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Validation and Adaptation of the Attentional Control Scale Among a French-Speaking Population Through Factor and Network Analysis

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Abstract
The Attentional Control Scale (ACS) is a widely used self-reported assessment of attentional control. Due to the importance of those executive processes in the phenomenology of mood-related disorders, the ACS has been translated in multiple languages. Our purpose was to explore psychometric properties of two versions of the French ACS. In study 1, 455 participants completed the original ACS, which yielded excellent fit to a two-dimensional model (CFI = 0.972). However, as one factor contained in majority reversed coded items, this raised question about its validity. A second sample (N = 452) therefore completed a modified version of the ACS without reverse-coded items, which also yielded excellent fit to a two-dimensional model (CFI = 0.970). Finally, network analyses explored the relations between the ACS and symptoms of depression, anxiety, and resilience. Our results support the use of the French version of the ACS with items coded in a straightforward manner.

Keywords Attentional control · Executive processes · Factor analysis · Network analysis · Resilience · Depression · Anxiety

Introduction

Attentional control (AC) is defined as the ability to voluntarily allocate one's attention to certain information, inhibiting distractors and being able to flexibly disengage one's attention from them when necessary (Cox & Olatunji, 2017). The notion of attentional control is based on the postulate that our attentional abilities are limited and that a selection must take place regarding the information that will benefit from increased attentional processing (Corbetta et al., 1993). The attentional control theory has been developed to explain the effects of anxiety on a range of tasks requiring attention and working memory in terms of specific executive control processes (Eysenck et al., 2007). In recent years there has been increased focus on the relationship between attentional control and both affective disorders (e.g., (Derryberry & Reed, 2002) and emotion regulation (Bardeen, 2019; Schäfer et al., 2015). Several studies have found a link between attentional control and negative psychological outcomes such as depression (Hsu et al., 2019), anxiety (Eysenck & Derakshan, 2011), post-traumatic stress disorder (Bardeen et al., 2015), obsessive-compulsive disorder (Armstrong et al., 2011), or personality disorders (Claes et al., 2009). Those authors posit that low attentional control abilities could contribute to the maintenance of pathogenic psychological processes, for example through difficulties in inhibiting negative and intrusive repetitive thoughts and disengaging from them to concentrate on another task. These hypotheses are consistent with studies on attentional biases showing that anxiety is linked with faster detection of emotional information to the detriment of ongoing activities (Cisler & Koster, 2010). Furthermore, Schäfer et al. (2015) investigated the relationships between attentional control and both attentional biases and resilience capacities. These authors showed that, in subjects with high trait-resilience (as measured by the Connor-Davidson resilience scale), the strategies employed when confronted to threatening stimuli differed according to the level of attentional control abilities.

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Most studies having assessed AC abilities used the Attentional Control Scale (ACS, Derryberry & Reed 2002). It is a 20 items self-reported questionnaire conceived to measure two functions of the attentional system: focusing (the ability to maintain attention while inhibiting attentional distractors) and shifting (the ability to move attention from one task to another). The authors originally described a 9 item-scale of attentional focusing, and a 11 item-scale of shifting (Derryberry & Reed, 2002). The validation of this English version performed by Judah et al. (2014) retained only 12 items from the full ACS. They described a good internal consistency for both the total score (α = 0.84). and the focusing subscale (α = 0.82), as well as an adequate one for the shifting subscale (α = 0.71). Due to its convenient use to quickly assess attentional control abilities, the 20 items ACS have been translated in several languages (Table S1).

A careful analysis of the existing 8 versions of the ACS allows to depict discrepancies within their psychometric properties (Abasi et al., 2017; Blekic et al., 2019; Clauss & Bardeen, 2018; Fajkowska & Derryberry, 2010; Judah et al., 2014; Michalko, 2018; (Ólafsson et al., 2011b; Quigley et al., 2017). First, while the consistency of the focusing subscale is acceptable, the shifting subscale tend to be unstable across the existing versions. Judah et al. (2014) argued that the shifting factor might gather both attentional shifting and divided attention components, which could be a possible explanation of the inconsistency of this subscale across languages. Additional psychometric limitations were highlighted by Clauss and Bardeen (2018) who observed that all of the reverse coded items loaded exclusively onto one of the two factors in the Icelandic version, which suggests the possibility that factor differentiation may only be a function of a method effect. Therefore, those authors proposed a modified version of the ACS in which all the reverse items were recoded in a straightforward manner. Though a bifactor examination, these authors suggested that the domain-specific factors of the ACS might be poorly defined, have poor construct replicability, and might not be sufficiently distinct from the general factor to warrant use as subscales. Among the domain-specific factors, the psychometric limitations of the shifting factor particularly raise concern.

Taken together, the extant literature raises concerns regarding the factor structure of the ACS and independent use of previously identified subscales leading to the following two studies. In addition, given the established association between attentional control and affective disorders, it is important to conduct a rigorous assessment of the convergent validity between the ACS and self-reported measures of depression, anxiety, and resilience. First, we aimed to perform an exploratory and confirmatory factor analyses on a French version of the ACS (study 1) (Blekic et al., 2019). Second, we compared those psychometric properties with those derived on the latest version of the ACS, that is without reverse items. The links between this newer version and self-reported trait resilience, depression and anxiety were then explored using network analysis (study 2).

Study 1: Psychometric Properties of the Original Attentional Control Scale

The purpose of study 1 was to explore the factor structure of a French version of the ACS. First, exploratory factor analysis (EFA) was used to identify the factor structure of the ACS. Previous research on the French version of ACS has selected items based on a loading > 0.30, which is a light selection criterion. Following factor analysis recommendations and prior works (Clauss & Bardeen, 2018; Matsunaga, 2010), we toughened the item inclusion and therefore expected a different factor structure to be retained in the EFA. Second, confirmatory factor analysis (CFA) was used to compare the fit of the model identified via EFA to other theoretically relevant models. With regards to theory highlighting the global influence of executive processes on the attentional control constructs targeted by the ACS, we expected that the bifactor model of the ACS would provide significantly better fit to the data than competing models.

Method

Participants

Students from the University of Mons (Belgium) and participants from the general population (N = 445) completed an online French version of the Attentional Control Scale. The total sample was randomly split into two samples of equal size (N = 223 and N = 222). First half of the sample was used to conduct an EFA and the second half to conduct an CFA. For both studies, we report how we determined our sample size, all data exclusions, all manipulations, and all measures used. For factor analyses, the sample size was derived from previous studies using the same analytic plan for ACS validation (Abasi et al., 2017; Fajkowska & Derryberry, 2010), along then in accordance with existing guidelines (Mundfrom et al., 2005).

Sample 1. The average age of participants was 31.72 years (SD = 10.13, range = 22 − 68) and the majority of the sample was female (76.13%). The majority of the sample had a bachelor's degree (33.78%), followed by high school (31.53%), master (25.22%), PhD (5.85%), middle school (1.35%) and elementary school (2.22%) education.

Sample 2. The average age of participants was 32.84 years (SD = 11.73, range = 22 − 73) and the majority of the sample was female (80.72%). The majority had a bachelor's degree (39.46%), followed by master's (29.60%), high school (21.08%), PhD (7.17%), elementary school (0.88%) and middle school (1.17%).

Measures and Procedure

The French version of the ACS is a 20-item scale scored on a 4-point scale from 1 (almost never) to 4 (always), containing 11 reverse-coded items. Higher scores indicate greater levels of attentional control. Internal consistency for the ACS total score was acceptable in Sample 1 ($\alpha = 0.79$, $M = 56.16$, $SD = 7.99$, skew = 0.01, kurtosis = –0.60) and Sample 2 ($\alpha = 0.79$, $M = 56.14$, $SD = 7.96$, skew = 0.07, kurtosis = –0.46). The correlation matrix is available in Fig. S1. Along with the ACS, participants provided informed consent and demographic information (including their age, gender, and level of education).

Analytic Strategy

Exploratory Factor Analysis. Analyses were conducted using R Studio (4.1.3). Because data did not follow a normal distribution, principal factor analysis was used to conduct EFA (Costello & Osborne, 2005; Matsunaga, 2010). Moreover, because previous research assumes a correlation between factors to be extracted (Abasi et al., 2017; Fajkowska & Derryberry, 2010; Judah et al., 2014; Ólafsson et al., 2011) an oblique rotation was applied. Number of factors to be extracted was determined by conducting a parallel analysis (*fa.parallel* function in R from the *psych* package) (Luo et al., 2019). Once parameters were determined, EFA was run. Consistently to Clauss and Bardeen (2018), we retained only items with loadings > 0.40 and those whose first largest loading on one factor was at least 0.40 points higher than second largest loading on another factor (Matsunaga, 2010).

Confirmatory Factor Analysis. In Sample 2, weighted least-squares estimation method was used to conduct CFA considering that the data were still not normally distributed. Four models were examined and compared with each other: a two-factor solution from a more inclusive model based on Blekic et al. (2019) accepting items with a load greater than 0.30 (Model 1), a strict two-factor solution from the current EFA (Model 2), the same two-factor solution allowing 2-items correlations (Model 3), and a bifactor model (Model 4) in which all items were simultaneously loaded onto a general factor and each of their respective domain-specific factors. All factor covariances were fixed to zero in the bifactor model (Brown, 2015).

To assess the goodness of fit of models tested, four indices were considered: the root mean square error of approximation (RMSEA), the Tucker–Lewis fit index (TLI), and the comparative fit index (CFI). The following guidelines were used to evaluate fit (Cheung & Rensvold, 2002; Singh, 2009; Xia & Yang, 2019). For CFI and TLI, values 0.95 and above are taken as indicating goof fit, and values of 0.90 and < 0.95 are taken as marginally acceptable fit. For RMSEA indexes, values close to 0.06 or below indicate good fit, 0.07 to 0.08 indicate moderate fit, and values from 0.08 to 0.1 indicate marginal fit, whereas values > 0.10 indicate inadequate fit (Meyers et al., 2006). Finally, $\chi 2$/ddl was used to compare the models tested with each other in order to determine the most parsimonious ones. If the value of this index is lower for one model than for another, then that model is considered to be more parsimonious.

Results

Exploratory Factor Analysis

First, the Kaiser-Meyer-Olkin value (KMO = 0.83) and the Bartlett's test results ($\chi = 1881.387(190)$, $p < .001$) indicated that EFA assumptions were met. EFA indicated that two factors had eigenvalues greater than 1 (3.79 and 1.31). These factors explained 15% and 11% of the variance. The parallel analysis indicated that four factors should be retained since they better explain the variance of the scores than factors generated randomly (Fig. S2). However, consistent with previous validation studies (Clauss & Bardeen, 2018; Judah et al., 2014), the identified four-factor model was uninterpretable. Only one item loaded onto Factor III and no items loaded sufficiently on Factor IV (Table S2). Therefore, the two-factor solution was retained for further testing (see Table 1 for factor loadings). Items 4, 9, 11, 12, 15, 16 and 20 had an initial loading of less than 0.40 and were removed from the analyses. Also, items 5, 6, 15, 17 and 18 were excluded because difference between their load values on the two factors was less than 0.40. Thus, the selected model was a two-factor solution consisting of 9 items.

Confirmatory Factor Analysis

Fit statistics are presented in Table 2. The previous more inclusive mode from Blekic et al. (2019) did not demonstrate an adequate fit to the data. The two-factor model presented in Table 1 resulted in good fit indexes, but modification indexes suggested a decrease of 16.73 in χ^2 if items 1 and 3 were allowed to correlate (Fig. 1A). This makes theoretical sense, as both items (1: "*It's very hard for me to concentrate on a difficult task when there are noises around*"; 3:"*When I am working hard on something, I still get distracted by events around me*") refers to the difficulty to focus in the

Table 1 Factor loadings for the original (study I) and modified (study II) Attentional Control Scale (ACS)

	Study 1		Study 2	
	Factors		Factors	
Items	1 (Focusing)	2 (Shifting)	1 (Focusing)	2 (Shifting)
ACS1[a]	**0.61**	0.16	**0.69**	0.02
ACS2[a]	**0.66**	0.02	**0.65**	0.10
ACS3[a]	**0.59**	0.04	**0.70**	0.01
ACS4	0.36	0.23	**0.51**	0.01
ACS5	0.48	0.36	**0.70**	0.14
ACS6[a]	0.43	0.06	**0.73**	0.05
ACS7[a]	**0.76**	0.16	0.50	0.14
ACS8[a]	**0.51**	0.07	0.06	0.04
ACS9	0.11	0.06	0.04	0.01
ACS10	0.02	**0.56**	0.12	**0.66**
ACS11[a]	0.31	0.14	0.00	**0.66**
ACS12[a]	0.16	0.31	0.16	0.51
ACS13	0.11	**0.45**	0.08	**0.54**
ACS14	0.03	**0.54**	0.05	0.44
ACS15[a]	0.04	0.35	0.19	0.47
ACS16[a]	0.15	0.37	0.15	0.52
ACS17	0.19	0.54	0.22	0.54
ACS18	0.42	0.16	0.30	0.26
ACS19	0.09	**0.63**	0.02	**0.68**
ACS20[a]	0.17	0.10	0.00	0.34

Note. [a] = reverse coded item in study 1. Bold items are retained in corresponding EFA

presence of distractors. This model provided a significantly better fit to the data. The latent correlation between Factors I and II was medium in size ($r = .31$, $p = .003$). Finally, the bifactor model did not reach an acceptable solution. A warning of structural misspecification was present, that was not solved by the use a log transformation of our data (Kunina-Habenicht et al., 2012; Xin et al., 2022). The bifactor solution was therefore not feasible for this version of the ACS. Internal consistency of focusing factor ($\alpha = 0.74$) was reasonable but did not meet acceptable criteria for the shifting factor ($\alpha = 0.57$).

Study 1 Summary

EFA and CFA results suggested the presence of two factors: factor 1 (focusing) composed of 5 items (1, 2, 3, 7 and 8) and factor 2 (shifting) gathering 4 items (10, 13, 14 and 19). As expected, this factor structure contained fewer items than previous research due to a strict item retention method. CFA results indicated that a stricter item selection method may be necessary, as the previous ACS structure did not fit the data as well as the present 9-item model. Interestingly, the focusing subscale was solely composed of reverse-coded items, while none loaded in the shifting subscale. In addition, the shifting subscale did not provide acceptable reliability ($\alpha = 0.57$). Therefore, those results question the possibility that the factors might be function of a method effect (i.e., reverse coding).

Study 2: Psychometric Properties of the Modified Version of the Attentional Control Scale

The first purpose of study 2 was to explore the factor structure of a French version of a forward-coded ACS. EFA was used to identify the factor structure of the modified ACS using the same item-selection as in study 1. CFA was then used to compare the fit of the model identified via EFA to other theoretically relevant model (bifactor model). The second purpose of study 2 was to investigate the convergent validity of the ACS using measures which are theoretically or empirically associated with attentional control. Previous work has drawn correlations between psychopathological behaviors and ACS subscales (Judah et al., 2014; Ólafsson et al., 2011). The ACS focusing subscale was negatively correlated with trait anxiety and social anxiety. The ACS shifting subscale was positively correlated with trait-depression, such as measured by subscale of the State and Trait Anxiety Inventory Form Y (STAI, Spielberger et al., 1983). The authors argued that unique relationships were drawn between focusing and trait anxiety and between shifting

Table 2 Goodness of fit

Model	χ^2	*df*	$\Delta\chi^2$	RMSEA 90% CI RMSEA	LL	UL	CFI	TLI
Study 1: classic version								
2 factors (Blekić et al. 2019)	309.23	134	258.58[a]	0.077	0.065	0.088	0.803	0.775
2 factors restrictive	50.649	26	15.48[b]	0.065	0.038	0.092	0.932	0.907
2 factors - items correlated	35.167	25	-	0.044	0.000	0.073	0.972	0.960
Study 2: modified version								
2 factors	75.24	34	75.241[b]	0.073	0.051	0.096	0.954	0.938
2 factors - items correlated	59.42	33	-	0.060	0.034	0.083	0.970	0.959

Note. Models computed using mean- and variance-adjusted weighted least squares (WLSMV) estimation. $\Delta\chi^2$ computed using R 4.1.3. *anova* function from the *psych* package. RMSEA = root mean square error of approximation; LL = lower limit; UL 1 = 4 upper limit; CFI = comparative fit index; TLI = Tucker–Lewis index. $\Delta\chi^2$a = comparing inclusive two-factor model from Blekić et al. (2019) and current two-factor model. All $\Delta\chi^2$ significant at p < .001

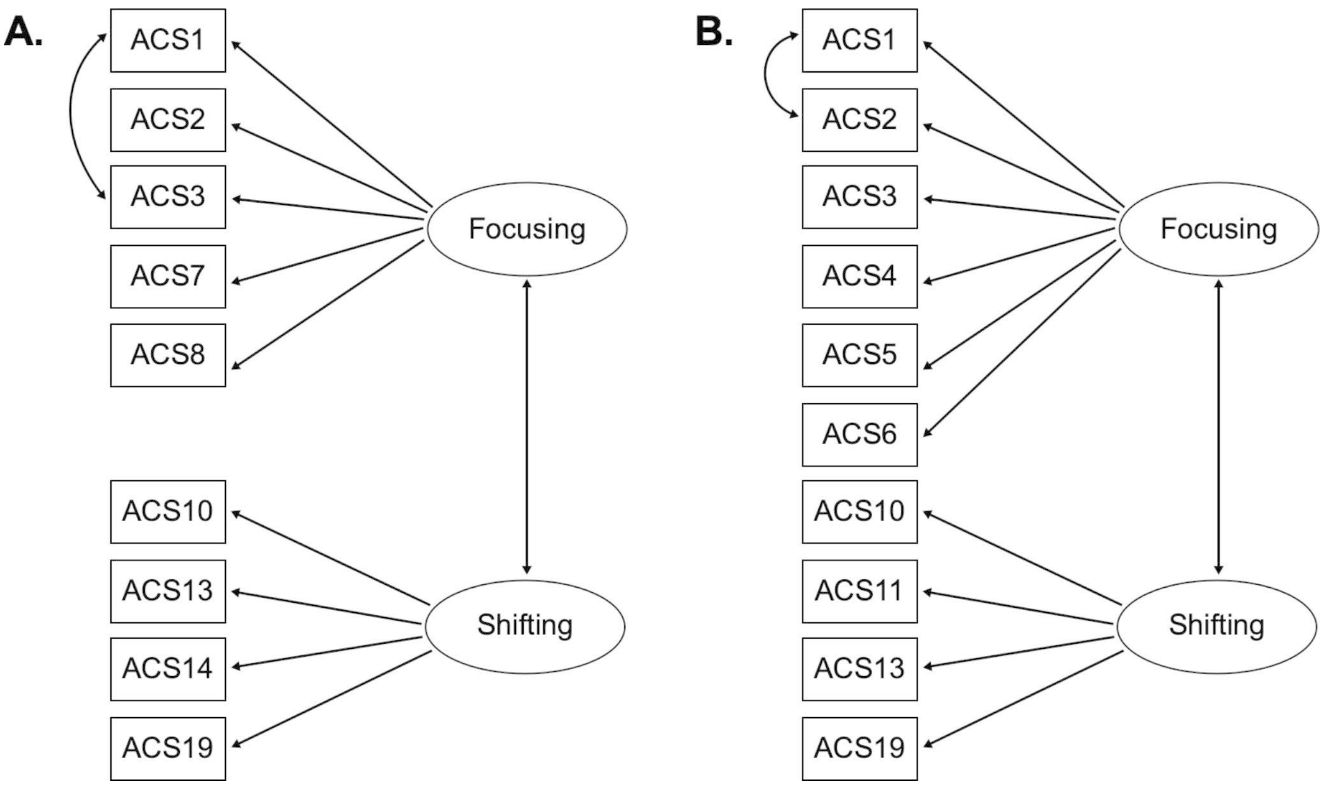

Fig. 1 Summary of the two final models tested. A Two factor model from the classic version of the ACS (study 1) / B Two factor model from the modified version of the ACS (study 2)

and depression. However, the use of classical correlational approach as well as the choice of the depression scale (trait-depression drawn from the STAI) raises concerns. We aim to answer these limitations by using a well-validated depression scale, and perform a network analysis instead of classic correlations.

Network analysis is a novel, flexible approach that can be preferred to correlational analyses (Weems, 2020). Compared to classic correlational approaches, network analysis can provide the centrality and predictability index for each node, allowing researchers to examine its importance and controllability within the whole network (Haslbeck & Fried, 2017; Haslbeck & Waldorp, 2018). Indeed, partial correlations obtained through network analysis represent the patterns of relationships (i.e., the edges) that remain after taking into consideration all the variables and their associated correlations in the network (Contreras et al., 2019), rather than associations with dichotomous outcomes. This is particularly interesting in concepts for which the strong individual correlations seem to appear between a single construct (i.e., the ACS) and highly comorbid symptomatology (i.e., depression and anxiety). Network analysis allowed us to examine the partial correlations between the ACS domain-specific factors with theoretically relevant constructs after accounting for a general ACS factor. These partial correlation networks are often estimated using regularization techniques from machine learning, which can help remove edges that are likely to be spurious from the model, resulting in networks that are easier to interpret (Epskamp et al., 2018). The goal of network analysis is to extract a general structure of a given psychopathology that can better understand the way symptoms interact with one another and guide therapeutic interventions.

The combined use of factor analysis and network analysis in this second study will enable us to obtain a more comprehensive understanding of the straightforward version of the ACS. We will investigate its basic psychometric properties using EFA, CFA and bifactor modeling, as well as its convergent validity with measures to which the ACS is theoretically linked and primarily used, through network analysis.

Method

Participants

A total of 452 students from the University of Mons (Belgium) and participants from the general population participates in this study. The total sample obtained was randomly split into two samples of equal size ($N = 226$). First half of the sample was used to conduct an EFA, followed by an CFA in the second half of the sample.

Sample 1. The average age of participants was 32.56 years (*SD* = 9.13, range = 18 – 50) and the majority of the sample was female (87.6%). Most of the sample had a bachelor's degree (42.92%), followed by master's (28.31%), high school (21.68%), middle school (4.87%) and PhD (2.21%).

Sample 2. The average age of participants was 34.41 years (*SD* = 9.24, range = 18 – 50) and the majority of the sample was female (90.7%). Most of the sample had a bachelor's degree (35.39%), followed by master's (31.41%), high school (28.32%), middle school (2.65%), PhD (1.79%), and elementary school (0.44%).

Measures and Procedure

The ACS items recoded in a straightforward manner by Bardeen et al. (2018) were translated in French (Table S3). This translation was developed as follows: (a) One French-English bilingual translated the 11 rewritten items of the modified ACS into French; (b) one other French-English bilingual translated the items back into English, and (c) discrepancies between the original items and the back-translations were discussed between the two translators until a satisfactory solution was found. In the modified French version of the ACS, higher scores indicate greater attentional control skills.

After providing informed consent and demographic information (age, gender, and level of education), participants completed an online version of the modified ACS along with three self-reported scale assessing trait resilience (*Connor-Davidson Resilience Scale 10 items*), depression (*Beck Depression Inventory-Short Form*) and anxiety (*State-Trait Anxiety Inventory*). Detailed information about those scales can be found in the supplemental material.

Methods to estimate power a priori for a network analysis are largely unknown. However, a general rule of thumb adopted from structural equation modeling is to include at least 10 participants per free parameter (Schreiber et al., 2006). Our largest network containing six nodes includes, 21 parameters need to be estimated (Epskamp & Fried, 2018), yielding a minimum sample size of 210, which our study far surpasses with a sample size of 452.

Analytic Strategy

First, this version of the ACS went through both EFA and CFA (as described above). The total sample was therefore slip in two, internal consistency being adequate in both samples (sample 1: $\alpha = 0.81$, $M = 53.64$, $SD = 7.62$, skew = – 0.2, kurtosis = – 0.19; sample 2 : $\alpha = 0.81$, $M = 54.64$, $SD = 7.6$, skew = – 0.13, kurtosis = – 0.3).

Second, we estimated the structure of two networks based on the total sample (prior to EFA and CFA split). Demographics of the total sample (N = 452) used for the networks analyzes can be found in the supplemental material. The first network included the total score of the modified ACS (11 items retained in the EFA) in the estimation procedure (N1). In the second network, we divided the ACS into its corresponding two subscales (N2). For both networks, we used the least absolute shrinkage and selection operator (LASSO) as regularization method that sets very small edges to zero (Tibshirani, 1996). Regularization uses a tuning parameter, which we selected using EBIC model selection with $\gamma = 0.5$, which is generally conservative and does not often falsely include edges(Epskamp et al., 2017). Both networks are described accordingly to most recent guidelines (Burger et al., 2022).

As we were expecting the presence of negative edges in the graph, indicating inverse relationships between the variables, we chose to use the Expected Influence (EI) measure to describe the importance of each variable in the GGM instead of other indices of centrality. Many centrality measures, such as degree centrality and betweenness centrality, are based on the concept of edge connectivity and are not designed to consider negative edges. In contrast, the EI measure is specifically designed to be used with GGMs presenting both positive and negative edges in the graph, making it a more appropriate choice in this context. The EI of a node is the sum of the edge weights incident on a given node and is used to assess the influence of each variable on the overall connectivity of the graph, taking into account both positive and negative relationships. To assess the stability of this centrality estimate, we performed a person-dropping bootstrap procedure (Costenbader & Valente, 2003), we performed a person-dropping bootstrap procedure to calculate the centrality stability coefficient (CS-coefficient). This procedure allows us to determine whether the relative order of node centrality is retained even when the sample size is reduced. The CS-coefficient is a measure of the consistency of the centrality measures across the resampled datasets and can be used to identify the most stable centrality measures in a GGM. Values of at least 0.25 indicate that the centrality is stable, while values above 0.5 are preferred.

In addition, we estimated domain predictability which quantifies how well that particular node can be predicted by all remaining nodes (Burger et al., 2022; Haslbeck & Fried, 2017; Haslbeck & Waldorp, 2018). In this study, R^2 was used to reflect the percentage of shared variance of a domain with surrounding domains in the network. EI and predictability are two different measures that can be used together to provide a more complete understanding of the role of a node in a GGM. EI can be used to identify the nodes that have the most influence on the overall connectivity of the graph, while predictability measures can provide insight into the relationships between the nodes and how well the values of one node can be predicted based on the values of others.

Results

Exploratory Factor Analysis

EFA with oblique rotation has been implemented with the same method of factor extraction and item retention than in study 1. Results are presented in Table 1. The assumptions of EFA were met (KMO = 0.85; Bartlett's test results: $\chi = 2695.105(190)$, $p = 0$). Two eigenvalues were > 1 (4.40 and 1.76). Both factors explained 16% of the variance. In contrast, parallel analysis indicated a four-factor solution. However, as indicated in Table S4, this model was uninterpretable (only one item loading in Factor III and Factor IV). Therefore, the two-factor solution was retained. Items 8, 9, 18 and 20 had an initial loading of less than 0.40 and were removed from the analyses. Cross-loading was also observed for Items 7, 12, 14, 15, 16, 17; leading to their exclusion from further analysis (Matsunaga, 2010).

Confirmatory Factor Analysis

Fit statistics are presented in Table 2. The two-factor model presented in Table 1 resulted in good fit indexes, but modification indexes suggested a decrease of 15.77 in χ^2 if items 1 and 2 were allowed to correlate (Fig. 1B). This model provided a significantly better fit to the data ($p < .001$). The latent correlation between Factors I and II was non-significant ($r = .093$, $p = .228$). Finally, the bifactor model did not reach an acceptable solution. While it showed excellent measures (CFI = 0.99, TLI = 0.99, RMSEA = 0.14), we suspect that it might be overfitted. As described in both Fig. S5 and Table S5, three items did not load on the general factor (item 5, 10 and 13). In conclusion, the bifactor solution was not retained. Internal consistency was good for the total score ($\alpha = 0.81$), the focusing factor ($\alpha = 0.85$) and the shifting factor ($\alpha = 0.82$).

Network 1: Attentional Control as a Total Score

The graphical LASSO is represented in Fig. 2A. The edges represent regularized partial correlations between variables. Most of the edges were positive (4), 3 were negative. Some pairwise connections stand out. First, the largest edge weights were between the depression and trait-anxiety ($r = .44$), followed by the positive relation between the trait and state anxiety scale ($r = .43$). Other large connections were noted between resilience and attentional control ($r = .24$) and between state anxiety and depression ($r = .28$). Finally, the largest negative correlation was found between trait anxiety and resilience ($r = -.22$). To estimate the accuracy of the edge weights, we bootstrapped confidence intervals for each of the edge weights, which showed that the edges appear stable, with homogeneous confidence intervals (Fig S6). However, the generally large bootstrapped CIs imply that interpreting the order of edges in the network should be done with care. A bootstrapped edge-weight difference test also showed that strongest edges are significantly different from one another (Fig S8).

Expected influence and predictability values are reported in Table 3. Mean node predictability ranges from 0.19 to 0.72, with an average of 0.48. This means that on average, 48% of the variance of the node in the network can be explained by its neighbors. The highest EI was found for state anxiety (0.71), while the highest predictability was found for trait anxiety (0.72). A bootstrapped difference test showed that nodes with low EI are statistically different from EI estimates in nodes with high EI (Fig. S9). Lastly, the person-dropping bootstrap procedure confirmed that EI values are highly stable (Fig. S7). The associated CS-coefficient for EI was 0.75, which is largely above the suggested 0.5 threshold.

Network 2: Attentional Control as Two Distinct Subscales

The graphical LASSO is represented in Fig. 2B. The edges represent regularized partial correlations between variables. Most of the edges were positive (4), 3 were negative. The largest edge weights were between depression and trait-anxiety ($r = .44$), followed by the positive relation between the trait and state anxiety scale ($r = .43$). Other large connections were noted between resilience and the focusing subscale of attentional control ($r = .30$) and between state anxiety and depression ($r = .28$). Finally, the largest negative correlation was found between trait anxiety and resilience ($r = -.22$). To estimate the accuracy of the edge weights, we bootstrapped confidence intervals for each of the edge weights, which showed that the edges appear stable, with homogeneous confidence intervals (Fig S10). However, the generally large bootstrapped CIs imply that interpreting the order of edges in the network should be done with care. A bootstrapped edge-weight difference test also showed that strongest edges are significantly different from one another (Fig S12).

Expected influence and predictability values are reported in Table 3. Mean node predictability ranges from 0.08 to

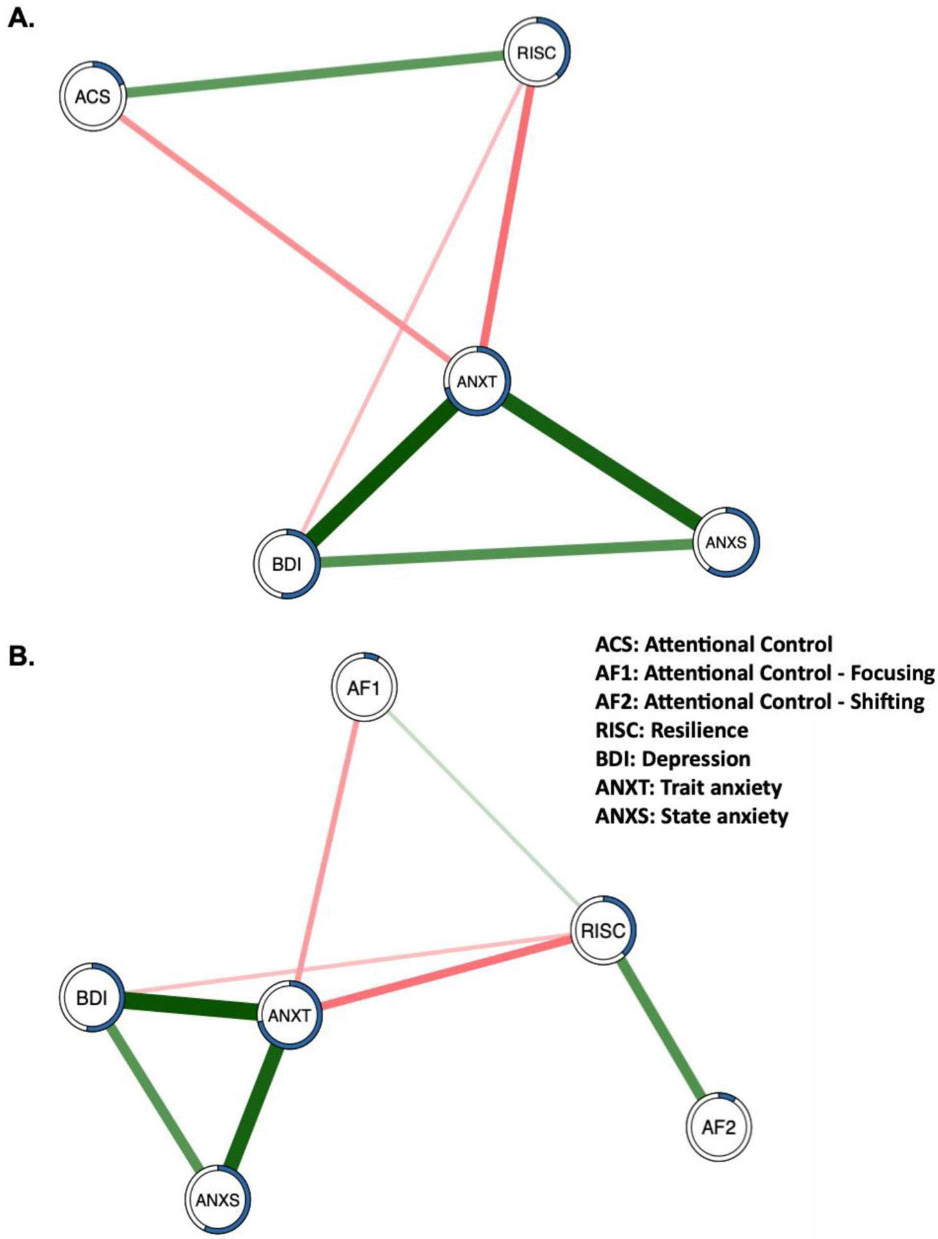

Fig. 2 Regularized partial correlation network including the 9 items modified ACS validated in study 2. Each node represents the total score of a given psychometric scale: ACS - Attentional Control; AF1 - Attentional Control Focusing Subscale; AF2 - Attentional Control Shifting Subscale; RISC- Resilience; BDI – Depression; ANXT - Trait anxiety; ANXS - State anxiety / Fig. 2A = Regularized partial correlation network including the total score of the 9 items modified ACS / Fig. 2B = Regularized partial correlation network including the specific score of the 9 items modified ACS. Greene edges represent positive connections and red edges represent negative connections; the thicker the connection, the stronger it is. The pie chart surrounding the node represents node predictability (percentage of shared variance with all connected nodes)

0.72, with an average of 0.39. The highest EI and predictability nodes did not differ from network 1. The bootstrapped difference test showed that nodes with low EI are statistically different from EI estimates in nodes with high EI (Fig. S13). Lastly, the person-dropping bootstrap procedure confirmed that EI values are highly stable (Fig. S11). The associated CS-coefficient for EI was 0.75, which is largely above the suggested 0.5 threshold.

Study 2 Summary

Firstly, the factor structure of the modified ACS was assessed. Importantly, while 6 items loaded similarly than in the original version (items 1, 2, 3 from Factor I and 10, 13, 19 from Factor II), several differences exist in comparison with the factor structure from study 1. Regarding Factor I, items 7 and 8 (previously reversed) were no longer retained, and item 6 (previously reversed) now passed the threshold for retention. Regarding Factor II, one originally straightforward item was removed (item 14) in favor of previously reversed (item 11).

Secondly, the links between self-reported attentional control, anxiety, depression, and resilience were explored through networks analyzes. Our main result is the correlation between attentional control and resilience scores (network 1). This result was deepened into the second network,

Table 3 Measures of node strength expected influence and predictability for both networks

	Expected Influence	Predictability
Network 1		
Resilience	-0.08	0.38
Depression	0.62	0.52
Attentional Control	0.07	0.19
Trait anxiety	0.48	**0.72**
State anxiety	**0.71**	0.59
Network 2		
Resilience	-0.03	0.38
Depression	0.61	0.53
Attentional Control - Focusing	-0.15	0.08
Attentional Control - Shifting	0.30	0.09
Trait anxiety	0.50	**0.72**
State anxiety	**0.71**	0.57

that showed that only the shifting subscale was positively correlated with resilience. In addition, resilience was strongly negatively correlated with anxiety. Taken together, those results are in line with previous findings that have considered attentional control as a moderator between resilience and anxiety (Schäfer et al., 2015).

Interestingly, while previous research has suggested a link between attentional control and anxiety, specifically between the focusing subscale of the ACS and trait anxiety, our results do not provide strong evidence of such association. Indeed, a common risk in any network is to falsely include edges that would not be present in the true model. Considering that our edge and node weight difference test was non significative for this particular node, and that it gathers all the weakest measures (Table 3), the present network cannot validate previous studies highlighting a predictive association between the focusing subscale of the ACS and anxiety.

Discussion

The factor structure of the French version of the ACS (Derryberry & Reed, 2002), in its original form and with forward coded items, was examined in this set of studies. For both versions of the measure, the two-factor structure using strict item-retention standards and allowing specific item correlation was compared to a bifactor model. We hypothesized that a common executive component could be common to both factors, leading to a better fit to the data if this general variance was taken into consideration. However, contrary to Clauss and Bardeen (2018) study, the bifactor model did not provide significantly better fit to the data compared to competing models. One possible explanation for the better fit of the two factors solution in comparison with the bifactor model could be the low correlation between our factors in comparison with previous studies (Table S1). Indeed, we highlighted a low (study 1: $r = .31$, $p = .003$) and non-significant (study 2: $r = .093$, $p = .228$) correlation between the two factors, suggesting an increased discriminant validity of such factors. This result tend to draw on previous conclusions stating that a shortened focusing and shifting subscales provide more precise measurement of these constructs (Judah et al., 2014; Quigley et al., 2017). The eliminated items may represent infrequently endorsed items and/or items that reflect constructs other than focusing and shifting, such as flexible thought and multitasking (i.e. item 15: It is easy for me to carry on two conversations at once.), leading to a lack of theoretical validity of the bifactor model. Altogether, those results tend to suggest the distinct use of the modified version of the ACS subscales for the French translation of this scale.

A two-factor model was consequently retained in both the original form of the ACS (study 1) and modified version (study 2). Results of the CFA provided support for this short version of ACS, which is close to the shortened two-factor model reported by Judah et al. (2014). Both models fitted well the corresponding ACS version, however the classic version did not provide acceptable reliability. The shifting subscale had a Cronbach's alpha value of 0.57. Considering two major ameliorations noted on the modified version of the ACS (study 2), we would advise researchers to use this scale. First, increased reliability of the shifting subscale has been observed (Cronbach's alpha = 0.82). Second, the percentage of variance due to both subscales are equivalent in the modified ACS (16%), whereas low explained variance for the shifting subscale has been targeted as an indicator of its poor reliability in the past.

Result from the network analyses have important implication. Firstly, a positive correlation between attentional control scores (specifically the shifting subscale) and resilience was found. This relation is particularly noteworthy regarding recent discussions linking emotional regulation theories and attentional control. That is, theories of information processing in emotional regulation suggest that the flexible use of attentional control is important for maintaining psychological well-being (Gross, 2015). Indeed, while the rigid use of attentional control to avoid emotional (potentially threatening) information have been highlighted in pathological population (i.e. PTSD), its *flexible* use tends to show a willingness to experience fluctuations in emotions and affective states and decreased negative mental health outcomes (Bardeen, 2019; Troy & Mauss, 2011). However, this result must be taken cautiously considering that convergent validity has not been assessed. To answer this question, it would be necessary for future research to assess convergent validity using both validated self-reported constructs assessing flexibility (such as the psychological inflexibility through the Acceptance and Action Questionnaire–II, Bond et al., 2011) and validated performance based measures of flexibility (as for example the antisaccade task, Eysenck & Derakshan 2011).

Secondly, we found a negative correlation between trait anxiety and the focusing subscale. However, this association was among the weakest one in the network. While we did not directly assess the *predictive* influence of trait anxiety on the focusing subscale as previous work (Judah et al., 2014; Ólafsson et al., 2011), we question the premise of a strong association between those constructs as it has been done in other translations of the ACS. Nonetheless, we noted a negative correlation between the total score of the ACS and trait anxiety which had acceptable magnitude (Fig. S8). Finally, when taking into consideration all other between variable correlations, no direct link between attentional control (or its shifting subscale) and depression was found. Rather, resilience seems to buffer the association between those constructs.

Our results must be interpreted in light of some limitations. First, the sample size used for EFA might constitute an issue. Even though our sample size was comparable with some ACS validation studies (Abasi et al., 2017; Fajkowska & Derryberry, 2010), it was also lower than other (Clauss & Bardeen, 2018; Judah et al., 2014). One potential influence of our relatively small sample size could be instability in factor loadings. In our study, this could partially explain the differences in which items were removed between the two set of analyzes. However, while lager sample size is often preferable, as discussed by de Winter et al. (2009), small sample size should not be the sole criterion for rejecting EFA. Indeed, results from simulation studies showed that when factors are well defined or their number is limited, small sample size EFA can yield reliable solutions. The consistency between our results and previous ACS translation tend to advocate in favor of reliability of our EFA results. Second, the scores obtained using our translation of the attentional control scale must be understood as self-reported abilities, and not as a strict representation of prefrontal processes. Those rely on an unconscious rapid cognitive processing that cannot be fully perceived by an individual. Therefore, the assessment of convergent validity through validated neuropsychological tasks designed to assess executive functions (such as developed by Miyake et al., 2000) would be recommended. Finally, our recruitment method might have been biased. Due to the necessity of large sample sizes, we used a convenience sample. While careful attention was devoted to select in majority a non-student sample (as denoted by the higher mean age in each study), study findings should be replicated in specific population samples, including in clinical settings.

Conclusion

Results from this set of studies have important implications for use of the French translation of the ACS. Results from study's 1 and 2 suggest the use of the modified version of the ACS (study 2). This recommendation is based on the doubt that emerges from the impact of reverse-coding on the classic version, and on the excellent CFA indexes yield by the modified version. In addition, due to the lack of correlation between both factors, we would not recommend using the total score. Further investigation on the modified version of the ACS, on larger sample size, is warranted to ensure the validity of such score. In addition, links between the ACS subscales, anxiety and resilience have been drawn in highly stable and reliable networks. Those results could further question the generalizability of the ACS factor structure across different languages and culture. We highly recommend authors to use the factor structure assessed in their own language.

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Declarations

Competing interests The authors have no conflict of interest to disclose.

References

Abasi, I., Mohammadkhani, P., Pourshahbaz, A., & Dolatshahi, B. (2017). The psychometric proprieties of attentional control scale and its relationship with symptoms of anxiety and depression: A study on iranian Population. *Iran Journal of Psychiatry*, *12*(2), 109–117.

Armstrong, T., Zald, D. H., & Olatunji, B. O. (2011). Attentional control in OCD and GAD: specificity and associations with core cognitive symptoms. *Behaviour Research and Therapy*, *49*(11), 756–762. Epub 2011 Aug 11. PMID: 21871608, PMCID: PMC3266065. https://doi.org/10.1016/j.brat.2011.08.003.

Bardeen, J. R. (2019). The regulatory role of attention in PTSD from an information processing perspective. In *Emotion in Posttraumatic*

Stress Disorder (pp. 311–341). Elsevier. https://doi.org/10.1016/B978-0-12-816022-0.00011-9

Bardeen, J. R., Fergus, T. A., & Orcutt, H. K. (2015). Attentional control as a prospective predictor of posttraumatic stress symptomatology. *Personality and Individual Differences*, *81*, 124–128. https://doi.org/10.1016/j.paid.2014.09.010.

Blekic, W., Wauthia, E., Loureiro, I. S., Arachchige, K., & Lefebvre, L. (2019). *Étude factorielle exploratoire de la version française de l'Échelle de Contrôle Attentionnel: Liens avec les symptômes d'anxiété et de dépression*. 10.

Bond, F. W., Hayes, S. C., Baer, R. A., Carpenter, K. M., Guenole, N., Orcutt, H. K., Waltz, T., & Zettle, R. D. (2011). Preliminary Psychometric Properties of the Acceptance and Action Questionnaire–II: A revised measure of psychological inflexibility and experiential avoidance. *Behavior Therapy*, *42*(4), 676–688. https://doi.org/10.1016/j.beth.2011.03.007.

Brown, T. A. (2015). *Confirmatory factor analysis for applied research* (2nd ed.). Guilford Press.

Burger, J., Isvoranu, A. M., Lunansky, G., Haslbeck, J. M. B., Epskamp, S., Hoekstra, R. H. A., Fried, E. I., Borsboom, D., & Blanken, T. F. (2022). Reporting standards for psychological network analyses in cross-sectional data. *Psychological Methods*. https://doi.org/10.1037/met0000471.

Cheung, G. W., & Rensvold, R. B. (2002). Evaluating goodness-of-fit indexes for Testing Measurement Invariance. *Structural Equation Modeling*, *9*(2), 233–255. https://doi.org/10.1207/S15328007SEM0902_5.

Cisler, J. M., & Koster, E. H. W. (2010). Mechanisms of attentional biases towards threat in anxiety disorders: An integrative review. *Clinical Psychology Review*, *30*(2), 203–216. https://doi.org/10.1016/j.cpr.2009.11.003.

Claes, L., Vertommen, S., Smits, D., & Bijttebier, P. (2009). Emotional reactivity and self-regulation in relation to personality disorders. *Personality and Individual Differences*, *47*(8), 948–953.

Clauss, K., & Bardeen, J. R. (2018). Addressing Psychometric Limitations of the Attentional Control Scale via Bifactor modeling and item modification. *Journal of Personality Assessment*, *102*(3), 415–427. https://doi.org/10.1080/00223891.2018.1521417.

Contreras, A., Nieto, I., Valiente, C., Espinosa, R., & Vazquez, C. (2019). The study of psychopathology from the Network Analysis Perspective: A systematic review. *Psychotherapy and Psychosomatics*, *88*(2), 71–83. https://doi.org/10.1159/000497425.

Corbetta, M., Miezin, F., Shulman, G., & Petersen, S. (1993). A PET study of visuospatial attention. *The Journal of Neuroscience*, *13*(3), 1202–1226. https://doi.org/10.1523/JNEUROSCI.13-03-01202.1993.

Costello, A. B., & Osborne, J. W. (2005). Best Practices in exploratory factor analysis: Four recommendations for getting the most from your analysis. *Practical Assessment Research & Evaluation*, *10*(7), 9.

Costenbader, E., & Valente, T. W. (2003). The stability of centrality measures when networks are sampled. *Social Networks*, *25*(4), 283–307. https://doi.org/10.1016/S0378-8733(03)00012-1.

Cox, R. C., & Olatunji, B. O. (2017). Linking attentional control and PTSD symptom severity: The role of rumination. *Cognitive Behaviour Therapy*, *46*(5), 421–431. https://doi.org/10.1080/16506073.2017.1286517.

de Winter, J. C. F., Dodou, D., & Wieringa, P. A. (2009). Exploratory factor analysis with small sample sizes. *Multivariate Behavioral Research*, *44*(2), 147–181. https://doi.org/10.1080/00273170902794206.

Derryberry, D., & Reed, M. A. (2002). Anxiety-related attentional biases and their regulation by attentional control. *Journal of Abnormal Psychology*, *111*(2), 225–236. https://doi.org/10.1037/0021-843X.111.2.225.

Epskamp, S., & Fried, E. I. (2018). A tutorial on regularized partial correlation networks. *Psychological Methods*, *23*(4), 617–634. https://doi.org/10.1037/met0000167.

Epskamp, S., Borsboom, D., & Fried, E. I. (2017). Estimating Psychological Networks and their Accuracy: A Tutorial Paper.Behavior Research Methods. https://arxiv.org/abs/1604.08462.

Epskamp, S., Borsboom, D., & Fried, E. I. (2018). Estimating psychological networks and their accuracy: A tutorial paper. *Behavior Research Methods*, *50*(1), 195–212. https://doi.org/10.3758/s13428-017-0862-1.

Eysenck, M. W., & Derakshan, N. (2011). New perspectives in attentional control theory. *Personality and Individual Differences*, *50*(7), 955–960. https://doi.org/10.1016/j.paid.2010.08.019.

Eysenck, M. W., Derakshan, N., Santos, R., & Calvo, M. G. (2007). Anxiety and cognitive performance: Attentional control theory. *Emotion*, *7*(2), 336–353. https://doi.org/10.1037/1528-3542.7.2.336.

Fajkowska, M., & Derryberry, D. (2010). Psychometric properties of Attentional Control Scale: The preliminary study on a polish sample. *Polish Psychological Bulletin*, *41*(1), 1–7. https://doi.org/10.2478/s10059-010-0001-7.

Gross, J. J. (2015). Emotion regulation: Current status and future prospects. *Psychological Inquiry*, *26*, 1–26.

Haslbeck, J. M. B., & Fried, E. I. (2017). How predictable are symptoms in psychopathological networks? A reanalysis of 18 published datasets. *Psychological Medicine*, *47*(16), 2767–2776. https://doi.org/10.1017/S0033291717001258.

Haslbeck, J. M. B., & Waldorp, L. J. (2018). How well do network models predict observations? On the importance of predictability in network models. *Behavior Research Methods*, *50*(2), 853–861. https://doi.org/10.3758/s13428-017-0910-x.

Hsu, K. J., Forgeard, M., Stein, A. T., Beard, C., & Björgvinsson, T. (2019). Examining differential relationships among self-reported attentional control, depression, and anxiety in a transdiagnostic clinical sample. *Journal of Affective Disorders*, *248*, 29–33. https://doi.org/10.1016/j.jad.2019.01.017.

Judah, M. R., Grant, D. M., Mills, A. C., & Lechner, W. V. (2014). Factor structure and validation of the attentional control scale. *Cognition and Emotion*, *28*(3), 433–451. https://doi.org/10.1080/02699931.2013.835254.

Kunina-Habenicht, O., Rupp, A. A., & Wilhelm, O. (2012). The impact of Model Misspecification on Parameter Estimation and Item-Fit Assessment in Log-Linear Diagnostic classification models. *Journal of Educational Measurement*, *49*, 59–81.

Luo, L., Arizmendi, C., & Gates, K. M. (2019). Exploratory factor analysis (EFA) programs in R. *Structural Equation Modeling: A Multidisciplinary Journal*, *26*(5), 819–826. https://doi.org/10.1080/10705511.2019.1615835.

Matsunaga, M. (2010). How to factor-analyze your data right: Do's, don'ts, and how-to's. *International Journal of Psychological Research*, *3*(1), 97–110. https://doi.org/10.21500/20112084.854.

Meyers, L. S., Gamst, G., & Guarino, A. J. (2006). *Applied multivariate research: Design and interpretation*. Sage.

Michalko, D. (2018). Factor structure of Slovak Adaptation of Attentional Control Scale. *Studia Psychologica*, *1*(60), 57–70. https://doi.org/10.21909/sp.2018.01.752.

Miyake, A., Friedman, N. P., Emerson, M. J., Witzki, A. H., Howerter, A., & Wager, T. D. (2000). The Unity and Diversity of Executive Functions and their contributions to Complex "Frontal Lobe" tasks: A latent variable analysis. *Cognitive Psychology*, *41*(1), 49–100. https://doi.org/10.1006/cogp.1999.0734.

Mundfrom, D. J., Shaw, D. G., & Ke, T. L. (2005). Minimum sample size recommendations for conducting factor analyses. *International Journal of Testing*, *5*(12), 159–168.

Ólafsson, R. P., Smári, J., Guðmundsdóttir, F., Ólafsdóttir, G., Harðardóttir, H. L., & Einarsson, S. M. (2011a). Self reported attentional control with the Attentional Control Scale: Factor structure and relationship with symptoms of anxiety and depression. *Journal of Anxiety Disorders*, *25*(6), 777–782. https://doi.org/10.1016/j.janxdis.2011.03.013.

Ólafsson, R. P., Smári, J., Guðmundsdóttir, F., Ólafsdóttir, G., Harðardóttir, H. L., & Einarsson, S. M. (2011b). Self reported attentional control with the Attentional Control Scale: Factor structure and relationship with symptoms of anxiety and depression. *Journal of Anxiety Disorders*, *25*(6), 777–782. https://doi.org/10.1016/j.janxdis.2011.03.013.

Quigley, L., Wright, C. A., Dobson, K. S., & Sears, C. R. (2017). Measuring attentional control ability or beliefs? Evaluation of the factor structure and convergent validity of the Attentional Control Scale. *Journal of Psychopathology and Behavioral Assessment*, *39*(4), 742–754. https://doi.org/10.1007/s10862-017-9617-7.

Schäfer, J., Wittchen, H. U., Höfler, M., Heinrich, A., Zimmermann, P., Siegel, S., & Schönfeld, S. (2015). Is trait resilience characterized by specific patterns of attentional bias to emotional stimuli and attentional control? *Journal of Behavior Therapy and Experimental Psychiatry*, *48*, 133–139. https://doi.org/10.1016/j.jbtep.2015.03.010.

Schreiber, J. B., Nora, A., Stage, F. K., Barlow, E. A., & King, J. (2006). Reporting structural equation modeling and confirmatory factor analysis results: A review. *The Journal of Educational Research*, *99*(6), 323–338. https://doi.org/10.3200/JOER.99.6.323-338.

Singh, R. (2009). Does my structural model represent the real phenomenon?: A review of the appropriate use of structural equation modelling (SEM) model fit indices. *The Marketing Review*, *9*(3), 199–212. https://doi.org/10.1362/146934709X467767.

Spielberger, C. D., Gorsuch, R. L., Lushene, R., Vagg, P. R., & Jacobs, G. A. (1983). *Manual for the state-trait anxiety inventory (form Y): Self-evaluation questionnaire*. Consulting Psychologists Press.

Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society: Series B (Methodological)*, *58*(1), 267–288.

Troy, A. S., & Mauss, I. B. (2011). Resilience in the face of stress: Emotion regulation as a protective factor. *Resilience and Mental Health: Challenges across the Lifespan* (p. 15). Dennis Charney, and Matthew J. Friedman. Steven M. Southwick, Brett T. Litz.

Weems, C. F. (2020). Commentary on the Special Issue on Network Analysis: Assessment, intervention, theory, and the nature of reality: Actualizing the potential of Network perspectives on posttraumatic stress disorder. *Journal of Traumatic Stress*, *33*(1), 116–125. https://doi.org/10.1002/jts.22482.

Xia, Y., & Yang, Y. (2019). RMSEA, CFI, and TLI in structural equation modeling with ordered categorical data: The story they tell depends on the estimation methods. *Behavior Research Methods*, *51*(1), 409–428. https://doi.org/10.3758/s13428-018-1055-2.

Xin, T., Wang, C., Chen, P., & Liu, Y. (2022). Editorial: Cognitive diagnostic Models: Methods for practical applications. *Frontiers in Psychology*, *13*, 895399. https://doi.org/10.3389/fpsyg.2022.895399.