

Supplemental Material

Table of Contents

ICS-S Measure Development	2
Study 1	3
Study 2	4
Table of model fit statistics for Study 1 & 2	5
Model Priors	6
Path coefficients for Study 1 & 2	7
Appendix. NGC Vignette.....	8

ICS-S Measure Development

To assess the factor structure of the ICS-S, we employed a Bayesian structural equation modeling (BSEM) approach to confirmatory factor analysis (CFA) (Muthén, & Asparouhov, 2012). Whilst the maximum likelihood approach to CFA views parameters as constants, the BSEM approach treats parameters as variables with means and distributions. The BSEM approach, therefore, allows researchers to specify more realistic and accurate measurement models that do not treat variables as fixed constants. Instead, variables are allowed small cross-loadings, small variances, and correlated residuals between other variables in a specified model (see Arthur, Callow, Roberts, & Glendinning, 2019; Niven & Markland, 2016 for further details). The first step in this process requires testing model convergence, which is assessed by potential scale reduction (PSR) factor. Model convergence is evident when the PSR value falls between 1.1 and 1.0. Whilst there is not a strict cut off, PSR values > 1.1 suggest that the multiple parallel Markov chain Monte Carlo chains that Bayesian analysis employs have converged to different values leading to difficulty with posterior parameter interpretation. BSEM model fit is assessed by using the posterior predictive p value (PPP). An excellent fitting model is indicated by a value close to .5, with values around .0 indicating poor fit (Gelman et al., 2014). Additional fit indices include examining the symmetry of the 95% confidence intervals for the difference between the observed and replicated χ^2 values. Credibility interval values that are symmetrical and centred closely to zero are also indicative of excellent model fit (Muthén, & Asparouhov, 2012).

It is also recommended that sensitivity analysis is performed on the measured parameters. This sensitivity analysis permits researchers to verify that their prior beliefs are robust (Depaoli & van de Schoot, 2017). Fundamentally, sensitivity analysis assesses how much impact the magnitude of the prior belief has on the posterior distribution of a parameter estimate. Whilst no strict guidelines are currently prescribed, for reasons of transparency, we

include our approach to sensitivity analysis. Using similar to methods used by Niven & Markland (2016), we used smaller (.005) and larger (.015) prior variances on the cross-loadings and residuals, we then examined how many parameters deviated $\pm 10\%$ from the original estimate.

Study 1

We followed contemporary procedures for Bayesian CFA were followed in line with previous research (Gucciardi & Zyphur, 2016). Model strategy focused on developing three models, the first model included no residuals or cross-loadings. The second model incorporated cross-loadings only. Finally, the third model incorporates cross-loadings, and correlated residuals between items. The third model (with cross-loadings and correlated residuals) on the 14-item questionnaire provided adequate convergence and excellent fit, with a PPP value of around .50 and symmetrical confidence intervals around zero (PPP = .52, CI = -46.180, 42.89, see Table S1 for all model fit statistics).

However, some items were problematic due to low factor loadings (i.e., $< .6$), and had correlated residuals that were high (i.e., items significantly correlating with non-intended factors beyond the level of the prior). Consequently, we removed items based on a combination of statistical grounds and theoretical relevance. This practice of item removal based on theory and data is accepted in measurement development (Biddle et al., 2001; Markland, 2007) and resulted in the removal of two task conflict, and one process conflict item. We removed the process conflict item *'How often is there tension in your team caused by members not performing?'* due to significant correlated residuals with several relationship conflict items. Therefore, we determined that this item did not adequately reflect process conflict. We removed the task conflict item *'To what extent are there differences of opinion in your team?'* as it was thought to be overly vague regarding any task conflict variable as 'opinions' could be relevant any one of the three conflict variables. Finally, we removed the

task conflict item '*How frequently are there conflicts about ideas in your team?*' due to a combination of ambiguity (similar to the other removed item and a low factor loading on the task conflict construct.

Following the item removal process, the 11-item measure (with cross-loadings and correlated residuals) yielded excellent model fit (PPP = .52, CI = -36.18, 34.98). All items loaded on to their intended factors, these were significant and were above .70. Inter-factor correlations were as follows: Task with Process ($r = .66$ [.46, .79]), Task with Relationship ($r = .53$ [.30, .70]), and Relationship with Process ($r = .80$ [.67, .89]).

To provide further confirmation that the three-factor structure best fitted the data, we ran a series of two-factor models (i.e., we ran models with task and relationship conflict, task and process conflict, and process and relationship conflict, with the third conflict variable as a distinct factor, in three separate analyses) which displayed relatively inferior model fit statistics (PPP values ranged between .30-.45). A single factor model displayed excellent model fit (PPP = .53, CI = -36.15, 33.40). However, all item loadings were $< .1$ and non-significant, thus items did not sufficiently represent a single-factor structure. Thus, we retained our 11-item three factor measure for use in Study 1.

Study 2

We assessed the 11-item ICS-S model fit in a confirmation sample, which yielded similar results to Study 1 with an excellent model fit evident (PPP = .52 CI = -35.88, 33.95). Inter-factor correlations were as follows: Task with Process ($r = .33$, [.04, .57]), Task with Relationship ($r = .28$ [.02, .51]) and Relationship with Process ($r = .74$, [.58, .84]). All items loaded on to their intended factors, these were significant and were above .60.

Again, we compared alternative factor structures with various two-factor models exhibiting lower PPP values than our three-factor structure (values ranged between .35-.45). We also found, similar to Study 1, that a single-factor structure yielded excellent model fit

(PPP = .50, CI = -36.18, 34.98), but again all item loadings on the factor structure were < .1 and non-significant.

Table S1

Model fit Statistics for ICS-S for Study 1 and Study 2

	Model	PPP	Confidence Intervals	
			Lower 2.5%	Higher 2.5%
Study 1	14-item Model 1	.00	174.23	249.51
	14-item Model 2 (cross-loadings)	.00	109.46	193.13
	14-item Model 3 (cross-loadings + residual correlations)	.52	-46.18	42.89
	11-item Model 1	.00	41.67	104.62
	11-item Model 2 (cross-loadings)	.01	7.97	77.79
	11-item Model 3 (cross-loadings + residual correlations)	.52	-36.18	34.98
	Study 2	11-item Model 1	.00	59.88
	11-item Model 2 (cross-loadings)	.02	3.31	72.59
	11-item Model 3 (cross-loadings + residual correlations)	.52	-35.88	33.95

Table S2*Priors employed for conditional indirect effects and sensitivity analysis.*

Path	Model 1		Model 1a		Model 1b	
	μ	σ^2	μ	σ^2	μ	σ^2
NPI → RC	.35	.03	.35	.01	.70	.12
NPI → TC	.35	.03	.35	.01	.70	.12
NPI → PC	.35	.03	.35	.01	.70	.12
RC → Task Cohesion	-.35	.03	-.35	.01	-.70	.12
TC → Task Cohesion	.00	.03	.00	.01	.00	.12
PC → Task Cohesion	-.35	.03	-.35	.01	-.70	.12
NPI × NGC → RC	-.35	.03	-.35	.01	-.70	.12
NPI × NGC → TC	-.35	.03	-.35	.01	-.70	.12
NPI × NGC → PC	-.35	.03	-.35	.01	-.70	.12

Note μ = mean; σ^2 = variance; NPI= Narcissistic Personality Inventory; RC = Relationship conflict; TC =Task conflict; PC = Process conflict NGC = Narcissistic Group Composition
All priors reflect a mean and variance on a normal distribution curve.

Table S3

Bayesian estimates for path coefficients with 95% credibility intervals for Model 1.

Parameter	Study 1		Study 2	
	GI-T	ATG-T	GI-T	ATG-T
NPI → RC	.40 [.28, .56]	.40 [.28, .55]	.12 [.02, .23]	.12 [.02, .23]
NPI → TC	.32 [.21, .45]	.32 [.21, .45]	.02 [-.07, .10]	.01 [-.07, .10]
NPI → PC	.43 [.31, .60]	.43 [.30, .59]	.15 [.04, .26]	.15 [.04, .26]
RC → Task cohesion	-.18[-.37, .002]	-.04[-.21, .13]	-.13 [-.36, .09]	-.12 [-.34, .11]
TC → Task cohesion	.23 [.06, .39]	.23 [.06, .39]	.17 [-.14, .47]	.16 [-.15, .46]
PC → Task cohesion	-.32 [-.53, -.11]	-.29 [-.46, -.11]	-.50 [-.73, -.26]	-.38 [-.62, -.14]
NGC → RC	.03 [-.16, .22]	-.01[-.17, .16]	.10 [.01, .18]	.10 [.01, .18]
NGC → TC	-.20[-.41, .004]	-.24[-.42, -.06]	.08 [.02, .15]	.08 [.02, .15]
NGC → PC	-.15[.35, .05]	-.10[-.27, .08]	.12 [.03, .21]	.13 [.03, .22]
RC NPI×NGC	-.01[-.06, .04]	.00 [-.04, .04]	-.15 [-.28, -.03]	-.16 [-.28, -.03]
TC NPI×NGC	-.02[-.07, .03]	-.01 [-.06, .04]	-.12 [-.22, -.02]	-.12 [-.22, -.02]
PC NPI×NGC	-.12 [-.18, -.05]	-.10 [-.15, -.04]	-.17 [-.30, -.03]	-.18 [-.31, -.04]

Note: RC = Relationship Conflict; TC = Task Conflict; PC = Process conflict; GI-T = Group

integration – Task; ATG-T = Attraction to group – Task; NPI = Narcissistic Personality

Inventory; NGC = Narcissistic group composition

Estimates in **bold** denote estimates which do not encompass zero

Appendix

NGC Vignette

Please read the following description of a sportsperson. Then consider this description in relation to members of your current team.

Andre/Andrea is an extremely confident player and is one of the biggest characters in the dressing room. However he/she has a reputation for being a flashy player who shows off. He/She has often been able to make difficult, spectacular plays at crucial times in important games. When the stakes are high and the spotlight is bright, Andre/Andrea is at his best. Andre has also developed a reputation as a moaner who complains when the ball is not passed to him/her. On one infamous occasion, Andre/Andrea, who feels he/she is the team's superstar, got visibly upset with his/her teammate for passing the ball to another player – even though the pass resulted in a goal that won the game. Andre/Andrea also tends to apply little effort and blow easy plays, especially during practice and in games that are relatively unimportant. One of his/her teammates once explained to a reporter, “Andre/Andrea can be a real pain in the neck. He/She is always late to practice, struts around like he's/she's God's gift to SPORT and I don't think I've ever seen him/her cover for another player. But when the game is on the line, we're all happy to have Andre/Andrea on our team.”

With the above description in mind, **please indicate the number of players on your current team who resemble Andre/Andrea:**

_____ players out of a total number of _____ players in the squad

References not included in main text

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