Academic Buoyancy and Coping Revisited: Are They More Strongly Related Than was Previously Thought?

- Supporting Information -

This document contains materials designed to supplement the main text. The materials include the following:

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Detailed Analytic Strategy

The analysis proceeded in three phases. First, we estimated latent bivariate correlations using a set-exploratory structural equation model (set-ESEM). Set-ESEM is a latent variable modeling approach that integrates principles of exploratory and confirmatory factor analysis (Marsh et al., 2009). In exploratory factor analyses, related constructs, such as emotion regulation strategies (e.g., Garnefski et al., 2001) can show item cross-loadings on non-target factors. When analyzed using confirmatory factor analysis the independent clusters assumption (item loadings on non-target factors are constrained to zero by default) can result in biased (overly high) correlations between factors and poor model fit (Marsh et al., 2009). In ESEM, the independent clusters assumption is relaxed; items can load on multiple factors. Set-ESEM allows for items to cross-load onto factors within a given set of related constructs but are constrained to be zero for factors outside of the set (Marsh et al., 2014, 2020), thus supporting parsimony of the resulting model. In the present set-ESEM, the emotion regulation (i.e., coping) items were modelled as one set, and the academic buoyancy items were modelled as a second set using target rotation (oblique). Academic achievement was added as manifest variables. Second, based on the aforementioned set-ESEM, we examined whether academic buoyancy was indirectly related to achievement, mediated by coping. Prior achievement and gender were included as covariates.

Third, we conducted a network analysis (NA) to establish how academic buoyancy and coping items cohered into distinct communities, and which items were particularly influential in the network and in bridging communities of items. Our network analysis drew on the following four sources of information: (1) a *visual representation* of the network using a graphical Gaussian model to allow for a judgement of the placing of items relative to one another and of their links; (2) an *Exploratory Graph Analysis* to assist in judging the number of coherent communities of items; (3) *expected influence* indices to identify items with more numerous, and stronger, connections to others; (4) *bridge indices* to identify items that are influential in linking communities of items.

The NA was conducted in R 4.2.1 using the "network tools" package version 1.5.0 (Jones, 2017). The Fruchterman-Reingold (1991) algorithm was used to estimate the graphical Gaussian model based on semi-partial correlations between item pairs (i.e., controlling for correlations with all other items). The coherence of items into distinct communities can be identified by their physical proximity and being connected by strong edge weights. We also referred to Kaiser criterion to assist with the detection of communities (see Figure S1). Influential items can be identified by: (a) close positioning to the center of the network, (b) a greater number of edges (correlations) to other items, and (c) thicker edge weights (stronger correlations).

Given the recommendations by Isvoranu and Epskamp (2023) (small sample size; and primary interest to discover a structure that resembles a true network and to discover the strongest edges) we used the Least Absolute Shrinkage and Selection Operator (LASSO) using the EBICglasso function that was applied to the Gaussian model in order to regularize semi-partial correlations (Friedman et al., 2008). LASSO shrinks small semi-partial correlations to zero, thereby eliminating potentially spurious relations and resulting in a network that contains fewer, but potentially more meaningful, edges. The hyperparameter γ is used to set the balance between an exiguous network of stronger edges and a network containing a greater number of potentially false edges.

Hyperparameter values between $\gamma = 0$ and 0.5 are typically chosen. Values closer to 0 lead to accepting models with a greater number of potentially false edges, and values closer to 0.5 lead to accepting models with fewer, but authentic, edges (Epskamp et al., 2012, 2017). We selected a value of 0.5 in order to estimate a conservative model that contained the most meaningful edges. A non-parametric bootstrapping procedure using 1000 draws was used to estimate the edge weights. To draw the edges, we used the default fading rule of the qgraph package (Epskamp et al., 2012; version 1.9.4), as recommended by Isvoranu and Epskamp (2023), in light of our research questions.. In order to guide the identification communities we estimated an Exploratory Graph Analysis via the R-package EGA which uses the walktrap algorithm to find communities of items in the network from the regularized partial correlation network (Golino et al., 2020).

One-step (EI1) and two-step (EI2) expected influence indexes were used to establish the connectivity of nodes within the network (Robinaugh et al., 2016). The term 'influence' is not intended to imply directionality or causality. Rather it is way of describing the relations between nodes in terms of their number, strength, and distance. The EI1 index is the sum of the edges (positive and negative) a node shares with neighboring nodes. For a node with predominantly positive edges, the presence of a negative edge will diminish the positive EI1 value and vice versa.

EI1 values do not account for the indirect influence of a node via the influence of neighboring nodes. That is, node A may only show an edge with node B, but if node B is showed edges with many other nodes, node A can still be influence by virtue of the link with node B. The EI2 index accounts for the secondary influence of a node, through adjacent items, by including the EI1 index plus the weighted EI1 values of all other nodes in the network. Weights are applied as the indirect influence of node A to others in the network via node B depends on the strength of the edge from node A to node B.

Bridge indexes show how one, or more, nodes may link different communities of nodes within a network. For instance, nodes A, B, and C, may cohere as one distinct community, and nodes X, Y, and Z, as another. If the two communities are linked by an edge from nodes A and X, these nodes would be considered as bridges. The bridge EI1 index represents the summed edges of one node (positive and negative) to other nodes that are part of different communities. The bridge EI2 index also includes the secondary influence of one node to those in other communities indirectly via other nodes.

Following Epskamp et al. (2018) we used the bootnet packpage (version 1.5.5) to investigate the stability and accuracy of the network with 2,500 nonparametric bootstrapped samples. Finally, to identify the presence different communities, we applied a spinglass algorithm to the network using the igraph package (Version 1.4.1; Reichardt & Bornholdt, 2006). The accuracy of the estimated network was check following Epskamp et al.'s (2018) threefold recommendations. First, use bootstrapped CIs to check the accuracy of edge weights (see Figure S2). Second, check the stability of EIs on subsets of the data (see Figure S3). Third, use bootstrapped difference tests to establish if pairs of nodes differ from one another (see Figure S4).

Treatment of Missing Data

The online survey platform prompted participants who had not answered a question to respond, hence there were no missing data. The responses of participants who recorded their gender as ‘other’ or ‘prefer not to say’ ($n = 22$) were recoded as missing to allow the inclusion of gender as a binomial covariate in subsequent analyses (hence 4% of gender data were coded as missing). A further 96 participants opted to complete the survey only, hence 18% of examination score data were missing. In total, 0.3% of data were missing. Little’s omnibus test (Little, 1988) for data being missing completely at random (MCAR) was not statistically significant, $\chi^2(57) = 50.48$, $p = .72$, indicating that MCAR could be assumed. Missing data were treated in subsequent analyses using Full Information Maximum Likelihood (FIML) estimation. FIML has been shown to result in unbiased parameter estimates (e.g., Nicholson et al., 2017; Rioux & Little, 2019).

Table S1

Factor Loadings from the ESEM Used to Estimate Latent Bivariate Correlations

Item	AB	SB	AC	RM	RF	PL	RA	PS	CT	OB
ER1		**.75**	.01	.03	-.04	.07	-.09	-.01	-.05	.04
ER2		**.53**	.07	.07	.07	-.02	-.18	-.01	.20	.02
ER3		**.89**	.02	-.01	.04	-.01	.05	.01	-.01	-.03
ER4		**.79**	.07	.03	-.03	-.09	.18	.02	.05	-.03
ER5		.28	**.25**	-.10	.08	.18	.04	.11	-.16	.01
ER6		-.07	**.55**	-.14	.12	-.05	.09	.11	-.01	.01
ER7		.05	**.79**	.04	-.08	.06	-.11	.03	.04	.01
ER8		.04	**.79**	.17	-.03	-.11	.05	-.09	-.03	.03
ER9		.15	-.01	**.54**	-.09	.15	-.18	-.01	.17	.02
ER10		.04	.05	**.63**	-.01	.22	-.12	.03	.06	-.03
ER11		.02	.10	**.31**	.12	.07	-.03	.08	.30	-.03
ER12		-.01	.03	**.91**	-.01	-.10	.15	-.02	-.02	.03
ER13		-.04	.10	-.04	**.61**	.12	.12	-.03	-.01	.01
ER14		.08	-.03	-.03	**.85**	-.02	-.07	.01	-.01	-.01
ER15		.04	-.06	-.01	**.92**	-.08	.03	-.06	.04	.01
ER 16		-.12	.04	.06	**.66**	.16	-.04	.11	.03	.00
ER 17		.05	-.01	-.03	-.02	**.61**	.27	-.04	.02	-.07
ER 18		-.08	.02	.22	.20	**.52**	.27	-.01	-.07	.03
ER 19		.07	-.24	.12	.01	**.46**	.03	.02	.04	-.03
ER 20		-.06	-.02	.08	.22	**.40**	.28	.13	.02	.00
ER 21		.01	-.03	-.04	-.09	.21	**.15**	.07	.02	-.09
ER 22		-.04	.04	-.07	.17	.19	**.49**	-.05	-.07	.13
ER 23		.03	-.12	-.01	.12	-.01	**.27**	.19	.04	.04
ER 24		-.01	.01	-.03	.19	-.16	**.37**	.37	-.13	.02
ER 25		-.03	.11	-.02	.10	.05	.17	**.48**	.07	.05
ER 26		.01	.01	-.01	-.08	-.11	.13	**.73**	.20	.01
ER 27		-.01	.01	.10	.01	-.05	.03	**.74**	-.08	.01
ER 28		.03	.01	-.04	.02	.02	-.15	**.84**	-.24	.01
ER 29		-.03	.07	-.04	-.02	-.05	.18	.10	**.55**	.02
ER 30		.20	-.04	.16	.02	.02	-.14	.02	**.61**	.05
ER 31		.06	.05	.04	.08	-.07	.08	-.12	**.55**	.10
ER 32		.06	.01	.31	-.04	-.03	-.04	.04	**.53**	.01
ER 33		-.07	.09	-.01	-.03	.09	-.10	.01	.02	**.62**
ER 34		.04	-.02	-.01	.02	-.08	.09	.05	.05	**.43**
ER 35		.05	-.04	.04	-.01	-.02	.02	-.02	-.09	**.88**
ER36		-.04	-.01	-.06	-.03	-.01	.05	.01	.09	**.70**
Buoy1	**.69**									
Buoy2	**.64**									
Buoy3	**.81**									
Buoy4	**.82**									

Note. AB = Academic Buoyancy, AC = Acceptance, RF = Positive Refocusing, PL = Refocus on Planning, RA = Positive Reappraisal, PS = Putting into Perspective, SB = Self-Blame, OB = Other-Blame, RM = Rumination, and CT = Catastrophizing. Target items for a specific factor are in bold font.

Table S2

Correlations Between Coping Strategies in the Structural Equation Model (Model 2).

	1	2	3	4	5	6	7	8	9
1. Acceptance	—	.17 (.05)	-.21 (.05)	-.16 (.06)	.20 (.05)	.24 (.05)	.21 (.05)	.09 (.06)	.23 (.05)
2. Positive Refocusing		—	.27 (.05)	.27 (.06)	.47 (.04)	.03 (.05)	.20 (.05)	.14 (.06)	.05 (.06)
3. Refocus on Planning			—	.31 (.06)	.20 (.06)	.20 (.05)	-.08 (.05)	.31 (.06)	.15 (.07)
4. Positive Reappraisal				—	.31 (.07)	.07 (.06)	-.02 (.05)	.11 (.07)	.05 (.05)
5. Putting into Perspective					—	.15 (.05)	.10 (.05)	.09 (.06)	-.14 (.05)
6. Self-Blame						—	-.10 (.05)	.34 (.05)	.27 (.05)
7. Other-Blame							—	.04 (.05)	.23 (.06)
8. Rumination								—	.48 (.06)
9. Catastrophizing									—

Note. Standard errors in parentheses.

Table S3

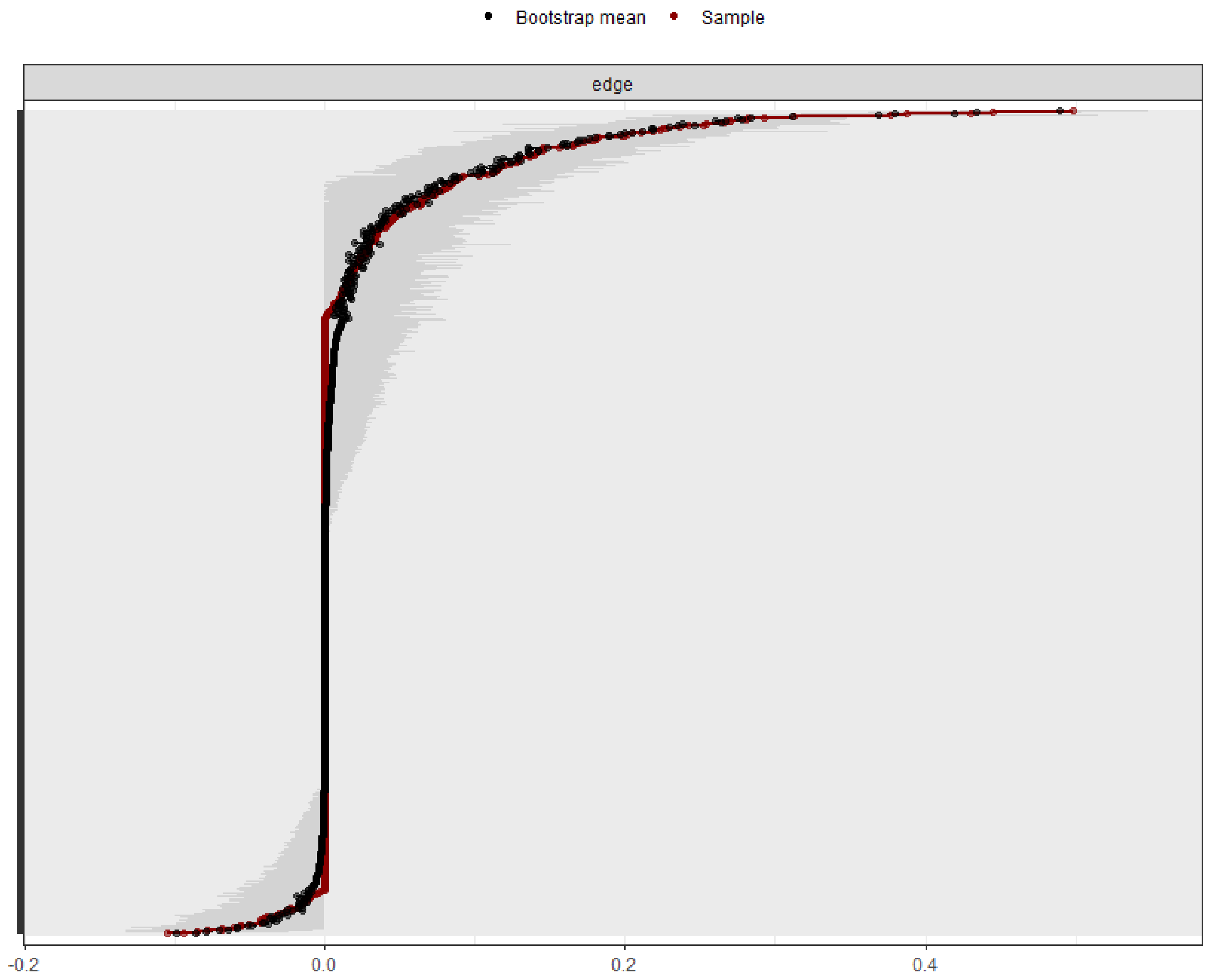
Standardized Regression Coefficients for Gender from the Structural Equation Model

	Gender
Academic Buoyancy	-.261 (.107)*
Acceptance	.048 (.076)
Positive Refocusing	-.113 (.070)
Refocus on Planning	.154 (.118)
Positive Reappraisal	-.106 (.135)
Putting into Perspective	.123 (.075)
Self-Blame	-.300 (.064)***
Other-Blame	-.091 (.064)
Rumination	.059 (.103)
Catastrophizing	.178 (.138)
GCSE English Grade	-.066 (.048)
GCSE Mathematics Grade	.118 (.051)*
Year 12 Academic Achievement	.079 (.056)

Note. Gender was coded as 0 = male and 1 = female.
* p <.05. ** p <.01. *** p <.001.

Figure S1

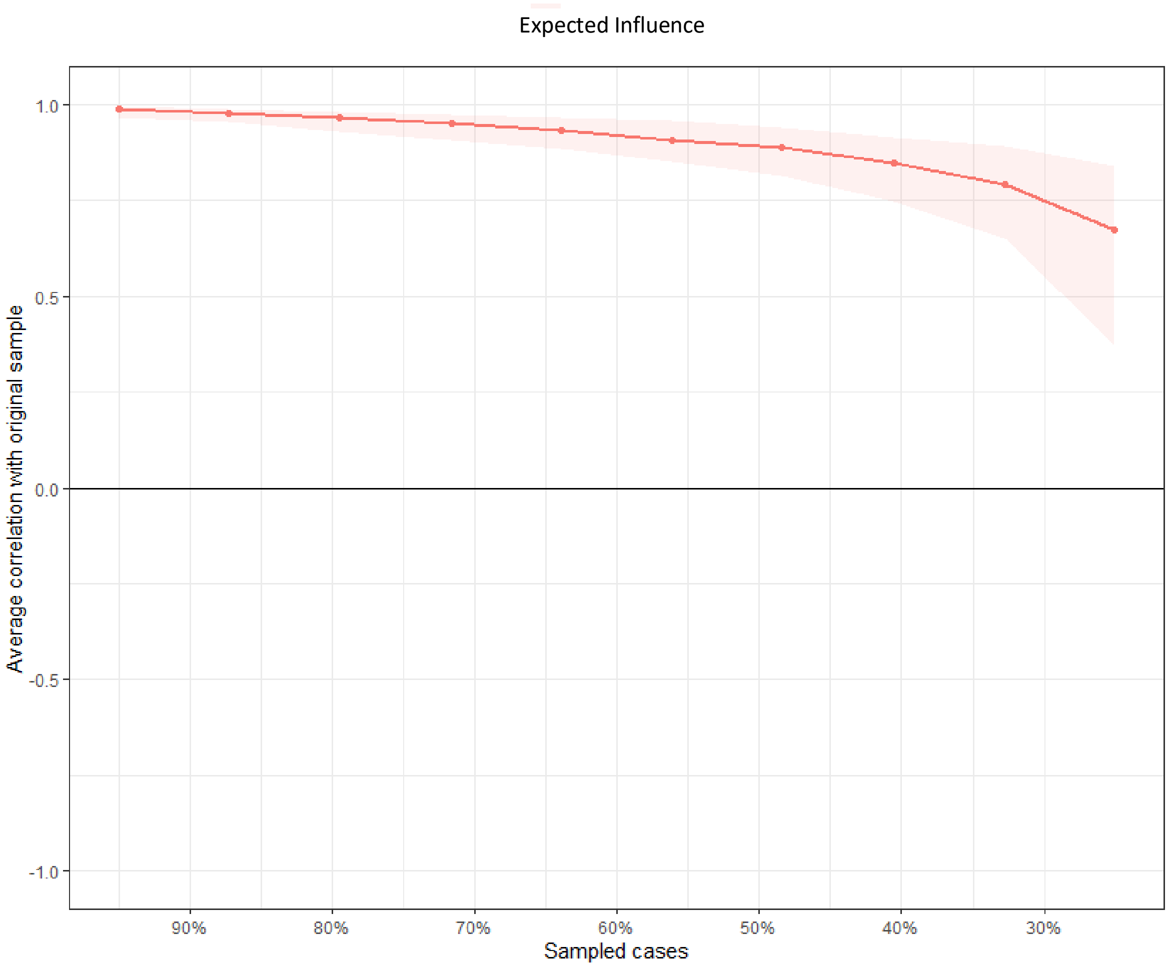
Bootstrapped Confidence Intervals of Edge-Weights for the Estimated Network.



Note. The red line indicates the sample values, and the gray area the bootstrapped CIs. Each edge in the network is represented as a horizontal line starting with strongest positive edge weights at the top and negative at the bottom. For edge-weights estimated to be zero, they were ordered using the mean of the bootstrapped samples.

Figure S2

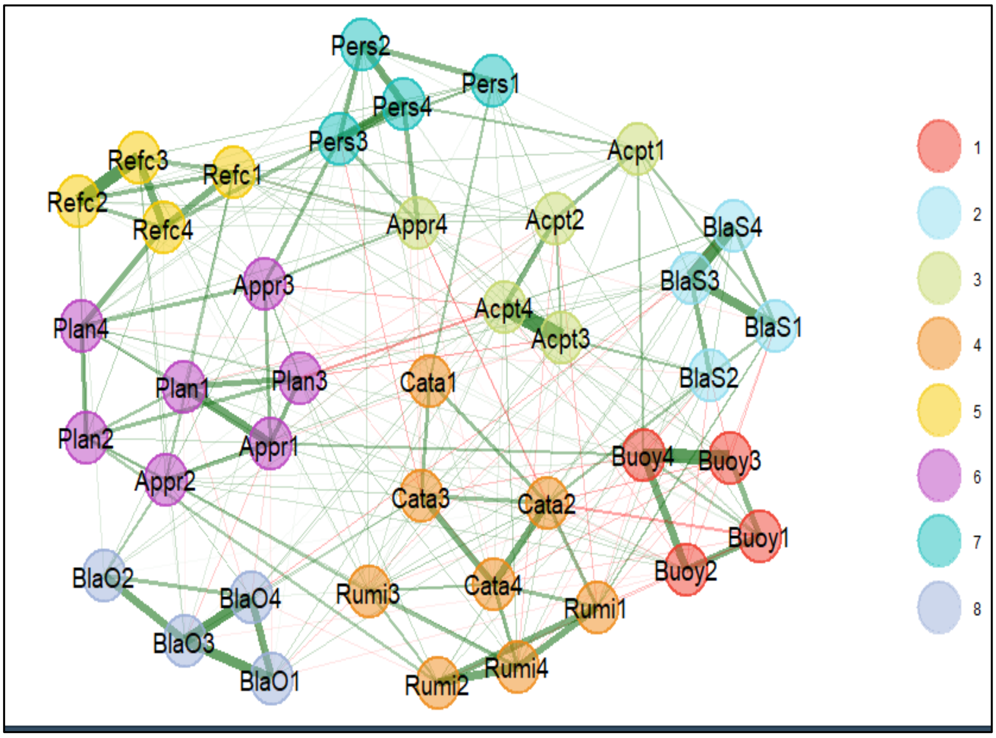
Average Correlations of Expected Influence Statistics Sampled with Persons Dropped and the Original Sample.



Note. The red line shows the average correlation between the EI indices between the original sample and sampled subsets with *n* persons dropped. The light red area represents the range of correlations from the 2.5th to the 97.5th percentile.

Figure S3

Exploratory Graph Analysis to Guide the Identification of Communities.



Note. Academic buoyancy items were labelled Buoy1 to Buoy4, self-blame items Blas1 to Blas4, acceptance items Acpt1 to Acpt4, rumination items Rumi1 to Rumi4, positive refocusing items Refc1 to Refc4, refocus on planning items Plan1 to Plan4, positive reappraisal items Appr1 to Appr4, putting into perspective items Pers1 to Pers4, catastrophizing items Cata1 to Cata4, and other-blame items BlaO1 to BlaO4. Colored nodes indicate which nodes formed independent communities. Positive edges are green and negative edges are red. As walktrap and spinglass algorithms are different, the architecture of the network has altered. The principal purpose of the exploratory graph analysis, was the idnetification of communities rather than the interpretation of the network.

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