders, such as posttraumatic stress disorder (Fried et al., 2018; Phillips et al., 2018), depression (Mullarkey, Marchetti, & Beevers, 2018), and autism (Ruzzano, Borsboom, & Geurts, 2015), but also psychological constructs such as empathy (Briganti, Kempenaers, Braun, Fried, & Linkowski, 2018), self-worth (Briganti, Fried, & Linkowski, 2019) and resilience (Fritz, Fried, Goodyer, Wilkinson, & van Harmelen, 2018; Briganti & Linkowski, 2019).

When considering a network model of a psychological construct (such as represented by a given questionnaire), a known challenge is that of redundancy of items in addressing the measure of the same aspect of a given construct. This may result in the case of an empirical study in a network where redundant items share very strong connections whose meaning is different (it represents shared variance rather than a true interaction between the two components). A solution to address this problem is the estimation of a network model of the domains of the construct instead of a network model of items (Briganti et al., 2019) to facilitate the process of inference (e.g. identifying relevant interactions between network components).

Network analysis is also useful to recover the true number of item communities (or factors) in a dataset; this can be achieved to the highly effective and reliable Exploratory Graph Analysis (EGA; Golino & Epskamp, 2017); in this case, a confirmatory factor analysis (CFA) is useful to authenticate the structure suggested by EGA, as suggested in a simulation study (Golino & Demetriou, 2017). A recent empirical study (Briganti & Linkowski, 2019) which applied the recommended EGA procedure showed that the problem of redundancy in psychological

networks is not exclusive to questionnaire items but can extend to construct domains as well; community detections in psychological networks may therefore also be useful to re-evaluate the construct themselves.

Network models of a construct such as alexithymia are particularly interesting to integrate in clinical practice since relevant components may serve as targets for intervention (Fried et al., 2018); in the case of alexithymia, finding and acting upon potentials targets is particularly interesting since it may attenuate the neurocognitive alterations that have been described in the literature.

The construct of alexithymia as represented by the Bermond-Vorst Alexithymia Questionnaire (BVAQ) and the Toronto Structured Interview for Alexithymia (TSIA) has already been explored through the lenses of network analysis (Watters, Taylor, & Bagby, 2016; Watters, Taylor, Quilty, & Bagby, 2016); in the case of the TSIA whose factors closely resemble those of the TAS, the domains *difficulty identifying feelings* and *difficulty describing feelings* formed one community and provided the most connected items.

We therefore aim to extend the conceptual framework of psychological networks to the construct of alexithymia as represented by the TAS.

In this study, we want first to explore alexithymia as both a network of items (as reported in the questionnaire) and domains. Second, we want to apply EGA to recover the number of communities in the network, compare the outcome with previous studies (Watters et al., 2016a; Watters et al., 2016b), and authenticate the suggested structure with CFA; if the result differs from the original three-domain structure, we want to estimate the network of the structure proposed by the community detection. Third, we want to explore the connectedness of items and domains with node predictability, which statistically represent the shared variance of a given network component with surrounding components (Haslbeck & Fried, 2017). These

exploratory analyses may have meaningful clinical implications and serve as basis for future replication studies to identify and act upon potential clinical targets in people with alexithymia.

2. Methods

2.1 Dataset

Our dataset is composed of 1925 university students from the French-speaking region of Belgium. Subjects were 17 to 25 years old ($M = 19$ years; $SD = 1.6$ years); 58% of them were women and 42% were men.

2.2 Measurement

The TAS (Table 1) is composed of 20 shuffled items that measure alexithymia in three domains: *difficulty identifying feelings*, *difficulty describing feelings* and *externally-oriented thinking*. The minimum score for each item is 1 (“I completely disagree”) and the maximum score is 5 (“I completely agree”). The questionnaire contains reverse-scored items whose score is reversed before data analysis (Table 1).

The dataset for this study is anonymized and provided with code within the supplementary materials (Briganti, 2019) to ensure the full reproducibility of our study.

The protocol for this study was approved by the ethical committee of the Erasme teaching hospital.

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Table 1. The 20-item Toronto Alexithymia Scale. WC represents the community assigned by the walktrap algorithm to each item.

N	Item	Domain	WC
1	I am often confused about what emotion I am feeling	Difficulty identifying feelings	1
2	It is difficult for me to find the right words for my feelings	Difficulty describing feelings	4
3	I have physical sensations that even doctors don't understand	Difficulty identifying feelings	1
4	I am able to describe my feelings easily (reversed)	Difficulty describing feelings	4
5	I prefer to analyse problems rather than just describe them (reversed)	Externally-oriented thinking	3
6	When I am upset, I don't know if I am sad, frightened, or angry	Difficulty identifying feelings	1
7	I am often puzzled by sensations in my body	Difficulty identifying feelings	1
8	I prefer to just let things happen rather than to understand why they turned out that way	Externally-oriented thinking	3
9	I have feelings that I can't quite identify	Difficulty identifying feelings	1
10	Being in touch with emotions is essential (reversed)	Externally-oriented thinking	3
11	I find it hard to describe my feelings more	Difficulty describing feelings	4
12	People tell me to describe my feelings more	Difficulty describing feelings	4
13	I don't know what's going on inside me	Difficulty identifying feelings	1
14	I often don't know why I am angry	Difficulty identifying feelings	1
15	I prefer talking to people about their daily activities rather than their feelings	Externally-oriented thinking	2
16	I prefer to watch "light" entertainment shows rather than psychological dramas	Externally-oriented thinking	2
17	It is difficult for me to reveal my innermost feelings, even to close friends	Difficulty describing feelings	4
18	I can feel close to someone, even in moments of silence (reversed)	Externally-oriented thinking	3
19	I find examination of my feelings useful in solving personal problems (reversed)	Externally-oriented thinking	3
20	Looking for hidden meanings in movies or plays distracts from their enjoyment.	Externally-oriented thinking	2

2.3 Network analysis

2.3.1 Software and packages

We used the software R (version 3.5.1, open source, available at <https://www.r-project.org/>). Packages and functions to carry out the analysis include qgraph (Epskamp, Cramer, Waldorp, Schmittmann, & Borsboom, 2012), glasso (Friedman, Hastie, & Tibshirani, 2014) for network estimation and visualization, mgm (Haslbeck & Waldorp, 2016) for node predictability, EGA (Golino & Epskamp, 2017) and igraph (Csardi & Nepusz, 2006) for community detection, lavaan (Rosseel, 2012) for CFA and bootnet (Epskamp, Borsboom, & Fried, 2017) for stability. Details about package versions used in this paper is found in the supplementary materials.

2.3.2 Item network

A correlation matrix was calculated for the 20 TAS items and used as input to estimate a Gaussian Graphical Model (GGM) which is a regularized partial correlation network (Epskamp & Fried, 2018). We regularized the parameters of the GGM with a graphical lasso (least absolute shrinkage and selection operator). Although recent relevant discoveries in the network field (Williams & Rast, 2019; Williams et al., 2019) showed that regularized partial correlation network estimation may provide an anti-conservative network model, our regularized TAS network model reports fewer edges (and is therefore easier to interpret) than the nonregularized partial correlation network, which we report in the supplementary materials (Briganti, 2019) as robustness analysis.

The item network is composed of nodes representing alexithymia questions from the TAS, and each node is surrounded by a pie chart representing its predictability (shared variance with surrounding nodes). The position of nodes in the network is determined by the Fruchterman-Reingold algorithm (Fruchterman & Reingold, 1991), which runs on the sum of connections that a given node has with other nodes. Nodes are connected through edges, which are interpreted as an association between two components, controlling for all other nodes in the

network. In the alexithymia item network, if two nodes A and B are connected, it means for instance that if the observed group scored high on A, then the observed group is also more likely to score high on B and vice versa (Briganti et al., 2018). Each edge in the network has a weight which is defined as the importance of association between two nodes and is denoted by thickness and color saturation; edges can therefore be positive (blue edges, denoting a positive association) or negative (red edges, denoting a negative association).

For this paper, we lowered the lambda parameter (tuning parameter, for more information see Briganti & Linkowski, 2019).

2.3.3 Three-domain network

To better explore the interactions between alexithymia domains from the TAS, we estimated a factor model for the three domains and obtained factor scores to estimate a GGM and therefore a domain network as described in recent empirical papers (Briganti et al., 2019; Briganti & Linkowski, 2019).

2.3.4 Network stability

To safely interpret results from network analysis several stability tests were performed as recommended in the literature (Briganti et al., 2019; Epskamp et al., 2017). To answer the question “are edge weights accurately estimated”, 95% confidence intervals (CI) were estimated through bootstrapping (2000 bootstraps were used). To answer the question “is edge A significantly stronger than edge B” we performed an edge weight difference test.

2.3.5 Network inference

Node predictability (Haslbeck & Fried, 2017) represents shared variance that a given node has with surrounding nodes; it has been defined as the upper bound of controllability: if one assumes that all edges for a given node are directed toward that node, then node predictability provides an estimate of how much influence one can have on that node via all other nodes

(Briganti *et al.*, 2019). Node predictability was estimated for all nodes in the item and domain network and is represented as a pie chart surrounding each node.

To detect the number of communities in our TAS dataset, an EGA was performed (Golino & Epskamp, 2016), which uses the walktrap algorithm. The algorithm is based on the principle that adjacent nodes tend to belong to the same community (Yang, Algesheimer, & Tessone, 2016).

Following the methodology of a recent study (Briganti & Linkowski, 2019) and because we found a different number of dimensions than the original model, we estimated an additional network structure based on the results from EGA.

2.3.6 Four-domain network

We used CFA to estimate a four-factor model in the data and used the scores to estimate an additional GGM. Node predictability and stability analyses were also carried out.

3. Results

3.1 Item network

Figure 1: 20-item alexithymia network. Each node represents an item from the TAS questionnaire. The pie chart surrounding each node represents node predictability.

Figure 1 shows the 20-item alexithymia network. Nodes connect both within and between communities. We will hereby detail some of the connections. Edge weight matrices for all networks can be found in the supplementary materials.

Item 2 (“It is difficult for me to find the right words for my feelings”) is highly connected to item 4 (“I am able to describe my feelings easily”, reversed) and both belong to *difficulty describing feelings*. Item 3 (“I have physical sensations that even doctors don’t understand”) shares a connection with item 7 (“I am often puzzled by sensations in my body”) and both belong to *difficulty identifying feelings*. In these two cases, items strongly resemble each other

and are therefore redundant; the meaning of edges in this case shifts and should be interpreted as shared variance.

Item 1 (“I am often confused about what emotions I am feeling”) from *difficulty identifying feelings* and 2 (“It is difficult for me to find the right words for my feelings”) from *difficulty describing feelings* are also strongly connected.

Item 8 (“I prefer to just let things happen rather than to understand why they turned out that way”) from *externally-oriented thinking* is associated with item 9 (“I have feelings that I can’t quite identify”) from *difficulty identifying feelings*.

Item 15 (“I prefer talking to people about their daily activities rather than their feelings”) from *externally-oriented thinking* is associated with item 17 (“It is difficult for me to reveal my innermost feelings, even to close friends”) from *difficulty describing feelings*.

Items 15, 16 and 20 from *externally-oriented thinking* are detached from the rest of the items from the same factor.

3.2 Three-domain network

Figure 2 illustrates the three-domain alexithymia network. The domain *difficulty describing feelings* is connected to the two other domains *difficulty identifying feelings* and *externally-oriented thinking* which share no connection with each other. The connection between *difficulty describing feelings* and *difficulty identifying feelings* is stronger than the connection between *difficulty describing feelings* and *externally-oriented thinking*.

Figure 2: three-domain network. Each node represents a domain from the TAS.

3.3 Network stability

Stability analyses are reported in the supplementary materials. Edges are overall accurately estimated in both the item network and the three-domain network, and we can safely interpret stronger edges in both networks to be significantly stronger than weaker edges.

3.4 Network inference

3.4.1 Node predictability

In the item network, the most predictable node is item 2 (“It is difficult for me to find the right words for my feelings”), which shares 54% of variance with surrounding nodes. Item 2 belongs to *difficulty describing feelings*, which is also the most predictable domain in the three-domain network and shares 72% of variance with the two other domains. The least predictable node in the item network is item 18 (“I can feel close to someone, even in moments of silence”) which belongs to *externally-oriented thinking* and shares only 8% of variance with other nodes. In the three-domain network, the least predictable node is *externally-oriented thinking* which shares

12% of variance with the two other domains. The mean node predictability is 24% in the item network and 51% for the three-domain network. In both networks, *difficulty describing feelings* shows the most connectivity and *externally-oriented thinking* the least connectivity.

3.4.2 Community detection

Figure 3: Community detection through Exploratory Graph Analysis.

Figure 3 shows the twenty-item TAS network with colors corresponding to the communities as detected by the EGA.

Four communities are reported by the EGA: a new community emerges from items 15, 16 and 20 from *externally-oriented thinking*. We defined the new community as *distraction*, and we report confirmatory factor analyses for both the three-factor and the four-factor model in the supplementary materials: both models report comparable and satisfactory construct validity.

3.5 Four-domain network

Figure 4: four-domain network. Blue edges represent positive connections, red edges represent negative connections.

Figure 4 shows the four-domain network.

In the four-domain network, two strong edges exist: the first shared between *distraction* and *externally-oriented thinking*, and the second between *difficulty identifying feelings* and *difficulty describing feelings*. *Distraction* and *difficulty describing feelings* share a weaker connection, such as *externally-oriented thinking* and *difficulty identifying feelings*. However, two weak negative connections are reported: the first between *difficulty identifying feelings* and *distraction* and the second between *externally-oriented thinking* and *difficulty describing feelings*. The highest node predictability (73%) is reported by *difficulty describing feelings*, and *externally-oriented thinking* reports the lowest node predictability (54%). The mean node predictability is 63%. Stability analyses show that edges are accurately estimated and each edge in the network is significantly different from other edges in the network.

4. Discussion

This is to our knowledge the first network analysis of the psychological construct of alexithymia as conceived in the TAS with state-of-the-art methods. The different analyses carried out bring new and interesting information on the construct and build on previous findings.

The TSA item network sheds light on the connectivity between items within the same domain and items from different domains of alexithymia. Several items that are strongly connected (for instance item 2,3,4 and 7), report a certain redundancy in measuring the same aspect of alexithymia with other items; other items share meaningful mutual interactions while measuring a different aspect of alexithymia. Items from the alexithymia questionnaire report different levels of interconnectedness. The EGA reported the existence of four communities; the domain *externally-oriented thinking* loses three of its items to a new component that we defined as *distraction*.

Because of the redundancy issue and the difficulty on extracting meaningful clinical implications from a network of items (Briganti et al., 2019), we estimated network models of three and four domains: these models help us better explore the connections between different domains of the TAS.

Difficulty describing feelings being the most connected domain in both network models, it may become of interest for future longitudinal studies associated with clinical interventions. From a three-domain network perspective, answers of the observed group to items from *difficulty describing feelings* can help us better predict answers to items from the two other domains, and vice versa.

In both models, the most interconnected domain shares the strongest connections with *difficulty identifying feelings*, which has similar connectivity; this may be due to the strong similarity between these two aspects of alexithymia, which have already been shown to merge in a single community in other network studies (Watters et al., 2016a; Watters et al., 2016b); in our dataset

however, the two domains remain separate, as shown by EGA. Future studies may also endeavor to explore the relationship between these two domains in other samples, as well as the evolution of their association when an intervention is carried out.

Externally-oriented thinking splits in two separate communities: this finding, along with the small negative edges found in the four-domain network should however first be replicated in other different samples before being considered as clinically meaningful.

This study reports meaningful, clinical implications even if carried out on university students, more so because it can build on previous findings.

We found similar findings as well as differences with previous network models of alexithymia measurement tools (Watters et al., 2016a; Watters et al., 2016b). For instance, in our TAS network models, *difficulty describing feelings* is the most interconnected domain and contains node 2, the most interconnected item in the questionnaire; this constitutes a similarity with the previous TSIA and BVAQ studies. However, this domain remains a separate community from *difficulty identifying feelings*, which constitutes a difference with previous studies. Because of these findings, we support the arguments made by the authors of previous alexithymia network analyses in stating that in a clinical setting, priority should be given in intervening on affect awareness to better identify and describe feelings. However, in our sample, because items from *externally-oriented thinking* and the domain itself do not show particularly strong connectivity (even so because the domain splits into two distinct communities in the EGA), it should not be given a higher priority in intervention than other components of alexithymia; future studies may endeavor to replicate and compare findings to further understand if it is a viable clinical target or not.

Our findings should be met with a number of limitations. First, our dataset is composed of university students, which likely limits the generalization of our findings to different samples.

Second, because this is a cross-sectional study, we cannot causality from connections between nodes; this can be obtained, for instance, with time-series analyses.

Network analysis is a powerful set of tools to explore alexithymia in both clinical and nonclinical samples. Future studies should endeavor to replicate findings from different measurement tools and also address clinical samples of individuals with psychopathology. This may help to confirm targets for clinical interventions (such as highly connected nodes from the domain networks) and respective outcome in different types of mental illness.

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