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A MACHINE LEARNING APPROACH TO RELATIONSHIPS AMONG ALEXITHYMIA COMPONENTS

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SUMMARY

Background: *The aim of this paper is to explore the network structures of alexithymia components and compare results with relevant prior literature.*

Subjects and methods: *In a large sample of university students, undirected and directed network structures of items from the Bermond Vorst Alexithymia Questionnaire form B are estimated with state-of-the-art network analysis and structure learning tools. Centrality estimates are used to address the topic of item redundancy and select relevant alexithymia components to study.*

Results: *Alexithymia components present positive as well as negative connections; poor fantasy and emotional insight are identified as central items in the network.*

Conclusions: *The undirected network structure of alexithymia components reports new features with respect to prior literature, and the directed network structures offers new insight on the construct.*

Key words: *machine learning – alexithymia - Bayesian networks*

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INTRODUCTION

Alexithymia is named from the Greek words "a", "léxis", and "thymos", meaning "lack of word for emotion" (Sifneos 1972): initially, it was used to describe emotional deficiencies in patients suffering from classic psychosomatic disorders and epilepsy; those patients were unaware of their feelings and were unable to fantasize about their inner thoughts, feelings, and attitudes. This personality construct has been described more than half a century ago and is characterized by several key features: difficulty identifying, verbalizing and analyzing emotions, poor fantasy life and poor insight (Loas et al. 2017); these features have been found to be constant over time, in contrast to what was initially observed.

Alexithymia is considered a subject of interest in psychiatric research, because it allows for a deeper understanding of the physiological basis of mental disorders that are associated with emotions, such as bipolar disorder, addiction and depression (Briganti & Linkowski 2019c). Important clinical implications include this construct, such as the potential overlap between alexithymia and other psychiatric disorders that present with a lack of empathy, such as psychopathy and autism, as reported by extensive neuroimaging research that has been conducted on the topic (Moriguchi & Komaki 2013). Some authors recommend to transpose the construct of alexithymia to that of "affective agnosia" (Lane et al. 2015).

Several psychometric tools have been validated to measure the construct of alexithymia. One of the most well-known and widespread tools is the Bermond Vorst Alexithymia Questionnaire (BVAQ, shortened to AQ in this manuscript) which describes the construct of alexithymia as a composed of five domains (Vorst & Bermond 2001): difficulty identifying emotions, difficulty analyzing emotions, difficulty verbalizing emotions, lack of emotional insight, and poverty of fantasy life. This last domain of alexithymia is what sets the AQ apart from its main counterpart, the Toronto Alexithymia Scale (Bagby et al. 1994), since the latter psychometric scale does not contain any items that reflect the difficulty in fantasizing. The AQ has been defined as a reliable tool for the study of alexithymia, and it has been heavily investigated with exploratory and confirmatory factor analyses in several populations (de Vroege et al. 2018).

From an ontological point of view, alexithymia as represented by psychometric tools such as the AQ, developed and validated through the lenses of factor analyses, is a common cause that can be measured via the items in the questionnaire; those items are a reflection of a given factor (such as poor fantasy life), and each factor is itself a consequence of the common cause that is the personality construct at hand ("the latent variable"). Hence, the observable variables (the items themselves) only represent passive and interchangeable elements of the latent variable. However, previous work on alexithymia highlighted the opportunity that is the study of relationships between observable variables as a complementary tool to factor analysis (Watters et al. 2016a,b).

The study of relationships between observable variables is allowed by network analysis, which is a new way of analyzing psychiatric constructs as complex systems arising from interactions between symptoms or components (Borsboom & Cramer 2013). Such systems are conceived as networks of nodes (the variables themselves) and edges (undirected connections among

variables): often, the unobserved connection among items are computed as partial correlations, either regularized (Epskamp & Fried 2018) or non-regularized (Williams & Mulder 2019); the latter has been shown to be a good fit for psychological data, since it is low dimensional (the number of subjects exceeds by far the number of variables) (Williams et al. 2019).

Network analysis is becoming more and more established in the field of psychometrics and has been used to explore several mental disorders, such as posttraumatic stress disorder (Fried et al. 2018, Phillips et al. 2018), depression (Mullarkey et al. 2018), autism (Ruzzano et al. 2015) and also psychological constructs, such as empathy (Briganti et al. 2018), self-worth (Briganti et al. 2019), resilience (Briganti & Linkowski 2019b, Fritz et al. 2018), and narcissism (Briganti & Linkowski 2019a).

Alexithymia has been analyzed three times with network analysis, two with the Toronto Alexithymia Questionnaire variants (Briganti & Linkowski 2019c, Watters et al. 2016b) and the AQ (Watters et al. 2016a): all these studied in depth the connections between the items from alexithymia scales as well as the regrouping of variables in domains.

The modeling of network structures of constructs such as alexithymia is particularly interesting to integrate in clinical practice, since relevant components may serve as targets for clinical intervention (Fried et al. 2018); in the case of alexithymia, finding and acting upon relevant components may attenuate the neurocognitive alterations that have been described in the literature.

However, the identification of the central components of a construct is complicated because of the redundancy of items in questionnaires (Briganti & Linkowski 2019d): the more redundancy exists in a questionnaire, the more the redundant items will be heavily connected, which in turn will boost their relative importance: this can be called "centrality corruption" (Briganti & Linkowski 2019c). Several strategies have been proposed to overcome redundancy, such as exploring networks of domains instead of networks of items (Briganti et al. 2019) and topological overlap. The latter has been proposed as a way of dropping (or regrouping) the items that repeat the same aspect of a construct as other items in a scale (Fried & Cramer 2017), but it has not been used experimentally to regroup items from a psychometric tool.

Moreover, because of the clinical relevance of alexithymia, it would be useful to uncover causal relationships (directed connections among items) between meaningful items in order to gain further information on the nature of connections among them. Such causal relationships can be identified with specific tools in network science, such as Directed Acyclic Graphs (DAGs). DAGs are the foundation of probabilistic models such as Bayesian networks and other machine learning approaches that are capable of learning the underlying causal graphs from data (Moffa et al. 2017), compute and represent such relationships. DAGs are well established at the crossroads of machine learning and network science literature (Scutari & Denis 2015) and have been previously used in empirical research to explore depression (McNally et al. 2017) and psychosis (Moffa et al. 2017).

Inspired by recent works in the field of both structure learning and alexithymia, we aim to explore several network structures of the AQ. First, we will estimate a partial correlation network of items from the AQ and infer their relative importance with established measures in the field (Briganti et al. 2018). Second, we will tackle the problem of centrality corruption by reducing the network to a group of five items from the scale based on their belonging to a given domain and their relative importance in the network. Third, we will apply a structure learning algorithm to construct a DAG of the main alexithymia components and therefore explore causal pathways.

SUBJECTS AND METHODS

Data set

The data set is composed of 537 university students attending programs from academic institutions in the French-Speaking region of Belgium. Subjects were 17 to 25 years old (M=20 years; SD=1.7 years). 71% of students were women and 29% were men.

Measurement

The AQ (Vorst & Bermond 2001) is composed of items assessing alexithymia in five domains: difficulty identifying emotions, difficulty analyzing emotions, difficulty verbalizing emotions, lack of emotional insight, and poverty of fantasy life. In this study, the form B of the questionnaire, which is composed of 20 items, was used. The data set for this study was anonymized before analysis, and the protocol for this study was approved by the ethical committee of the Erasme teaching hospital.

Network analysis

Software and packages

We used the software R for statistical computing (version 3.6.1, open source, available at https://www.r-project.org/). The package used to carry out the analysis include qgraph (Epskamp et al. 2012) for the undirected network estimation and visualization, bootnet (Epskamp & Fried 2018) for stability analyses and bnlearn (Scutari 2010) for DAG estimation.

Partial correlation network

Estimation of the partial correlation network

We estimated a Gaussian Graphical Model (GGM), that is, a partial correlation network for the items in the AQ. The GGM is calculated as the inverse-covariance matrix: it is a network that includes a set of nodes that

correspond to the alexithymia items in the AQ and a set of edges that connect the nodes in the network. If two nodes are connected, that means they are conditionally dependent given all other nodes in the network (i.e their partial correlation is nonzero).

In the network of alexithymia components, if two nodes A and B are connected, it means for instance that if the observed group scored high on component A, then the observed group is also more likely to score high on component B, and vice versa, controlling for other nodes in the network (Briganti et al. 2018). Each edge in the network has a weight representing the strength of association between two alexithymia components; edges can be positive (and therefore represent a positive association) or negative (denoting a negative association). In the network the edge weight is represented as a combined thickness and saturation of the edge; positive edges are shown in blue, and negative edges in red. Nodes are placed in the network by the Fruchterman-Reingold algorithm, based on the sum of the connections a given node has with other nodes (Fruchterman & Reingold 1991).

Network inference

To find comparatively important items in the partial correlation network, we used strength centrality, which represents the absolute sum of the edges that nodes in the network share with other nodes (Boccaletti et al. 2006).

Network accuracy and stability. Accuracy and stability analyses were carried out following state-of-the-art methods (Epskamp & Fried 2018) that were applied in previous empirical papers (Briganti et al. 2018) and can be found in the supplementary materials.

Accuracy analyses were carried out to answer the question: "is edge X accurately estimated?"; 95% confidence intervals (CI) were estimated through bootstrapping (i.e., repeated re-sampling from the original dataset to re-estimate network parameters; 2000 bootstraps were used). Edge weight difference tests were carried out to answer the question: "is edge X significantly stronger than edge Y?".

Stability analyses were carried out to answer the question "is the centrality order stable?" with the same bootstrapping method. Centrality difference tests were carried out to answer the question "is the centrality of node A significantly stronger than the centrality of node B?".

Topological overlap

To address the important topic of redundancy (i.e., items in the questionnaire measuring the same aspect of the construct of alexithymia), the approach proposed by Fried and Cramer (2017) of topological overlap was used. Because items from the same domain strongly resemble each other, the most central item from each domain (i.e items reporting the highest strength centrality score) was selected to represent the corresponding facet of the construct in a five-item network.

Five-item network structure

A five-item network structure was constructed with the same methods described in the section "Estimation of the partial correlation network", and it was studied with inference analysis (that is, strength centrality computation) as well as stability and accuracy analyses. Only the five-item network is the partial correlation network structure detailed in the Results section, with the full 20-item network reported in the supplementary materials.

Directed Acyclic Graphs

In Bayesian networks an edge may represent a causal pathway between two nodes. The structure of a Bayesian network can be estimated using constraint-based algorithms, which analyze conditional independence relations among the nodes in the network. Constraint-based algorithms produce a network model that can be interpreted as a causal model even from observational data, under assumptions that in clinical terms exclude confounding and sampling bias. In this paper the PC-algorithm is used, which is a constraint-based algorithm (Spirtes et al. 1993).

To estimate a network model, the PC-algorithm first estimates an undirected network model in which all pairs of nodes are connected, then deletes edges between conditional independent pairs of variables, and directs edges starting with v-structures (two disconnected nodes causing a third node). The estimated network was investigated using stability analysis through bootstrapping.

Afterwards, a network is reported with a minimum connection strength (% of fitted networks in which a given connection appears) of 85 and a minimum connection direction (% of fitted networks in which a given connection has a given direction) of 50. This resulting network therefore reports connections that are presents in more than 85% of the fitted networks. Moreover, these connections present a direction (for instance, from node A to node B) which is found in more than half of the fitted networks resulting from the bootstrapping procedure. By default, with the software we used all edges are represented as red, and their strength are represented as a combination of thickness and color saturation in the edges.

RESULTS

Partial correlation network

Central items in the AQ

The five items showing the highest strength centrality values in each of the five domains are reported in table 1.

"Difficulty identifying emotions" is represented by item 22, "I rarely let myself go to my imagination"; "difficulty analyzing emotions" is represented by item 30, "I think one should stay in touch with one's feelings" (reversed item);

Table 1. Central items from the Bermond Vorst Alexithymia Questionnaire

N	Item	Domain
22	I rarely let myself go to my imagination	Difficulty Identifying Emotions
26	When I am upset by something, I tell others about how I feel	Difficulty Verbalizing Emotions
29	I often get upset by unexpected events	Poor Emotional Insight
30	I think one should stay in touch with one's feelings	Difficulty Analyzing Emotions
33	When I'm tired of myself, I can't know if I'm sad, afraid, or unhappy	Poor Fantasy

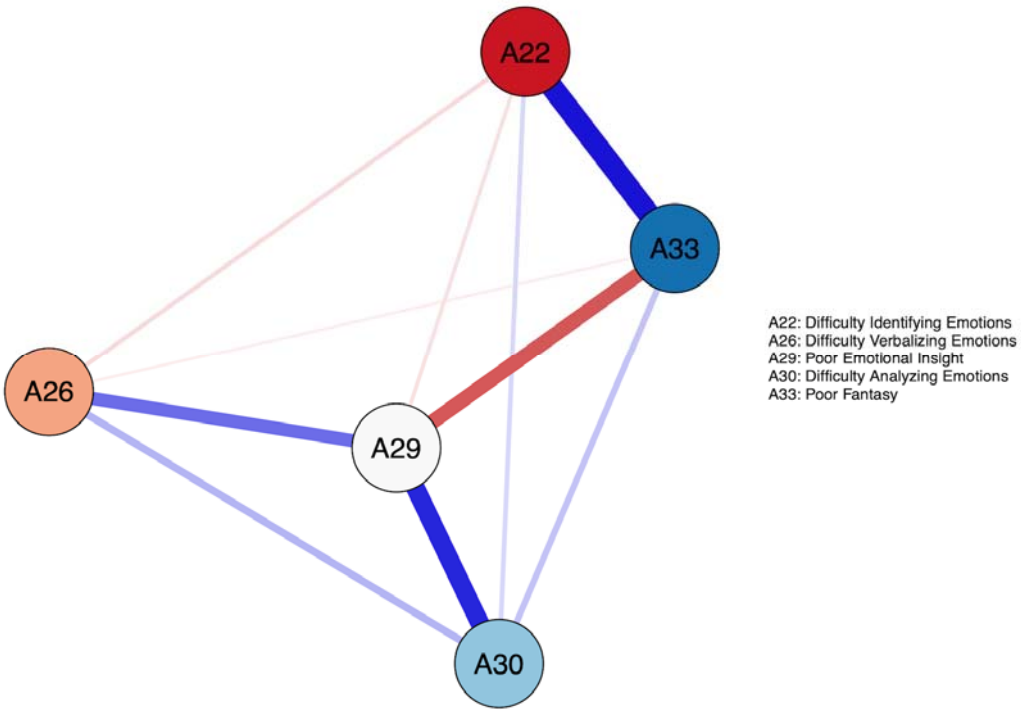

Figure 1. Partial correlation network. Each item represents one of the five domains in the AQ. Blue connections represent positive edges, red connections represent negative edges

"difficulty verbalizing emotions" is represented by item 26, "When I am upset by something, I tell others about how I feel" (reversed item); "lack of emotional insight" is represented by item 29, "I often get upset by unexpected events" (reversed item), and "poverty of fantasy life" is represented by item 33, "When I'm tired of myself, I can't know if I'm sad, afraid, or unhappy". Three of the five items with the highest centrality in the AQ twenty-item network have reversed scores.

Partial correlation network structure

The five-item network is represented in figure 1. As opposite as most construct networks reported in the literature (Briganti et al. 2019, 2018, Briganti & Linkowski 2019a,b,c), the AQ network is not overall positively connected, as it includes several positive as well as negative edges. Some of the connections in the network are described in the following. The domains "difficulty identifying emotions" and "poor fantasy" show a positive connection, as well as the domains "difficulty verbalizing emotions" and "emotional insight", "poor emotional insight" and "difficulty analyzing emotions", and "difficulty verbalizing emotions" and "difficulty analyzing emotions". The domains "poor emotional insight" and "poor fantasy", are negatively connected in the network. The full list of edge weights is reported in the supplementary materials.

Network inference

The centrality estimates for the five-item network are reported in figure 2. Item 33 from the domain "poor fantasy" and item 29 from the domain "poor emotional insight" report the highest strength centrality estimates. Centrality estimates for the twenty-item network are reported in the supplementary materials.

Network accuracy and stability

Accuracy and stability analyses are reported in the supplementary materials for both the five-item and twenty item networks. Edges are overall accurately estimated in both the five-item and twenty-item network. We can safely interpret stronger edges to be significantly stronger than weaker edges in the network. Centrality estimates of nodes 29 and 33 in the five-item network are not significantly different, which means we cannot say which of the two items is the most central.

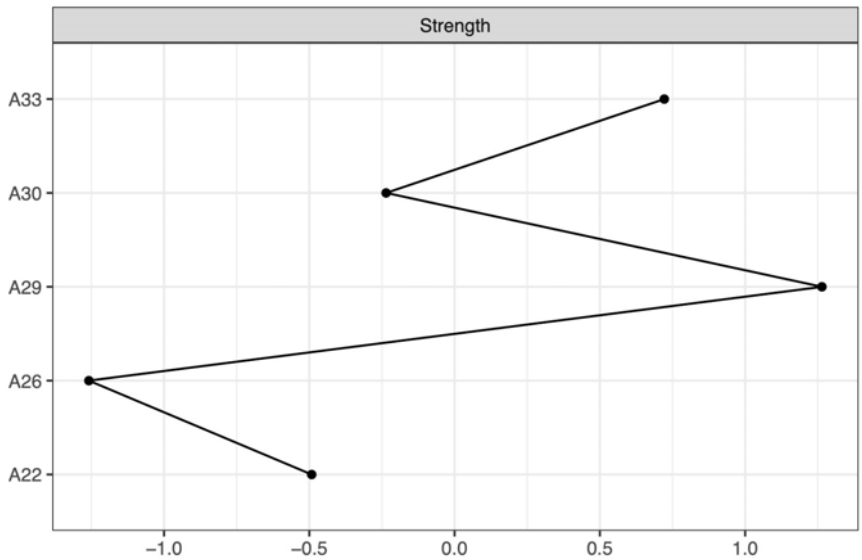

Figure 2. Strength centrality estimates for the five-item network. The x-axis reports the standardized z-scores and the y-axis reports the corresponding item

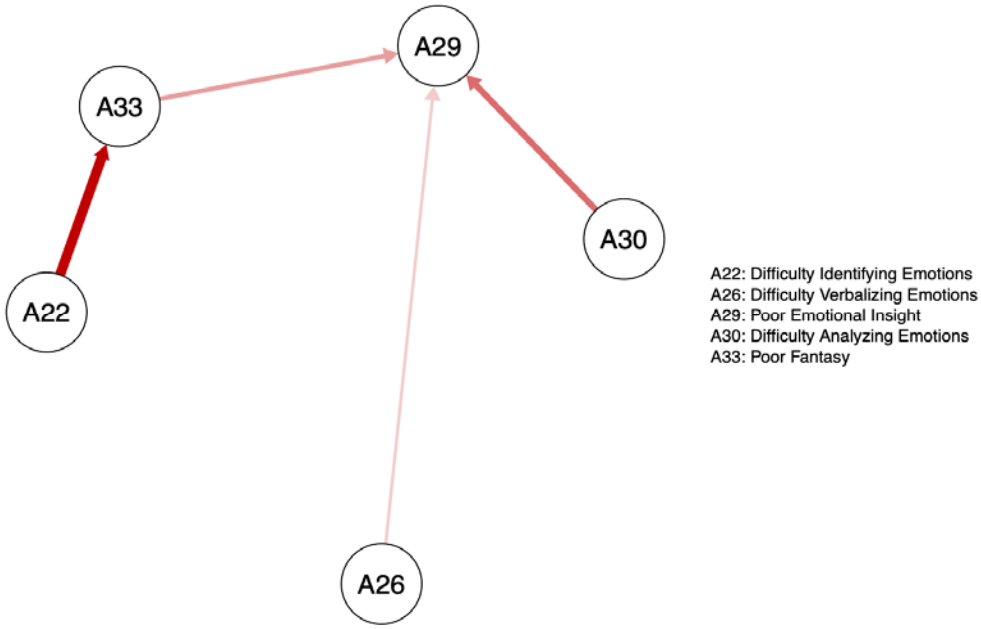

Figure 3. Directed Acyclic Graph of alexithymia components obtained with the constraint-based PC-algorithm. Relationships between nodes (arrows) can be understood as causal pathways under certain assumptions

Directed Acyclic Graph

The DAG of alexithymia components is reported in figure 3. Item 29 from the domain "poor emotional insight" has three incoming edges from "poor fantasy" (item 33), "difficulty verbalizing emotions" (item 26) and "difficulty analyzing emotions" (item 30). Item 22 from the domain "difficulty identifying emotions" has an outgoing edge to item 33 from the domain "poor fantasy".

DISCUSSION

This is to our knowledge the first network analysis of alexithymia components that combines the classic partial correlation network approach with the Bayesian network approach. Several of the resulting analyses bring new and interesting information on the construct of alexithymia.

The partial correlation network for the twenty-item AQ reports a structure with an overall mixture of positive and negative connections among items. Because items from the same domain tend to measure the same aspect of the construct of alexithymia (that is, the domain they belong to), the solution of topological overlap is applied: the original twenty-item network is translated to a network of the five items in the AQ that have the highest centrality values in their respective domains and that are reported in table 1. In this work, the exploratory analyses on the twenty-item network (representing the full questionnaire) was important to

highlight with network inference methods relevant alexithymia components so as to analyze a more simple and non-redundant network structure.

The five-item network reports, similarly to the twenty-item network, a set of positive and negative edges: alexithymia components therefore present a heterogeneous connectivity. Items from domains "poor emotional insight", "difficulty verbalizing emotions", "difficulty analyzing emotions" share a set of positive connections: this means that the average score of the observed group on one of these three questions can be predicted based on the score on the other two questions. The same phenomenon is observed with items representing the domains "difficulty identifying emotions" and "poor fantasy". However, "poor fantasy" and "poor emotional insight" are negatively connected, which from an undirected network perspective, can be interpreted as follows: given all other alexithymia components in the network, if the average score on one component is high, we may expect that the average score of the observed group on the other component is low, and vice versa. Our findings differ slightly in that respect from the recent work of Watters et al. (2016a), in which the two domains sharing a negative connection are "difficulty identifying emotions" and "poor fantasy".

The inference analyses show that items 29 and 33 share a negative connection in the five-item network and are also the two items with the highest centrality estimates. However, stability analyses show how the two centrality indices are not statistically different from each other, hence we cannot say whether item 29 (that reports the highest centrality estimate) is really the most central item.

In this work, the study of the undirected interplay among relevant alexithymia components was an important preliminary step before entering the realm of causal inference through the lenses of Bayesian networks. The DAG structure derives from the constraint-based PC-algorithm. Directed connections between alexithymia components can be interpreted as causal pathways under assumptions that in clinical terms exclude confounding and sampling bias. The DAG reports that "poor emotional insight", the lack of ability to fantasize, is essentially a consequence of a poor ability to fantasize, a difficulty in verbalizing emotions and a difficulty in analyzing emotions.

The information from the undirected five-item network inference analyses and the Bayesian network analyses can be combined to obtain some interesting insights. First, in the partial correlation network, "poor emotional insight" has a high estimated centrality, and the overall item connectivity to other items in the network can be interpreted as predictability. Second, the DAG shows that all edges that item 29 shares with other nodes point towards "poor emotional insight", which means that not only is "poor emotional insight" is a highly "predictable" domain of alexithymia, but that it is also a highly "controllable" domain of the construct. This notion can be interpreted as that the aspect of alexithymia that deals with the lack of insight regarding emotional arousal can be controlled through other aspects of the construct.

The two network models proposed in this paper present similarities as well as differences: for instance, both the partial correlation network and the DAG share several edges between the same nodes; however, some nodes that are connect in the partial correlation network are not connected in the DAG. The reason is the different definitions of the two models: in a DAG two nodes are not automatically connected when they share a common child node (such as item 29), but they will be connected in the corresponding partial correlation network because of the indirect dependence conditional on that child node.

Our results must be interpreted in light of several limitations. First, our data set is composed of university students, which may limit the generalization of our findings to different samples. Second, DAG structures do not involve loops: if in a three-node network a component A causes component B and a component C, component C cannot cause component A (the structure is therefore acyclic). However, it is plausible to consider that in the case of alexithymia components, certain items may activate each other in a loop. Third, causation may be inferred from a connection between two nodes in a DAG assuming there are no confounding or sampling bias.

CONCLUSIONS

This paper aimed to study the important construct of alexithymia through a network approach of both Bayesian and non-Bayesian methods. Poor fantasy and Poor emotional insight are identified as key feature of this construct that play an important role in the self-determination of the network structure: they should be considered as important aspects of the construct in clinical studies. Future works may endeavor to replicate our findings of network structures (both Bayesian and non-Bayesian) of alexithymia components in different samples, both non-clinical and clinical.

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Contribution of individual authors:

Giovanni Briganti: came up with the idea of the manuscript, collected the data set, wrote the manuscript.

Paul Linkowski: collected the data set, reviewed the manuscript.

Marco Scutari: performed a review of the statistical methods used, reviewed the manuscript.

All the authors contributed to the article, all participated to the literature search and writing. All are answerable for published reports of the research.

This publication has been approved by all co-authors, as well as by responsible authorities where the work has been carried out.

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