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The Use of Exploratory Graph Analysis to Validate Trust in Relationships Scale

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Abstract: Today, various methods have been developed with a purpose to determine the number of factors underlying a construct. However, there is no definitive agreement on which techniques to be preferred to extract the underlying dimensions. To this end, Exploratory Graphical Analysis (EGA), a recently proposed method, has been compared with traditional methods and the results have revealed that the EGA is less affected from conditions like sample size and inter-dimensional correlation. Besides, it provides more stable results across different conditions. Considering the attractive opportunities it offers, this method has taken its place in the literature as a remarkable alternative to traditional methods. The EGA provides unique outputs compared to other factor extraction techniques. Considering this, interpreting the results obtained within this new and promising framework is assumed to contribute to validation studies. Based on this reality, this study aims to apply the EGA method to Trust in Relations Scale (TRS) and therefore to contribute to its validity. The investigation of TRS's reliability and validity has already been documented, presenting research opportunities to researchers in the field of positive psychology. The results revealed that, the EGA produces dimensionality structures identical to confirmatory factor analysis (CFA) and exploratory factor analysis (EFA). In addition, further psychometrical indicators within the framework of network analysis are provided. The findings of the study are believed to contribute to the validity of the already existing Trust in Relationships Scale.

1. INTRODUCTION

Uncovering the latent structure underlying human behavior and cognitive abilities is important in social science studies with a very old history. Deciding on the number of underlying dimensions of human behaviors or abilities was firstly made possible by the development of factor analysis (Spearman, 1904). Since its invention, factor analysis technique has become widely popular among researchers. Today, examining the structure of underlying latent traits or dimensions in multivariate data is an important issue in the process of designing and validating assessment tools in psychology (Timmerman & Lorenzo-Seva, 2011). Currently, factor analysis is an inevitably most widely used method as one of the first steps routinely applied in the process of studying construct validity (Osborne & Costello, 2009). Furthermore,

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investigating the underlying dimensions of constructs is very important for a better understanding of characteristics of individuals and human behavior (Garcia-Garzon et al., 2019).

Today, various methods have been developed for factor extraction decisions. Traditionally, Kaiser's eigenvalue greater than 1 (K1) rule (Guttman, 1954; Kaiser, 1960) and scree plot test (Cattell, 1978) are the most common methods. This popularity is somewhat related to their old history and availability in most of the statistical software. Bandalos and Boehm-Kaufman (2009) state that most of the commercial software programs present K1 rule as default option factor extraction decisions. In addition, parallel analysis (PA) technique (Horn, 1965) and minimum average partial (MAP) technique (Velicer, 1976) are other commonly used methods.

Studies conducted in the past have shown that PA and MAP methods provide more robust and accurate results for factor extraction decisions (i.e. Ledesma & Valero-Mora, 2007; Osborne et al., 2008). However, there is no definitive agreement on which technique should be preferred to unveil the underlying dimensions. The studies carried out indicate that each of these techniques has their own limitations (Garrido et al., 2013; Keith et al., 2016; Velicer et al., 2000; Lubbe, 2019). This ambiguity reveals the necessity of developing new techniques in order to obtain more accurate estimates when deciding on the number of dimensions.

In response to this necessity, the efforts to develop new factor extraction techniques by researchers still continue today. The EGA is a recently proposed method and has already been compared with traditional techniques (Golino & Epskamp, 2017). Accordingly, the results of such studies revealed that the EGA provides comparable results to the traditional methods and outperforms them when the number of dimensions is higher when the number of items is less and the correlation between dimensions are higher. In addition, it has been reported that EGA's precision shows less fluctuation across different conditions like sample size and inter-dimensional correlation. All these results prove its robustness.

1.1. Overview of the EGA Approach

In a recently published study Golino and Epskamp (2017) introduced a new approach as an alternative to factor analysis. This method called as the EGA uses network psychometric to determine the number of dimensions in psychological data. Network psychometrics recently been adapted the network modeling approach to the quantitative field in psychometrics (Epskamp et al., 2017). In these network models, nodes represent random variables. These variables correspond to items in measurement instruments. Nodes are connected by edges or links and show the level of interaction between these variables. These models focus on the prediction of direct relationships between these variables rather than defining the observed variables as a function of a latent common cause. This approach extracts the dimensions by clustering the variables in the dataset.

The EGA uses undirected network models. In this method, the focus is on the estimation of the number of dimensions in the psychological datasets of undirected network models called Markov Random Fields (Lauritzen, 1996). EGA models are based on the Gaussian Graphic Model (GGM) and directly model the multivariate normal distribution network with a reverse covariance matrix. Each unit of the inverse covariance matrix corresponds to the edge. These edges can be standardized and visualized and the link between the two variables can be interpreted as associations between the nodes. (Lauritzen, 1996).

The use of partial correlations is the most common approach used for the estimation of network models; however, it poses an important problem in itself: Even if two variables are conditionally independent, the estimated coefficient is not possibly being estimated as zero due to sample variability (Epskamp & Fried, 2016). Even if there is no conditional association between the two nodes, the resulting estimated correlation value can be slightly different from zero. In this case, partial correlation may reflect spurious correlations. This problem can be solved by using regularization techniques such as the least absolute shrinkage and selection operator (LASSO) algorithm as described by Tibshirani (1996). With the use of LASSO, the parameters corresponding to the low relationship between node pairs are estimated to be exactly zero and estimation of a model provides sparser networks. In this way, the interpretability of the network structure becomes easier and more meaningful. Because of these features, LASSO estimation has gained popularity as a preliminary analysis for the prediction of network models (van Borkulo et al., 2014). The level of correction, formally expressed as regularization, is determined by a tuning parameter to estimate GGM. Using this penalty approach, the researcher can avoid the risk of model overfitting, control the sparsity of the network and produce an optimum network model that diminishes the Extended Bayesian Information Criterion (EBIC) (Chen & Chen, 2008). The tuning parameter is set by the researcher before the analysis process starts.

In general terms, the EGA works as follows: firstly, the correlation values between the observed variables are calculated; then, using the LASSO estimation, a sparse inverse covariance matrix is obtained; and using the walktrap algorithm (Pons & Latapy, 2005), the number of dense subgraphs (factors, communities or clusters) is specified using the partial correlation matrix calculated in the previous step.

The walktrap algorithm provides a measure of the similarities between vertices based on random walks that can extract the community/cluster structure in the graph (Pons & Latapy, 2005). The number of clusters identified corresponds to the number of latent factors in the dataset. These sub-graphics are undirected weighted networks in clusters. As a result of this process, the number of factors underlying the latent trait of interest and the size of each item's associations with the rest of items are estimated and presented in a graph consisting of nodes and edges. Traditionally, nodes are represented with green or blue circles in the graph. In addition, thinness of edges gives information about the association between node pairs as the association gets stronger, the lines get thicker.

2.1. Aim of the Study

Considering the attractive opportunities it offers, this method has taken its place in the literature as a remarkable alternative to traditional factor extraction techniques. Based on this reality, the aim of this study is to apply the EGA method with a real data set and to contribute to the validity of the Trust in Relations Scale by interpreting the obtained findings within this new and promising framework.

2. METHOD

2.1. Participants

A total of 736 university students were included in the current study. They were being selected from a large state owned university in a Metropolis in Turkey. The data were collected from the participants via an online data collection platform. Even online data collection posits some challenges to the validity of results (Al-Salom & Miller, 2017), the 2020 pandemic outbreak led universities to continue their education via online classes which made it impossible to collect data by meeting face-to-face. The participants were informed about the voluntary nature of participation and security of the information they provided to minimize those possible threats against the validity of the study. After completion of the data collection of process, 28 questionnaires were decided not to be included in the final dataset because incomplete information was available in them. The final dataset was composed of 611 (83%) female and 125 males (17%). Their ages varied between 18 and 27 (Mean=20.25±1.85).

2.2. Instrument

Trust in Relations Scale (TRS) was developed by Demirci and Ekşi (2018). The scale has two dimensions: trust and reliability. Each dimension is composed of five Likert type items. The dimensionality of TRS was evaluated with EFA and CFA. According to the results of EFA, two factors were extracted, explaining 54% of the total variance. In addition, CFA results also confirmed two dimensional structure of TRS [χ^2 (34, N = 450) = 63,40, p < .001; CFI = .99; NFI = .98; SRMR = .033; RMSEA = .044]. The criterion related validity of TRS was tested with the PERMA well-being scale (Demirci, Ekşi, Dinçer & Kardaş, 2017) and results revealed significant correlations between trust in relationships and well-being. The reliability of TRS was investigated by estimating Cronbach alpha coefficient and test-retest reliability. The results suggest that both trust and reliability sub dimensions have good internal consistency and stability of test scores over time.

2.3. Analysis

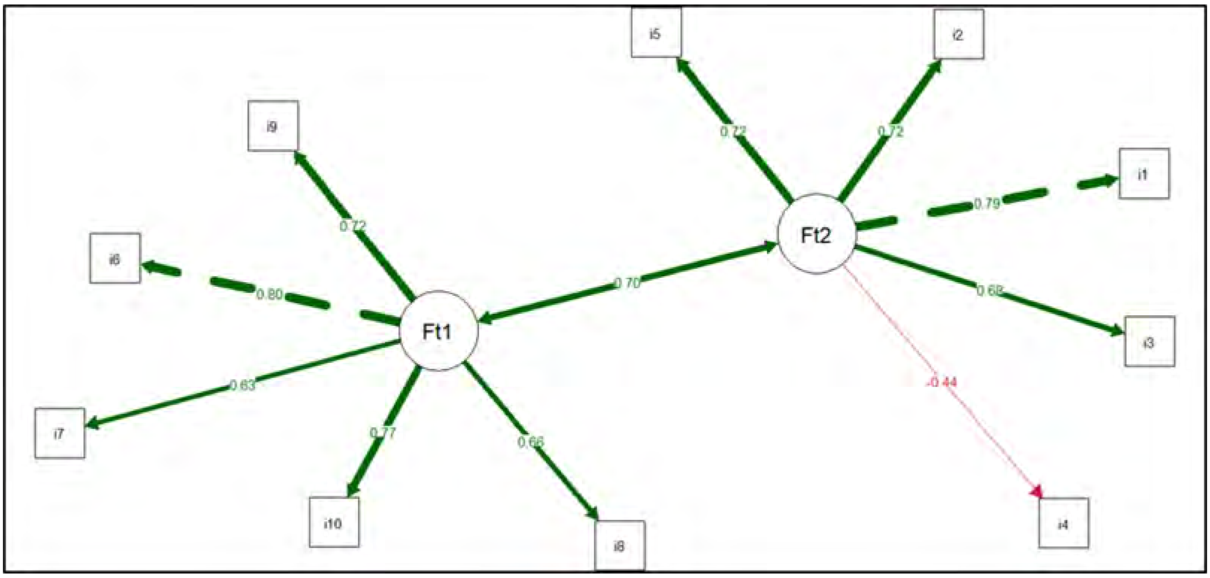
As stated previously, this study was carried out to investigate the underlying dimensionality of TRS using the EGA. The "*EGAnet*" package developed by Golino and Christensen (2020) was used. The package is available in the R environment (R Core Team, 2019). In addition, conventional EFA and CFA were also conducted for comparison. First of all, CFA was carried out using "*lavaan*" package (Rosseel, 2012) to analyze the dimensional structure of TRS. A further EFA was run with SPSS 21 to investigate the factor structure. Later, the network structure of TRS was examined based on the GLASSO algorithm using the "*EGA*" function. Because LASSO procedure includes the use of EBIC, a tuning parameter needs to be selected to control the sparsity of estimated network. For the current study the parameter was set as 0.5 which is used as default option in "*EGAnet*" package. By conducting this analysis, graphical model and edge weights were calculated. The weight matrix can be obtained with "*EGA.estimate*" function. After the model was estimated and two dimensional structure was obtained, "*dimStability*" function was used to examine the structural consistency of the predicted network model and the stability of the items in the extracted dimensions. After this inspection, "*bootEGA*" function was used to obtain the estimated network structure based on the bootstrap method. After obtaining bootstrapped model, factor loadings, termed as standardized node strengths, were calculated by using "*net.loads*" function followed by obtaining item stability statistics which indicate reliability of the scale. As a last step, EGA based standardized and unstandardized factor scores were calculated and compared with the conventional raw scores.

3. RESULTS / FINDINGS

3.1. Examining the dimensionality of TRS with CFA

Before estimating the network structure with the EGA, CFA was performed to provide evidence for the two-dimensional structure of TRS. The results showed that data fit well to the model [$\chi^2$148.328, df=34.000, χ^2/df=4.36, CFI=0.960, TLI=0.947, NFI=0.949, NNFI=0.947, RMSEA=0.068, SRMR, 0.041]. If "*lavaan*" (Rosseel, 2012) package is already installed and called with "*library()*" function in R program, "*EGAnet*" package provides a function to run CFA with the function "*lavTestLRT*" without running additional codes with another package. The graph for the CFA analysis was presented in Figure 1. In Figure 1, Ft1 represents trust dimension and Ft2 represents reliability dimension. Negative relationship was obtained only for item 4 (as inferred from redline between Ft2 cluster and item 4) in Trust dimension. This result was expected because the 4th item is negatively worded.

Figure 1. *Dimensions Estimated via CFA.*



Moreover, a further EFA was conducted to examine the underlying dimensionality of TRS. Results supported a two dimensional structure while these two dimensions explained 59.7% of the total variance. As in the CFA, EFA results yielded similar results: The first five items were retained in the first dimension and the second five items were in the second dimension.

3.2. Estimating Edge Weights Matrix

The EGA was estimated by using the GLASSO algorithm which estimated the model based on partial correlations and using penalty approach to obtain sparser networks. The EGA process primarily begins with the calculation of the weight matrices of the edges between the nodes. The estimated values are given in Table 1. The highest edge weight values are between item6-item10 and item1-item2 pairs. Higher values imply that these item pairs showed relatively higher associations. Table 1 also includes many zero values. These values result from the absence of links between the corresponding item pairs and occur due to applying LASSO algorithm. For example, there has been no connection of item 8 with items 2, 3, 4 and 5.

Table 1. *Symmetric network edge weights estimated using GLASSO.*

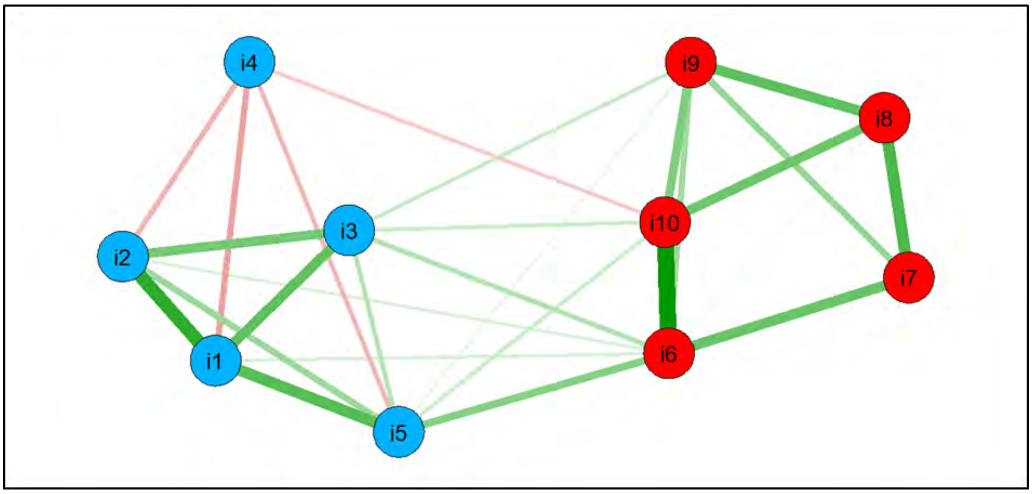
	Item 1	Item 2	Item 3	Item 4	Item 5	Item 6	Item 7	Item 8	Item 9	Item 10
Item 1	-	0.32	0.24	-0.14	0.26	0.06	0.00	0.00	0.00	0.00
Item 2		-	0.21	-0.11	0.15	0.05	0.00	0.00	0.00	0.00
Item 3			-	0.00	0.11	0.11	0.01	0.00	0.08	0.08
Item 4				-	-0.11	0.00	0.00	0.00	-0.00	-0.08
Item 5					-	0.18	0.00	0.00	0.04	0.08
Item 6						-	0.23	0.02	0.14	0.40
Item 7							-	0.27	0.16	0.00
Item 8								-	0.24	0.22
Item 9									-	0.19
Item 10										-

After obtaining weight matrix, the EGA model was graphed based on the estimated partial correlations. For this process, Walktrap algorithms, were used. This graphical presentation of estimated model is given in Figure 2. The resulting dimensions coincide with the original dimensional structure of the TRS scale. Accordingly, the first 5 items and the last 5 items of the

TRS scale constitute two different clusters. The partial correlations between items in reliability dimension (as represented with red lines) are relatively higher (as inferred from the thickness of lines). At the same time, the red lines in the network graph show that the relationships between the 4th item of trust dimension and the other items are negative this item is negatively worded. Also, this item is negatively related with the 10th item which belongs to reliability dimension.

The thickness of the edges between the items located in the same cluster is an indication of the homogeneity of the clusters. Although the relationships between the items in different dimensions are relatively thinner, the 5th and 6th items are connected with a relatively thicker edge. This implies that even those two items are not in the same dimensions, their associations are relatively higher. In addition, it was found that even located in the same clusters item pairs 1-2 and 7-8 are connected with relatively thinner lines.

Figure 2. *The dimensions estimated using exploratory graph analysis.*



3.3. Estimating Standardized Node Strengths

It was stated that node strengths are equivalent to factor loadings (Christensen, Golino & Silvia, 2019). Accordingly, they are regarded as the association of each node to the cluster to which it belongs. For the current study, these values were obtained by using the "*net.loads*" function. The obtained standardized node strengths of TRS items are given in Table 2. Accordingly, node strength values vary between 0.38 and 0.31 for the reliability dimension, while these values range between 0.48 and -0.18 for the trust dimension. On the other hand, as expected, each items' association with the dimension it does not belong to is relatively weaker.

Table 2. *Standardized Node Strength for TRS Items.*

Item #	Reliability	Trust
Item 6	0.37	0.20
Item 7	0.31	0.00
Item 8	0.36	0.00
Item 9	0.34	0.06
Item 10	0.38	0.12
Item 1	0.03	0.48
Item 2	0.03	0.39
Item 3	0.13	0.28
Item 4	-0.04	-0.18
Item 5	0.14	0.31

3.4. Structural Consistency of TRS

Another concept related to standardized node strengths is structural consistency values. Structural consistency values are calculated for each dimension by evaluating the rate of times that items staying in the same dimension are indicative of the internal consistency of the clusters. In this process, the bootstrap technique was used by taking subsamples from empirical correlation matrix. Structural consistency values indicate the proportion of the times that items are located in the correct dimensions across iterations. It is possible to interpret these values as Cronbach Alpha values.

Prior to calculating the structural consistency, the first step is to apply bootstrap analysis. It can be performed using the "bootEGA" function. The analysis was performed with 500 replications as recommended by Golino and Christensen (2020). The predicted structural consistency value for the first dimension was 0.994 and the estimated structural consistency value for the second dimension was 0.998. These values show the dimensions to be consistently extracted as same rate.

By this analysis, it is also possible to examine the item-level consistencies to identify items that prevent the dimensions from being perfectly structurally consistent. Those statistics are similar to conventional reliability values if an item is deleted. Item level stability statistics values are given in Table 3. As can be seen in Table 3, items 6 and 10 for reliability dimensions were extracted in the unidentified 3rd dimension for 0.6% of replications. Likewise, item 3 in the trust dimension was located similarly in a different 3rd dimension for 0.2% of these replications. Those items could be regarded as distorting the stability of dimensions. Overall, those results suggested that almost all of the replications that located the items in their original dimensions except for the only ignorable rate of replications provided results that produce different structures.

Table 3. *Item Stability Across Dimensions of TRS.*

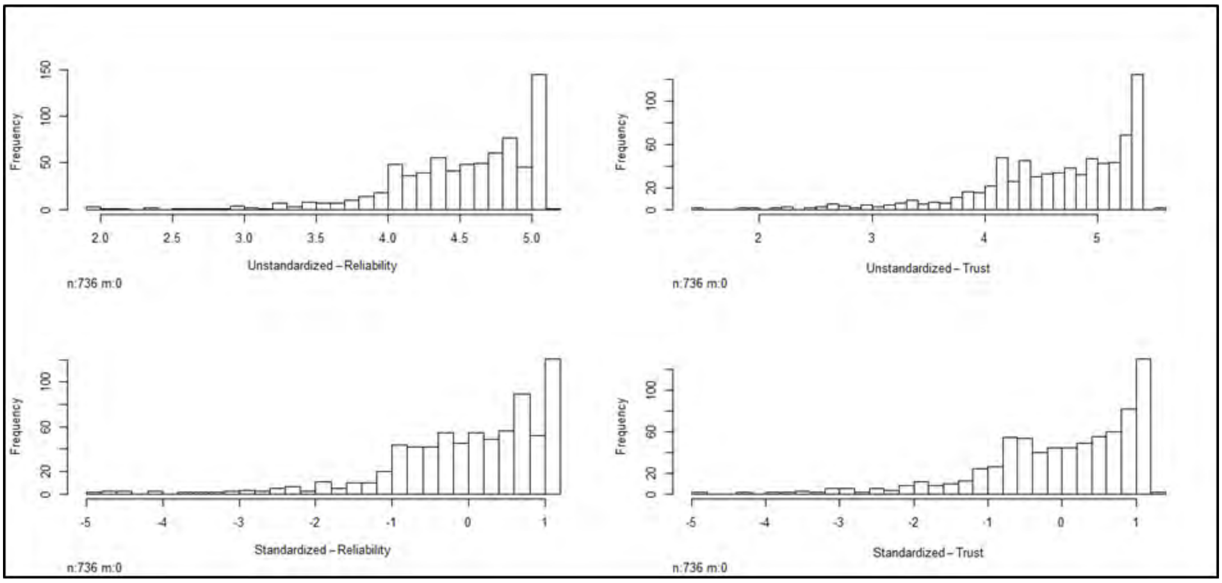
Item #	Reliability	Trust
Item 10	0.99	
Item 6	0.99	
Item 9	1	
Item 8	1	
Item 7	1	
Item 3		0.99
Item 5		1
Item 4		1
Item 2		1
Item 1		1

3.5. Obtaining Scores Based on the EGA Framework

It is also possible to obtain standardized and non-standardized network scale scores of individuals using the "*net.scores*" function available in the package. Network scores are calculated based on the node strength values within each factor. In the CFA approach, scores are generally calculated using a simple structure (items loaded on only one factor) and some regression-based techniques. As to the EFA approach, factor scores are calculated using saturated model approach where each item is allowed to be loaded on more than one factor. On the other hand, scores computed in network models are calculated using a complex structure and can be considered as a weighted composite rather than a latent factor (Christensen & Golino, 2021).

The distribution of the scores obtained for each sub-dimension of the TRS scale was provided in Figure 3. In addition, Pearson correlation coefficients between standardized scores and conventional raw scores were calculated to examine the relationship between the network scores and the observed raw scores. For the Trust sub-dimension, this value was estimated as 0.89 and, for the reliability sub-dimension, this value was estimated as 0.86. This finding suggested that estimated network model of TRS with the EGA approach provided similar ability scores with conventional observed raw scores.

Figure 3. *Standardized and Unstandardized Network Scores of TRS scale for Each Dimension*.



4. DISCUSSION and CONCLUSION

In this study, the factor structure TRS, which had been already reported as having two dimensional structure by Demirci and Ekşi (2018), was re-analyzed with a recently proposed EGA approach. In this study, the factor structure of TRS was firstly examined with the EFA and CFA. The results of these analyzes were found to be in line with the original two dimensional solution. After this preliminary checking, EGA model based on the network psychometric approach was estimated using GLASSO and and the original two factor solution was therefore supported. Afterwards, the bootstrap method was used to see the stability of this predicted model and the results revealed that the stability of the model was 99%. These results further provided additional evidence and contribution to construct validity of TRS. In addition, these analyzes implied item-level stability for TRS. Finally, in this study, the raw scores obtained with the classical approach were compared with the standardized scores obtained with the EGA method, and they were found to be highly correlated and comparable. Regarding these findings, TRS can be inferred to be a valid scale within the network modeling perspective.

The results obtained in this study are consistent with the findings that traditional EFA and CFA yielded. This consistency supported EGA to be an alternative technique that can be preferred during validation studies. Further, considering the richness and the novelty of the output that the EGA provides, it can be said that researchers gain more insights into psychometrical properties of the construct they aim to validate by adopting EGA in their studies. To put it more clearly, EGA provides network graph for visual representations of the interconnectedness of items and help researchers about item level stability statistics. These outputs are easy to interpret and provide unique outputs for researchers to draw important implications for the factor structure of psychological constructs.

This study has shown that EGA is a considerable alternative to the methods traditionally used in the investigation of the underlying dimensionality of psychological latent traits. In this regard, the findings obtained by this study are similar to those of relevant literature (Golino & Epskamp, 2017; Golino & Demetriou, 2017) in terms of the similarity of the number of dimensions both EGA and traditional approaches extracted.

Existing literature on EGA has generally focused on modeling dichotomous items. On the other hand, in this study polytomous items were used. Considering that most of the assessment tools in Psychology use polytomous items, it can be inferred that this study contributes to our understanding for using EGA with polytomous items in the field of psychology. The psychological network approach offers a different way of understanding the psychological structures than the traditional methods. When the findings obtained in this study are considered together with the findings obtained in previous studies, it is clear that EGA can be used in many different subareas of psychology (Borsboom & Cramer, 2013; Kossakowski et al., 2015). Moreover, the EGA method can offer significant advantages compared to traditional factor extraction techniques as it offers an advantage of visual representation of observed relationship patterns between variables.

In this study, dimensional structure of TRS was analyzed. The scale is composed of five point Likert items, which are widely preferred in psychological instruments. On the other hand, since the effect of the number response category on EGA estimates is unknown, as also suggested in a previous study by Golino and Demetriou (2017), the effect of the number of response categories needs to be investigated. Such a study, could enlarge the applicability of EGA to different testing conditions. For this reason, in the future studies, the effectiveness of EGA in investigating the underlying factor structure can be examined by using alternative measurement tools with differing response categories (3 or 7 may be preferred). Overall, it would be useful to compare the similarities of the estimated factor loading of conventional methods with the node strengths and also simulation studies under which conditions this similarity may be affected should be conducted.

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Declaration of Conflicting Interests and Ethics

The author declare no conflict of interest. This research study complies with research publishing ethics. The scientific and legal responsibility for manuscripts published in IJATE belongs to the author. **Ethics Committee Number**: Marmara University/Institute of Educational Sciences, 2000310195.

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