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Supplementary Material

Measurement invariance model selection for MCS

Maladaptive cognitive schemas (MCS) are theoretically conceived as a hierarchically structured and multidimensional construct, encompassing both a general maladaptive schema tendency and several domain-specific schema dimensions (e.g., disconnection & rejection, impaired autonomy & performance). Recent psychometric literature has raised concerns about using traditional confirmatory factor analysis (CFA) to evaluate longitudinal measurement invariance in such complex constructs (Marsh et al., 2014; Alamer, 2022). CFA imposes a simple structure by allowing each item to load only on its designated factor, while constraining all cross-loadings to zero. This rigid specification can distort the true factor structure in multidimensional constructs like MCS, leading to inflated inter-factor correlations and poorer overall model fit.

Table S1 Model fit indices for four measurement models of the MCS.

	Model	$\chi2$	*df*	CFI	TLI	RMSEA
T1	CFA	3072.214	84	0.838	0.797	0.108
	Bifactor-CFA	2321.683	77	0.878	0.834	0.098
	ESEM	459.031	51	0.978	0.954	0.051
	Bifactor-ESEM	232.137	40	0.990	0.973	0.04
T2	CFA	4066.943	84	0.841	0.801	0.127
	Bifactor-CFA	2779.355	77	0.892	0.853	0.109
	ESEM	554.238	51	0.980	0.959	0.058
	Bifactor-ESEM	220.199	40	0.993	0.981	0.039

T1 Time 1, *T2* Time 2, *CFA* Confirmatory factor analysis, *ESEM* Exploratory structural equation modeling, χ^2 Chi-square Statistic, *df* Degrees of Freedom, *CFI* Comparative Fit Index, *TLI* Tucker–Lewis Index, *RMSEA* Root Mean Square Error of Approximation, *MCS* maladaptive cognitive schemas

To address this limitation, we followed recent psychometric guidelines for modeling multidimensional instruments (Alamer, 2022). Specifically, when a construct is theorized to reflect both a general latent dimension and multiple specific factors—as is the case for MCS—it is essential to compare and evaluate the fit of four models: (1) confirmatory factor analysis (CFA), (2) bifactor-CFA, (3) exploratory structural equation modeling (ESEM), and (4) bifactor-ESEM. Comparing these models helps identify the structure that most accurately reflects the data, both theoretically and empirically. The best-fitting model can then serve as the basis for testing longitudinal measurement invariance across time points.

Among the fout models, the Bifactor-CFA allows items to load on a general factor and one specific factor but still imposes simple structure by disallowing cross-loadings across specific factors. ESEM relaxes this by estimating cross-loadings under target rotation, thus accounting for item-level multidimensionality. However, it lacks a general factor component. In contrast, bifactor-ESEM integrates both general and specific factors while permitting cross-loadings, making it particularly suitable for constructs like MCS that exhibit multidimensional features (Morin et al., 2016).

We estimated all four models at each time point (T1 and T2). As shown in Table S1, the bifactor-ESEM model consistently demonstrated the best fit across multiple indices (e.g., CFI, TLI, RMSEA). For instance, at T1, bifactor-ESEM achieved a CFI of .990 and RMSEA of .040, outperforming both CFA (CFI = .838, RMSEA = .108) and bifactor-CFA (CFI = .878, RMSEA = .098). The pattern was similar at T2, with bifactor-ESEM yielding CFI = .993 and RMSEA = .039. These results align with prior findings suggesting that bifactor-ESEM provides the most accurate representation of complex psychological constructs (Stenling et al., 2017; Morin et al., 2016).

Based on its theoretical appropriateness and empirical superiority, we retained the bifactor-ESEM solution for evaluating the longitudinal measurement invariance of MCS.

Table S2 Model fit statistics for tests of longitudinal measurement invariance

	Model Tested	$\chi 2$	*df*	CFI	TLI	RMSEA	ΔCFI
MCS (15 items)	Configural invariance	1431.10	296	0.976	0.964	0.035	
	Metric invariance	**1601.84**	**340**	**0.973**	**0.965**	**0.035**	**<0.01**
	Scalar invariance	**2090.87**	**355**	**0.963**	**0.954**	**0.040**	**0.010**
	Error variance invariance	**2325.41**	**370**	**0.958**	**0.951**	**0.042**	**<0.01**
AFN (7 items)	Configural invariance	1847.29	69	0.986	0.981	0.092	
	Metric invariance	**1927.10**	**75**	**0.985**	**0.980**	**0.090**	**<0.01**
	Scalar invariance	**1940.39**	**81**	**0.985**	**0.983**	**0.087**	**<0.01**
	Error variance invariance	**2750.56**	**88**	**0.979**	**0.978**	**0.100**	**<0.01**

Bolded text refers to the accepted measurement invariance test.
χ^2 Chi-square Statistic, *df* Degrees of Freedom, *CFI* Comparative Fit Index, *TLI* Tucker–Lewis Index, *RMSEA* Root Mean Square Error of Approximation, *MCS* maladaptive cognitive schemas, *NSSI-AF* non-suicidal self-injury addictive features

References

Alamer, A. (2022). Exploratory structural equation modeling (ESEM) and bifactor ESEM for construct validation purposes: Guidelines and applied example. *Research Methods in Applied Linguistics*, *1*(1), 100005.

Marsh, H. W., Morin, A. J., Parker, P. D., & Kaur, G. (2014). Exploratory structural equation modeling: An integration of the best features of exploratory and confirmatory factor analysis. *Annual review of clinical psychology*, *10*(1), 85-110.

Morin, A. J. S., Arens, A. K., & Marsh, H. W. (2016). A Bifactor Exploratory Structural Equation Modeling Framework for the Identification of Distinct Sources of Construct-Relevant Psychometric Multidimensionality. *Structural Equation Modeling*, *23*(1), 116–139.

Stenling, A., Ivarsson, A., Lindwall, M., & Gucciardi, D. F. (2018). Exploring longitudinal measurement invariance and the continuum hypothesis in the Swedish version of the Behavioral Regulation in

Sport Questionnaire (BRSQ): An exploratory structural equation modeling approach. *Psychology of Sport and Exercise*, *36*, 187-196.