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ORIGINAL ARTICLE

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The three-dimensional community structure of attention-deficit hyperactivity disorder (ADHD) traits captured by the Adult ADHD Self-Report Scale: An exploratory graph analysis

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Abstract

Objective: To employ a novel analytic method—namely, exploratory graph analysis (EGA)—to subclinical attention-deficit hyperactivity disorder (ADHD) trait scores in order to reveal their dimensional structure, as well as compare EGA's performance with traditional factor-analytic techniques in doing so.

Method: 1149 respondents from a survey panel completed the ASRS, a common ADHD scale made up of 18 distinct trait measures. EGA and factor analysis were applied to identify traits which associate with each other.

Results: EGA revealed 3 distinct communities, and ruled out a 2-community structure. This was in contrast to the 2-factor structure suggested by the factor analysis, and the conventional division of ADHD into two subdimensions (hyperactivity and inattention).

Conclusion: A dimensional structure of three clusters (hyperactivity, impulsivity and inattention) may better reflect the traits underlying ADHD. EGA has benefits in terms of both analytic approach and interpretability of findings.

KEYWORDS
ADHD, attention deficit hyperactivity disorder, EGA, exploratory graph analysis, factor analysis, network analysis, traits

1 | INTRODUCTION

Attention-deficit hyperactivity disorder (ADHD) is a behavioral disorder defined by either an attentional dysfunction, hyperactive/impulsive behavior, or both (DSM-5, American Psychiatric Association, 2013). ADHD is the most commonly diagnosed neurodevelopmental disorder in children (Barkley, 1997; Faraone et al., 2003) with ADHD symptoms often persisting into adulthood for roughly half of the diagnosed children (Faraone & Biederman, 2005).

The symptoms are thought to be similar for adults and children but fewer symptoms are required in adults in order to receive a diagnosis (American Psychiatric Association, 2013). Evidence from clinical studies, however, suggests that there are differences in the way adult ADHD manifests; for instance, hyperactivity symptoms are less frequent and replaced with a sense of internal restlessness. In addition to this, ADHD symptomatology tends to be more diverse in adults, who report distractibility and difficulties in maintaining goal-directed behavior (Barkley et al., 2010; Biederman et al., 2010).

It has been argued that ADHD psychopathology can be viewed dimensionally, with inattentive and hyperactive-impulsive symptoms distributed continuously in the general population (Hudziak et al., 2007; Panagiotidi et al., 2018, 2019, 2020). Genetic studies provide further support for this argument by showing that ADHD represents the extreme end of traits present in the general population (Martin et al., 2014). This approach has been adopted by a number of recent studies. More specifically, significant behavioral and cognitive differences have been observed between healthy individuals displaying high and low levels of ADHD traits (Panagiotidi et al., 2017a, 2017b, 2018, 2019, 2020; Polner et al., 2015).

A number of questionnaires and screeners have been created to measure DSM symptoms of ADHD in adults. The most commonly used ones are the Adult ADHD Self-Report Scale (ASRS, Kessler et al., 2005) and the Conners' Adult ADHD Rating Scale—Self-Report: Long Version (CAARS, Conners et al., 1999). Most screeners are based on the DSM criteria for ADHD and require individuals to state how frequently they experience such symptoms. Conducting exploratory factor analyses of this expanded symptom set among patients with ADHD and controls allows us to further understand adult manifestations of ADHD.

The ASRS is an instrument consisting of the 18 DSM-IV-TR criteria and was developed in conjunction with the World Health Organization (WHO), and the Workgroup on Adult ADHD. The scores obtained through the ASRS have been found to be predictive of symptoms consistent with ADHD (L. A. Adler et al., 2006). The ASRS contains 18 items from DSM-IV-TR (American Psychiatric Association, 2000) but measures the frequencies of the symptoms. The subjects are asked to report how often they experience each symptom in a period of 6 months on a five point Likert scale which ranges from 0 for never, 1 for rarely, 2 for sometimes, 3 for often, and 4 for very often (Kessler et al., 2005).

The ASRS is conventionally regarded as having a two-factorial structure (Reuter et al., 2006) which includes an inattention scale and a hyperactivity/impulsivity scale. Each subscale contains nine items (Table 1). The ASRS examines only current adult symptoms of ADHD. The reliabilities (Cronbach's alpha) for the two subscales of inattention (0.75) and impulsivity (0.77) as well as for the total ASRS (0.82) tend to be satisfactory (Reuter et al., 2006). The ASRS is split into two parts; Part A and Part B. The Part A of the ASRS can be administered alone as the ASRS screener or ASRS-6. It contains six questions most strongly associated with ADHD (Kessler et al., 2005).

A 2-factor structure is often reported in studies using the ASRS. Recently, Brevik et al. (2020) found that a two-factor solution for the ASRS explained 62.2% of the variance. The first factor included items reflecting symptoms of inattention, the second factor symptoms of hyperactivity and impulsivity. The items reflecting impulsive behavior obtained the highest loadings on the second factor. Other studies report a 3-factor structure for the ASRS, which includes an Inattention, Hyperactivity, and a separate Impulsivity factor (Yu et al., 2021). Factor analysis of alternative measures of ADHD symptoms have reported alternative, four-factor, structure (Adler et al., 2017). As such there is room to explore further both the clustering of ADHD traits and the advantages and disadvantages of different analytic methods for exploring dimensional structure among traits.

The ASRS-6 is a brief screener, taking less than a minute for respondents to complete.It comprises four items taken from the original subscale of the ASRS-18 measuring inattention and two items from the original subscale measuring hyperactivity (Kessler et al., 2005). This raises the question whether these six items load on a single ADHD factor or two factors representing inattention and hyperactivity, respectively. The ASRS has been subjected to a principal factor analysis (PFA, Kessler et al., 2007). The PFA supported a single factor model for the ASRS based on eigenvalues >1. Hesse (2013) used confirmatory factor analysis (CFA) to test a one- and a 2-factor model for ASRS6 and found that the ASRS is a two-dimensional measure. Across both samples, the two-factor model produced acceptable goodness-of-fit statistics, whereas the one-factor model failed to fit the data. All fit indices improved when the two-factor model was analysed instead of the one-factor model. The single-factor model did not fit the data well. A 2-factor solution was also reported by Carlucci et al. (2017).

2 | EXPLORATORY GRAPH ANALYSIS

A way to address these discrepancies in factor structures of the ASRS is to use alternate statistical techniques. Recent years have seen the emergence of a new statistical technique - Exploratory Graph Analysis [EGA; Golino, Christensen, and Moulder (2020)], an extension of network analyses that offers an alternative way of investigating the dimensional structure of psychological constructs. In psychological networks, highly interactive variables tend to cluster together, forming "communities" (comparable to the "factors" of factor analysis). EGA offers one way of revealing communities. It has the advantages that it is deterministic, with low research degrees of freedom required, or possible, around parameterisation of the model output. The uncovered network structure is presented graphically, which is a non-trivial benefit for interpretation of the output. Numerous simulation studies have established EGA's comparable–––and in certain cases even superior–––performance over more traditional factor-analytic techniques (Golino & Demetriou, 2017; Golino & Epskamp, 2017; Golino, Shi, et al., 2020).

A further advantage of EGA over traditional factor analytic methods is that it is not dependent on rotation methods (the choice of which can result in differing factor structures, Browne (2001)) or choice of factor number from the interpretation of eigenvalues and/or associated scree plots. The community extraction process does not require the researcher to interpret a factor loading matrix before assigning items to different factors/communities.

The current investigation takes ASRS data (n = 1149) and explores the factor structure with EGA and traditional factor analytic methods.

TABLE 1 Items, item number and subscale membership for the two factor structure of long (full) and short (screener) ASRS scales (Kessler et al., 2005).

Item	Number	ASRS-18	ASRS-6
How often do you have trouble wrapping up the final details of a project, once the challenging parts have been done?	1	Inattention	Inattention
How often do you have difficulty getting things in order when you have to do a task that requires organization?	2	Inattention	Inattention
How often do you have problems remembering appointments or obligations?	3	Inattention	Inattention
When you have a task that requires a lot of thought, how often do you avoid or delay getting started?	4	Inattention	Inattention
How often do you fidget or squirm with your hands or feet when you have to sit down for a long time?	5	Hyperactivity	Hyperactivity
How often do you feel overly active and compelled to do things, like you were driven by a motor?	6	Hyperactivity	Hyperactivity
How often do you make careless mistakes when you have to work on a boring or difficult project?	7	Inattention	-
How often do you have difficulty keeping your attention when you are doing boring or repetitive work?	8	Inattention	-
How often do you have difficulty concentrating on what people say to you, even when they are speaking to you directly?	9	Inattention	-
How often do you misplace or have difficulty finding things at home or at work?	10	Inattention	-
How often are you distracted by activity or noise around you?	11	Inattention	-
How often do you leave your seat in meetings or other situations in which you are expected to remain seated?	12	Hyperactivity	-
How often do you feel restless or fidgety?	13	Hyperactivity	-
How often do you have difficulty unwinding and relaxing when you have time to yourself?	14	Hyperactivity	-
How often do you find yourself talking too much when you are in social situations?	15	Hyperactivity	-
When you're in a conversation, how often do you find yourself finishing the sentences of the people you are talking to, before they can finish them themselves?	16	Hyperactivity	-
How often do you have difficulty waiting your turn in situations when turn taking is required	17	Hyperactivity	-
How often do you interrupt others when they are busy?	18	Hyperactivity	-

Note: ASRS materials copyright World Health Organization, available for unrestricted use see https://www.hcp.med.harvard.edu/ncs/asrs.php.

3 | METHODS

3.1 | Data collection

1149 participants were recruited from a large consumer panel in the USA. Responses on the ASRS scale were completed as a filler task which was inserted into an online study of perceptions of litter (Grimes et al., 2016). The mean age of participants was 45.4 years (range 18–83). 481 identified as male, 665 identified as female.

3.2 | Analysis

To estimate the number of dimensions in the ASRS short and long forms, the Exploratory Graph Analysis (EGA) technique was employed with the use of 'EGAnet' R package (Golino, Christensen, & Moulder, 2020). EGA makes use of the walktrap and graphical lasso (least absolute shrinkage and selection operator, Friedman et al., 2008) methods for its community detection procedure. EGA works by first estimating a Gaussian Graphical model, applying a penalization on its parameters based on the Extended Bayesian Information Criterion (EBIC; Chen & Chen, 2008; Epskamp et al., 2018). This model is a network graph that contains nodes, which represent variables, and edges, which represent the estimated statistical associations between nodes. EGA then employs the walktrap algorithm; with the use of 'random walks' over the network, the walktrap algorithm is able to form the community-boundaries of different clusters of nodes (Golino & Epskamp, 2017). In this way, the walktrap algorithm deterministically allocates the variables in their respective communities. Both mathematically and empirically speaking, node communities (i.e., clusters of highly interconnected variables) are equal to reflective latent variables (Golino & Epskamp, 2017). Thus, the number of communities identified by EGA are indicative of the dimensional structure of the modelled constructed.

A new bootstrapped technique - namely, bootEGA - allows for investigating the stability of the EGA-identified community structure (see Christensen & Golino, 2021). bootEGA works by first estimating a sampling distribution of networks––using either a parametric or a non-parametric (resampling—used here, 1000 iterations) procedure for its data-generation process––and then employing the EGA algorithm on them. This analysis yields a sampling distribution of replica networks and a set of statistics describing their features––one of them being their community structure. Two of such statistics were of most interest to the current investigation. First, the typical network structure, that is, the median network of the sampling distribution of networks. Second, the dimension frequency statistic, that is, the occurrence of a specific community structure in the sampling distribution of networks. For the EGA-community structure to be regarded as stable, the dimension frequency statistic should indicate that the EGA-community structure is the most prevalent one in the sampling distribution of networks, and that, ideally, the typical network structure converges with the EGA network structure. For a more thorough discussion on the procedures, the reader is referred to Christensen & Golino (2021).

For comparison, an exploratory factor analysis was performed for both the full and short forms of the ASRS. In each case PCA was used to generate a scree plot. As in each case factors were correlated promax was used as the choice of rotation method. The number of factors were selected by examination of the scree plot, and this compared to the number of communities suggested by EGA.

To further investigate the number of factors suggested by exploratory factor analysis a parallel analysis was conducted (Lim & Jahng, 2019). The mean eigenvalues and their 95 percentile value were generated for 1000 surrogate data sets for each factor and compared to the actual eigenvalues. Factors were accepted if their associated eigenvalue was higher than the 95th percentile.

3.3 | Data and code availability

The data and R code for running the analysis presented in this paper are freely available at https://osf.io/sd6f5/

4 | RESULTS

4.1 | Exploratory graph analysis

The items of the full ASRS scale were subjected to Exploratory Graph Analysis (Figure 1, which revealed that the ASRS could be represented as 3 communities (CI: 1.19–4.81). The results of the bootstrapping procedure (Table 2 suggested that although 3 communities were the most likely solution (f = 0.49), a four-community solution was also significantly represented (f = 0.38). A 2-community solution was not likely (f = 0.00).

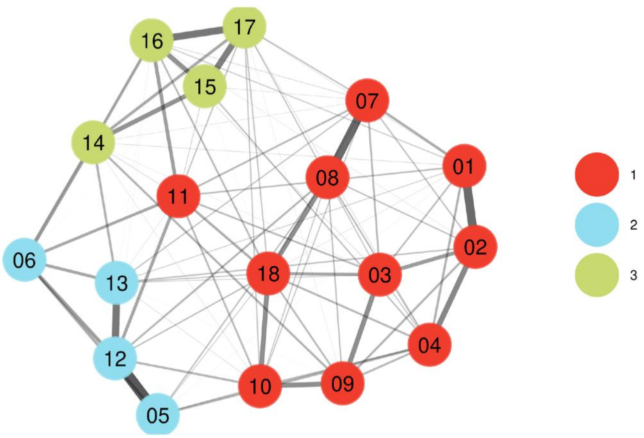

FIGURE 1 The items of the full ASRS scale displayed following Exploratory Graph Analysis (EGA).

TABLE 2 Frequencies each community number solution occurred following 1000 bootstrap iterations.

Number of communities	Frequency
1	0112
2	0001
3	0491
4	0382
5	0014

Note that the items from the original inattention subscale group together in a single community, although with the addition of item 18 (Compare Figure 1 and Table 1). The items from the original hyperactivity subscale divide into two communities: one associated with hyperactivity items (e.g., fidgeting) and one associated with impulsivity items (e.g., interrupting).

The items of the short ASRS scale were subjected to Exploratory Graph Analysis (Figure 2, which revealed that the short ASRS reflects 1 community - i.e. is unidimensional. To check the stability of the community structure a bootstrap procedure was performed (Table 3), which suggested that 1 community was overwhelmingly the most likely and stable solution (f = 1.00).

4.2 | Factor analysis

The full ASRS scale was subjected to traditional factor analytic methods, using the exploratory factor analysis tools in SPSS version 27. PCA was used to generate a scree plot. KMO was over 0.6 (0.951). Bqrlet was p = 0.000 and chi squared = 10,113.507. Principal axis factoring was done with promax, since factors were correlated at 0.762 preventing the use of varimax rotation. The patter matrix was thresholded at 0.35.

The scree plot (Figure 3) suggested that either a two or 3 factor solution might be appropriate, without indicating a clearly superior option. A 2-factor solution gives similar items assigned to each factor

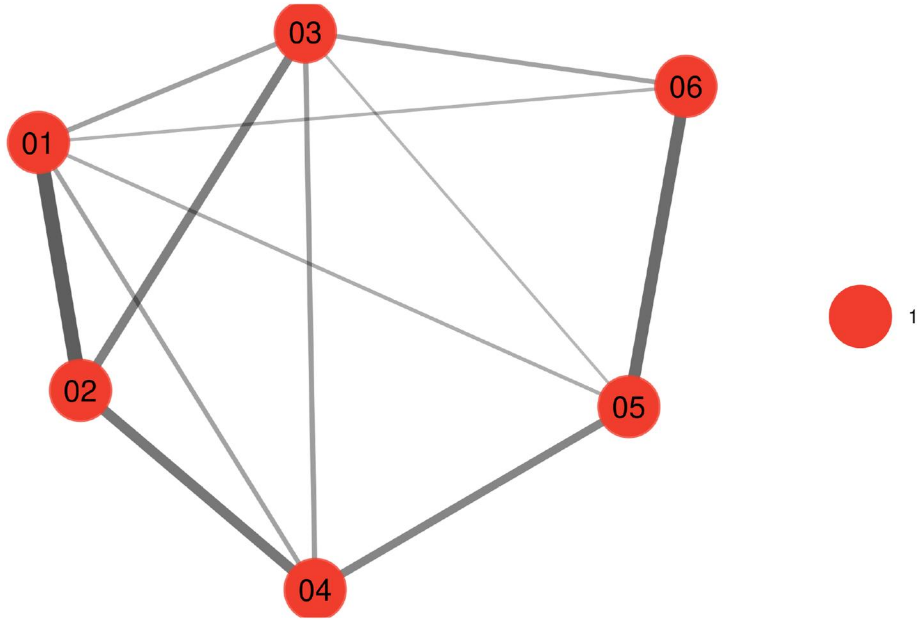

FIGURE 2 The items of the short ASRS scale displayed following Exploratory Graph Analysis (EGA).

TABLE 3 Frequencies each community number solution occurred following 1000 bootstrap iterations.

Number of communities	Frequency
1	0999
2	0001

as the original validation of the scale (Table 1 apart from items 18 and 17 loaded on to factor 1 rather than 2 and item 11 loaded on to factor 2 rather than 1 (see Table 4). Selection of a 3-factor solution resulted in identical items being assigned to each factor as the communities revealed by exploratory graph analysis (Table 4), compare to Figure 1).

The short ASRS scale was subjected to traditional factor analytic methods. The scree plot suggested that a 2-factor solution might be appropriate (Figure 4). A 2-factor solution gives identical items assigned to each factor as the original validation of the scale (Table 5. This does not align with the item assigned to the single community revealed by exploratory graph analysis, cf Figure 2).

To further investigate the number of factors suggested by exploratory factor analysis a parallel analysis was conducted (Lim & Jahng, 2019). The mean eigenvalues and their 95 percentile value were generated for 1000 surrogate data sets for each factor and compared to the actual eigenvalues. Factors were accepted if their associated eigenvalue was higher than the 95th percentile. For the long scale, parallel analysis suggested a unidimensional structure. However, The eigenvalue for the second factor was close to the 95% threshold of bootstrapped data and above the mean of the bootstrapped data. Furthermore Lim and Jahng (2019) suggest that following parallel analysis the accepted solution should be the number of factors suggested $+/-1$. As such this analysis also suggests that a 2 factor solution could be plausible. In the case of the short scale, parallel analysis suggested a unitary structure (in line with EGA). However, again as (Lim & Jahng, 2019) suggested that a $+1$ factor solution following parallel analysis, this could also suggest a 2 factor solution.

5 | DISCUSSION

5.1 | Summary of results

While the ASRS has conventionally been interpreted in terms of 2 factors, factor analysis of the full scale suggests that the assignment of items to factors may not be stable, with several items crossing factors from the conventional assignment of the 2-factor model. In addition, the choice of 2 factors rather than 3 may not be unambiguously directed by the data - the scree plot suggests that a 3-factor structure could also be legitimate. These ambiguities underscore the uncertainty in the literature around the exact structure of the ASRS. A recent independent report also suggests there may be a 3 community structure in the ASRS (Liu et al., 2022).

Exploratory graph analysis is a novel method with a number of benefits over traditional factor analysis (see below). Application of this technique suggests that a 2, 3 or 4 community structure could be legitimate for our data. A three cluster structure would reflect the conventional inattention subscale with a division of the hyperactivity subscale into separate hyperactivity and impulsivity subscales.

This division can be replicated by requiring a 3-factor solution from the traditional factor analysis, but we note that without the exploratory graph analysis such an analytic choice would appear arbitrary.

For the six item ASRS screener the EGA gives 1 community which *does not* align with the results of the exploratory factor analysis and

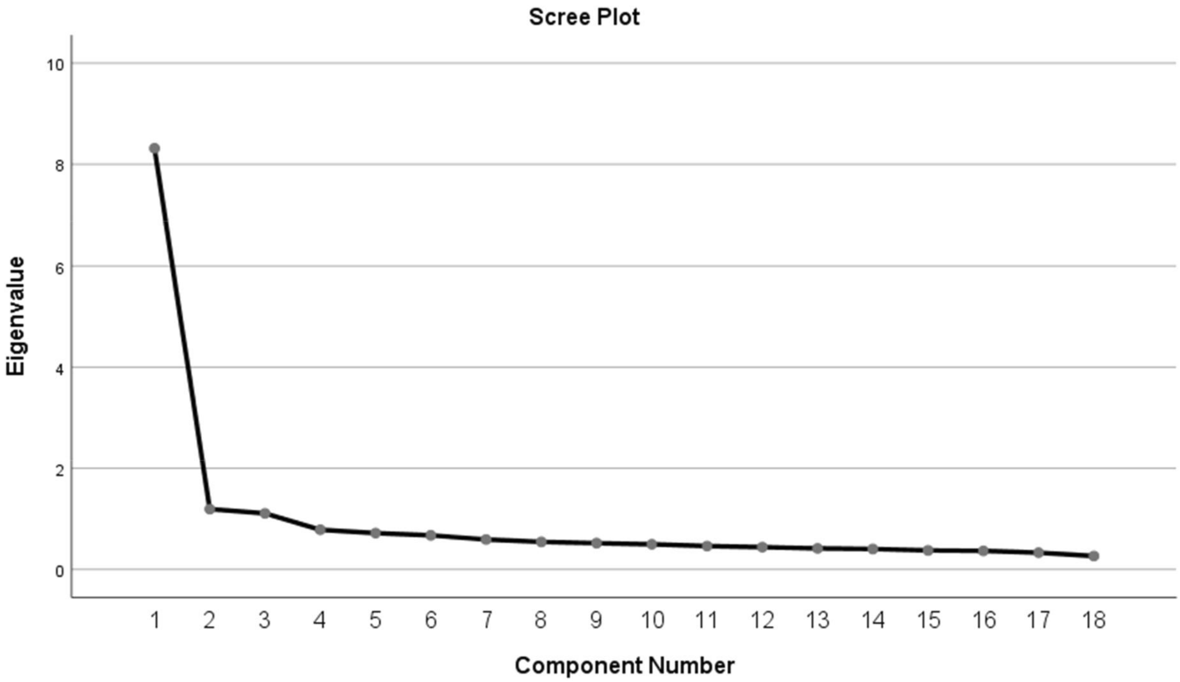

FIGURE 3 Scree plot following principal component analysis of full ASRS scale.

TABLE 4 Factor loadings for ASRS items for the full scale.

Item	I	II	Item	I	II	III
ASRS02	0.883	-	ASRS02	0.867	-	-
ASRS04	0.702	-	ASRS04	0.693	-	-
ASRS03	0.677	-	ASRS08	0.624	-	-
ASRS01	0.663	-	ASRS01	0.623	-	-
ASRS09	0.638	-	ASRS09	0.622	-	-
ASRS07	0.573	-	ASRS03	0.619	-	-
ASRS08	0.558	-	ASRS07	0.546	-	-
ASRS18	0.527	-	ASRS18	0.527	-	-
ASRS10	0.446	-	ASRS10	0.466	-	-
ASRS17	0.408	-	ASRS12	0.867	-	-
ASRS12	-	0.857	ASRS05	-	0.944	-
ASRS06	-	0.774	ASRS06	-	0.728	-
ASRS05	-	0.669	ASRS13	-	0.556	-
ASRS13	-	0.587	ASRS15	-	0.503	-
ASRS14	-	0.491	ASRS17	-	-	0.736
ASRS11	-	0.450	ASRS16	-	-	0.732
ASRS16	-	0.376	ASRS14	-	-	0.692
ASRS15	-	0.358	ASRS11	-	-	0.336

Note: A. 2 Factor Solution. Note that items 11, 12, 17 & 18 load to a different factor than in original validation. B. 3 factor solution.

the conventional assignment of items to subscales. We note that others have warned against the use of exploratory factor analysis for assessing unidimensionality (Ziegler & Hagemann, 2015). Simulation studies suggest EGA outperforms exploratory factor analysis in terms of identifying true cases of unidimensionality (Golino, Shi, et al., 2020).

Although EFA supplemented with parallel analysis pointed to a unidimensional structure, a more theoretically plausible structure might be the two-factorial one (which was also hinted at, but not validated, by our parallel analysis). Such a two-factorial structure is supported both statistically (by our scree plot) and theoretically (by previous research on this scale) and is particularly plausible, given contemporary recommendations of considering at least two alternative solutions to parallel-analytic results (in particular, ± 1 factors of its bootstrapped estimates). So, even with the addition of bootstrapping methods, traditional EFA remains ambiguous in it's factor solutions. Our results support the claim of Golino et al. (2021) that bootstrapped EGA provides a less arbitrary method of deciding factor number solution.

5.2 | Benefits of exploratory graph analysis

Exploratory graph analysis brings a principled network analysis framework to the discovery of dimensional substructures. The network graph output lends itself to easier interpretation than the output of factor analysis. The dimension frequency statistic which mimics traditional confidence interval indices keeps open multiple

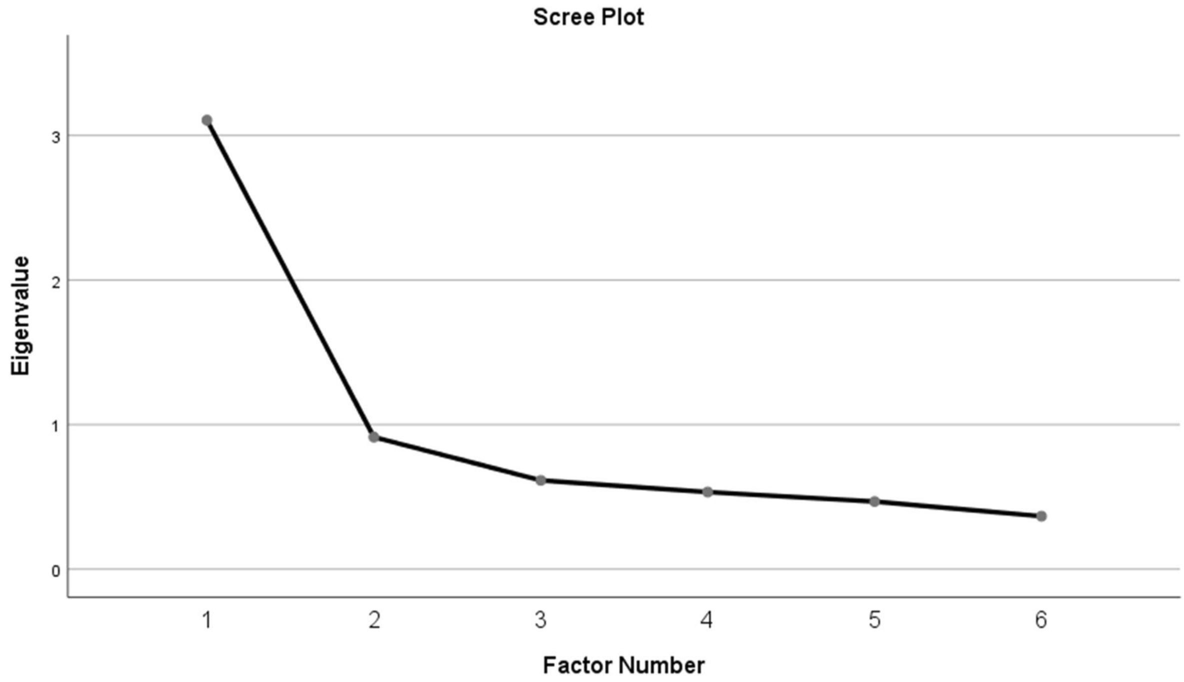

FIGURE 4 Scree plot following principal component analysis of short ASRS scale.

TABLE 5 Factor loadings for ASRS items for the short scale.

Item	Factor 1	Factor 2
ASRS02	0.940	-
ASRS01	0.665	-
ASRS04	0.549	-
ASRS03	0.547	-
ASRS05	-	0.789
ASRS06	-	0.543

interpretations over the number of communities discovered, and the refinement on this interval offered by bootstrap analysis keep open multiple interpretations of data which inevitably contain some irreducible ambiguity.

A further advantage of the graph analysis is there are minimal researcher degrees of freedom (Simmons et al., 2011) in making arbitrary analytic choices. However, a major arbitrary choice of EGA is of the initial hyperparameter of how conservative to make initial thresholding (pruning) of the edges between nodes, which among researchers using as EGA is becoming conventionally set at 0.5.

For factor analysis, research degrees of freedom are present at several (as noted by Ziegler & Hagemann, 2015) The most salient is when visual inspection of the scree plot is used to determine the cut off threshold for factors. In addition, there are choices such as whether to hide factor loadings/factor correlations below a certain value - this can improve clarity of the output but can also be misleading as items may load highly on several factors but one of the factor loadings may be just below your arbitrary threshold.

5.3 | Implications for the dimensional nature of developmental conditions

There has been an ongoing debate about the nature of developmental disorders; are they dimensional or categorical? The categorical approach suggests that the difference between individuals diagnosed with a developmental disorder and neurotypicals is qualitative (Sonuga-Barke, 1998). The dimensional approach proposes that psychopathology can be viewed dimensionally, with symptoms distributed continuously in the general population (Hudziak et al., 2007). The results of the EGA show that ADHD symptoms have a 3-community structure in a non-clinical population, replicating the 3 main clusters of ADHD symptomatology: inattention, hyperactivity, and impulsivity. This finding provides further support to the dimensional approach of ADHD and suggests that the methodology described here could help resolve inconsistencies resulting from the limitations of factor analysis in other developmental conditions. EGA has also proved useful for examining the association between different inventories and constructs where subscales of inventories are used rather than individual items (Zavlis & Jones, 2020).

AUTHOR CONTRIBUTION

Maria Panagiotidi: Formal analysis; Writing – original draft; Writing – review & editing. **Orestis Zavlis**: Formal analysis; Visualization; Writing – review & editing. **Myles Jones**: Conceptualization; Formal analysis; Visualization; Writing – original draft; Writing – review & editing. **Tom Stafford**: Conceptualization; Data curation; Formal analysis; Writing – original draft; Writing – review & editing.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

All data and analysis code are freely available at https://osf.io/sd6f5/

ETHICS STATEMENT AND PARTICIPANT CONSENT STATEMENT

The data was originally collected with informed consent and approval by the University of Sheffield, Department of Psychology ethics board. The analysis presented here represents secondary analysis of anonymised data.

PERMISSION TO REPRODUCE MATERIAL FROM OTHER SOURCES

The ASRS scale is reproduced with the attribution and permission detailed here https://www.hcp.med.harvard.edu/ncs/asrs.php.

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