Supplementary Material

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Appendix A – Overview and Results of the Traditional Frequentist Approach to Measurement Invariance

As a supplement to the Bayesian analyses presented in the main document, we also performed measurement invariance analyses using a traditional exact approach with a robust maximum likelihood estimator (MLR). In contrast to the Bayesian approach, residual covariances were specified as uncorrelated and therefore forced to be zero in this frequentist approach to measurement invariance. Model-data fit was assessed using established indices, namely the χ^2 goodness-of-fit index, comparative fit index (CFI), Tucker-Lewis index (TLI), and root mean square error of approximation (RMSEA). According to typical interpretation guidelines for adequate or acceptable model-data fit (e.g., Browne & Cudeck, 1993; Hu & Bentler, 1998; Marsh, Hau, & Grayson, 2005; Marsh, Hau, & Wen, 2004; Tabachnick & Fidell, 2007), values of CFI/TLI ≥ .90 and RMSEA ≤ .06 (with the upper bound of the 90% RMSEA confidence interval ≤ .10) provide evidence of adequate or acceptable overall fit. Nevertheless, it is important to acknowledge that these values represent *guidelines* rather than ‘golden rule’s (i.e., yes/no decision). With regard to exact measurement invariance analyses with the frequentist approach, scaled χ^2 difference tests were corrected for non-normality between nested models because we utilized the MLR estimator (Satorra & Bentler, 2001). As χ^2 difference tests can be sensitive to sample size (Tabachnick & Fidell, 2007), we also considered two additional recommendations for support of invariance between two competing models, namely a change in CFI of less than .01 (Cheung & Rensvold, 2002), and a change in RMSEA of less than .015 (Chen, 2007).

Factorial Validation of the MTI

Analyses indicated that the 8-item unidimensional model was a good fit with the data in the Australian, $\chi^2(20) = 39.41$, $p = .006$, CFI = .965, TLI = .951, RMSEA = .052 (90% CI = .027 to .076) and Malaysian athletes, $\chi^2(20) = 35.50$, $p = .02$, CFI = .944, TLI = .922, RMSEA = .048 (90% CI = .020 to .073); however, model-data fit was inadequate with the Chinese athletes, $\chi^2(20) = 80.77$, $p < .001$, CFI = .916, TLI = .882, RMSEA = .109 (90% CI = .085 to .135). Modification indices revealed that model-data fit could be improved by modeling several residual covariances among the mental toughness items; because this issue is dealt in an a priori manner with Bayesian estimation, we decided not to make these post hoc modifications within the frequentist approach. Across all three samples, factor loadings and latent factor reliability estimates were excellent (see Table 2).

Cross-Cultural Invariance of the MTI

Analyses provided support for model-data fit with the configural, χ^2 (60) = 144.57, $p < .001$, CFI = .940, TLI = .916, RMSEA = .067 (90% CI = .053 to .081), and metric models, χ^2 (74) = 156.37, $p < .001$, CFI = .941, TLI = .933, RMSEA = .059 (90% CI = .046 to .072), but not the scalar model, χ^2 (88) = 253.30, $p < .001$, CFI = .882, TLI = .888, RMSEA = .077 (90% CI = .066 to .088). Model comparisons revealed that the difference between the metric model and the configural model was not statistically significant, $\Delta\chi^2$ (14) = 8.55, $p = .86$, ΔCFI = .001, ΔRMSEA = .008 thus supporting invariance of factor loadings. However, the difference between the scalar model and the metric model was statistically significant, $\Delta\chi^2$ (14) = 130.63, $p < .001$, ΔCFI = .059, ΔRMSEA = .018, thereby failing to support the invariance of item intercepts. In cases where a specific level of invariance is not supported (e.g., scalar invariance), researchers can explore partial invariance by releasing equality constraints of parameters where there is a large difference between groups (Byrne, Shavelson, & Muthén 1989). Accordingly, we released the constraints of the intercepts of items 1, 3, 4, 7, and 8 and found support for this model of partial scalar invariance, χ^2 (78) = 170.31, $p < .001$, CFI = .934, TLI = .929, RMSEA = .061 (90% CI = .049 to .074). Model comparisons revealed that the difference between the metric model and the partial scalar invariance model was not statistically significant, $\Delta\chi^2$ (4) = 13.94, $p < .001$, ΔCFI = .007, ΔRMSEA = .002. Across all three samples and levels of measurement invariance, factor loadings were excellent (see Tables 3, 4, and 5).

Discussion

With the exact approach to measurement invariance, we found that item scores do not have the same scaling across the three cultural groups. An inspection of item-level descriptive statistics indicated that Malaysian athletes typically provided higher means than both the Australian and Chinese participants, whereas Australian athletes generally reported higher means than the Chinese participants. Because there is evidence that some of the items are not invariant across the three cultural groups, the comparison of composite or observed means of mental toughness between these groups is not advisable (Cheung & Rensvold, 2002; Vandenberg & Lance, 2000).

Table 2. *Standardized factor loadings (λ), error terms (Ɵ), and latent factor reliability estimates of the mental toughness inventory for Australian, Malaysian, and Chinese athletes for the single-sample factor analyses with a robust maximum likelihood estimator*.

	Australian athletes (n = 353)		Malaysian athletes (n = 341)		Chinese athletes (n = 254)	
	λ	Ɵ	λ	Ɵ	λ	Ɵ
I believe in my ability to achieve my goals	.62	.62	.58	.67	.60	.64
I am able to regulate my focus when performing tasks	.68	.54	.65	.57	.73	.47
I am able to use my emotions to perform the way I want to	.67	.55	.61	.63	.82	.33
I strive for continued success	.63	.60	.72	.48	.71	.50
I execute my knowledge of what is required to achieve my goals	.65	.58	.53	.72	.69	.53
I consistently overcome adversity	.59	.65	.54	.71	.64	.59
I am able execute appropriate skills or knowledge when challenged	.55	.69	.58	.67	.74	.45
I can find a positive in most situations	.56	.69	.60	.65	.76	.42
McDonald's omega (ω) coefficient	.83		.82		.89	

Table 3. *Standardized factor loadings (λ) and item intercepts (ν) of the mental toughness inventory for Australian, Malaysian, and Chinese athletes for the configural invariance models with a robust maximum likelihood estimator.*

	Australian athletes (n = 353)		Malaysian athletes (n = 341)		Chinese athletes (n = 254)	
	λ	ν	λ	ν	λ	ν
I believe in my ability to achieve my goals	.62	5.66	.58	6.02	.60	5.61
I am able to regulate my focus when performing tasks	.68	5.46	.65	5.59	.73	5.47
I am able to use my emotions to perform the way I want to	.67	5.19	.61	5.76	.82	5.36
I strive for continued success	.63	5.70	.72	6.26	.71	5.77
I execute my knowledge of what is required to achieve my goals	.65	5.63	.53	5.60	.69	5.32
I consistently overcome adversity	.59	5.34	.54	5.49	.64	5.07
I am able execute appropriate skills or knowledge when challenged	.55	5.70	.58	5.75	.74	5.16
I can find a positive in most situations	.56	5.60	.60	6.02	.76	5.37

Table 4. *Standardized factor loadings (λ) and item intercepts (ν) of the mental toughness inventory for Australian, Malaysian, and Chinese athletes for the metric invariance models with a robust maximum likelihood estimator.*

	Australian athletes (*n* = 353)		Malaysian athletes (*n* = 341)		Chinese athletes (*n* = 254)	
	λ	ν	λ	ν	λ	ν
I believe in my ability to achieve my goals	.60	5.66	.59	6.02	.62	5.61
I am able to regulate my focus when performing tasks	.68	5.46	.63	5.59	.75	5.47
I am able to use my emotions to perform the way I want to	.63	5.19	.63	5.76	.83	5.36
I strive for continued success	.63	5.70	.70	6.26	.73	5.77
I execute my knowledge of what is required to achieve my goals	.66	5.63	.52	5.60	.68	5.32
I consistently overcome adversity	.60	5.34	.51	5.49	.65	5.07
I am able execute appropriate skills or knowledge when challenged	.58	5.70	.59	5.75	.71	5.16
I can find a positive in most situations	.59	5.60	.63	6.02	.72	5.37

Table 5. *Standardized factor loadings (λ) and item intercepts (ν) of the mental toughness inventory for Australian, Malaysian, and Chinese athletes for the scalar invariance models with a robust maximum likelihood estimator.*

	Australian athletes (n = 353)		Malaysian athletes (n = 341)		Chinese athletes (n = 254)	
	λ	ν	λ	ν	λ	ν
I believe in my ability to achieve my goals	.60	5.66	.59	6.02	.62	5.61
I am able to regulate my focus when performing tasks	.68	5.46	.63	5.59	.75	5.47
I am able to use my emotions to perform the way I want to	.63	5.19	.63	5.76	.83	5.36
I strive for continued success	.63	5.70	.70	6.26	.73	5.77
I execute my knowledge of what is required to achieve my goals	.66	5.63	.52	5.60	.68	5.32
I consistently overcome adversity	.60	5.34	.51	5.49	.65	5.07
I am able execute appropriate skills or knowledge when challenged	.58	5.70	.59	5.75	.71	5.16
I can find a positive in most situations	.59	5.60	.63	6.02	.72	5.37

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Table S1. *Malay version of the 8-item Mental Toughness Inventory.*

ARAHAN : Menggunakan skala di bawah, sila nyatakan betapa benarnya setiap kenyataan berikut yang menunjukkan bagaimana cara biasa anda berfikir, rasa dan bertindak sebagai pemain bola jaring – *sila ambil ambil maklum bawa tiada jawapan yang betul atau salah, oleh itu buat dengan sejujurnya*.

1	2	3	4	5	6	7
Palsu, 100% tidak benar pada setiap masa						*Benar, 100% benar pada setiap masa*

Saya yakin dengan keupayaan saya untuk mencapai matlamat saya	1	2	3	4	5	6	7
Saya dapat menyelaraskan tumpuan saya ketika melakukan tugasan	1	2	3	4	5	6	7
Saya mampu bangkit dari kesusahan yang dialami	1	2	3	4	5	6	7
Saya berusaha gigih untuk kejayaan yang berterusan	1	2	3	4	5	6	7
Saya dapat melihat sesuatu yang positif dalam kebanyakan situasi	1	2	3	4	5	6	7
Saya dapat menggunakan emosi saya untuk capai prestasi yang saya inginkan	1	2	3	4	5	6	7
Saya mampu mengekalkan tahap terbaik prestasi apabila dicabar	1	2	3	4	5	6	7
Saya menggunakan pengetahuan saya dengan berkesan untuk mencapai matlamat saya	1	2	3	4	5	6	7

Table S2. *Chinese version of the 8-item Mental Toughness Inventory.*

心理堅韌性指標

指導語：使用下述標準，請指出你對下述句子代表你作為一名運動員如何進行思考、感覺和行動的同意程度。*記住答案沒有對錯，因此請盡可能誠實地回答。*

1	2	3	4	5	6	7
100%的時候						*100%的時候*
不符合						*符合*

1. 我相信自己有實現目標的能力。	1	2	3	4	5	6	7
2. 執行任務時，我能夠控制自己注意力的焦點。	1	2	3	4	5	6	7
3. 我努力、堅持地克服逆境。	1	2	3	4	5	6	7
4. 我為每一次的成功而奮鬥。	1	2	3	4	5	6	7
5. 在多數情形下，我都能找到積極的一面。	1	2	3	4	5	6	7
6. 我能夠掌握情緒以自己想要的方式來表現。	1	2	3	4	5	6	7
7. 遇到挑戰時，我能夠運用恰當的技能或知識。	1	2	3	4	5	6	7
8. 我有效地運用自己所需的知識與技能來實現目標。	1	2	3	4	5	6	7

Table S3. *Mplus syntax for single-sample factor analysis of unidimensional mental toughness inventory with Bayesian estimation*. (Note: code preceded by an exclamation mark is not read by Mplus when the run is executed).

```
TITLE: Cross-cultural invariance analyses of the MTI – baseline model
DATA: ! informs Mplus which file to use in the analysis
FILE = Australian data.csv;
! FILE = Malaysian data.csv;
! FILE = Chinese data.csv;

VARIABLE: NAMES = country mti1 mti2 mti3 mti4 mti5 mti6 mti7 mti8;

USEVARIABLES = mti1 mti2 mti3 mti4 mti5 mti6 mti7 mti8;

MISSING = ALL (999); ! informs Mplus which responses are missing

MODEL:
MT BY mti1* mti2 mti3 mti4 mti5 mti6 mti7 mti8; ! * used to freely estimate first loading
MT@1; ! fix the factor variance to 1
mti1-mti8 (rv1-rv8); ! freely estimate residual variances (provides a name for each(
mti1-mti8 WITH mti1-mti8 (cr1-cr28); ! freely estimate residual covariances (provides a
! name for each)

ANALYSIS:
ESTIMATOR = BAYES; ! Bayesian estimation using a Markov chain Monte Carlo (MCMC)
! algorithm  (see pp. 608-609 of the user guide)
PROCESSOR = 4; ! when multiple processors are available, computation can be speeded up
! by specifying the number of processors available for parallel computing, with one chain per
! processor (see pp. 648-650 of the user guide)
CHAINS = 4; ! specifies 4 independent MCMC chains to be employed in the analysis
! (see p. 642 of the user guide)
FBITERATIONS = 150000; ! specifies a fixed number of iterations for MCMC estimation
! (see p. 645 of the user guide)
MODEL PRIORS:
   rv1-rv8~IW(1,15); ! priors for residual variances modeled with inverse-Wishart distribution
   cr1-cr28~IW(0,15); ! priors residual covariances modeled with inverse-Wishart distribution

OUTPUT: STDYX CINTERVAL(HPD) TECH1 TECH8;
! (see pp. 736-757 of the user guide)
```

Table S4. *Mplus syntax for single-sample factor analysis of unidimensional mental toughness inventory with robust maximum likelihood estimator*. (Note: code preceded by an exclamation mark is not read by Mplus when the run is executed).

```
TITLE: Cross-cultural invariance analyses of the MTI – baseline model
DATA:
FILE = Australian data.csv;
! FILE = Malaysian data.csv;
! FILE = Chinese data.csv;

VARIABLE: NAMES = country mti1 mti2 mti3 mti4 mti5 mti6 mti7 mti8;

USEVARIABLES = mti1 mti2 mti3 mti4 mti5 mti6 mti7 mti8;

MISSING = ALL (999);

MODEL:
MT BY mti1* mti2 mti3 mti4 mti5 mti6 mti7 mti8;
MT@1;

ANALYSIS:
ESTIMATOR = MLR; ! robust maximum likelihood estimator (see pp. 605-608 of the user
! guide)

OUTPUT: STDYX SAMPSTAT;
```

Table S5. *Mplus syntax for exact zero invariance analysis of unidimensional mental toughness inventory with robust maximum likelihood estimator*. (Note: code preceded by an exclamation mark is not read by Mplus when the run is executed).

```
TITLE: Cross-cultural invariance analyses of the MTI – exact zero invariance test
DATA:
FILE = Combined data.csv; ! data for each country have been combined in a single file

VARIABLE: NAMES = country mti1 mti2 mti3 mti4 mti5 mti6 mti7 mti8;

GROUPING = country (0 = aus, 1 = mal, 2 = chi) ! informs Mplus which variable contains
! group membership information when data is stored in single data file
USEVARIABLES = mti1 mti2 mti3 mti4 mti5 mti6 mti7 mti8;

MISSING = ALL (999);

MODEL:
MT BY mti1 mti2 mti3 mti4 mti5 mti6 mti7 mti8; ! unlike the previous examples, here the
! first factor loading is fixed to 1 to set the metric of the factor (i.e., default in Mplus)

ANALYSIS:
ESTIMATOR = MLR;
MODEL = CONFIGURAL METRIC SCALAR; ! informs Mplus to estimate these models
! using the multi-group convenience feature of Mplus. One can specify each of these levels of
! invariance in isolation (e.g., MODEL = METRIC;)

OUTPUT: STDYX SAMPSTAT;
```

Table S6. *Mplus syntax for exact zero configural invariance analysis of unidimensional mental toughness inventory with Bayesian estimation*. (Note: code preceded by an exclamation mark is not read by Mplus when the run is executed).

```
TITLE: Cross-cultural invariance analyses of the MTI – exact configural invariance with
Bayesian estimation ! see example 5.33 of the user guide
DATA: FILE = Combined data.csv; ! data for each country have been combined in a single file

VARIABLE: NAMES = country mti1 mti2 mti3 mti4 mti5 mti6 mti7 mti8;

KNOWNCLASS IS g(country=0 country=1 country=2); ! In Mplus, Bayesian multi-group
! analysis requires the CLASSES and KNOWNCLASS options and TYPE=MIXTURE.
CLASSES IS g(3);
USEVARIABLES = mti1 mti2 mti3 mti4 mti5 mti6 mti7 mti8;

MISSING = ALL (999);

MODEL:
%overall% ! part of the model common to all classes, which is known groups in this instance
MT BY mti1* mti2 mti3 mti4 mti5 mti6 mti7 mti8 (fl#_1-fl#_8); ! no constraints on factor
! loadings across groups (provides a name for each; e.g., fl#_1 is assigned to the factor loading
! for item 1)
MT@1;
[MT@0];
[mti1-mti8*] (nu#_1-nu#_8); ! no constraints on item intercepts (provides a name for each)
mti1-mti8 (rv#_1-rv#_8); ! no constraints on residual variances (provides a name for each)
mti1-mti8 WITH mti1-mti8 (cr#_1-cr#_28); ! no constraints on residual covariances (provides
! a name for each) (see p. 612 of the user guide for naming details when using TYPE=mixture)

ANALYSIS:
MODEL = allfree; ! frees parameters for TYPE=MIXTURE (pp. 611-612 of the user guide)
TYPE = mixture; ! Bayesian invariance is executed using mixture modeling in Mplus
ESTIMATOR = BAYES;
PROCESSOR = 4;
CHAINS = 4;
FBITERATIONS = 150000;
MODEL PRIORS:
   DO(1,3)rv#_1-rv#_8~IW(1,15); ! retain small-variance priors for residual variances from
! baseline model (single-sample) in the multi-group analysis; DO(1,3) gives the range of values
! for the DO loop (i.e., the number of classes), whereas rv#_1-rv#_8 are the parameters to
! which to the priors (in parentheses) are attached; IW = inverse Wishart distribution (for an
! explanation of IW, see Muthén & Asparouhov, 2012; DOI: 10.1037/a0026802)
   DO(1,3)cr#_1-cr#_28~IW(0,15); ! retain small-variance priors for residual covariances from
! baseline model (single-sample) in the multi-group analysis

OUTPUT: STDYX TECH1 TECH8;
```

Table S7. *Mplus syntax for exact zero metric invariance analysis of unidimensional mental toughness inventory with Bayesian estimation*. (Note: code preceded by an exclamation mark is not read by Mplus when the run is executed).

```
TITLE: Cross-cultural invariance analyses of the MTI – exact metric invariance with Bayesian
estimation
DATA: FILE = Combined data.csv;

VARIABLE: NAMES = country mti1 mti2 mti3 mti4 mti5 mti6 mti7 mti8;

KNOWNCLASS IS g(country=0 country=1 country=2);
CLASSES IS g(3);
USEVARIABLES = mti1 mti2 mti3 mti4 mti5 mti6 mti7 mti8;

MISSING = ALL (999);

MODEL:
%overall%
MT BY mti1* mti2 mti3 mti4 mti5 mti6 mti7 mti8 (fl1-fl8); ! constrains factor loadings to be
! equal across groups by specifying the labels fl1-fl18 [here is the difference with the exact
! configural invariance model depicted in Table S6]
MT@1;
[MT@0];
[mti1-mti8*] (nu#_1-nu#_8);
mti1-mti8 (rv#_1-rv#_8);
mti1-mti8 WITH mti1-mti8 (cr#_1-cr#_28);

ANALYSIS:
MODEL = allfree;
TYPE = mixture;
ESTIMATOR = BAYES;
PROCESSOR = 4;
CHAINS = 4;
FBITERATIONS = 150000;
MODEL PRIORS:
   DO(1,3)rv#_1-rv#_8~IW(1,15);
   DO(1,3)cr#_1-cr#_28~IW(0,15);

OUTPUT: STDYX TECH1 TECH8;
```

Table S8. *Mplus syntax for exact zero scalar invariance analysis of unidimensional mental toughness inventory with Bayesian estimation*. (Note: code preceded by an exclamation mark is not read by Mplus when the run is executed).

```
TITLE: Cross-cultural invariance analyses of the MTI – exact metric invariance with Bayesian
estimation
DATA: FILE = Combined data.csv;

VARIABLE: NAMES = country mti1 mti2 mti3 mti4 mti5 mti6 mti7 mti8;

KNOWNCLASS IS g(country=0 country=1 country=2);
CLASSES IS g(3);
USEVARIABLES = mti1 mti2 mti3 mti4 mti5 mti6 mti7 mti8;

MISSING = ALL (999);

MODEL:
%overall%
MT BY mti1* mti2 mti3 mti4 mti5 mti6 mti7 mti8 (fl1-fl8);
MT@1;
[MT@0];
[mti1-mti8*] (nu1-nu8); ! constrains item intercepts to be equal across groups [here is the
! difference with the exact metric invariance model depicted in Table S7]
mti1-mti8 (rv#_1-rv#_8);
mti1-mti8 WITH mti1-mti8 (cr#_1-cr#_28);

ANALYSIS:
MODEL = allfree;
TYPE = mixture;
ESTIMATOR = BAYES;
PROCESSOR = 4;
CHAINS = 4;
FBITERATIONS = 150000;
MODEL PRIORS:
   DO(1,3)rv#_1-rv#_8~IW(1,15);
   DO(1,3)cr#_1-cr#_28~IW(0,15);

OUTPUT: STDYX TECH1 TECH8;
```

Table S9. *Mplus syntax for approximate metric invariance analysis of unidimensional mental toughness inventory with Bayesian estimation*. (Note: code preceded by an exclamation mark is not read by Mplus when the run is executed).

```
TITLE: Cross-cultural invariance analyses of the MTI – approximate metric invariance with
Bayesian estimation
DATA: FILE = Combined data.csv;

VARIABLE: NAMES = country mti1 mti2 mti3 mti4 mti5 mti6 mti7 mti8;

KNOWNCLASS IS g(country=0 country=1 country=2);
CLASSES IS g(3);
USEVARIABLES = mti1 mti2 mti3 mti4 mti5 mti6 mti7 mti8;

MISSING = ALL (999);

MODEL:
%overall%
MT BY mti1* mti2 mti3 mti4 mti5 mti6 mti7 mti8 (fl#_1-fl#_8);
MT@1;
[MT@0];
[mti1-mti8] (nu#_1-nu#_8);
mti1-mti8 (rv#_1-rv#_8);
mti1-mti8 WITH mti1-mti8 (cr#_1-cr#_28);

ANALYSIS:
MODEL = allfree;
TYPE = mixture;
ESTIMATOR = BAYES;
PROCESSOR = 4;
CHAINS = 4;
FBITERATIONS = 150000;
MODEL PRIORS:
   DO(1,3)rv#_1-rv#_8~IW(1,15);
   DO(1,3)cr#_1-cr#_28~IW(0,15);
! below, we set the priors for differences in factor loading between groups with a normal
! distribution, mean of zero and prior variance of .05 (which can be altered using the
! exclamation marks for the 3 options)
! DIFF produces “modification indices” by flagging non-invariant items as significantly
! deviating from average
   DO(1,8)DIFF(fl1_#-fl3_#)~N(0,.05);
   ! DO(1,8)DIFF(fl1_#-fl3_#)~N(0,.01);
   ! DO(1,8)DIFF(fl1_#-fl3_#)~N(0,.005);

OUTPUT: STDYX TECH1 TECH8;
```

Table S10. *Mplus syntax for approximate scalar invariance analysis of unidimensional mental toughness inventory with Bayesian estimation*. (Note: code preceded by an exclamation mark is not read by Mplus when the run is executed).

```
TITLE: Cross-cultural invariance analyses of the MTI – approximate metric and scalar
invariance with Bayesian estimation
DATA: FILE = Combined data.csv;

VARIABLE: NAMES = country mti1 mti2 mti3 mti4 mti5 mti6 mti7 mti8;

KNOWNCLASS IS g(country=0 country=1 country=2);
CLASSES IS g(3);
USEVARIABLES = mti1 mti2 mti3 mti4 mti5 mti6 mti7 mti8;

MISSING = ALL (999);

MODEL:
%overall%
MT BY mti1* mti2 mti3 mti4 mti5 mti6 mti7 mti8 (fl#_1-fl#_8);
MT@1;
[MT@0];
[mti1-mti8] (nu#_1-nu#_8);
mti1-mti8 (rv#_1-rv#_8);
mti1-mti8 WITH mti1-mti8 (cr#_1-cr#_28);

ANALYSIS:
MODEL = allfree;
TYPE = mixture;
ESTIMATOR = BAYES;
PROCESSOR = 4;
CHAINS = 4;
FBITERATIONS = 150000;
MODEL PRIORS:
   DO(1,3)rv#_1-rv#_8~IW(1,15);
   DO(1,3)cr#_1-cr#_28~IW(0,15);
! below, we set the priors for differences in factor loading between groups with a normal
! distribution, mean of zero and prior variance of .05 (which can be altered using the
! exclamation marks for the 3 options)
! DIFF produces "modification indices" by flagging non-invariant items as significantly
! deviating from average
   DO(1,8)DIFF(fl1_#-fl3_#)~N(0,.05);
   ! DO(1,8)DIFF(fl1_#-fl3_#)~N(0,.01);
   ! DO(1,8)DIFF(fl1_#-fl3_#)~N(0,.005);
! below, we set the priors for item intercept differences with a normal distribution, mean of zero
! and prior variance of .05 (which can be altered using the exclamation marks for the 3 options)
   DO(1,8)DIFF(nu1_#-nu3_#)~N(0,.05);
   ! DO(1,8)DIFF(nu1_#-nu3_#)~N(0,.01);
   ! DO(1,8)DIFF(nu1_#-nu3_#)~N(0,.005);

OUTPUT: STDYX TECH1 TECH8;
```

Table S11. *Mplus syntax for 'partial measurement' invariance analysis of unidimensional mental toughness inventory with Bayesian estimation*. (Note: code preceded by an exclamation mark is not read by Mplus when the run is executed).

```
TITLE: Cross-cultural invariance analyses of the MTI – partial measurement invariance with
Bayesian estimation (Step 2 as recommended by Muthén and Asparouhov, 2013)
DATA: FILE = Combined data.csv;

VARIABLE: NAMES = country mti1 mti2 mti3 mti4 mti5 mti6 mti7 mti8;

KNOWNCLASS IS g(country=0 country=1 country=2);
CLASSES IS g(3);
USEVARIABLES = mti1 mti2 mti3 mti4 mti5 mti6 mti7 mti8;

MISSING = ALL (999);

MODEL:
%overall%
MT BY mti1* mti2 mti3 mti4 mti5 mti6 mti7 mti8 (fl1-fl8);
MT@1;
[MT@0];
[mti1-mti8] (nu1-nu8);
mti1-mti8 (rv#_1-rv#_8);
mti1-mti8 WITH mti1-mti8 (cr#_1-cr#_28);

%g#2% ! class specific information for the Malaysian athletes; code in this section will differ
! what is captured in the overall model above (%overall%)
MT@1;
[mti1 mti3 mti4 mti7 mti8]; ! releases the equality constraint for these item intercepts in the
! Malaysian athletes

%g#3% ! class specific information for the Chinese athletes; code in this section will differ
! what is captured in the overall model above (%overall%)
MT@1;
[mti5 mti6 mti7 mti8]; ! releases the equality constraint for these item intercepts in the
! Chinese athletes

ANALYSIS:
MODEL = allfree;
TYPE = mixture;
ESTIMATOR = BAYES;
PROCESSOR = 4;
CHAINS = 4;
FBITERATIONS = 150000;
MODEL PRIORS:
   DO(1,3)rv#_1-rv#_8~IW(1,15);
   DO(1,3)cr#_1-cr#_28~IW(0,15);

OUTPUT: STDYX TECH1 TECH8;
```