Supplemental Electronic-Only Materials

Appendix A

EFA in ESEM

The EFA in ESEM can be written with two general equations: one for the measurement model and one for the latent variable model (Bollen, 1989). The measurement model can be written as:

$$\mathbf{Y}_{p\,x\,1} = \boldsymbol{\nu}_{p\,x\,1} + \boldsymbol{\Lambda}_{p\,x\,m}\boldsymbol{\eta}_{m\,x\,1} + \boldsymbol{\varepsilon}_{p\,x\,1}, \text{ where} \tag{1}$$

p is the number of continuous observed dependent variables
m is the number of continuous latent variables
q is the number of observed independent variables
and
$\mathbf{Y}$ is a vector of continuous observed dependent variables
$\boldsymbol{\nu}$ is a vector of intercepts or means
$\boldsymbol{\Lambda}$ is a matrix of pattern coefficients
$\boldsymbol{\eta}$ is a vector of continuous latent variables
$\boldsymbol{\varepsilon}$ is a vector of residuals for $\mathbf{Y}$
$\boldsymbol{\Theta}$ is a p x p covariance matrix for $\boldsymbol{\varepsilon}$

The second equation can be conceptualized as the latent variable model:

$$\boldsymbol{\eta}_{m\,x\,1} = \boldsymbol{\alpha}_{m\,x\,1} + \boldsymbol{\zeta}_{m\,x\,1}, \text{ where} \tag{2}$$

$\boldsymbol{\eta}$ is a vector of continuous latent variables
$\boldsymbol{\alpha}$ is a vector of intercepts or means
ζ is a vector of residuals for $\boldsymbol{\eta}$
$\boldsymbol{\Psi}$ is a m x m covariance matrix for ζ

Appendix B_1

Rotation. Direct analytic rotation of the pattern matrix is based on several decades of research within the EFA framework (e.g., Jennrich, 2007; Jennrich & Sampson 1966) as detailed in Browne (2001). Rotation of the pattern matrix is accomplished via post-multiplication of the pattern matrix by the inverse of an optimal transformation matrix:

$$\mathbf{\Lambda}^{*}_{p\,x\,r} = \mathbf{\Lambda}_{p\,x\,r}\left(\mathbf{H}^{*}_{r\,x\,r}\right)^{-1}. \tag{3}$$

An optimal transformation matrix, $\mathbf{H}^{*}$, is determined by minimizing a continuous complexity function of the elements in the pattern matrix, $f\,(\mathbf{\Lambda})$. A mechanical rotation criterion can be thought of as being easy to implement but providing little to no opportunity to incorporate a priori measurement theory into the $f\,(\mathbf{\Lambda})$.Various rotation techniques define $f\,(\mathbf{\Lambda})$ differently but each was typically designed to provide the simplest solution. In practice, a simple structure is often interpreted as having only one non-zero pattern coefficient per row (variable complexity, *vc*, = 1); though this a more restrictive approach than advocated by Thurstone (1947).

Geomin rotation (Yates, 1987) minimizes row (e.g., variable) complexity in a way that is more consistent with Thurstone's (1947) conceptualization of simple structure as compared to the more restrictive perfect simple structure. Accordingly, geomin has performed relatively well when *vc* > 1 both in empirical examples (e.g., McDonald, 2005) and in a simulation study when compared to other mechanical rotation criteria (Sass & Schmitt, 2010). Currently geomin is the default rotation criterion in M*plus* and, therefore, may be used frequently in practice. The $f\left(\mathbf{\Lambda}\right)$ for geomin implemented in M*plus* is:

$$\sum_{i=1}^{p}\left(\prod_{j=1}^{r}\left(\lambda_{ij}^{2}+\varepsilon\right)\right)^{1/r}, \text{ where} \tag{4}$$

ε is a small positive constant added by Browne (2001) to reduce the problem of indeterminacy. In Asparouhov and Muthén (2009), geomin performed well when *vc* was moderate ($vc \le 2$), *m* was small ($m = 2$), and the factors were moderately correlated. Geomin, however, "…fails for more complicated loading matrix structures involving three or more factors and variables with complexity 3 and more;…For more complicated examples the Target rotation criterion will lead to better results" (Asparouhov & Muthén, p. 407).

Target rotation has been developed over several decades and can be thought of as "a non-mechanical exploratory process, guided by human judgment" (Browne, 2001, p.125). Current versions of target rotation are direct and can be based on only a partially specified target matrix, $\mathbf{B}_{pxr}$. The $f\left(\boldsymbol{\Lambda}\right)$ for target rotation can be written as:

$$\sum_{i=1}^{p}\sum_{j=1}^{r} a_{ij}\left(\lambda_{ij} - b_{ij}\right)^2, \text{ where} \tag{5}$$

a_{ij} = 1 if λ_{ij} is a target and 0 if λ_{ij} is not a target, and
b_{ij} = the targeted value.

Note that the user must provide a_{ij} and b_{ij}, and therefore, helps to define f ($\boldsymbol{\Lambda}$) for target rotation. Thus, EFA with target rotation can be conceptualized as "situated between CFA and EFA" (Asparouhov & Muthén, p. 399, 2009). It is important to note that a solution will be mathematically equivalent under either target or geomin rotation. Simulation research suggests, however, that in some cases the factors may be defined more consistent with a well-developed a priori theory under target rotation as compared to geomin rotation (Myers, Jin, & Ahn, 2012).

Rotation identification. Some known conditions for rotation identification in factor analysis exist (e.g., Algina, 1980; Hayashi & Marcoulides, 2006). Under oblique rotation $\mathbf{H}^*$ is a non-symmetric square matrix that results in m^2 indeterminacies (Asparouhov & Muthén, 2009). Imposing m^2 constraints on $\boldsymbol{\Lambda}$ and $\boldsymbol{\Psi}$ is a necessary condition for rotation identification. Setting the scale for each latent variable to unity provides m constraints. A set of sufficient conditions for imposing the remaining $m(m-1)$ constraints include: (a) each column of $\mathbf{\Lambda}$ has $m-1$ elements specified as zeros, and (b) each submatrix $\mathbf{\Lambda}_s$, where $s = 1,\ldots,m$, of $\mathbf{\Lambda}$ composed of the rows of $\mathbf{\Lambda}$ that have fixed zeros in the sth column must have rank $m-1$. Allow the rank of a matrix to be defined as the maximum number of independent rows or columns in that matrix.

An example. Target rotation can meet condition (a) and condition (b) by strategic specification of the target matrix ($\mathbf{B}_{p\ x\ m}$). Note that the dimensions of $\mathbf{B}_{p\ x\ m}$ match the dimensions of $\mathbf{\Lambda}_{p\ x\ m}$. Allow the targeted elements within $\mathbf{B}$ to be those pattern coefficients that were expected to be 0 (i.e., an item was expected to have a trivial loading on a particular factor) and the non-targeted elements to be denoted by a 1. The athlete-level measurement model for the APCCS II-HST was selected for demonstration because it appears to be better understood than the athlete-level measurement model for the CCS (see Figure 1s below). Note that condition (a) was met in that each column had four zeros. Figure 2s displays how condition (b) was met. The logic embedded in this worked example can easily be extended to other applications.

Figure 1s. A possible target matrix for the APCCS II-HST

Item	GS	PC	M	T	CB
GS1	1	1	1	1	1
GS2	1	0	0	0	0
GS3	1	1	1	1	1
GS4	1	1	1	1	1
PC2	1	1	1	1	1
PC3	0	1	0	0	0
M1	1	1	1	1	1
M2	1	1	1	1	1
M3	1	1	1	1	1
M4	0	0	1	0	0
T1	0	0	0	1	0
T2	1	1	1	1	1
T3	1	1	1	1	1
T4	1	1	1	1	1
CB1	1	1	1	1	1
CB2	1	1	1	1	1
CB3	0	0	0	0	1

Figure 2s. Rank for each submatrix within the specified target matrix

$$\mathbf{B}_1 = \begin{bmatrix} \beta_{62} & \beta_{63} & \beta_{64} & \beta_{65} \\ \beta_{10,2} & \beta_{10,3} & \beta_{10,4} & \beta_{10,5} \\ \beta_{11,2} & \beta_{11,3} & \beta_{11,4} & \beta_{11,5} \\ \beta_{17,2} & \beta_{17,3} & \beta_{17,4} & \beta_{17,5} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \ \mathrm{rank}(\mathbf{B}_1) = 4$$

$$\mathbf{B}_2 = \begin{bmatrix} \beta_{21} & \beta_{23} & \beta_{24} & \beta_{25} \\ \beta_{10,1} & \beta_{10,3} & \beta_{10,4} & \beta_{10,5} \\ \beta_{11,1} & \beta_{11,3} & \beta_{11,4} & \beta_{11,5} \\ \beta_{17,1} & \beta_{17,3} & \beta_{17,4} & \beta_{17,5} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \ \mathrm{rank}(\mathbf{B}_2) = 4$$

$$\mathbf{B}_3 = \begin{bmatrix} \beta_{21} & \beta_{22} & \beta_{24} & \beta_{25} \\ \beta_{6,1} & \beta_{62} & \beta_{64} & \beta_{65} \\ \beta_{11,1} & \beta_{11,2} & \beta_{11,4} & \beta_{11,5} \\ \beta_{17,1} & \beta_{17,2} & \beta_{17,4} & \beta_{17,5} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \ \mathrm{rank}(\mathbf{B}_3) = 4$$

$$\mathbf{B}_4 = \begin{bmatrix} \beta_{21} & \beta_{22} & \beta_{23} & \beta_{25} \\ \beta_{6,1} & \beta_{62} & \beta_{63} & \beta_{65} \\ \beta_{10,1} & \beta_{10,2} & \beta_{10,3} & \beta_{10,5} \\ \beta_{17,1} & \beta_{17,2} & \beta_{17,3} & \beta_{17,5} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \ \mathrm{rank}(\mathbf{B}_4) = 4$$

$$\mathbf{B}_5 = \begin{bmatrix} \beta_{21} & \beta_{22} & \beta_{23} & \beta_{24} \\ \beta_{6,1} & \beta_{62} & \beta_{63} & \beta_{64} \\ \beta_{10,1} & \beta_{10,2} & \beta_{10,3} & \beta_{10,4} \\ \beta_{11,1} & \beta_{11,2} & \beta_{11,3} & \beta_{11,4} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \ \mathrm{rank}(\mathbf{B}_5) = 4$$

References that appear in Appendix B_1 only

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Appendix B_2

Constraints imposed in the Model 2 (baseline model)

Constraints imposed for identification purposes included partial invariance of the thresholds across groups, latent factor means fixed to zero for the reference group, the unique factor covariance matrix fixed to an identity matrix for the reference group, the first pattern coefficient within each factor fixed to 1.00 across groups, and the latent intercepts fixed to 0.00 for both groups. The subset of invariant thresholds consisted of the first threshold for all latent response variates (*) and the first and second thresholds for each reference variate.

Appendix C

Table 1s

Deriving Measures from the APCCS II-HST: Key Results from Question 1 and Question 2

	Question 1: number of factors (*m*)					Question 1: *m* - 1 versus *m*	
Model	$\chi^2(df)$, *p*	*Par*	*RMSEA*	*CFI*	*TLI*	Complex	$\Delta\chi^2(\Delta df)$, *p*
Model 1: *m*=1, E, G	470(119),<.001	68	.063(.057,.069)	.943	.935	Model 2	135(16), <.001
Model 2: *m*=2, E, G	333(103),<.001	84	.055(.048,.061)	.963	.951	Model 3	112(15), <.001
Model 3: *m*=3, E, G	240(88),<.001	99	.048(.041,.055)	.975	.962	Model 4	99(14), <.001
Model 4: *m*=4, E, G	147(74),<.001	113	.036(.028,.045)	.988	.978	Model 5	62(13), <.001
Model 5: *m*=5, E, G	88(61),.013	126	.024(.012,.035)	.996	.990	Model 6	31(12), .002
Model 6: *m*=6, E, G	59(49),.157	138	.016(.000,.030)	.998	.996	-----	-----
	Question 2: CFA versus EFA in ESEM						
Model	$\chi^2(df)$, *p*	*Par*	*RMSEA*	*CFI*	*TLI*	Complex	$\Delta\chi^2(\Delta df)$, *p*
Model 7: *m*=5, E, T	88(61),.013	126	.024(.012,.035)	.996	.990	-----	-----
Model 8: *m*=5, C	154(108),.002	79	.024(.015,.032)	.993	.991	Model 7	75(47), .006
Model 9: *m*=5, C, g3	146(107),.008	80	.022(.012,.030)	.994	.992	Model 7	67(46), .024

Note. m = number of factors, E = ESEM, C = CFA, G = geomin; T = target; PAR = number of parameters estimated; Complex = more complex model that a nested simpler model was compared to; g3 = free to cross-load on motivation.

Table 2s

Interfactor Correlation Matrix (Ψ) by Exploratory Structural Equation Model (ESEM) and Confirmatory Factor Analysis (CFA) from some Key Models in Table 1s

Interfactor Correlation Matrix - ESEM, Geomin (Model 5)

	GS	PC	T	M	CB
GS	1.00				
PC	.71	1.00			
T	.76	.74	1.00		
M	.68	.58	.68	1.00	
CB	.54	.54	.62	.64	1.00

Interfactor Correlation Matrix - ESEM, Target (Model 7)

	GS	PC	T	M	CB
GS	1.00				
PC	.77	1.00			
T	.80	.78	1.00		
M	.71	.65	.67	1.00	
CB	.73	.68	.73	.69	1.00

Interfactor Correlation Matrix - CFA (Model 9)

	GS	PC	T	M	CB
GS	1.00				
PC	.83	1.00			
T	.87	.80	1.00		
M	.80	.68	.78	1.00	
CB	.77	.71	.84	.79	1.00

Note. GS = game strategy; PC = physical conditioning; T = technique; M = motivation; M = motivation; CB = character building.

Table 3s

Deriving Measures from the CCS: Key Results from Question 1 and Question 2

	Question 1: number of factors (m)								Question 1: m - 1 versus m	
Model	$\chi^2(df)$, p	*Par*	*AIC*	*BIC*	*RMSEA*	*SRMR*	*CFI*	*TLI*	Complex	$\Delta\chi^2(\Delta df)$, p
Model 1: m=1, E, G	2363(250), <.001	74	43599	43922	.120(.116,.125)	.057	.953	.948	Model 2	1110(23), <.001
Model 2: m=2, E, G	1343(227), <.001	97	42364	42788	.092(.087,.096)	.034	.975	.969	Model 3	532(22), <.001
Model 3: m=3, E, G	869(205), <.001	119	41814	42334	.074(.069,.080)	.024	.985	.980	Model 4	207(21), <.001
Model 4: m=4, E, G	617(184), <.001	140	41499	42111	.063(.058,.069)	.017	.990	.985	Model 5	213(20), <.001
Model 5: m=5, E, G	427(164), <.001	160	41310	42010	.052(.046,.058)	.012	.994	.990	Model 6	102(19), <.001
Model 6: m=6, E, G	320(145), <.001	179	41206	41989	.045(.039,.052)	.011	.996	.993	Model 7	59(18), <.001
Model 7: m=7, E, G	253(127), <.001	197	41141	42002	.041(.034,.049)	.009	.997	.994	-----	-----

	Question 2: CFA versus EFA in ESEM									
Model	$\chi^2(df)$,p	*Par*	*AIC*	*BIC*	*RMSEA*	*SRMR*	*CFI*	*TLI*	Complex	$\Delta\chi^2(\Delta df)$, p
Model 8: m=4, E, T	617(184), <.001	140	41499	42111	.063(.058,.069)	.017	.990	.985	-----	-----
Model 9: m=4, C	920(243), <.001	81	41929	42283	.069(.064,.074)	.035	.985	.983	Model 8	273(59), <.001

Note. m = number of factors, E = ESEM, C = CFA, G = geomin; T = target; PAR = number of parameters estimated; Complex = more complex model that a nested simpler model was compared to.

Table 4s

Target-Rotated Pattern Coefficients (Λ), Standard Errors (SE), Target-Rotated Standardized Pattern Coefficients ($Λ^{*0}$), and Percentage of Variance Accounted For (R^2)*

	Factor 1 = GS			Factor 2 = M			Factor 3 = T			Factor 4 = CB			
Item	$λ^*_{p1}$	*SE*	$λ^{*0}_{p1}$	$λ^*_{p2}$	*SE*	$λ^{*0}_{p2}$	$λ^*_{p3}$	*SE*	$λ^{*0}_{p3}$	$λ^*_{p4}$	*SE*	$λ^{*0}_{p4}$	R^2
gs2	**1.46**	.29	**0.94**	0.14	.07	0.09	-0.23	.14	-0.15	-0.04	.07	-0.02	.73
gs4	**1.46**	.29	**0.90**	0.18	.10	0.11	-0.03	.23	-0.02	-0.14	.11	-0.08	.79
gs8	**1.56**	.32	**0.93**	0.22	.11	0.13	-0.14	.22	-0.08	-0.12	.13	-0.07	.79
gs9	**1.33**	.23	**0.85**	0.00	.00	0.00	0.00	.00	0.00	0.00	.00	0.00	.72
gs11	**1.10**	.35	**0.62**	**0.37**	.14	**0.21**	0.15	.34	0.09	0.01	.11	0.01	.73
gs17	0.60	.34	0.34	0.23	.20	0.13	0.80	.43	0.46	0.02	.11	0.01	.79
gs21	**0.74**	.36	**0.43**	-0.06	.18	-0.04	0.75	.42	0.44	0.13	.15	0.07	.76
m1	**0.68**	.20	**0.37**	**1.49**	.17	**0.82**	-0.27	.22	-0.15	**-0.24**	.11	**-0.13**	.76
m3	**1.23**	.33	**0.70**	**0.91**	.17	**0.52**	-0.28	.30	-0.16	**-0.31**	.12	**-0.18**	.68
m6	0.00	.00	0.00	**1.88**	.18	**0.92**	0.00	.00	0.00	0.00	.00	0.00	.85
m10	0.72	.38	0.37	**1.35**	.22	**0.69**	-0.22	.42	-0.11	0.02	.18	0.01	.77
m12	0.52	.31	0.27	**0.98**	.20	**0.51**	-0.11	.34	-0.06	**0.36**	.18	**0.19**	.67
m15	-0.45	.28	-0.22	**1.65**	.19	**0.81**	**0.78**	.30	**0.39**	-0.09	.10	-0.05	.87
m23	0.22	.27	0.11	**1.34**	.20	**0.67**	0.09	.35	0.05	0.29	.15	**0.15**	.81
t7	0.48	.25	0.26	**0.38**	.15	**0.21**	**0.85**	.32	**0.47**	**-0.37**	.15	**-0.20**	.52
t14	-0.40	.31	-0.23	**0.36**	.18	**0.20**	**1.80**	.46	**1.01**	**-0.25**	.12	**-0.14**	.76
t16	-0.32	.36	-0.18	**0.36**	.16	**0.20**	**1.65**	.49	**0.95**	-0.10	.10	-0.06	.81
t18	0.43	.38	0.22	0.31	.25	0.16	0.77	.48	0.40	0.22	.18	0.11	.67
t20	0.19	.35	0.11	-0.10	.17	-0.06	**1.22**	.44	**0.70**	0.19	.14	0.11	.71
t22	0.00	.00	0.00	0.00	.00	0.00	**1.48**	.24	**0.88**	0.00	.00	0.00	.77
cb5	0.33	.23	0.17	**0.72**	.13	**0.36**	-0.36	.26	-0.18	**1.20**	.23	**0.61**	.78
cb13	0.27	.24	0.14	**0.38**	.14	**0.21**	-0.14	.26	-0.07	**1.18**	.21	**0.63**	.71
cb19	0.00	.00	0.00	0.00	.00	0.00	0.00	.00	0.00	**1.70**	.26	**0.92**	.84
cb24	0.09	.19	0.04	**0.58**	.17	**0.30**	-0.07	.23	-0.04	**1.26**	.20	**0.64**	.78

Note. Statistically significant coefficients were bolded. GS = game strategy; M = motivation; T = technique; CB = character building.

Table 5s

Confirmatory Factor Analytic Pattern Coefficients (Λ), Standard Errors (SE), Standardized Pattern Coefficients (Λ0),and Percentage of Variance Accounted For (R^2)

	Factor 1 = GS			Factor 2 = M			Factor 3 = T			Factor 4 = CB			
Item	λ_{p1}	*SE*	λ_{p1}^{0}	λ_{p2}	*SE*	λ_{p2}^{0}	λ_{p3}	*SE*	λ_{p3}^{0}	λ_{p4}	*SE*	λ_{p4}^{0}	R^2
gs2	**1.28**	.25	**0.83**	----	----	----	----	----	----	----	----	----	.68
gs4	**1.42**	.24	**0.87**	----	----	----	----	----	----	----	----	----	.76
gs8	**1.47**	.22	**0.88**	----	----	----	----	----	----	----	----	----	.77
gs9	**1.30**	.24	**0.83**	----	----	----	----	----	----	----	----	----	.69
gs11	**1.51**	.26	**0.86**	----	----	----	----	----	----	----	----	----	.74
gs17	**1.54**	.25	**0.89**	----	----	----	----	----	----	----	----	----	.79
gs21	**1.50**	.23	**0.87**	----	----	----	----	----	----	----	----	----	.76
m1	----	----	----	**1.56**	.18	**0.85**	----	----	----	----	----	----	.73
m3	**0.80**	.18	**0.46**	**0.68**	.16	**0.39**	----	----	----	----	----	----	.64
m6	----	----	----	**1.82**	.18	**0.89**	----	----	----	----	----	----	.80
m10	----	----	----	**1.72**	.20	**0.88**	----	----	----	----	----	----	.78
m12	----	----	----	**1.56**	.23	**0.82**	----	----	----	----	----	----	.67
m15	----	----	----	**1.83**	.16	**0.90**	----	----	----	----	----	----	.81
m23	----	----	----	**1.82**	.22	**0.91**	----	----	----	----	----	----	.83
t7	----	----	----	----	----	----	**1.31**	.20	**0.72**	----	----	----	.52
t14	----	----	----	----	----	----	**1.51**	.22	**0.85**	----	----	----	.72
t16	----	----	----	----	----	----	**1.54**	.22	**0.89**	----	----	----	.79
t18	----	----	----	----	----	----	**1.57**	.24	**0.81**	----	----	----	.66
t20	----	----	----	----	----	----	**1.45**	.22	**0.83**	----	----	----	.69
t22	----	----	----	----	----	----	**1.48**	.24	**0.87**	----	----	----	.76
cb5	----	----	----	----	----	----	----	----	----	**1.77**	.25	**0.90**	.80
cb13	----	----	----	----	----	----	----	----	----	**1.58**	.23	**0.85**	.71
cb19	----	----	----	----	----	----	----	----	----	**1.62**	.25	**0.87**	.76
cb24	----	----	----	----	----	----	----	----	----	**1.73**	.25	**0.88**	.78

Note. Statistically significant coefficients were bolded. GS = game strategy; M = motivation; T = technique; CB = character building.

Table 6s

Interfactor Correlation Matrix (Ψ) by Exploratory Structural Equation Model (ESEM) and Confirmatory Factor Analysis (CFA) from some Key Models in Table 3s

Interfactor Correlation Matrix - ESEM, Geomin (Model 4)

	GS	M	T	CB
GS	1.00			
M	.57	1.00		
T	.80	.65	1.00	
CB	.68	.61	.67	1.00

Interfactor Correlation Matrix - ESEM, Target (Model 8)

	GS	M	T	CB
GS	1.00			
M	.62	1.00		
T	.90	.72	1.00	
CB	.72	.71	.74	1.00

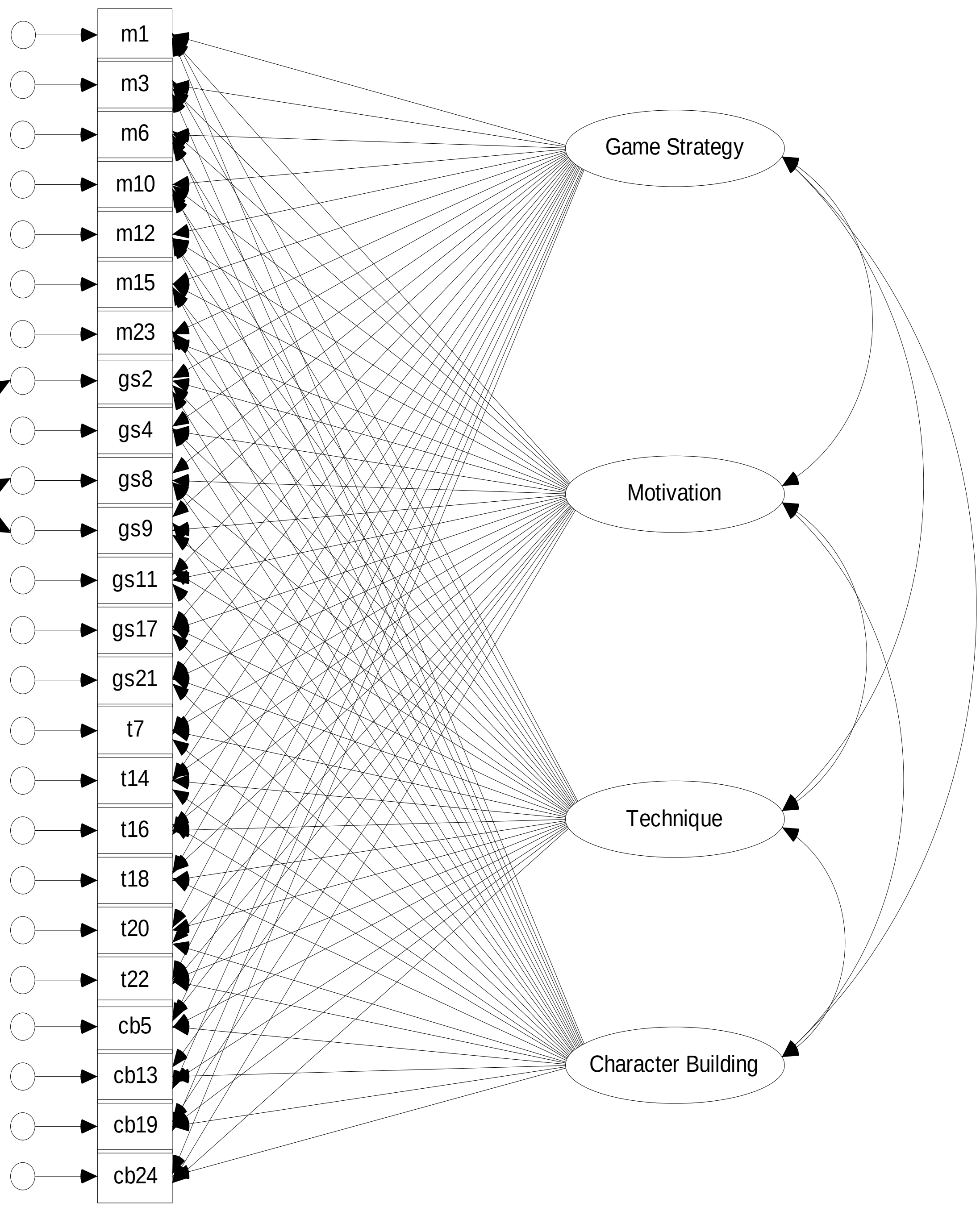
Interfactor Correlation Matrix - CFA (Model 9)

	GS	M	T	CB
GS	1.00			
M	.81	1.00		
T	.94	.85	1.00	
CB	.79	.86	.80	1.00

Note. GS = game strategy; M = motivation; T = technique; CB = character building.

Appendix D

Figure 3s. Athlete-level ESEM measurement model for the CCS. Factors were named consistent with output from Table 4.



Appendix E

```
TITLE:
APCCS II-HST, Model 7, ESEM, Target

DATA:
FILE = APCCS II-HST.dat;

VARIABLE:
NAMES = teamname g1 g2 g3 g4 p1 p2 p3 m1 m2 m3 m4 t1 t2 t3 t4 c1 c2 c3;
USEVARIABLES = g1 g2 g3 g4 p2 p3 m1 m2 m3 m4 t1 t2 t3 t4 c1 c2 c3;
CATEGORICAL = g1 g2 g3 g4 p2 p3 m1 m2 m3 m4 t1 t2 t3 t4 c1 c2 c3;
CLUSTER = teamname;

ANALYSIS:
TYPE = COMPLEX;
PARAMETERIZATION = THETA;
ITERATIONS = 10000;
ESTIMATOR = WLSMV;
DIFFTEST = deriv.dat;
ROTATION = TARGET;

MODEL:
GS BY g1-c3 p3~0 t1~0 m4~0 c3~0 (*t);
PC BY g1-c3 g2~0 t1~0 m4~0 c3~0 (*t);
T  BY g1-c3 g2~0 p3~0 m4~0 c3~0 (*t);
M  BY g1-c3 g2~0 p3~0 t1~0 c3~0 (*t);
CB BY g1-c3 g2~0 p3~0 t1~0 m4~0 (*t);

OUTPUT:
SAMPSTAT MODINDICES(1) STANDARDIZED tech1 tech9;
```

```
TITLE:
APCCS II-HST, Model 6, ESEM, Geomin

DATA:
FILE = APCCS II-HST.dat;

VARIABLE:
NAMES = teamname g1 g2 g3 g4 p1 p2 p3 m1 m2 m3 m4 t1 t2 t3 t4 c1 c2 c3;
USEVARIABLES = g1 g2 g3 g4 p2 p3 m1 m2 m3 m4 t1 t2 t3 t4 c1 c2 c3;
CATEGORICAL = g1 g2 g3 g4 p2 p3 m1 m2 m3 m4 t1 t2 t3 t4 c1 c2 c3;
CLUSTER = teamname;

ANALYSIS:
TYPE = COMPLEX;
PARAMETERIZATION = THETA;
ITERATIONS = 10000;
ESTIMATOR = WLSMV;
DIFFTEST = deriv.dat;

ANALYSIS:
TYPE = COMPLEX;
PARAMETERIZATION = THETA;
ITERATIONS = 10000;
ESTIMATOR = WLSMV;
DIFFTEST = deriv.dat;

MODEL:
f1-f6 BY g1-c3(*1);

OUTPUT:
SAMPSTAT MODINDICES(1) STANDARDIZED tech1;

SAVEDATA:
DIFFTEST IS deriv.dat;
```

```
TITLE:
APCCS II-HST, Model 9, CFA

DATA:
FILE = APCCS II-HST.dat;

VARIABLE:
NAMES = teamname g1 g2 g3 g4 p1 p2 p3 m1 m2 m3 m4 t1 t2 t3 t4 c1 c2 c3;
USEVARIABLES = g1 g2 g3 g4 p2 p3 m1 m2 m3 m4 t1 t2 t3 t4 c1 c2 c3;
CATEGORICAL = g1 g2 g3 g4 p2 p3 m1 m2 m3 m4 t1 t2 t3 t4 c1 c2 c3;
CLUSTER = teamname;

ANALYSIS:
TYPE = COMPLEX;
PARAMETERIZATION = THETA;
ITERATIONS = 10000;
ESTIMATOR = WLSMV;

MODEL:
GS BY g1* g2*1 g3*1 g4*1 m2*1;
PC BY p2*1 p3*1;
ME BY m1*1 m2*1 m3*1 m4*1 g3*1;
TE BY t1*1 t2*1 t3*1 t4*1;
CB BY c1*1 c2*1 c3*1;
GS@1; PC@1; ME@1; TE@1; CB@1;

OUTPUT:
SAMPSTAT MODINDICES(1) STANDARDIZED tech1;

SAVEDATA:
DIFFTEST IS deriv.dat;
```

```
TITLE:
CCS, Model 4, ESEM, Geomin

DATA:
FILE = CCS.dat;

VARIABLE:
NAMES = school id
g2 g4 g8 g9 g11 g17 g21
m1 m3 m6 m10 m12 m15 m23
t7 t14 t16 t18 t20 t22
c5 c13 c19 c24;
USEVARIABLES =
g2 g4 g8 g9 g11 g17 g21
m1 m3 m6 m10 m12 m15 m23
t7 t14 t16 t18 t20 t22
c5 c13 c19 c24;
CLUSTER = school;

ANALYSIS:
TYPE = COMPLEX;
ITERATIONS = 10000;
ESTIMATOR = MLR;

MODEL:
f1-f4 BY g2-c24(*1);
g2 WITH g9; g8 WITH g9;

OUTPUT:
SAMPSTAT MODINDICES(1) STANDARDIZED tech1;
```

```
TITLE:
CCS, Model 9, CFA

DATA:
FILE = CCS.dat;

VARIABLE:
NAMES = school id
g2 g4 g8 g9 g11 g17 g21
m1 m3 m6 m10 m12 m15 m23
t7 t14 t16 t18 t20 t22
c5 c13 c19 c24;
USEVARIABLES =
g2 g4 g8 g9 g11 g17 g21
m1 m3 m6 m10 m12 m15 m23
t7 t14 t16 t18 t20 t22
c5 c13 c19 c24;
CLUSTER = school;

ANALYSIS:
TYPE = COMPLEX;
ITERATIONS = 10000;
ESTIMATOR = MLR;

MODEL:
GS BY g2*1 g4*1 g8*1 g9*1 g11*1 g17*1 g21*1 m3*1;
ME BY m1*1 m3*1 m6*1 m10*1 m12*1 m15*1 m23*1;
TE BY t7*1 t14*1 t16*1 t18*1 t20*1 t22*1;
CB BY c5*1 c13*1 c19*1 c24*1;
GS@1; ME@1; TE@1; CB@1;
g2 WITH g9; g8 WITH g9;

OUTPUT:
SAMPSTAT MODINDICES(1) STANDARDIZED tech1;
```

```
TITLE:
APCCS II-HST, MG, Model 1a, US

DATA:
FILE = APCCS II-HST MG.TXT;

VARIABLE:
NAMES = teamname g1 g2 g3 g4 p2 p3 m1 m2 m3 m4 t1 t2 t3 t4 c1 c2 c3 country;
USEVARIABLES = g1 g2 g3 g4 p2 p3 m1 m2 m3 m4 t1 t2 t3 t4 c1 c2 c3;
CATEGORICAL = g1 g2 g3 g4 p2 p3 m1 m2 m3 m4 t1 t2 t3 t4 c1 c2 c3;
CLUSTER = teamname;
SUBPOPULATION = country EQ 1;

ANALYSIS:
TYPE = COMPLEX;
PARAMETERIZATION = THETA;
ITERATIONS = 10000;
ESTIMATOR = WLSMV;

MODEL:
f1-f5 BY g1-c3(*1);

OUTPUT:
SAMPSTAT MODINDICES(3.8) STANDARDIZED tech1;
```

```
TITLE:
APCCS II-HST, MG, Model 1b, UK

DATA:
FILE = APCCS II-HST MG.TXT;

VARIABLE:
NAMES = teamname g1 g2 g3 g4 p2 p3 m1 m2 m3 m4 t1 t2 t3 t4 c1 c2 c3 country;
USEVARIABLES = g1 g2 g3 g4 p2 p3 m1 m2 m3 m4 t1 t2 t3 t4 c1 c2 c3;
CATEGORICAL = g1 g2 g3 g4 p2 p3 m1 m2 m3 m4 t1 t2 t3 t4 c1 c2 c3;
CLUSTER = teamname;
SUBPOPULATION = country EQ 3;

ANALYSIS:
TYPE = COMPLEX;
PARAMETERIZATION = THETA;
ITERATIONS = 10000;
ESTIMATOR = WLSMV;

MODEL:
f1-f5 BY g1-c3(*1);

OUTPUT:
SAMPSTAT MODINDICES(3.8) STANDARDIZED tech1;
```

```
TITLE:
APCCS II-HST, MG, Model 2, baseline

DATA:
FILE = APCCS II-HST MG.TXT;

VARIABLE:
NAMES = teamname g1 g2 g3 g4 p2 p3 m1 m2 m3 m4 t1 t2 t3 t4 c1 c2 c3 country;
USEVARIABLES = g1 g2 g3 g4 p2 p3 m1 m2 m3 m4 t1 t2 t3 t4 c1 c2 c3;
CATEGORICAL = g1 g2 g3 g4 p2 p3 m1 m2 m3 m4 t1 t2 t3 t4 c1 c2 c3;
CLUSTER = teamname;
GROUPING IS country (1=USA 3=UK);

ANALYSIS:
TYPE = COMPLEX;
PARAMETERIZATION = THETA;
ITERATIONS = 10000;
ESTIMATOR = WLSMV;

MODEL:
f1-f5 BY g1-c3(*1);

[g1$3 g2$2 g2$3 g3$2 g3$3 g4$2 g4$3
p2$3 p3$2 p3$3
m1$3 m2$2 m2$3 m3$2 m3$3 m4$2 m4$3
t1$3 t2$2 t2$3 t3$2 t3$3 t4$2 t4$3
c1$3 c2$2 c2$3 c3$2 c3$3];

MODEL UK:
f1-f5 BY g1-c3(*1);

[g1$3 g2$2 g2$3 g3$2 g3$3 g4$2 g4$3
p2$3 p3$2 p3$3
m1$3 m2$2 m2$3 m3$2 m3$3 m4$2 m4$3
t1$3 t2$2 t2$3 t3$2 t3$3 t4$2 t4$3
c1$3 c2$2 c2$3 c3$2 c3$3];

OUTPUT:
SAMPSTAT MODINDICES(3.8) STANDARDIZED  TECH1;

SAVEDATA:
DIFFTEST IS deriv.dat;
```

```
TITLE:
APCCS II-HST, MG, Model 3, invariant pattern

DATA:
FILE = APCCS II-HST MG.TXT;

VARIABLE:
NAMES = teamname g1 g2 g3 g4 p2 p3 m1 m2 m3 m4 t1 t2 t3 t4 c1 c2 c3 country;
USEVARIABLES = g1 g2 g3 g4 p2 p3 m1 m2 m3 m4 t1 t2 t3 t4 c1 c2 c3;
CATEGORICAL = g1 g2 g3 g4 p2 p3 m1 m2 m3 m4 t1 t2 t3 t4 c1 c2 c3;
CLUSTER = teamname;
GROUPING IS country (1=USA 3=UK);

ANALYSIS:
TYPE = COMPLEX;
PARAMETERIZATION = THETA;
ITERATIONS = 10000;
ESTIMATOR = WLSMV;
DIFFTEST IS deriv.dat;

MODEL:
f1-f5 BY g1-c3(*1);

[g1$3 g2$2 g2$3 g3$2 g3$3 g4$2 g4$3
p2$3 p3$2 p3$3
m1$3 m2$2 m2$3 m3$2 m3$3 m4$2 m4$3
t1$3 t2$2 t2$3 t3$2 t3$3 t4$2 t4$3
c1$3 c2$2 c2$3 c3$2 c3$3];

MODEL UK:

[g1$3 g2$2 g2$3 g3$2 g3$3 g4$2 g4$3
p2$3 p3$2 p3$3
m1$3 m2$2 m2$3 m3$2 m3$3 m4$2 m4$3
t1$3 t2$2 t2$3 t3$2 t3$3 t4$2 t4$3
c1$3 c2$2 c2$3 c3$2 c3$3];

OUTPUT:
SAMPSTAT MODINDICES(3.8) STANDARDIZED  TECH1;
```

```
TITLE:
APCCS II-HST, MG, Model 4, invariant pattern, threshold

DATA:
FILE = APCCS II-HST MG.TXT;

VARIABLE:
NAMES = teamname g1 g2 g3 g4 p2 p3 m1 m2 m3 m4 t1 t2 t3 t4 c1 c2 c3 country;
USEVARIABLES = g1 g2 g3 g4 p2 p3 m1 m2 m3 m4 t1 t2 t3 t4 c1 c2 c3;
CATEGORICAL = g1 g2 g3 g4 p2 p3 m1 m2 m3 m4 t1 t2 t3 t4 c1 c2 c3;
CLUSTER = teamname;
GROUPING IS country (1=USA 3=UK);

ANALYSIS:
TYPE = COMPLEX;
PARAMETERIZATION = THETA;
ITERATIONS = 10000;
ESTIMATOR = WLSMV;
DIFFTEST IS deriv.dat;

MODEL:
f1-f5 BY g1-c3(*1);

[g1$3 g2$2 g2$3 g3$2 g3$3 g4$2 g4$3
p2$3 p3$2 p3$3
m1$3 m2$2 m2$3 m3$2 m3$3 m4$2 m4$3
t1$3 t2$2 t2$3 t3$2 t3$3 t4$2 t4$3
c1$3 c2$2 c2$3 c3$2 c3$3];

MODEL UK:

OUTPUT:
SAMPSTAT MODINDICES(3.8) STANDARDIZED  TECH1;
```

```
TITLE:
APCCS II-HST, MG, Model 5, invariant pattern, threshold, residual variance

DATA:
FILE = APCCS II-HST MG.TXT;

VARIABLE:
NAMES = teamname g1 g2 g3 g4 p2 p3 m1 m2 m3 m4 t1 t2 t3 t4 c1 c2 c3 country;
USEVARIABLES = g1 g2 g3 g4 p2 p3 m1 m2 m3 m4 t1 t2 t3 t4 c1 c2 c3;
CATEGORICAL = g1 g2 g3 g4 p2 p3 m1 m2 m3 m4 t1 t2 t3 t4 c1 c2 c3;
CLUSTER = teamname;
GROUPING IS country (1=USA 3=UK);

ANALYSIS:
TYPE = COMPLEX;
PARAMETERIZATION = THETA;
ITERATIONS = 10000;
ESTIMATOR = WLSMV;
DIFFTEST IS deriv.dat;


MODEL:
f1-f5 BY g1-c3(*1);

[g1$3 g2$2 g2$3 g3$2 g3$3 g4$2 g4$3
p2$3 p3$2 p3$3
m1$3 m2$2 m2$3 m3$2 m3$3 m4$2 m4$3
t1$3 t2$2 t2$3 t3$2 t3$3 t4$2 t4$3
c1$3 c2$2 c2$3 c3$2 c3$3];

MODEL UK:
g1@1; g2@1; g3@1; g4@1;
p2@1; p3@1;
m1@1; m2@1; m3@1; m4@1;
t1@1; t2@1; t3@1; t4@1;
c1@1; c2@1; c3@1;

OUTPUT:
SAMPSTAT MODINDICES(3.8) STANDARDIZED  TECH1;
```

```
TITLE:
APCCS II-HST, MG, Model 6, invariant pattern, threshold, residual variance, factor var

DATA:
FILE = APCCS II-HST MG.TXT;

VARIABLE:
NAMES = teamname g1 g2 g3 g4 p2 p3 m1 m2 m3 m4 t1 t2 t3 t4 c1 c2 c3 country;
USEVARIABLES = g1 g2 g3 g4 p2 p3 m1 m2 m3 m4 t1 t2 t3 t4 c1 c2 c3;
CATEGORICAL = g1 g2 g3 g4 p2 p3 m1 m2 m3 m4 t1 t2 t3 t4 c1 c2 c3;
CLUSTER = teamname;
GROUPING IS country (1=USA 3=UK);

ANALYSIS:
TYPE = COMPLEX;
PARAMETERIZATION = THETA;
ITERATIONS = 10000;
RITERATIONS = 100000;
ESTIMATOR = WLSMV;
DIFFTEST IS deriv.dat;

MODEL:
f1-f5 BY g1-c3(*1);

[g1$3 g2$2 g2$3 g3$2 g3$3 g4$2 g4$3
p2$3 p3$2 p3$3
m1$3 m2$2 m2$3 m3$2 m3$3 m4$2 m4$3
t1$3 t2$2 t2$3 t3$2 t3$3 t4$2 t4$3
c1$3 c2$2 c2$3 c3$2 c3$3];

f1 WITH f2 (1);
f1 WITH f3 (2);
f1 WITH f4 (3);
f1 WITH f5 (4);
f2 WITH f3 (5);
f2 WITH f4 (6);
f2 WITH f5 (7);
f3 WITH f4 (8);
f3 WITH f5 (9);
f4 WITH f5 (10);

f1-f5@1;
```

```
MODEL UK:
g1@1; g2@1; g3@1; g4@1;
p2@1; p3@1;
m1@1; m2@1; m3@1; m4@1;
t1@1; t2@1; t3@1; t4@1;
c1@1; c2@1; c3@1;

OUTPUT:
SAMPSTAT MODINDICES(3.8) STANDARDIZED  TECH1;
```

```
TITLE:
APCCS II-HST, MG, Model 7, invariant pattern, threshold, residual variance, factor var, factor
means

DATA:
FILE = APCCS II-HST MG.TXT;

VARIABLE:
NAMES = teamname g1 g2 g3 g4 p2 p3 m1 m2 m3 m4 t1 t2 t3 t4 c1 c2 c3 country;
USEVARIABLES = g1 g2 g3 g4 p2 p3 m1 m2 m3 m4 t1 t2 t3 t4 c1 c2 c3;
CATEGORICAL = g1 g2 g3 g4 p2 p3 m1 m2 m3 m4 t1 t2 t3 t4 c1 c2 c3;
CLUSTER = teamname;
GROUPING IS country (1=USA 3=UK);

ANALYSIS:
TYPE = COMPLEX;
PARAMETERIZATION = THETA;
ITERATIONS = 10000;
RITERATIONS = 100000;
ESTIMATOR = WLSMV;
DIFFTEST IS deriv.dat;

MODEL:
f1-f5 BY g1-c3(*1);

[g1$3 g2$2 g2$3 g3$2 g3$3 g4$2 g4$3
p2$3 p3$2 p3$3
m1$3 m2$2 m2$3 m3$2 m3$3 m4$2 m4$3
t1$3 t2$2 t2$3 t3$2 t3$3 t4$2 t4$3
c1$3 c2$2 c2$3 c3$2 c3$3];

f1 WITH f2 (1);
f1 WITH f3 (2);
f1 WITH f4 (3);
f1 WITH f5 (4);
f2 WITH f3 (5);
f2 WITH f4 (6);
f2 WITH f5 (7);
f3 WITH f4 (8);
f3 WITH f5 (9);
f4 WITH f5 (10);

f1-f5@1;

[f1-f5@0];
```

```
MODEL UK:
g1@1; g2@1; g3@1; g4@1;
p2@1; p3@1;
m1@1; m2@1; m3@1; m4@1;
t1@1; t2@1; t3@1; t4@1;
c1@1; c2@1; c3@1;

OUTPUT:
SAMPSTAT MODINDICES(3.8) STANDARDIZED  TECH1;
```