A Guide to Exploratory Structural Equation Modeling (ESEM) and Bifactor-ESEM in Body Image Research

Viren Swami[1-2], Christophe Maïano[3-5], & Alexandre J. S. Morin[5]

[1]School of Psychology and Sport Science, Anglia Ruskin University, Cambridge, United Kingdom
[2]Centre for Psychological Medicine, Perdana University, Kuala Lumpur, Malaysia
[3]Department of Psychoeducation and Psychology, Université du Québec en Outaouais, Saint-Jérôme, Canada
[4]Cyberpsychology Laboratory, Department of Psychoeducation and Psychology, Université du Québec en Outaouais, Saint-Jérôme, Canada
[5]Substantive-Methodological Synergy Research Laboratory, Department of Psychology, Concordia University, Montreal, Canada

This is the prepublication version of the following manuscript:

Swami, V., Maïano, C., & Morin, A.J.S. (2023). A guide to Exploratory Structural Equation Modeling (ESEM) and Bifactor-ESEM in body image research. *Body Image*, *47*, 101641. https://doi.org/10.1016/j.bodyim.2023.101641

Address correspondence to: Prof. Viren Swami, School of Psychology and Sport Science, Anglia Ruskin University, Cambridge, Cambridgeshire CB1 1PT, United Kingdom. Email: viren.swami@aru.ac.uk.

Abstract

Traditionally, assessments of factor validity of body image instruments have relied on exploratory or confirmatory factor analysis. However, the emergence of exploratory structural equation modeling (ESEM), a resurgence of interest in bifactor models, and the ability to combine both models (bifactor-ESEM) is beginning to shape the future of body image research. For these analytic approaches to truly advance body image research, scholars will need to have a deep understanding of their use and application. To facilitate such understanding, we describe ESEM and bifactor-ESEM models for body image researchers and provide them with the tools they need to apply these methods in their own work. Specifically, we provide an overview of ESEM and bifactor-ESEM models, and describe their broad applicability to body image research. Next, we describe how ESEM and bifactor models can be used and, using an existing dataset of responses to the Acceptance of Cosmetic Surgery Scale, demonstrate how ESEM and bifactor-ESEM models can be deployed. To facilitate wider application of these ideas, we provide our Mplus syntax (inputs) in Supplementary Materials. Through this manuscript, we hope to assist researchers to better understand the strengths ESEM and bifactor models, and to use these approaches in their own work.

Keywords**:** Exploratory structural equation modeling; Bifactor models; Confirmatory factor analysis; Exploratory factor analysis; Body image; Acceptance of cosmetic surgery

1. Introduction

Issues of *factor validity* – that is, the extent to which the expected structure of scores on an instrument can be recovered in a set of real test scores (Piedmont, 2014) – are central to quantitative research on body image. For instance, factor validity is relevant not only to scale construction (i.e., determining how the structure of scores on a novel instrument should be represented; Worthington & Whittaker, 2006) and test adaptation (i.e., determining how the structure of scores on an existing instrument should be represented in a novel linguistic or cultural group; Swami & Barron, 2019), but also informs decisions about score computation (Byrne, 2001; Hair et al., 2009). In most cases, factor validity is determined through factor analysis, with exploratory and confirmatory factor analyses being the traditional methods of choice for most body image scholars. However, emerging alternatives have the potential to contribute to, and support, the refinement of multidimensional body image theories.

In particular, the development of exploratory structural equation modeling (ESEM; Asparouhov & Muthén, 2009), a resurgence of interest in bifactor models (Reise, 2012), and their combination (Morin et al., 2016) has spurred rapid theoretical advancements across diverse fields of psychological research (e.g., Alamer, 2022; Gegenfurtner, 2022; Morin et al., 2020; Tóth-Király et al., 2017) and is beginning to shape body image research (e.g., Lazarescu et al., 2023; Swami, Maïano, & Morin, 2022). However, for these analytic approaches to truly help advance body image research, scholars need to have a deeper understanding of their use and application. Currently, the application of ESEM and bifactor-ESEM to body image research remains piecemeal, possibly because of a lack of familiarity among body image scholars of the intended purpose and utility of these analytic approaches. Body image researchers may also have limited practical knowledge of these methods, which can impede their application relative to traditional factor analytic methods.

In this article, our objective is to describe ESEM and bifactor-ESEM for body image researchers, while providing them with the tools to apply these methods in their own research. To achieve these goals, we begin by describing how body image researchers have historically approached issues of factor validity. Next, we provide an overview of ESEM and bifactor-ESEM, and describe their broad applicability to body image research. Then, we describe how ESEM and bifactor-ESEM can be used in practice and, using an existing dataset, demonstrate how they can be used to advance knowledge in a specific area of body image research. To facilitate wider application, we provide our Mplus syntax (inputs) for all models estimated in this article in the Supplementary Materials. Through this manuscript, we hope to assist body image researchers to better understand the strengths and limitations of ESEM and bifactor-ESEM, to use both approaches in their own research, and to correctly interpret findings from ESEM and bifactor-ESEM solutions.

2. Exploratory Structural Equation Modeling and Bifactor Models

2.1. Background

2.1.1. Exploratory factor analysis. Factor validity refers to the extent to which scores on the items (i.e., typically observed scores on questions used to assess the presence of a construct) included in a measure share strong associations with the one construct that it is supposed to define (i.e., the latent factor). Some also erroneously consider that factor validity assumes scores on these items should also share no, or only negligible, associations (i.e., cross-loadings) with the other constructs assessed within the instrument, when in fact it simply refers to the presence of the expected item-factor associations while allowing for the presence of smaller (or stronger but explainable) cross-associations (e.g., Morin et al., 2020). In body image research, factor validity is typically assessed using exploratory factor analysis (EFA), confirmatory factor analysis (CFA), or a combination of both methods (for a review, see Swami & Barron, 2019).

EFA, often used as a first analytic step, allows scholars to determine the most appropriate method of conceptualising scores in a given dataset without any modeling limitations. In other words, EFA is typically used to either "explore" the structure of responses to an instrument in the absence of clear *a priori* expectations. EFA is, therefore, viewed as especially useful when researchers do not have a clear theoretically derived picture of the factor structure of their data (Worthington & Whittaker, 2006). However, EFA can also be used as a more robust test of whether the *a priori* factor structure will be supported when the researchers are not providing any guidance in this regard to the analytic procedure (e.g., Marsh et al., 2009; Morin & Maïano, 2011).

Historically, the factor structure of some body image instruments – such as the widely used

Multidimensional Body-Self Relations Questionnaire (MBSRQ; Brown et al., 1990; Cash, 2000) and the Drive for Muscularity Scale (DMS; McCreary et al., 2004) – was determined using EFA (or principal components analysis, which is often erroneously assumed to pursue similar objectives; Fabrigar et al., 1999) alone. However, there is now wider recognition that the factor validity of constructs cannot be fully determined by classical applications of EFA (Swami & Barron, 2019). This recognition stems, in part, from the inability of traditional EFA methods to control for different types of methodological artefacts or to test the measurement invariance (or equivalence) of a model in different samples or over time, and from its lack of connection with the broader Structural Equation Modeling (SEM) framework. Because of these limitations, EFA is now often viewed as useful for preliminary analyses, but lacking in its ability to inform more complex decision-making about factor validity (Morin, 2023). As such, body image scholars are increasingly using EFA as a first analytic step, which is then followed by CFA as a second or cross-validation step, based on the (often erroneous) assumption that CFA will provide a more accurate theory-driven representation of their data (Morin et al., 2020).

2.1.2. Confirmatory factor analysis. CFA allows researchers to explore how well a predefined theoretical or hypothesised model fits a given dataset. In other words, researchers begin by formulating an *a priori* hypothesis about the factor structure of a measure before testing their assumptions (Brown, 2015). A traditional benefit of CFA, relative to EFA, as a second step method was the ability to test the adequacy of a model against the data via an examination of the model fit indices (e.g., Hu & Bentler, 1999). However, fit indices have been available for some time for EFA in certain statistical packages (e.g., MPlus, *R*). Beyond this, true benefits of CFA as a second step method came from its ability to test measurement invariance and criterion-related validity of factors within a latent variable framework corrected for unreliability. As a result, in psychology generally and in body image research specifically, CFA remains the most widely used method for testing the factor validity of scores on an instrument. Indeed, despite calls to avoid doing so (Swami & Barron, 2019; Swami, Todd et al., 2021), it is not uncommon to see CFA used as the sole method of estimating factor validity in body image research.

A key feature of CFA is that items are typically allowed to load only on their respective *a priori* latent factor (see Figure 1a), while cross-loadings across latent factors are forced to be exactly zero (Marsh et al., 2009, 2014; Morin et al., 2016). This is not a concern when an instrument is assumed to reflect one and only one latent variable (Wei et al., 2022); that is, when all items on an instrument are expected to measure the same latent construct. This is the case with many existing body image instruments, such as the Body Appreciation Scale-2 (Tylka & Wood-Barcalow, 2015), the Functionality Appreciation Scale (Alleva et al., 2017), and the Breast Appreciation Scale (Swami, Todd et al., 2022) – all of which are hypothesised to measure a single unidimensional construct. In situations such as these, the reliance on an initial assessment of factor structure using EFA (to ensure the presence of a single factor) followed by a cross-validation using CFA is appropriate.

However, the assumption of zero cross-loadings in CFA is more problematic when dealing with multidimensional instruments (i.e., where scores on an instrument consist of multiple, independent components; Morin, 2023; Morin et al., 2016, 2020). This is because the assumption that items on a scale will have zero cross-loadings is, in practice, improbable and unrealistic in most cases, especially when an instrument measures conceptually related constructs (Marsh et al., 2014; Morin et al., 2016, 2020). Consider, for instance, the Appearance Scales of the MBSRQ (MBSRQ–AS; Cash, 2000), which includes items assessing appearance evaluation (e.g., "I like my looks just the way they are") and appearance orientation (e.g., "Before going out in public, I always notice how I look"). Estimating a CFA with responses obtained on the MBSRQ–AS would mean assuming that items load only on their respective hypothesised latent factors (i.e., appearance evaluation or appearance orientation, respectively) and no other factor. In reality, however, items designed to measure appearance evaluation are likely to present weaker, though still meaningful, associations with conceptually related constructs, such as appearance orientation.

In fact, there is now much wider recognition that items designed to assess conceptually related factors tend to share at least some construct-relevant associations with the other factors included in the model (Asparouhov & Muthén, 2009; Gillet et al., 2020; Guay et al., 2015; Marsh, Nagengast et al., 2013; Morin et al., 2013, 2020). This, in turn, means that CFA is often an unrealistically restrictive approach to tests of factor validity and increases the likelihood that a well-defined EFA factor structure will be difficult to replicate using CFA (Marsh, Nagengast et al., 2013; Marsh et al., 2009). As a result, CFA is likely to result in inflated estimates of factor correlations (i.e., the only way for unmodelled cross-loadings to be expressed is via an inflation of factor correlations) and of associations between these factors and other variables as a result of these inflated factor correlations (e.g., Asparouhov & Muthén, 2009; Marsh et al., 2014; Morin et al., 2020; Shao et al., 2022; Zhang et al., 2023). Supporting this claim, statistical simulation studies have clearly shown that failure to model even negligible cross-loadings (i.e., as small as .10) results in biased estimates of factor correlations and regressions, whereas allowing for the free estimation of unnecessary cross-loadings still results in unbiased parameter estimates (Asparouhov et al., 2015; Mai et al., 2018; Wei et al., 2022).

Beyond these biased estimates, the restrictive nature of CFA also means that researchers are often faced with ill-fitting models despite using measures with a well-replicated factor structure (e.g., Marsh, Nagengast et al., 2013; Marsh et al., 2009). Scholars usually deal with such model misspecification through *post hoc* data-driven procedures designed to improve model fit (e.g., examining modification indices to locate potential areas of misspecification, adding correlated uniqueness, etc.; Schumacker & Lomax, 2004). However, these strategies are rarely grounded in theory and, as a result, lack generalisability. For instance, correlating measurement error usually implies that there is an underlying, confounding factor that the researcher has failed to take into account. However, using this approach in a situation where one is unable to clearly identify this confounding factor is more likely to represent capitalisation on chance than in the identification of a replicable factor structure. In fact, even when these *post hoc* modifications result in an improved model fit, well-fitting CFA models may still hide misspecifications given their ability to absorb unmodelled cross-loadings through an inflation of factor correlations, without letting them impact model fit (e.g., Morin et al., 2016, 2020).

These observations have important implications for body image research, the most pertinent of which is the difficulty replicating hypothesised multidimensional factor structures based on CFA in new datasets or populations. For example, the Body and Appearance Self-Conscious Emotions Scale (BASES; Castonguay et al., 2014) was originally conceptualised through the use of CFA as consisting of four independent factors assessing the discrete emotions of guilt, shame, authentic pride, and hubristic pride. Because the BASES was developed using CFA, an implicit assumption is that items in the instrument load only on their respective *a priori* latent factors (e.g., items assessing hubristic pride will only load on the Hubristic Pride factor), while cross-loadings are ignored. However, such an assumption is unlikely to be realistic and, in fact, when alternative analytic methods are used (e.g., EFA), cross-loadings have been shown to be more common and substantial than previously acknowledged (e.g., Alcaraz-Ibáñez & Sicila, 2018; Swami, Maïano, Wong et al., 2021). In practice, this has meant that scholars have found it very difficult to replicate the 4-factor BASES structure using CFA with new datasets (Swami, Maïano, & Morin, 2022; Swami, Maïano, Wong et al., 2021).

Similar problems affect other multidimensional body image and body image-related scales, including the MBSRQ–AS (see Lizana-Calderón et al., 2023; Swami et al., 2019) and the Intuitive Eating Scale-2 (IES-2; Tylka & Kroon Van Diest, 2013). The latter was originally developed using an EFA-to-CFA approach and, while the original development study led to the extraction of four independent factors (i.e., where items do not cross-load across factors), recent work has shown both that cross-loadings are in fact substantial and that the 4-factor model is not recoverable in some contexts (Anastasiades et al., 2022; Swami, Maïano, Todd et al., 2021), including in the national group in which it was originally developed (i.e., the United States; Swami, Maïano, Furnham et al., 2022). We do not highlight these examples to disparage the developers of these instruments, but rather to highlight the limitations of CFA in body image research. Recognising that CFA is an imperfect analytic tool does not require us to throw out these instruments and does not imply that the underlying constructs are problematic. Instead, it points to the need to account for cross-loadings – even if they are small in magnitude – in our analyses (Morin, 2023).

2.2. Exploratory Structural Equation Modeling

The development of exploratory structural equation modeling (ESEM; Asparouhov & Muthén, 2009) made it possible to benefit from the advantages usually associated with CFA while still relying on EFA measurement. Specifically, ESEM is an analytic framework that represents a connection between EFA measurement models and the overarching CFA framework, making it possible to benefit from all of the advantages typically associated with CFA, while relying on an EFA measurement model (incorporating cross-loadings; see Figure 1b). Moreover, the development of target rotation (e.g., Browne, 2001) makes it possible rely on an *a priori* specification of the main factor loadings, while constraining the cross-loadings to be as close to zero as possible, yet freely estimated. This rotation thus makes it possible to rely on confirmatory applications (i.e., based on an *a priori* factor structure) of measurement models while adopting an EFA-like factor structure (Morin et al., 2020). In this sense, ESEM can be used for purely confirmatory or exploratory purposes, while retaining the benefits of both EFA and CFA (Marsh et al., 2014; Morin et al., 2020).

To better illustrate ESEM benefits, consider again the example of the MBSRQ–AS and its factors assessing appearance evaluation and appearance orientation. While the application of CFA would mean considering both factors as distinct (which often results in poor CFA-based fit; Brytek-Matera & Rogoza, 2015; Lizana-Calderón et al., 2023), a more realistic assumption is that items related to each factor tap into conceptually related constructs (e.g., some items may simultaneously tap into appearance evaluation *and* appearance orientation). This would be consistent with the idea that individuals with higher appearance orientation (e.g., always noticing how one appears before going out) will also have high scores on appearance evaluation (e.g., considering oneself to be sexually appealing). With ESEM, the possibility of cross-loadings would be specifically accounted for while still allowing researchers to rely on *a priori* specifications of the constructs.

Emerging research has shown that ESEM-based models typically provide an improved, and more accurate, representation of the data than CFA-based models (for a review, see Gegenfurtner, 2022), including for some multidimensional body image(-related) instruments, such as the BASES (Swami, Maïano, & Morin, 2022; Swami, Maïano, Wong et al., 2021), the IES-2 (Anastasiades et al., 2022; Swami, Maïano, Furnham et al., 2022; Swami, Maïano, Todd et al., 2021), the Acceptance of Cosmetic Surgery Scale (Lazarescu et al., 2023), the Body Checking Questionnaire and the Body Checking Cognitions Scale (Maïano et al., 2021), and the Sociocultural Attitudes Toward Appearance Questionnaire-3 (Sánchez-Carracedo et al., 2012). For instance, initial CFA investigations of the short form of the Physical Self-Inventory have revealed problematically high factor correlations (Maïano et al., 2008). Interestingly, these correlations are far more aligned with the theoretical distinctiveness of the factors when modelled while allowing for cross-loadings (e.g., Morin & Maïano, 2011). Moreover, relying on ESEM has also led to the identification of problems with some items that remained unseen with CFA, leading to the development of a more accurate, revised version of this instrument (e.g., Morin et al., 2018). However, while the superiority of ESEM is now well-established in diverse fields (e.g., Guay et al., 2015; Howard et al., 2018), its use in body image research remains piecemeal and occasional.

2.3. Higher-Order Models

Although ESEM accounts for construct-relevant psychometric multidimensionality occurring when an instrument assesses conceptually-related factors, multidimensionality also occurs with hierarchically-ordered constructs; that is, when specific factors are designed to reflect facets of a more global construct (Morin et al., 2016, 2020). In the example of the MBSRQ–AS we presented above, this form of multidimensionality would reflect participants' overall body image, over and above their specific levels of appearance orientation, appearance evaluation, and so on. Historically, body image researchers have tended to model this form of global/specific multidimensionality through higher-order factor models, in which first-order factors are used to model second-order factors derived empirically (e.g., McCreary et al., 2004; Swami et al., 2018) or theoretically (e.g., Henderson-King & Henderson-King, 2005; Wu et al., 2020).

No matter how this higher-order representation is derived, items are used to define first-order factors, which are in turn used to define a second-order factor reflecting the variance that is shared among the first-order factors (see Figures 1c and 1d, which represent higher-order CFA and ESEM models). Such models may appear intuitive, but they present one important limitation: they rely on a very stringent proportionality constraint in defining how the items relate to the higher-order factor and to the specific part of the first-order factors that is not explained by the higher-order factors (i.e., its disturbance; Reise, 2012). More specifically, the relation between an item and the higher-order factor is assumed to be indirect (i.e., mediated by the first order factor; Brunet et al., 2016; Gignac, 2016). This indirect effect is reflected as the product of (a) the item's first-order factor loading by (b) the loading of this first-order factor on the higher-order factor. This second term (b) is thus a constant for all items associated with a specific first-order factor. Likewise, the relation between an item and the disturbance of the first-order factor to which it is associated is also reflected by the product of this item's loadings on the first-order factor (a) and another constant representing the link between the first order factor and its disturbance (c). These implicit proportionality constraints imply that the ratio of global/specific variance (ab/ac) will be exactly the same for all items associated with a specific first-order factor (i.e., corresponding to b/c). However, this proportionality constraint rarely makes sense theoretically and is unlikely to hold in real life (Reise, 2012).

2.4. Bifactor-CFA and Bifactor-ESEM Models

Bifactor models provide a more viable alternative and have recently gained popularity in diverse fields of research (Alamer, 2022; Giordano et al., 2020; Markon, 2019; Morin et al., 2016, 2020; Reise, 2012). In bifactor models, items are typically allowed to define a global G-factor and one specific S-factor, with all S-factors specified as orthogonal to one another and in relation to the G-factor (Morin et al., 2016, 2020). This method separates the total item covariance into: (i) a global component (the G-factor) that explains the variance shared among responses to all items, and; (ii) specific factors (S-factors) that explain the covariance associated with items subsets not already explained by the global component. Thus, in a *f*-factor bifactor model, one G-factor (e.g., body image) and *f*-1 S-factors (e.g., appearance evaluation, appearance orientation, etc.) are used to explain the covariance among a set of *n* items. A bifactor model thus partitions the total covariance into a G component underlying all items and *f*-1 S components reflecting the residual covariance not explained by the G-factor. Bifactor models thus test the presence of a global unitary construct underlying the answers to all items (G-factor) and whether this global construct co-exists with meaningful specificities (S-factors) defined by the part of the items not explained by the G-factor.

Bifactor modeling can be used in conjunction with CFA (where items load onto their specified S-factors and the G-factor) and ESEM (where all items load and cross-load on all S-factors, in addition to the G-factor; Morin et al., 2020; see Figures 1e and 1f, which represent bifactor-CFA and bifactor-ESEM models). Through their reliance on direct associations between items and all factors, bifactor models are able to estimate co-existing and properly disaggregated global and specific constructs, but are able do so without imposing the restrictive proportionality constraints inherent in higher-order factor models. This makes bifactor models a more tenable alternative to the representation of a hierarchically organised factor structure (Gillet et al., 2020; Morin et al., 2016, 2020). Accordingly, Morin (2023; see also Morin et al., 2022) recommended that higher-order models should be avoided, unless there are very strong theoretical and/or empirical reasons supporting the incorporation of rigid implicit proportionality constraints into a model. Even when estimated, higher-order models should always be contrasted with bifactor models. When both models can be shown to result in an equivalent representation of the data, the more parsimonious higher-order model can be retained (Morin et al., 2022). Otherwise, bifactor models should be favoured.

For body image scholars, bifactor models can be particularly useful because of their ability to separate the variance associated with a G-factor from that associated with the S-factors. More often than not, body image scholars will want to know whether a general factor is present in their data and, if so, what content characterises it (see Bornovalova et al., 2020). Consider the example of the Drive for Muscularity Scale (DMS; McCreary et al., 2004), which is conceptualised as consisting of factors assessing muscularity-oriented attitudes and behaviours, respectively. If all DMS indicators load similarly and strongly onto a G-factor, then this would support the notion that drive for muscularity shares a common core (e.g., Simone et al., 2021). However, if some indicators (say, attitudinal indicators) load more strongly onto the G-factor, then this might suggest that those indicators are more likely to explain the meaning of drive for muscularity as measured using the DMS. Importantly, when relying on bifactor models, the S-factors can be directly interpreted as the extent to which scores on a specific dimension deviate from scores on the global construct in a way that is untainted by multicollinearity and redundancy. In contrast, this disaggregation is not present in higher-order models, where what is unique to the first-order factors (relative to the higher-order one) is pushed into the disturbances of the first-order factors (Morin et al., 2020). This means that using the first- and second- order factors together in an analysis will result in conceptual redundancy as the content of the first-order factors overlaps with that of the second-order factor (Morin et al., 2020).

Increasingly, body image research suggests that bifactor models – and particularly bifactor-ESEM models – offer an improved representation of the data relative to alternative models (for a review, see Gegenfurtner, 2022), including instruments such as the IES-2 (Anastasiades et al., 2022; Swami, Maïano, Furnham et al., 2022; Swami, Maïano, Todd et al., 2021), the Acceptance of Cosmetic Surgery Scale (Lazarescu et al., 2023), the Body Concealment Scale for Scleroderma (Jewett et al., 2015), and the Body Checking Questionnaire and the Body Checking Cognitions Scale (Maïano et al., 2021). However, there are also cases where a bifactor model may not make conceptual sense. For instance, when we consider the BASES, which posits discrete body- and appearance-related emotions, a G-factor would not be plausible (Swami, Maïano, & Morin, 2022). In other words, bifactor representations should ideally be supported by theory or at least empirical logic supporting the idea that a global construct might underpin responses to various dimensions covered in a measure (Decker, 2021; Morin et al., 2020). To date, however, the use of bifactor-ESEM models to understand multidimensional body image constructs remains relatively limited.

3. When Should ESEM and Bifactor-ESEM Be Used?

ESEM and bifactor-ESEM can help scholars better understand the structure of body image instruments. There are several instances where ESEM and bifactor-ESEM may be particularly useful. Most obviously, these methods lend themselves well to studies reporting on the development of novel instruments for which a multidimensional factor structure is hypothesised, on test adaptation studies where the original development study has proposed a multidimensional factor structure, or on studies seeking to re-assess or refine the structure of an existing instrument following reports of inconsistent results. Figure 2 presents a decision tree that researchers may find useful in determining when CFA, ESEM, bifactor-CFA, and bifactor-ESEM should be used. Table 1 provides a summary of each of these models.

When no clear *a priori* structure exists (i.e., empirically-derived new instruments), when previous research has supported a variety of alternative solutions, or when an existing instrument is being deployed in a new linguistic context, one could rely on the traditional approach where an initial EFA is followed-up by a sequential strategy (described in more detail below) to compare alternative models based on the EFA-structure identified in the first step (for examples of this approach, see Anastasiades et al., 2022; Lazarescu et al., 2022; Swami, Maïano, Todd et al., 2021; Swami, Maïano, Wong et al., 2021). In contrast, when a clear *a priori* multidimensional factor structure can be specified, or has been identified previously, one should rely on a sequential strategy testing alternative CFA, ESEM, bifactor-CFA, and bifactor-ESEM models. When more than one sample is available, then the second sample should be used to cross-validate the structure retained in the first sample (for examples of this approach, see Garrido et al., 2020; Maïano et al., 2021; Winkens et al., 2018). This sequential comparison should incorporate ESEM only when the factors can be seen as conceptually related and should incorporate bifactor models only when they can be seen as presenting a global/specific structure (Morin et al., 2020).

The sequential strategy mentioned above is described more fully in Morin (2023) and Morin et al. (2020). Examples of their application in the body image literature can be found in Swami, Maïano, Furnham et al. (2022) and Swami, Maïano, and Morin (2022). In brief, this strategy involves an initial comparison of standard CFA and ESEM models for conceptually related constructs. Model fit (see Section 5.1) and indicators of measurement quality (e.g., standardised factor loadings, item uniqueness, levels of tolerance for cross-loadings) should be used to determine whether CFA, ESEM, or both models should be retained. If both models present an adequate level of fit to the data, then the researcher proceeds by comparing their parameter estimates. In this situation, the ESEM representation is supported when: (a) model fit is improved relative to CFA; (b) factor correlations are reduced in ESEM relative to CFA; (c) the ESEM factors are defined as well as their CFA counterparts (i.e., by similarly strong main factor loadings; most of them should be > .40 and ideally > .50), and; (d) cross-loadings do not interfere with the interpretation of the solution (in which case one could decide to re-assess the relevance of all items or factors). For criterion (d), cross-loadings can be seen as interfering with the interpretation of the factors when they are higher than, or similar to, the main loading in a way that cannot be explained by theory or logic.

In each of these cases, there are no "golden rules" to be followed, so we recommend that researchers use their judgement to determine whether distinct patterns of results are observed between the ESEM and CFA models, explain their decision-making process, and comprehensively report (even if only in Supplementary Materials) all results used in their decision-making (i.e., model fit of all models and parameters estimates for all models supported by model fit indices). For example, when comparing factor correlations across ESEM and CFA models, researchers should ask whether the former provides a clearer differentiation between factors compared to the CFA model (i.e., whether there is a unique distinction of factors in the ESEM model), report their conclusion, and make these correlations available to readers. Given that ESEM tends to provide a better representation of the true factor correlations when cross-loadings are present in the population model, lower (by any magnitude) factor correlations in ESEM compared to CFA can be taken as evidence favouring the former. Although the model with the smallest factor correlations is usually preferred, decisions should be based on a holistic evaluation of the other considerations mentioned above.

Once this is done, the best solution (CFA or ESEM) can then be compared with its bifactor counterpart when one can assume that the constructs follow a global/specific structure. In this comparison, the bifactor model should be preferred when: (a) the G-factor and a subset of S-factors are well-defined by their *a priori* factor loadings (minimally higher than .30, but ideally higher than .50 on at least one of the G- or S-factors); (b) when model fit is improved relative to the initial CFA or ESEM model, and; (c) when cross-loadings are reduced (by any magnitude) relative to the ESEM solution or at least remain non-problematic. Again, researchers should use their best judgement when making these comparisons across models and avoid relying on “golden rules”. That is, researchers should closely inspect all models that are tested holistically and make decisions to retain a final model based on the context of all considerations described above.

4. When Should ESEM and Bifactor-ESEM *Not* Be Used?

One might also flip the question posed in the previous section and ask: when should ESEM and bifactor-ESEM *not* be used? There are some situations where these approaches are unhelpful or inappropriate. For instance, the Sociocultural Attitudes Toward Appearance Questionnaire-4-Revised (SATAQ-4R; Schaefer et al., 2017) postulates separate factors assessing internalisation of appearance ideals (thin/low body fat, muscular, general attractiveness) and pressure to attain appearance ideals (media, peers, and significant others). Both theory (Thompson et al., 1999) and empirical evidence (e.g., Schaefer et al., 2017; Stefanile et al., 2019) support the conceptualisation of these factors as unidimensional and a global construct as conceptually meaningless. Even were a SATAQ-4-R G-factor identified, it is not clear that such a global factor would offer improved conceptual understanding or meaning. In this case, therefore, application of an ESEM or bifactor-ESEM approach would not be appropriate. Ultimately, the decision of whether or not to rely on an ESEM or bifactor-ESEM approach should be based on existing theory and data, and consideration of the conceptual meaning of bifactor modeling (Morin et al., 2016, 2020).

ESEM and bifactor-ESEM should also not be used when the constructs under assessment are not conceptually related. This is unlikely to be the case for most body image instruments. ESEM and bifactor-ESEM are also not recommended for constructs assessed from different instruments (unless a particularly strong case can be made to support that modeling decision) and should never be used among factors located at different stages of the theoretical causal link under investigation (i.e., predictors, mediators, moderators, outcomes) or measured at different time points (Morin, 2023; Morin et al., 2020). Indeed, having the items from an outcome contribute to the definition of its predictors would create a very problematic feedback loop in the model. However, when one relies on multiple conceptually related or hierarchically ordered factors for different measures, from measures located at different stages of the causal process, or from measures taken at different time points, one could use Set-ESEM, or Set-Bifactor-ESEM (Marsh et al., 2020).

In Set-ESEM or Set-Bifactor-ESEM, items from conceptually related/hierarchically ordered factors located at the same causal stage/time-points are allowed to cross-load with one another (forming one “Set”), while another Set of items are also allowed cross-load with one another but not with those from the first Set. For example, if body image concerns (e.g., appearance orientation, appearance evaluation, body satisfaction) as measured by the MBSRQ–AS and symptoms of disordered eating (e.g., drive for thinness, body dissatisfaction, as measured using the Eating Disorder Inventory-3 or EDI-3) are estimated within Set-ESEM, then both Sets of factors would be modeled simultaneously. Here, the first-order latent factors would be permitted to covary, and cross-loadings between the MBSRQ-AS factors and cross-loadings between the EDI-3 factors, respectively, would be allowed. However, in contrast to a typical ESEM model, items from the MBSRQ–AS would not be allowed to cross-load on to the EDI-3 factors and *vice versa*. While we are not aware of any current application of Set-ESEM to body image research, Yukhymenko and Gilbert (2021) provide a useful application of both ESEM and Set-ESEM in the context of scale construction in a related field.

5. How Should ESEM and Bifactor-ESEM Be Used?

5.1. Estimation and Model Fit

It is currently only possible to fully estimate ESEM and bifactor-ESEM analyses in Mplus (Muthén & Muthén, 2022), although a partial implementation is possible in *R* (see Geiser, 2023; Prokofieva et al., 2023). In Mplus, ESEM and bifactor-ESEM (as well as any other models) should be estimated using the Maximum Likelihood Robust (MLR) estimator for models with continuous indicators (to avoid the need to test for normality, as this estimator is robust to non-normality), or the weighted least square estimator using a diagonal weight matrix (WLSMV) for models with ordinal indicators, asymmetric response thresholds, and/or involving four or fewer response categories (e.g., Finney & DiStefano, 2013; Morin, 2023).

ESEM and bifactor-ESEM models, like any other model, can be assessed using traditional fit indices (Marsh et al., 2014), namely the comparative fit index (CFI; values ≥ .95 indicative of excellent fit and ≥ .90 indicative of acceptable fit), the Tucker-Lewis Index (TLI; values ≥ .95 indicative of excellent fit and ≥ .90 indicative of acceptable fit), and the root mean square of error approximation (RMSEA; values ≤ .06 indicative of excellent fit and ≤ .08 indicative of acceptable fit; Hu & Bentler, 1999; Marsh et al., 2005; West et al., 2023). When comparing models (e.g., in tests of measurement invariance), decreases in CFI/TLI of ≤ .01 and increases in RMSEA of ≤ .015 provide evidence that the more parsimonious model should be retained (Chen, 2007; Cheung & Rensvold, 2002). Although early statistical evidence suggested that similar interpretation guidelines seem to apply to model fit when relying on WLSMV estimation (Yu, 2002), more recent statistical research suggests that more lenient guidelines may be needed with WLSMV (Shi et al., 2018; Xia & Yang, 2019).

5.2. Rotation

In ESEM and bifactor-ESEM, the choice of rotation method is crucial as it determines the size and direction of the estimated factor correlations and cross-loadings (Marsh et al., 2014; Morin et al., 2020). The two most popular rotation methods in ESEM and bifactor-ESEM are the geomin (oblique) rotation and the target rotation, which should both be oblique for ESEM (allowing factors to be correlated and orthogonal for bifactor-ESEM, as factors should not be correlated to achieve a proper variance decomposition; Morin, 2023; Morin et al., 2020). The geomin rotation is a mechanical procedure (i.e., it does not incorporate input from the researcher about the expected factor structure) with an epsilon value that researchers can change to reduce the size of cross-loadings or the size of factor correlations. Morin et al. (2013; see also Marsh et al., 2009) recommended using an epsilon value of .5 to maximally reduce factor correlations, which in turn helps to obtain more accurate estimates of relations between constructs. Asparouhov and Muthén (2009) concluded that a geomin rotation performs well for relatively simple models.

Target rotation, conversely, is a non-mechanical procedure that is guided by the researchers' theoretical assumptions. When using a target rotation, researchers are able to specify the main indicators for each construct, allowing these loadings to be freely estimated, but "targeting" all cross-loadings to be as close to zero as possible while allowing them to be freely estimated. When based on a target rotation procedure, ESEM can be considered a fundamentally confirmatory method (Marsh et al., 2014; Morin et al., 2020). Informed targets can be used to specify a precise solution *a priori* and the available evidence supports the value of identifying informed targets when they are consistent with the true population model but problematic when they are not (e.g., Guo et al., 2019; Morin et al., 2020). When this is done, researchers should be able to document and justify the relevance of their identified target. Otherwise, Morin (2023) recommended using this basic target approach.

5.3. Bifactor Modeling

In bifactor models, indicators load on to more than one factor, meaning that variance explanation is split between two latent variables. In other words, each observed variable is an indicator of both the G-factor and an S-factor (i.e., each observed variable comes with at least two main estimates of factor loadings, in addition to its cross-loadings, the first capturing its association with the G-factor and the second with its S-factor). The G-factor can be interpreted as reflecting the variance shared among all indicators (i.e., all items define the G-factor). Importantly, this is not the case for higher-order modeling, where the mediating role for the first-order factors means that the second-order factor represents a distilled estimate of an overall score rather than a more direct estimate (Markson, 2019). However, the S-factors indicate the variance shared among a subset of indicators forming a subscale left unexplained by the G-factor. They reflect the specificity, or unique nature, of each subscale net of what it shares with the other subscales. Contrary to first-order factors estimated in a higher-order model, which reflect the subscale-relevant variance in its entirety (including that explained by the first-order factor and that explained by the second-order factor), the S-factors reflect the extent to which participants' scores on each dimension deviate from their scores across all dimensions (i.e., on the G-factor).

Because bifactor models divide the reliable (i.e., true score) item variance into two components (the G- and S-factors), factor loadings and reliability estimates tend to be smaller than those observed in higher-order models (Morin et al., 2020). As such, it has been suggested that more lenient guidelines should be applied when considering the composite reliability of S-factors from bifactor models (approaching ≥ .50, rather than .70). Morin et al. (2020) recommended that well-defined G- and S-factors should ideally be accompanied by large enough loadings (minimally > .30, but ideally > .50 on at least one of the G- or S-factors) to support their interpretation as key indicators. In fact, bifactor solutions often reveal items that are predominantly associated with only one of these two sets of factors, but such findings do not indicate problems with these items. Instead, they demonstrate they these items represent stronger indicators of one layer of measurement (Morin et al., 2020). It should also be noted that, although support for a bifactor solution requires that at least some S-factor retain some specificity, bifactor solutions are known to be robust to "vanishing" S-factors, which suggest that the items associated with these subscales mainly serve to define the G-factor and retain limited specificity once this G-factor has been taken into account (Morin et al., 2020).

5.4. Construct-Irrelevant Sources of Psychometric Multidimensionality

Thus far, we have considered instances of construct-relevant psychometric multidimensionality (i.e., when the multidimensional structure refers to conceptually important characteristics of the model). However, psychometric multidimensionality is not always a function of the constructs being measured; that is, it may sometimes be construct-irrelevant. One of the most common forms of construct-irrelevant psychometric multidimensionality is the inclusion of negatively and positively worded items in the same instrument. For instance, the Consider subscale of the Acceptance of Cosmetic Surgery Scale includes four positively worded items (e.g., "I have sometimes thought about having cosmetic surgery") and one negatively worded item ("I would never have any kind of plastic surgery"). While the inclusion of negatively and positively worded items in the same instrument is often justified to minimise respondent acquiescence, affirmation, or agreement biases (Weijters et al., 2013), they also often create methodological artefacts (i.e., items with the same valence share commonalities unrelated to the constructs being measured; Marsh et al., 2010) that jeopardise the psychometric properties of an instrument (Suárez-Alvarez et al., 2018). Parallel wording – where items share a similar stem or wording (e.g., "In general, I have felt proud that I am more attractive than others" and "In general, I have felt proud of the effort I place on maintaining my appearance" from the BASES) – could also result in a similar methodological artefact (Marsh, Abduljabbar et al., 2013). The same would also apply when one asks different informants to complete the same measure in relation to one target individual (i.e., a child, their parents, and their teachers all rating the same behaviours).

These sources of construct-irrelevant psychometric multidimensionality should be controlled so that they are not absorbed in other parts of the model. The two main methods to achieve this are: (a) the addition of correlated uniqueness among the relevant indicators, or (b) the addition of an orthogonal method factor reflecting the variance shared between relevant indicators. The latter has the advantage of resulting in an explicit and interpretable estimate of construct-irrelevant sources of variance, but also adds complexity to the resultant model and can create convergence problems. Irrespective of which method is used to control for construct-irrelevant psychometric multidimensionality, Morin (2023) recommended that the control is applied in an *a priori* manner (see also Schweizer, 2012). Additionally, when multiple sources of construct-irrelevant multidimensionality (e.g., negatively worded items and parallel wording) need to be controlled, it may be difficult to incorporate method factors for all sources. In these cases, Morin (2023) recommended using method factors for negatively worded items and correlated uniqueness for parallel wording. More complex multitrait-multimethod models are also available to account for more complex forms of construct-irrelevant psychometric multidimensionality (such as in the multiple-raters example), and are discussed more extensively by Eid et al. (2023) and Morin (2023).

5.5. Measurement Invariance and Differential Item Functioning

A critical issue in the assessment of factor validity is whether an instrument measures the same construct(s) across individuals with a different demographic background (e.g., gender, racialised status, age), coming from different cultures or samples, or across time-points (e.g., longitudinal assessments, test-retest). If an instrument and its measurement properties behave differently in different groups of respondents or over time, then measurement biases could occur, leading to biased results (Guenole & Brown, 2014). Conversely, if an instrument operates in the same way across groups or over time, then it becomes possible to generalise findings, compare latent scores across groups, and examine differential relations between constructs across groups (Boer et al., 2018; Chen, 2008). These assumptions can be verified using tests of measurement invariance (Millsap, 2011).

Measurement invariance should be tested sequentially (Millsap, 2011; Morin, 2023; Widaman & Olivera-Aguilar, 2023). This sequential process begins with an examination of *configural invariance* (i.e., the same measurement model), followed by tests of *weak invariance* (i.e., equality of factor loadings), *strong invariance* (i.e., equality of item intercepts for continuous indicators or of response thresholds for ordinal indicators), *strict invariance* (i.e., equality of item uniqueness), *latent variance-covariance invariance* (i.e., equivalence of the factor variances and covariances), and *latent mean invariance* (i.e., equivalence of the factor means). The first four steps determine the presence of measurement biases related to the nature (configural), structure (weak), and the relative strength of item ratings for people with similar scores on the constructs (strong) or reliability (strict), whereas the final two steps assess the presence of group-based differences at the level of variance, covariances, and means (Marsh et al., 2009). Configural and weak invariance are a prerequisite to any comparison, strong invariance is a prerequisite to tests of latent mean differences, and strict invariance is a prerequisite of comparisons involving observed scores (Marsh et al., 2009). An online tool was recently developed by De Beer and Morin (2022) to help users generate Mplus syntax and results tables for tests of measurement invariance using continuous or ordinal items.

There may be some situations where this taxonomy of measurement invariance cannot be realistically applied, such as when sample sizes are too small, when testing for measurement biases occurring as a function of continuous variables (e.g., age, body mass index), or when testing for measurement biases occurring as a joint function of multiple variables (and sometimes when authors want to assess the presence of interactions among predictors). Because of their complexity, these issues tend to be more frequent with ESEM and bifactor-ESEM than with CFA and bifactor-CFA. In these situations, scholars could instead conduct tests of differential item functioning (DIF) using multiple indicators multiple causes (MIMIC) models (Morin et al., 2013). MIMIC models involve the addition of one (or more) observed predictor(s) to a previously retained measurement model. Tests of DIF correspond to tests of strong invariance through the verification of whether the effect of the predictor on the item responses can be captured entirely by its effect on the factors, or whether it also influences item response beyond its impact on the factors. However, one drawback of the MIMIC approach is that it assumes the invariance of factor loadings but does not easily allow for a test of this assumption. So, whenever possible – at least when relying on categorical grouping variables – the complete taxonomy of measurement invariance tests should be implemented. However, when sample size is small, when authors want to jointly test for the joint effects of multiple predictors (i.e., assessing their unique effects beyond what they share with the others), when predictors are continuous (continuous variables should never be arbitrarily categorised), or when they want to assess interactions among predictors, then the MIMIC approach should be favoured.

Morin et al. (2013) recommended testing for DIF using three alternative models, namely a null effects model (which assumes that the predictors have no effect on the factors and on the item responses), a saturated model (involving the free estimation of all paths linking the predictors to item responses while keeping the effects of the predictors on the factors constrained to 0), and a factors-only model (involving the free estimation of all paths linking the predictors to the factors while keeping the effects of the predictors on the item responses constrained to 0). Comparing the null effects model and the saturated model tests whether the predictors influence item responses. When this is the case, comparing the saturated model and the factors-only model tests whether this influence can (if both models have a similar fit) or not (if the saturated model fits better) be fully explained in terms of their association with the factors. When the saturated model fits better than the factors-only model (i.e., ΔCFIs/TLIs ≥ .01 and ΔRMSEAs ≥ .015), then there is evidence of monotonic DIF (Morin, 2023; Morin et al., 2013)[1]. Marsh et al. (2006, 2009, 2013) also proposed a hybrid approach in which multigroup tests of measurement invariance (e.g., gender as discrete categories) are combined with MIMIC test of DIF (e.g., age as a continuous variable). This approach can also be extended to test for the generalisation of the DIF conclusions as a function of the grouping variable.

5.6. ESEM- and Bifactor-ESEM-Within-CFA

One current limitation of ESEM and bifactor-ESEM is that it is not possible to test for partial invariance of factor loadings/cross-loadings, latent variances/covariances, and latent means. Another limitation is that all factors forming a single Set have to be related in the same manner to all other variables. Likewise, it is not possible to directly implement a higher-order structure on ESEM factors, and joint applications of ESEM with multilevel or mixture models are limited. One work-around some of these limitations is the ESEM-within-CFA approach (Marsh, Nagengast et al., 2013; Morin et al., 2013). ESEM-within-CFA imposes a number of restrictions similar to that typically imposed by the rotation procedure by converting an ESEM solution to a CFA approximation. More precisely, in ESEM-within-CFA, all factor variances are set to 1 and one referent indicator is selected per factor. For this referent indicator, all cross-loadings are fixed to their exact ESEM value. For other parameters, the values from the final ESEM solution are used as start values (using * in Mplus). Morin (2023) recommended selecting referent indicators with a strong main loading and weak cross-loadings. The resulting solution will then have the same degrees-of-freedom and, within rounding error, the same chi-square, goodness of fit statistics, and parameter estimates as the original solution, and can be used as the starting point for the remaining analyses. There are two important caveats to this strategy. First, when the factors themselves are endogenous (i.e., predicted by something), then the main factor loading of the reference indicators should also be fixed to their ESEM values, and factor variances should be given a start value of 1 (*1) rather than being fixed to 1 (@1) (Morin & Asparouhov, 2018). Second, with bifactor-ESEM models, the factor covariances have to be fixed to 0 (rather than simply rotated to 0) to preserve the orthogonality of the factors, which results in a bifactor-ESEM-within-CFA model that will differ in terms of degrees-of-freedom from the original model by a number corresponding to the number of correlations fixed to 0 (Morin, 2023).

5.7. A Note on Power and Sample Size

Researchers may have concerns about adequate *power*, that is, the ability to detect effects present in a population as being statistically significant in their sample (Feng & Hancock, 2023). Power analyses can be used to determine sample size requirements *a priori* (e.g., when designing a study) or *post hoc* (i.e., to assess the power linked to specific aspects of the analyses once data has already been collected). Although issues of power can sometimes be important (e.g., when planning a data collection process to ensure recruitment of a large enough sample), Morin (2023) argued that concerns over sample size may not be especially pressing when it comes to ESEM and bifactor-ESEM. This is because power analyses depend on many factors that are difficult to know *a priori* (e.g., effect size, the number of indicators per factor, the number of factors, the strength of the factor loadings, the quantity and type of missing data), which make it difficult to propose sample size guidelines, and because these analyses are typically robust to very small sizes (e.g., De Winter et al., 2009). Additionally, in ESEM and bifactor-ESEM measurement models, the interpretation of the results does not rely on statistical significance but on the relative size of loadings, cross-loadings, and factor correlations. As such, power is not an issue for comparisons of measurement models using the sequential strategy outlined above and would normally only become an issue when moving to more complex predictive models.

In practice, researchers faced with very small sample sizes are much more likely to face a different problem in analyses, that of non-convergence. As Morin (2023) has noted, there is always a limit of the type of model that can be estimated using any specific sample. When one goes beyond this limit, analyses will stop converging and no attempt to rectify this will achieve convergence. Because convergence problems typically arise well before power becomes an issue, results based on converging solutions can be taken as a safeguard against a lack of power. Our recommendation, therefore, is for researchers to recruit as large a sample size as is feasible (balancing issues such as time, cost, effort) and to use their best judgement to determine whether an adequate sample size has been achieved. Then, when analysing their data, if they face convergence issues that are impossible to resolve, they should think about ways to simplify their model (removing variables or subscales, testing different parts of the model separately, or even using factor scores for some of their constructs). Where necessary, traditional approaches for sample size estimation used for Structural Equal Modeling (e.g., the non-centrality parameter, a model's potential to obtain an acceptable RMSEA value, or Monte Carlo simulations; Muthén & Muthén, 2002; Wolf et al., 2013) could be used.

5.8. A Note on Scoring

We are often asked to discuss the implications of these types of measurement models for scoring decisions. More precisely, many researchers, as well as practitioners working with surveys for the purposes of assessment, monitoring progress, and/or assessing success, rely on manifest scores. Manifest scores represent the sum, or the average, of the responses provided by participants on the various items forming a single subscale. Such manifest scores are flawed for at least two different reasons. To understand their limitation, let us first consider a simple instrument, involving a single unidimensional four-item scale (each rated on a 1 to 4 response scale). A participant selecting the response choice "2" on Item #1, "4" on Item #2, "3" on Item #3, and "2" on Item #4 would thus obtain a manifest average score of 2.75 or a manifest sum score of 11. The first limitation of this procedure is that all items are assumed to have the same weight, or to contribute equivalently to the definition of the constructs. Decades of psychometric research have demonstrated that this is rarely the case, and that some items provide a better reflection of constructs than others. When relying on factor analyses, the factor loadings linking each item to their factor reflect how well each of them represents the factor.

So, in theory, to obtain more accurate scores, one could use the unstandardised CFA factor loadings[2] associated with each item to weight them before calculating the manifest score. If these loadings were 1.25, 0.85, 1.51, and 0.91, then the resulting average weighted manifest score would be of 3.06 and the sum weighed score would be 12.25. Obviously, to use such a weighted scoring procedure, one would need to rely on unstandardised factor loadings obtained in a representative (normative) sample. However, even these weighted scores would be limited, as they would be based on all of the information included in the item, when we know that each item does include a part of information unrelated to the construct of interest, including random measurement error. In factor analyses, the latent factor is based on a weighted combination of the part of the items that is connected to the factor and excludes this unique information (that is absorbed into the item uniquenesses), resulting in perfect reliability. When relying on instruments on which responses match a CFA structure, these two types of biases are routinely assumed to be minimal, at least in applied contexts, while they do highlight the value of latent variable models to achieve accurate research results untainted by unreliability. Moreover, these biases will be substantially reduced when responses to an instrument are best captured by large factor loadings (i.e., more reliable) similar in size (limiting the need for weights) across items. In summary, even in a very basic CFA model, average or sum scores are not ideal, although their use remain quite frequent.

When we move to more complex models including a global/specific structure (bifactor-CFA, bifactor-ESEM), models including cross-loadings (EFA, ESEM, and bifactor-ESEM), and even models including correlated uniquenesses or method factors, manifest scoring procedures become even more problematic. For models involving cross-loadings, we could theoretically use the unstandardised loadings and cross-loadings in a similar manner to obtained weighted manifest sum scores based on all items (manifest average scores would not be appropriate, as the average would be based on a majority of cross-loadings, whereas their sum ensures that cross-loadings have less impact than main loadings). However, the unreliability issue would become even more problematic, as weighing secondary items as a function of their cross-loadings would still rely on the whole information included in this item, rather than on the much smaller part of these items explained by the model. As these items are more numerous than the main indicators, they should have a minimal contribution that is likely to be at least doubled by the lack of control for unreliability. Furthermore, with bifactor models, there is simply no way to achieve the global/specific variance separation that should be a prerequisite to achieving manifest scores.

From a research perspective, the recommendation is quite clear: all researchers, particularly those relying on multidimensional measures, should avoid relying on manifest scoring and base their research on latent variable models (i.e., the factors – derived from factor analysis – that account for variation and covariation in a set of items). Latent variable models are not only controlled for unreliability, they also provide empirically optimal weights and variance separation. Fortunately, these models are reasonably robust to smaller sample sizes (e.g., De Winter et al., 2009) and can be built in sequence. More precisely, even with smaller sample sizes, it is often possible to estimate preliminary measurement models on a subset of constructs. Factor scores can then be saved from these models and used on primary analyses instead of manifest scores. Factor scores do provide a partial, albeit imperfect, correction for unreliability (e.g., Skrondal & Laake, 2001), but have the clear advantage of preserving the measurement structure (and variance decomposition) of the models from which they were taken (Morin, 2023; Morin et al., 2020).

From a practical perspective, things are more complex, as the proper scoring of multidimensional instruments would ideally require the development of computerised algorithms, and those would require normative data to avoid capitalising on the unique nature of specific samples. In the meantime, as noted by Perreira et al. (2018), the Mplus statistical package could be used to generate factor scores based on the exact parameter estimates obtained in an optimal model (fixing start values using the @ function). Scores from new participants will simply need to be added at the end of a larger dataset. Otherwise, scoring procedures could be conducted so as to ignore cross-loadings, although this should be done while acknowledging that the distinctiveness of the factors will be substantially reduced by a magnitude similar to the difference in the size of the CFA versus ESEM factor correlations. With bifactor models, the G-factor could theoretically be calculated as the (weighted or not) sum or average of all items used to define it. Although the same can be done with S-factors, one would need to remember that these should not be interpreted in and of themselves, but in terms of deviations from the G-factor. For instance, for someone with a score of “5” on the G-factor and a score of “6” on an S-factor, the S-factor score would need to be interpreted as a positive deviation (higher score) of one unit on the S-factor. In any case, scoring is clearly an area where further developments will be needed.

6. An Applied Example

Despite the many benefits of ESEM and bifactor-ESEM, these approaches remain infrequently used in body image research. There may be a number of reasons for this, including the perception that these methods are relatively complex analytically and a lack of understanding and training among researchers about how to use these methods and how to score measures and interpret findings. Additionally, it is currently only possible to estimate ESEM using Mplus, which is a relatively expensive program that requires working with syntax (rather than drop-down menus), although the Mplus syntax remains language-based (rather than code-based). In the remainder of this paper, we provide a practical tutorial on how to estimate ESEM and bifactor-ESEM in Mplus. Specifically, we use the Acceptance of Cosmetic Surgery Scale (Henderson-King & Henderson-King, 2005) to provide an overview of ESEM and bifactor modeling, guidelines for estimating and interpreting these models, and our Mplus syntax in Supplementary Materials.

6.1. The Acceptance of Cosmetic Surgery Scale

The Acceptance of Cosmetic Surgery Scale (ACSS; Henderson-King & Henderson-King, 2005) is a 15-item instrument originally designed to assess multidimensional attitudes toward cosmetic surgery. Based on multiple principal components analyses (commonly employed at the time for scale validation) conducted using adult responses obtained in the United States, Henderson-King and Henderson-King (2005) originally extracted a 3-component model assessing Intrapersonal (self-oriented benefits of cosmetic surgery; 7 items), Social (social motivations for cosmetic surgery; 5 items), and Consider (likelihood of obtaining cosmetic surgery; 5 items) components. Two anomalous items from the Intrapersonal component were dropped and a third principal component analysis realised on the same dataset supported extraction of a 15-item, 3-component model of ACSS scores. Additionally, although higher-order functioning was not directly assessed, Henderson-King and Henderson-King (2005) indicated that it was permissible to compute an overall (higher-order) ACSS score comprising all 15 items, which in their study had adequate scale score reliability (Cronbach’s α = .91 to .93).

However, beyond this original study, further research examining the factor validity of the ACSS is equivocal (for a recent review, see Lazarescu et al., 2023). Thus, scholars using EFA have variously extracted a unidimensional model including all 15 items (Swami et al., 2012), various permutations of 2-factors models (Swami, 2010; Wu et al., 2020), or the original 3-factor model (Swami et al., 2011). For models with two and three factors, cross-loadings were common, suggestive of at least some multidimensionality. Other studies have directly relied on CFA (Jovic et al., 2017; Meskó & Lang, 2021) and, although these studies have found that the 3-factor model of ACSS scores has adequate fit to the data, this was typically only achieved following the *post hoc* addition of various correlated uniquenesses. Lazarescu et al. (2023) recently suggested that the difficulty in replicating the 3-factor structure of the ACSS may be due to the failure to account for cross-loadings.

In examining the psychometric properties of a Romanian adaptation of the ACSS, Lazarescu et al. (2023) relied on a 2-step strategy consisting of an initial EFA followed by a sequential strategy to compare alternative models (CFA, ESEM, bifactor-CFA, and bifactor-ESEM). EFA results supported a 3-factor solution mirroring the original factor structure reported by Henderson-King and Henderson-King (2005), revealing small cross-loadings. Comparison of the alternative models indicated that all four variants had acceptable fit, but that the bifactor-ESEM model had a significantly improved fit relative to the other models. Factor correlations were relatively high in CFA, but substantially reduced in ESEM. The bifactor-ESEM solution revealed a well-defined G-factor and reasonably well-defined S-factors. This bifactor-ESEM model was also invariant across gender and showed adequate patterns of convergent validity (Lazarescu et al., 2023).

6.2. The Data Used in the Present Illustration

We rely on the complete dataset used by Lazarescu et al. (2023) to demonstrate the sequential strategy advocated by Morin (2023) and tests of measurement invariance. Briefly, this dataset includes responses from 1,275 Romanian participants (889 women, 385 men) ranging in age from 18 to 73 years (M = 24.60, SD = 9.46). All participants completed the Romanian version of the 15-item ACSS, which is the focus of the present analyses. The dataset also contained responses to Romanian versions of the Body Appreciation Scale-2 (Tylka & Wood-Barcalow, 2015), the Body Image Screening Questionnaire for Eating Disorder Early Detection (BISQ; Jenaro et al., 2011), and the Rosenberg Self-Esteem Scale (RSES; Rosenberg, 1965). Unlike Lazarescu et al. (2023), who conducted a sequential assessment using half of their total sample, we rely on the total sample for illustrative purposes. Further details on this dataset are available in Lazarescu et al. (2023).

6.3. Analyses

6.3.1. Model estimation. All analyses were performed using Mplus 8.10 (Muthén & Muthén, 2022) and the MLR estimator. There were no missing responses on ACSS items in the dataset. One ACSS item (Item #10) was reverse-coded so that all reported loadings were positive. The 3-factor and bifactor solutions of the ACSS were examined using CFA and ESEM[3] (see pp. T3-6 in the Supplementary Materials). As recommended in Section 5.2., oblique geomin (epsilon value of .5) and target rotations were used for ESEM solutions and orthogonal bifactor-geomin (epsilon value of .5) and orthogonal bifactor target rotations were used for bifactor-ESEM solutions. It is important to note that solutions based on the same items and including the same numbers of factors are mathematically equivalent in ESEM and bifactor-ESEM, which means that changes of rotation procedures always converge on models with an equivalent level of fit to the data (i.e., rotational indeterminacy; Morin et al., 2020). For this reason, we focus on results obtained with target rotation in the main body of this text, but still provide the syntax required to estimate their goemin counterparts in the Supplementary Materials.

6.3.2. Construct-irrelevant psychometric multidimensionality. Only one item (Item #10) is negatively worded in the ACSS, which also includes no parallel wording. Thus, for purposes of illustrating how to control for construct-irrelevant sources of psychometric multidimensionality (as discussed in Section 5.3), in addition to Item #10, we arbitrarily selected two additional items (Items #5 and 15) to showcase the incorporation of correlated uniqueness (CU) or of an orthogonal method factor (MF) to the model (see p. T8 in the Supplementary Materials).

6.3.3. Model fit and comparisons. As recommended in Section 3, parameter estimates (i.e., loadings, cross-loadings, correlations, composite reliability) from all solutions were carefully examined. Model fit and model comparisons were also examined using the fit indices (CFI, TLI, RMSEA) and interpretation guidelines described in Section 5.1.

6.3.4. ESEM- and bifactor-ESEM-within-CFA. ESEM- and bifactor-ESEM-within CFA solutions were respectively estimated based on the original ESEM and bifactor-ESEM solutions (see pp. T10-12 in the Supplementary Materials). Values of the parameters used to estimate the ESEM- and bifactor-ESEM-within CFA solution were obtained from the original ESEM and bifactor-ESEM solutions (by adding “SVALUES” in the “OUTPUT” section of the Mplus input file). These can be found in the Mplus output section labelled “CFA MODEL COMMAND WITH FINAL ROTATED ESTIMATES USED AS STARTING VALUES”. ESEM- and bifactor-ESEM-within CFA solutions were then estimated as recommended in Section 5.6.

6.3.5. Predictive model with bifactor-ESEM-within-CFA. For illustrative purposes, the bifactor-ESEM-within-CFA solution was used to estimate a model in which the scores on the ACSS latent factors (G- and S-factors) were used to predict scores on measures of body appreciation, symptoms of disordered eating, and self-esteem (see pp. T14-16 in the Supplementary Materials). Although the basic ESEM and bifactor-ESEM framework allow us to simultaneously use all factors from a single Set in predictions, our main objective was to examine the added-value of the S-factors relative to that of the G-factor in the prediction of body appreciation, symptoms of disordered eating, and self-esteem. As these tests involve using different predictions for the G- versus S-factors, we needed to rely on bifactor-ESEM-within-CFA to conduct these analyses. Two models were examined. In the first model, the paths from the S-factors to body appreciation, symptoms of disordered eating, and self-esteem were fixed at 0, whereas those from the G-factor were free. In the second model, all paths from the G- and S-factors of the ACSS to body appreciation, symptoms of disordered eating, and self-esteem were free.

6.3.6. Measurement invariance. Measurement invariance of the solution across gender was examined as recommended in Section 5.5. (i.e., configural, weak, strict, latent variance-covariance, and latent mean invariance; see pp. T17-24 in the Supplementary Materials). Similar analyses were conducted to test the invariance of the bifactor-ESEM solution across samples (see pp. T25-31 in the Supplementary Materials).

6.3.7. Differential Item Functioning. The presence of measurement bias in the ACSS was also examined through tests of DIF, as recommended in Section 5.5 (i.e., null effects model, saturated model, and factors-only model; see pp. T32-35 in the Supplementary Materials). More specifically, in the ESEM model, DIF was examined as a function of age and body mass index (BMI), whereas in the bifactor-ESEM model, DIF was examined as function of sample, gender, and sample x gender. To ease interpretations and facilitate estimation, age and BMI were standardised.

6.3.8. Hybrid MIMIC. As recommended in Section 5.5, hybrid MIMIC was used to examine the association between predictors (continuous and categorical) and the ACSS items responses and latent factors as a function of gender and the two split-half samples used in Lazarescu et al. (2023). In ESEM, predictors were age and BMI, whereas in bifactor-ESEM, predictors were age, gender, and BMI (see pp. T36-45 in the Supplementary Materials). To ease interpretations and facilitate estimation, age and BMI were standardised. These models were developed from the most invariant multiple-group model identified in the gender (ESEM) and sample (bifactor-ESEM) invariance models, to which the predictors were included. The first three models (null effects, saturated, and factors-only) were the same as those used in the DIF tests and were freely estimated across gender (ESEM) and samples (bifactor-ESEM). Then, the most appropriate model was retained and compared to an alternative model in which associations were constrained to be equal across gender (ESEM) and samples (bifactor-ESEM).

6.4. Results

6.4.1. Sequential comparisons. Table 2 presents the goodness-of-fit indices for all measurement models. The CFA (Model 1-1) and bifactor-CFA (Model 1-5) solutions both had an adequate level of fit to the data (CFI and TLI > .90 and RMSEA ≤ .08). The 3-factor ESEM solution (Model 1-2) had an excellent level of fit to the data and displayed a substantial improvement in model fit relative to the CFA solution (ΔCFI = +.043/+.044, ΔTLI = +.042/+.040, ΔRMSEA = -.024/-.022). Finally, the bifactor-ESEM solution (Model 1-6) also had an excellent level of fit to the data, and displayed a substantial improvement in model fit relative to the bifactor-CFA solution (ΔCFI = +.021, ΔTLI = +.020, ΔRMSEA = -.026), as well as a noteworthy increase in fit relative to the ESEM solution (ΔCFI = +.011, ΔTLI = +.013, ΔRMSEA = -.010). These results suggest that, based solely on model fit, the bifactor-ESEM solution seems to be the optimal solution for ACSS responses.

However, Morin (2023; also see Morin et al., 2020) noted that a careful examination of parameter estimates, composite reliability, and factor correlations was needed to support this conclusion. As such, we first compare the CFA and ESEM solutions, before contrasting the optimal model with its bifactor counterpart. The detailed parameter estimates from the CFA, bifactor-CFA, ESEM, and bifactor-ESEM solutions are respectively reported in Tables 3 to 6. In the CFA solution (see Table 3), factor loadings were reasonably high (|λ| = .653 to .905) and associated with adequate composite reliability coefficients (ω = .885 to .930, M_ω = .906). However, factor correlations remained high (M_r = .676). The ESEM solution (see Table 4) resulted in similarly well-defined (|λ| = .417-.906) and reliable factors (ω = .875 to .927, M_ω = .901), but also estimates of factor correlations that were slightly reduced relative to the CFA solution (M_r = .636), thus supporting the value of the ESEM solution.

Turning our attention to the bifactor-ESEM solution, this solution revealed a well-defined (|λ| = .521 to .851) and reliable (ω = .959) G-factor, as well as reasonably well-defined Intrapersonal (|λ| = .440 to .594, ω = .789) and Consider (|λ| = .377 to .539, ω = .809) S-factors. In contrast, the Social S-factor was slightly more weakly defined (|λ| = -.082 to .718), which seems to be primarily due to two items (Items #11 and 12) that essentially serve to define the G-factor, but retained an acceptable level of reliability (ω = .723). Overall, these sequential steps support the superiority of the bifactor-ESEM representation of the ACSS.

6.4.2. Construct-irrelevant psychometric multidimensionality. Adding correlated uniqueness or an orthogonal method factor among three items (#5, 10, and 15) in the retained ESEM (Models 1-3 and 1-4) and bifactor-ESEM (Models 1-7 and 1-8) solutions did not substantively change fit indices, consistent with the lack of utility of these controls in the present study. We note, however, that instruments truly including wording artefacts (reversed or parallel wording) need to incorporate such controls from the start to all of their models (Morin et al., 2020), as the decision to include or exclude them is not a matter of model fit, but anchored in the need to control for a true methodological artefact (better yet, instrument developers should ensure, as far as possible, that novel instruments do not include methodological artefacts).

6.4.3. ESEM-within-CFA, bifactor-ESEM-within-CFA, and predictive analyses. The final ESEM and bifactor-ESEM solutions were converted to their ESEM-within-CFA and bifactor-ESEM-within-CFA for illustrative purposes (see syntax provided in the Supplementary Materials). The bifactor-ESEM-within-CFA model was then used to test the predictive added-value of the S-factors relative to that of the G-factor. Both models had excellent levels of fit to the data: (a) G-factor only: $\chi^2(99)$ = 396.124, CFI = .976, TLI = .963, RMSEA = .049 (90% CI = .044, .054); (b) G- and S-factors: $\chi^2(90)$ = 274.512, CFI = .985, TLI = .975, RMSEA = .040 (90% CI = .035, .046). Furthermore, the results suggested that the S-factors had a meaningful contribution to prediction beyond that of the G-factor, as indicated by model fit improvement (i.e., ΔTLI = +.012). More precisely, as reported in Table 7, the G-factor, the Social S-factor, and the Consider S-factors all significantly and negatively predicted body appreciation and self-esteem, and positively predicted symptoms of disordered eating. The Intrapersonal S-factor also significantly and negatively predicted symptoms of disordered eating and positively predicted self-esteem.

6.4.4. Measurement invariance. As reported in Table 2, ESEM results (Models 2-1 to 2-7) supported the weak and strong invariance, but not the strict invariance, of this solution as function of gender. Examination of the freely estimated uniquenesses from the model of strong invariance and of the modification indices form the failed model of strict invariance suggested that the lack of strict invariance seemed limited to two items (Items #1 and 15). Allowing the uniquenesses to be freed across gender resulted in a satisfactory model of partial strict invariance. The invariance of the latent variances/covariances was also supported, but not that of the latent means. This last result revealed that compared to men, women presented significantly higher latent means on the Intrapersonal (+.52 *SD*, p < .001) and Consider (+.82 *SD*, p < .001) factors. In contrast, bifactor-ESEM results (Models 3.1 to 3.6) supported the full measurement invariance (weak, strong, strict, variance and covariances and latent means) of this solution across samples.

6.4.5. Differential Item Functioning. As reported in Table 2, the ESEM results revealed that the saturated (Model 4-2) and factors-only (Model 4-3) models did not result in a substantial improvement in model fit relative to the null effects model (Model 4-1). These results indicate a lack of DIF, as well as a lack of association between age or BMI and scores on the ACSS latent factors. In contrast, the bifactor-ESEM results revealed a substantial improvement in model fit in the saturated (Model 5-2) and factors-only models (Model 5-3) relative to the null effects model (Model 5-1). This suggests an association between at least some of the predictors (sample, gender, and their interaction) and ACSS responses. However, the factors-only model resulted in a similar level of fit to the saturated model (ΔCFI = -.005, ΔTLI = +.006, ΔRMSEA = -.004), supporting a lack of DIF and effects limited to the factors themselves. More specifically, these results showed that gender significantly and positively predicted scores on the Consider S-factor (b = .753, SE = .274, p = .006, β = .327), suggesting that women presented higher values on this S-factor relative to men.

6.4.6. Hybrid MIMIC. As shown in Table 2, the estimation of the Hybrid MIMIC models started from the most invariant ESEM (Gender Model 2-6: latent variances-covariances invariance) and bifactor-ESEM (Sample Model 3-6: latent means invariance) solutions. The ESEM results revealed that both the saturated (Model 6-2) and factors-only (Model 6-3) models did not result in a substantial improvement in fit relative to the null effects model (Model 6-1). These results indicate a lack of DIF, as well as a lack of association between age, BMI, and scores on the ACSS latent factors as a function of gender and sample. Although we do test the equivalence (and found support for it) of the factors-only predictions as a function of gender groups for illustrative purposes, the initial selection of the null effects models makes this last test unnecessary. In contrast, the bifactor-ESEM results revealed a substantial improvement in model fit for the saturated (Model 7-2) and factors-only models (Model 7-3) relative to the null effects model (Model 7-1). This suggests an association between at least some of the predictors (age, gender, and BMI) and ACSS responses. Additionally, the factors-only model resulted in a similar level of model fit to the saturated model (ΔCFI = -.006, ΔTLI = -.001, ΔRMSEA = +.001), supporting a lack of DIF as a function of age, gender identity, and BMI. Finally, the last model (Model 7-4), built from the retained factors-only model, showed that associations between the predictors (age, gender, and BMI) and the G- and S-factors of the ACSS were equivalent across samples. Table 8 presents results from the invariant factors-only model (Model 7-4). First, these results showed that age significantly and negatively predicted scores on the Consider S-factor. This means that older participants presented significantly higher scores on the Consider S-factor relative to younger participants. Second, gender significantly and positively predicted scores on the Consider S-factor. Thus, women presented significantly higher scores on the Consider S-factor relative to men. Finally, BMI significantly and positively predicted scores on the Social S-factor. This means that participants with higher BMIs presented significantly higher scores on the Social S-factor relative to participants with lower BMIs.

7. Conclusion

In this paper, we have sought to introduce ESEM and bifactor-ESEM models to body image researchers, and highlight the applicability of these approaches through our re-analysis of an existing dataset. Broadly speaking, the results of our re-analysis are consistent with other recent studies showing that ESEM and bifactor-ESEM models provide an improved representation of responses to multidimensional body image measures relative to alternative CFA-based models (e.g., Anastasiades et al., 2022; Lazarescu et al., 2023; Maïano et al., 2021, 2023; Morin & Maïano, 2011; Morin et al., 2018; Swami, Maïano, Furnham et al., 2022; Swami, Maïano, & Morin, 2022; Swami, Maïano, Todd et al., 2021; Swami, Maïano, Wong et al., 2021). We also showed how the basic ESEM framework can be extended with tests of measurement invariance, DIF, and a hybrid MIMIC model. In making our Mplus syntax available to researchers (in our Supplementary Materials), we also hope to facilitate future use of these analytic approaches in body image research.

Our general argument here is that ESEM and bifactor-ESEM should be seen as valuable analytic frameworks for body image scholars. In fact, the failure to consider implementing these models is likely to result in biased, artefactual, or misleading conclusions, which in turn could delay theoretical understandings of key issues in the body image literature. Moreover, from a practical point-of-view, such biases may potentially be harmful if misleading models of body image constructs come to be applied in clinical practice. As such, it is our hope that this paper helps body image scholars – those conducting primary research, reviewing manuscripts, developing theory, applying existing models of body image to new populations, and so on – to more fully understand the value and purpose of ESEM and bifactor-ESEM.

Our key message here is that ESEM and bifactor-ESEM models should allow body image scholars to more fully, realistically, and comprehensively investigate questions regarding the proper conceptualisation and modeling of body image constructs, as well as how best to conceptualise the relations between these constructs and antecedent or outcome variables (Meadows & Higgs, 2020). In doing so, we suggest that the apparent complexity of these models should be embraced rather than feared: it is only by going through this process, at least once, that scholars will be able to arrive at more realistic and appropriate models and theories of body image. Conversely, failure to consider the full range of possible models – or worse, choosing to ignore such models – will likely interfere with theoretical and conceptual developments in the field. To use the example of the ACSS, ESEM and bifactor-ESEM models may help to resolve some of the equivocal findings *vis-à-vis* the factor validity of this instrument (Lazarescu et al., 2023), thereby helping drive forward our understanding of cosmetic surgery acceptance.

Over the years, some have erroneously argued that including cross-loading items means accepting modeling a source of noise that is likely to mask poorly constructed items or to taint the meaning of our constructs (Stromeyer et al., 2015). This flawed argument, however, ignores the fact that statistical research has demonstrated that including cross-loadings helped to better capture the true meaning of our constructs (Asparouhov et al., 2015; Mai et al., 2018; Wei et al., 2022). It also ignores the fact that incorporating cross-loadings helps, rather than interferes with, researchers' efforts to properly locate problematic items in their measures (Morin & Maïano, 2011). A related concern is that cross-loadings should not be theoretically permissible and that scholars should be aiming for instruments that adequately capture target constructs without being associated with other constructs (Stromeyer et al., 2015). Without disagreeing with the idea that the quest for perfect items is a valid endeavour, we have to note (as others have done before us; Asparouhov et al., 2015) that such "pure" items are rarely present in psychological research more generally, and in body image research more specifically. Seeking purity when measuring a complex object of study such as body image appears to us an unrealistic objective. Indeed, even very carefully constructed instruments are likely to present at least some degree of true association with non-target constructs (Asparouhov et al., 2015), which in turn means that scholars need to account for cross-loadings in their modeling. At the very least, ESEM may allow scholars to more fully understand the impact of cross-loadings on instrument functioning and identify items that may be in need of revision.

Having said all this, there are several issues that should be considered by scholars intending to use these novel methodologies in their research. The first is that, given that the relative youth of ESEM and the relatively recent resurgence of interest in bifactor models, the best and most appropriate ways to use these methodologies are still being expanded upon (Morin, 2023; Sellbom & Tellegen, 2019). As such, it is vital that scholars interested in ESEM and bifactor-ESEM keep up-to-date on best practice, guidance, and recommendations. In this regard, we note that the website associated with the Mplus statistical package has thus far done a very good job at posting recent developments related to the use of these models (https://www.statmodel.com/ESEM.shtml). Relatedly, and as we noted earlier, for scholars interested in instrument construction and test adaptation particularly, different approaches are available and it is unlikely that any one approach will be universally appropriate. While we have reviewed some strategies that are available to researchers in Section 4, we encourage scholars to choose the approach that it is most suitable to their study objectives and to clearly justify said approach in any write-up. Doing so will ensure that readers will have a clear understanding of decision-making processes and be able to clearly situate their analyses.

In summary, we have sought to introduce ESEM and bifactor-ESEM to body image researchers, which we hope will lead to wider uptake of these analytic methods in the body image literature. It is our view that ESEM and bifactor-ESEM have the potential to drive forward theorising and conceptualisations in the field of body image, but only if these methods are properly understood and results correctly interpreted. Of course, ESEM and bifactor-ESEM are not panaceas for all issues of factor validity facing body image scholars, but a fuller understanding of these methods will undoubtedly offer scholars vital tools.

Footnotes

[1]We do not recommend use of the standardized root mean square residual (SRMR) for model fit assessment, as it is sample size-dependent (Marsh et al., 2005) and its performance varies widely as a function of a range of conditions.

[2]In factor analyses, we only report standardised factor loadings, as these have a direct interpretation that is independent from the response scale used to score the items. More precisely, the square of the factor loading (also called communality) reflects the proportion of the item variance explained by the factor (and 1 minus the square loadings thus refers to the proportion of the item variance not explained by the factor, or its uniqueness). The unstandardised factor loadings are typically less useful as they are connected to the scaling of the items, but are those that we would need to use to obtain weighted scores.

[3]When it necessary to conduct an initial EFA (e.g., development of a novel instrument, test adaptations, etc.), this can also be conducted in Mplus. The relevant syntax for this can be found in Example 5.27 of the *Mplus User's Guide* (Muthén & Muthén, 2022).

Acknowledgements

We are grateful to Giănină Lazarescu and Mona Vintilă for sharing their Romanian ACSS data with us.

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. https://doi.org/10.1016/j.rmal.2022.100005

Alcaraz-Ibáñez, M., & Sicilia, A. (2018). Psychometric evaluation and sex invariance of the Spanish version of the Body and Appearance Self-Conscious Emotions Scale. *Body Image*, *25*, 78-84. https://doi.org/10.1016/j.bodyim.2018.02.006

Alleva, J. M., Tylka, T. L., & Kroon Van Diest, A. M. (2017). The Functionality Appreciation Scale (FAS): Development and psychometric properties in U.S. community women and men. *Body Image*, *23*, 28-44. https://doi/org/10.1016/j.bodyim.2017.07.008

Anastasiades, E., Maïano, C., Argyrides, M., & Swami, V. (2022). Psychometric properties of a Greek translation of the Intuitive Eating Scale-2 (IES-2) in adults from Cyprus. *Body Image*, *43*, 348-361. https://doi.org/10.1016/j.bodyim.2022.09.014

Asparouhov, T., & Muthén, B. (2009). Exploratory structural equation modeling. *Structural Equation Modeling*, *16*(3), 397-438. https://doi.org/10.1080/1075510903008204

Asparouhov, T., Muthén, B., & Morin, A. J. S. (2015). Bayesian structural equation modeling with cross-loadings and residual covariances. *Journal of Management*, *41*(6), 1561-1577. https://doi.org/10.1177/0149206315591075

Boer, D., Hanke, K., & He, J. (2018). On detecting systematic measurement error in cross-cultural research: A review and critical reflection on equivalence and invariance tests. *Journal of Cross-Cultural Psychology*, *49*(5), 713-734. https://doi.org/10.1177/0022022117749042

Bornovalova, M. A., Choate, A. C., Fatimah, H., Petersen, K. J., & Wiernik, B. (2020). Appropriate use of bifactor analysis in psychopathology research. *Biological Psychiatry*, *88*(1), 18-27. https://doi.org/10.1016/j.biopsych.2020.01.013

Brown, T. A. (2015). *Confirmatory factor analysis for applied research* (2nd ed.). Guilford.

Brown, T. A., Cash, T. F., & Mikulka, P. J. (1990). Attitudinal body image assessment: Factor analysis of the Body-Self Relations Questionnaire. *Journal of Personality Assessment*, *55*(1-2), 135-144. https://doi.org/10.1080/00223891.1990.9674053

Browne, M. W. (2001). An overview of analytic rotation in exploratory factor analysis. *Multivariate Behavioral Research*, *36*(1), 111-150. https://doi.org/10.1207/S15327906MBR3601_05

Brunet, J., Gunnel, K. E., Teixeira, P., Sabiston, C. M., & Bélanger, M. (2016). Should we be looking at the forest or the trees? Overall psychological need satisfaction and individual needs as predictors of physical activity. *Journal of Sport and Exercise Psychology*, *38*(4), 317-330. https://doi.org/10.1123/jsep.2016-0256

Brytek-Matera, A., & Rogoza, R. (2015). Validation of the Polish version of the Multidimensional Body-Self Relations Questionnaire among women. *Eating and Weight Disorders*, *20*, 109-117. https://doi.org/10.1007/s40519-014-0156-x

Byrne, B. M. (2001). Structural equation modeling with AMOS, EQS, and LISREL: Comparative approaches to testing for the factorial validity of a measuring instrument. *International Journal of Testing*, *1*(1), 55-86. https://doi.org/10.1207/S15327574IJT0101_4

Cash, T. F. (2000). *The Multidimensional Body-Shape Relations Questionnaire users' manual* (3rd ed.). Available from the author at: www.body-images.com

Castonguay, A. L., Sabiston, C. M., Crocker, P. R. E., & Mack, D. E. (2014). Development and validation of the Body and Appearance Self-Conscious Emotions Scale (BASES). *Body Image*, *11*(2), 126-136. https://doi.org/10.1016/j.bodyim.2013.12.006

Chen, F. F. (2007). Sensitivity of goodness of fit indexes to lack of measurement. *Structural Equation Modeling*, *14*(3), 464-504. https://doi.org/10.1080/10705510701301834

Chen, F. F. (2008). What happens if we compare chopsticks with forks? The impact of making inappropriate comparisons in cross-cultural research. *Journal of Personality and Social*

Psychology, *95*(5), 1005. https://doi.org/10.1037/a0013193
Cheung, G. W., & Rensvold, R. B. (2002). Evaluating goodness-of-fit indexes for testing measurement invariance. *Structural Equation Modeling*, *9*(2), 233-255. https://doi.org/10.1207/s15328007sem0902_5
De Beer, L. T., & Morin, A. J. S (2022). (B)ESEM invariance syntax generator for Mplus. https://doi.org/10.6084/m9.figshare.19360808
De Winter, J. C. F., Dodou, D., & Wieringa, P. A. (2009). Exploratory factor analysis with small sample sizes. *Multivariate Behavioral Research*, *44*(2), 147-181. https://doi.org/10.1080/00273170902794206
Decker, S. L. (2021). Don't use a bifactor model unless you believe the rrue structure is bifactor. *Journal of Psychoeducational Assessment*, *39*(1), 39-49. https://doi.org/10.1177/0734282920977718
Eid, M., Koch, T., & Geiser, C. (2023). Multitrait-multimethod models. In R. H. Hoyle (Ed.), *Handbook of structural equation modeling* (2nd ed., in press). Gulford.
Fabrigar, L. R.,Wegener, D. T., MacCallum, R. C., & Strahan, E. J. (1999). Evaluating the use of exploratory factor analysis in psychological research. *Psychological Methods*, *4*(3), 272-299. https://doi.org/10.1037/1082-989X.4.3.272
Feng, Y., & Hancock, G. (2023). Power analysis within a structural equation modeling framework. In R. H. Hoyle (Ed.), *Handbook of structural equation modeling* (2nd ed., pp. 418-432). Guilford.
Finney, S. J., & DiStefano, C. (2013). Non-normal and categorical data in structural equation modeling. In G. R. Hancock & R. O. Mueller (Eds), *Structural equation modeling: A second course* (2nd ed., pp. 439-492). IAP.
Garrido, L. E., Barrada, J. R., Aguasvivas, J. A., Martínez-Molina, A., Arias, V. B., Golino, H. F., Legaz, E., Ferrís, G., & Rojo-Moreno, L. (2020). Is small still beautiful for the Strengths and Difficulties Questionnaire? Novel findings using exploratory structural equation modeling. *Assessment*, *27*(6), 1349-1367. https://doi.org/10.1177/1073191118780461
Gefen, D., & Straub, D. (2005). A practical guide to factorial validity using PLS-Graph: Tutorial and annotated example. *Communications of the Association for Information Systems*, *16*, 91-109.
Gegenfurtner, A. (2022). Bifactor exploratory structural equation modeling: A meta-analytic review of model fit. *Frontiers in Psychology*, *13*, 1037111. https://doi.org/10.3389/fpsyg.2022.1037111
Geiser, C. (2023). Structural equation modeling with Mplus and lavaan programs. In R. H. Hoyle (Ed.), *Handbook of structural equation modeling* (2nd ed., in press). Guilford.
Gignac, G. E. (2016). The higher-order model imposes a proportionality constraint: That is why the bifactor model tends to fit better. *Intelligence*, *55*, 57-68. https://doi.org/10.1016/j.intell.2016.01.006
Giordano, C., Ones, D. S., Wallers, N. G., & Stanek, K. C. (2020). Exploratory bifactor measurement models in vocational behavior research. *Journal of Vocational Behavior*, *120*, 103430. https://doi.org/10.1016/j.jvb.2020.103430
Gillet, N., Morin, A., Huart, I., Colombat, P., & Fouquereau, E. (2020). The forest and the trees: Investigating the globality and specificity of employees' basic need satisfaction at work. *Journal of Personality Assessment*, *102*(5), 702-713. https://doi.org/10.1080/00223891.2019.1591426
Guay, F., Morin, A. J. S., Litalien, D., Valois, P., & Vallerand, J. (2015). Application of exploratory structural equation modeling to evaluate the Academic Motivation Scale. *The Journal of Experimental Education*, *83*(1), 51-82. https://doi.org/10.1080/00220973.2013.876231
Guenole, N., & Brown, A. (2014). The consequences of ignoring measurement invariance for path coefficients in structural equation models. *Frontiers in Psychology*, *5*, 980. https://doi.org/10.3389/fpsyg.2014.00980
Guo, J., Marsh, H. W., Parker, P. D., Dicke, T., Lüdtke, O., & Diallo, T. M.O. (2019). A systematic evaluation and comparison between exploratory structural equation modeling and Bayesian structural equation modeling. *Structural Equation Modeling*, *26*(4), 529-556. https://doi.org/10.1080/10705511.2018.1554999
Hair, J. F. Jr., Black, W. C., Babin, B. J., & Anderson, R. E. (2009). *Multivariate data analysis* (7th ed.). Macmillan.

Henderson-King, D., & Henderson-King, E. (2005). Acceptance of cosmetic surgery: Scale development and validation. *Body Image*, *2*(2), 137-149. https://doi.org/10.1016/j.bodyim.2005.03.003

Howard, J. L., Gagné, M., Morin, A. J. S., & Forest, J. (2018). Using bifactor exploratory structural equation modeling to test for a continuum structure of motivation. *Journal of Management*, *44*(7), 2638-2664. https://doi.org/10.1177/0149206316645653

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling*, *6*(1), 1-55. https://doi.org/10.1080/10705519909540118

Jenaro, C., Flores, N., Tomsa, R., & Bermejo, M. B. (2011). Body Image Screening Questionnaire for Eating Disorder Early Detection. *Journal of Experiential Psychotherapy*, *14*(3), 3-11.

Jewett, L. R., Malcarne, V. L., Kwakkenbos, L., Harcourt, D., Rumsey, N., Korner, A., Steele, R. J., & Canadian Scleroderma Research Group (CSRG). Development and validation of the Body Concealment Scale for Scleroderma (BCSS). *Arthritis Care & Research*, *68*(8), 1158-1165. https://doi.org/10.1002/acr.22819

Jovic, M., Sforza, M., Jovanovic, M., & Jovic, M. (2017). The Acceptance of Cosmetic Surgery Scale: Confirmatory factor analyses and validation among Serbian adults. *Current Psychology*, *36*, 707-718. https://doi.org/10.1007/s12144-016-9458-7

Lazarescu, G., Maïano, C., Vintilă, M., Goian, C., & Swami, V. (2023). Psychometric properties of a Romanian translation of the Acceptance of Cosmetic Surgery Scale (ACSS): An examination using bifactor exploratory structural equation modelling. *Body Image*, *45*, 273-283. https://doi.org/10.1016/j.bodyim.2023.03.011

Lizana-Calderón, P., Alvarado, J. M., Cruzat-Mandich, C., Diaz-Castrillón, F., & Quevedo, S. (2023). Psychometric properties of the Multidimensional Body-Self Relations Questionnaire–Appearance Scales (MBSRQ–AS) in Chilean youth. *International Journal of Environmental Research and Public Health*, *20*(1), 628. https://doi.org/10.3390/ijerph20010628

Mai, Y., Zhang, Z., & Wen, Z. (2018). Comparing exploratory structural equation modeling and existing approaches for multiple regression with latent variables. *Structural Equation Modeling*, *25*(5), 737-749. https://doi.org/10.1080/10705511.2018.1444993

Maïano, C., Morin, A. J. S., Aimé, A., Lepage, G., & Bouchard, S. (2021). Psychometric properties of the Body Checking Questionnaire (BCQ) and of the Body Checking Cognitions Scale (BCCS): A bifactor-exploratory structural equation modeling approach. *Assessment*, *28*(2), 632-646. https://doi.org/10.1177/1073191111858411

Maïano, C., Morin A.J.S., Ninot G., Monthuy-Blanc J., Stephan Y., J-F. Florent, & Vallée, P. (2008). A short and very short form of the Physical Self-Inventory for adolescents: Development and factor validity. *Psychology of Sport and Exercise*, *9*(6), 830-847. https://doi.org/10.1016/j.psychsport.2007.10.003

Maïano, C., Morin, A. J. S., Tietjens, M., Bastos, T., Luiggi, M., Corredeira, R., Griffet, J., & Sánchez-Oliva, D. (2023). German, Portuguese and Spanish versions of the revised short form of the Physical Self-Inventory (PSI-S-R). *Measurement in Physical Education and Exercise Science*, 27, 10-20. https://doi.org/10.1080/1091367X.2022.2034164

Markon, K. E. (2019). Bifactor and hierarchical models: Specification, inference, and interpretation. *Annual Review of Clinical Psychology*, *15*, 51-69. https://doi.org/10.1146/annurev-clinpsy-050718-095522

Marsh, H. W., Abduljabbar, A. S., Abu-Hilal, M. M., Morin, A. J. S., Abdelfattah, F., Leung, K. C., Xu, M. K., Nagengast, B., & Parker, P. (2013). Factorial, convergent, and discriminant validity of timss math and science motivation measures: A comparison of Arab and Anglo-Saxon countries. *Journal of Educational Psychology*, *105*(1), 108-128. https://doi.org/10.1037/a0029907

Marsh, H. W., Guo, J., Dicke, T., Parker, P. D., Craven, R. G. (2020). Confirmatory factor analysis (CFA), exploratory structural equation modeling (ESEM) and Set-ESEM: Optimal balance between goodness of fit and parsimony. *Multivariate Behavioral Research*, *55*(1), 102-119. https://doi.org/10.1080/00273171.2019.1602503

Marsh, H. W., Hau, K., & Grayson, D. (2005). Goodness of fit in structural equation models. In A. Maydeu-Olivares & J. J. McArdle (Eds.), *Contemporary psychometrics* (pp. 275-340).

Erlbaum.
Marsh, H. W., Morin, A. J. S., 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*, 85-110. https://doi.org/10.1146/annurev-clinpsy-032813-153700
Marsh, H. W., Muthén, B., Asparouhov, T., Lüdtke, O., Robitzsch, A., Morin, A. J. S., & Trautwein, U. (2009). Exploratory structural equation modeling, integrating CFA and EFA: Application to students' evaluations of university teaching. *Structural Equation Modeling*, 16(3), 439-476. https://doi.org/10.1080/10705510903008220.
Marsh, H. W., Nagengast, B., & Morin, A. J. S. (2013). Measurement invariance of big-five factors over the life span: ESEM tests of gender, age, plasticity, maturity, and la dolce vita effects. *Developmental Psychology*, *49*(6), 1194-1218.
Marsh, H. W., Scalas, L.F., & Nagengast, B. (2010). Longitudinal tests of competing factor structures for the Rosenberg Self-Esteem Scale. *Psychological Assessment*, *22*(2), 366-381. https://doi.org/10.1037/a0019225
Marsh, H. W., Tracey, D. K., & Craven, R. G. (2006). Multidimensional self-concept structure for preadolescents with mild intellectual disabilities. *Educational and Psychological Measurement*, *66*(5), 798-818. https://doi.org/10.1177/0013164405285910
McCreary, D. R., Sasse, D. K., Saucier, D. M., & Dorsch, K. D. (2004). Measuring the drive for muscularity: Factorial validity of the Drive for Muscularity Scale in men and women. *Psychology of Men & Masculinity*, *5*(1), 49-58. https://doi.org/10.1037/1524-9220.5.1.49
Meadows, A., & Higgs, S. (2020). A bifactor analysis of the Weight Bias Internalization Scale. *Body Image*, *33*, 137-151. https://doi.org/10.1016/j.bodyim.2020.02.013
Meskó, N., & Láng, A. (2021). Acceptance of cosmetic surgery among Hungarian women in a global context: The Hungarian version of the Acceptance of Cosmetic Surgery Scale (ACSS). *Current Psychology*, *40*, 5822-5833. https://doi.org/10.1007/s12144-019-00519-z
Millsap, R. E. (2011). *Statistical approaches to measurement invariance*. Taylor and Francis.
Morin, A. J. S. (2023). Exploratory structural equation modeling. In R. H. Hoyle (Ed.), *Handbook of structural equation modeling* (2nd ed., pp. 503-524). Guilford.
Morin, A. J. S., Arens, A., & Marsh, H. (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. https://doi.org/10.1080/10705511.2014.961800
Morin, A. J. S., & Asparouhov, T. (2018). *Webnote: Estimation of a hierarchical Exploratory Structural Equation Model (ESEM) using ESEM-within-CFA*. Substantive Methodological Synergy Research Laboratory.
Morin, A. J. S., Blais, A.-R., & Chénard-Poirier, L.-A. (2022). Doubly latent multilevel procedures for organizational assessment and prediction. *Journal of Business & Psychology*, *37*, 47-72. https://doi.org/10.1007/s10869-021-09736-5
Morin, A. J. S., & Maïano, C. (2011). Cross-validation of the short form of the Physical Self-Inventory (PSI-S) using structural equation modeling (ESEM). *Psychology of Sport and Exercise*, *12*(5), 540-554. https://doi.org/10.1016/j.psychsport.2011.04.003
Morin, A. J. S., Maïano, C., Scalas, L. F., Aşçı, F. H., Boughattas, W., Abid, S., Mascret, N., Kara, F. M., Fadda, D., & Probst, M. (2018). Cross-cultural validation of the short form of the Physical Self Inventory (PSI-S). *Sport, Exercise, and Performance Psychology*, *7*(1), 60-79. https://doi.org/10.1037/spy0000096
Morin, A. J. S., Marsh, H. W., & Nagengast, B. (2013). Exploratory structural equation modeling. In G. R. Hancock, & R. O. Mueller (Eds.), *Structural equation modeling: A second course (2nd ed.*, pp. 395-436). Information Age.
Morin, A. J. S., Myers, N. D., & Lee, S. M. (2020). Modern factor analytic techniques: Bifactors models, exploratory structural equation modeling (ESEM), and bifactor-ESEM. In G. Tenenbaum & R. C. Eklund (Eds.), *Handbook of sport psychology* (4th ed., pp. 1044-1073). Wiley. https://doi.org/10.1002/9781119568124.ch51
Muthén, L. K., & Muthén, B. (2002). How to use a Monte Carlo study to decide on sample size and determine power. *Structural Equation Modeling*, *9*, 599-620.

https://doi.org/10.1207/S15328007SEM0904_8
Muthén, L. K., & Muthén, B. (2022). *Mplus user's guide.* Muthén & Muthén.
Perreira, T. A., Morin, A. J. S., Hebert, M., Gillet, N., Houle, S. A., & Berta, W. (2018). The short form of the Workplace Affective Commitment Multidimensional Questionnaire (WACMQ-S): A bifactor-ESEM approach among healthcare professionals. *Journal of Vocational Behavior, 106*, 62-83. https://doi/org/10.1016/j.jvb.2017.12.004
Piedmont R. L. (2014) Factorial validity. In A. C. Michalos (Ed.), *Encyclopedia of quality of life and well-being research*. Springer.
Prokofieva, M., Zarate, D., Parker, A., Palikara, O., & Stavropoulos, V. (2023). Exploratory structural equation modeling: A streamlined step by step approach using the *R* Project software. *BMC Psychiatry*, *23*, 546 (2023). https://doi.org/10.1186/s12888-023-05028-9
Reise, S. P. (2012). The rediscovery of bifactor measurement models. *Multivariate Behavioral Research*, *47*(5), 667-696. https://doi.org/10.1080/00273171.2012.715555
Rosenberg, M. (1965). *Society and the adolescent self-image*. Princeton University Press.
Sánchez-Carracedo, D., Guimerà, J., Barrada, J. R., Lòpez-Guimerà, G., Fauquet, J., Almenara, C. A., & Trepat, E. (2012). Analysis of the factor structure of the Sociocultural Attitudes Towards Appearance Questionnaire (SATAQ-3) in Spanish secondary-school students through exploratory structural equation modeling. *Body Image*, *9*(1), 163-171. https://doi.org/10.1016/j.bodyim.2011.10.002
Schaefer, L. M., Harriger, J. A., Heinberg, L. J., Soderberg, T., & Thompson, J. K. (2017). Development and validation of the Sociocultural Attitudes Toward Appearance Quesyionnaire-4-Revised (SATAQ-4R). *International Journal of Eating Disorders*, *50*(2), 104-117. https://doi.org/10.1002.eat.22590
Schumacker, R. E., & Lomax, R. G. (2004). *A beginner's guide to structural equation modeling* (3rd ed.). Taylor and Francis.
Schweizer, K. (2012). On correlated errors. *European Journal of Psychological Assessment*, *28*, 1-2. https://doi.org/10.1027/1015-5759/a000094
Sellbom, M., & Tellegen, A. (2019). Factor analysis in psychological assessment research: Common pitfalls and recommendations. *Psychological Assessment*, *31*(12), 1428-1441. https://doi.org/10.1037/pas0000623
Shao, K., Elahi Shirvan, M., & Alamer, A. (2022). How accurate is your correlation? *Frontiers in Psychology*, *13*, 901412. https://doi.org/10.3389/fpsyg.2022.901412
Shi, D., Maydeu-Olivares, A., & Rosseel, Y. (2020). Assessing fit in ordinal factor analysis models: SRMR vs. RMSEA. *Structural Equation Modeling*, *27*, 1-15. https://doi.org/10.1080/10705511.2019.1611434
Simone, M., Donahue, J. M., Anderson, L. M., & Anderson, D. (2021). Sexual orientation-based differential item functioning in measures of body image concerns and ideals among men. *Psychology of Men & Masculinities, 22*(1), 1-6. https://doi.org/10.1037/men0000273
Skrondal, A., & Laake, P. (2001). Regression among factor scores. *Psychometrika*, *66*, 563-576. https://doi.org/10.1007/BF02296196
Stefanile, C., Nerini, A., Matera, C., Schaefer, L. M., & Thompson, J. K. (2019). Validation of an Italian version of the Sociocultural Attitudes Toward Appearance Quesyionnaire-4-Revised (SATAQ-4R) on non-clinical Italian women and men. *Body Image*, *31*, 48-58. https://doi.org/10.1016/j.bodyim.2019.08.005
Suárez-Alvarez, J., Pedrosa, I., Lozano, L. M., García-Cueto, E., Cuesta M., & Muñiz, J. (2018). Using reversed items in Likert scales: A questionable practice. *Psicothema*, *30*(2), 149-158. https://doi.org/10.7334/psicothema2018.33
Swami, V. (2010). Translation and validation of the Malay Acceptance of Cosmetic Surgery Scale. *Body Image*, *7*(4), 372-375. https://doi.org/10.1016/j.bodyim.2010.07.005
Swami, V., & Barron, D. (2019). Translation and validation of body image instruments: Challenges, good practice guidelines, and reporting recommendations for test adaptation. *Body Image*, *31*, 204-220. https://doi.org/10.1016/j.bodyim.2018.08.014
Swami, V., Campana, A. N. N. B., Ferreira, L., Barrett, S., Harris, A. S., Tavares, M. C. G. C. D. (2011). The Acceptance of Cosmetic Surgery Scale: Initial examination of its factor structure and correlates among Brazilian adults. *Body Image*, *8*(2), 179-185.

https://doi.org/10.1016/j.bodyim.2011.01.001
Swami, V., Hwang, C.-S., & Jung, J. (2012). Factor structure and correlates of the Acceptance of Cosmetic Surgery Scale among South Korean university students. *Aesthetic Surgery Journal*, *32*(2), 220-229. https://doi.org/10.1177/1090820X11431577
Swami, V., Maïano, C., Furnham, A., & Robinson, C. (2022). The Intuitive Eating Scale-2: Re-evaluating its factor structure using a bifactor exploratory structural equation modelling framework. *Eating and Weight Disorders*, *27*(4), 1349–1357. https://doi.org/10.1007/s40519-021-01271-9
Swami, V., Maïano, C., & Morin, A. J. S. (2022). The Body and Appearance Self-Conscious Emotions Scale (BASES): A comprehensive examination of its factorial validity, with recommendations for researchers. *Body Image*, *42*, 173-182. https://doi.org/10.1016/j.bodyim.2022.06.009
Swami, V., Maïano, C., Todd, J., Ghisi, M., Cardi, V., Bottesi, G., & Cerea, S. (2021). Dimensionality and psychometric properties of an Italian translation of the Intuitive Eating Scale-2 (IES-2): An assessment using a bifactor exploratory structural equation modelling framework. *Appetite*, *166*, 105588. https://doi.org/10.1016/j.appet.2021.105588
Swami, V., Maïano, C., Wong, K. Y., Zahari, H. S., & Barron, D. (2021). Psychometric properties of a Bahasa Malaysia (Malay) translation of the Body and Appearance Self-Conscious Emotions Scale (BASES): An assessment using exploratory structural equation modelling. *Body Image*, *39*, 293-304. https://doi.org/10.1016/j.bodyim.2021.10.003
Swami, V., Todd, J., & Barron, D. (2021). Translation and validation of body image instruments: An addendum to Swami and Barron (2019) in the form of frequently asked questions. *Body Image*, *37*, 214–224. https://doi.org/10.1016/j.bodyim.2021.03.002
Swami, V., Todd, J., Mohd. Khatib, N. A., Toh, E. K. L., Zahari, H. S., & Barron, D. (2019). Dimensional structure, psychometric properties, ans sex invariance of a Bahasa Malaysia (Malay) translation of the Multidimensional Body-Self Relations Questionnaire–Appearance Scales (MBSRQ–AS) in Malaysian Malay adults. *Body Image*, *28*, 81-92. https://doi.org/10.1016/j.bodyim.2018.12.007
Swami, V., Todd, J., & Tylka, T. L. (2022). Measuring positive breast experience: Development and psychometric evaluation of the Breast Appreciation Scale (BrAS). *Body Image*, *43*, 275-291. https://doi.org/10.1016/j.bodyim.2022.09.007
Swami, V., Vintila, M., Tudorel, O., Goian, C., & Barron, D. (2018). Factor structure and psychometric properties of a Romanian translation of the Drive for Muscularity Scale (DMS) in university men. *Body Image*, *25*, 48-55. https://doi.org/10.1016/j.boidyim.2018.02.004
Thompson, J. K., Heinberg, L. J., Altabe, M., & Tantleff-Dunn, S. (1999). *Exacting beauty: Theory, assessment, and treatment of body image disturbance.* American Psychological Association. https://doi.org/10.1037/10312-000
Tóth-Király, I., Bõthe, B., Rigó, A., & Orosz, G. (2017). An illustration of the exploratory structural equation modeling (ESEM) framework on the Passion Scale. *Frontiers in Psychology*, *8*, 1968. https://doi.org/10.3389/fpsyg.2017.10968
Tylka, T. L., & Wood-Barcalow, N. L. (2015). The Body Appreciation Scale-2: Item refinement and psychometric evaluation. *Body Image*, *12*, 53-67. https://doi.org/10.1016/j.bodyim.2014.09.006
Wei, X., Huang, J., Zhang, L., Pan, D., & Pan, J. (2022). Evaluation and comparison of SEM, ESEM, and BSEM in estimating structural models with potentially unknown cross-loadings. *Structural Equation Modeling*, *29*(3), 327-338. https://doi.org/10.1080/10705511.2021.2006664
Weijters, B., Baumgartner, H., & Schillewaert, N. (2013). Reversed item bias: An integrative model. *Psychological Methods*, *18*(3), 320-334. https://doi.org/10.1037/a0032121
West, S. G., Wu, W., McNeish, D., & Savord, A. (2023). Model fit in structural equation modeling. In R. H. Hoyle (Ed.), *Handbook of structural equation modeling* (2nd ed., in press). Guilford.
Widaman, K. F., & Olivera-Aguilar, M. (2023). Investigating measurement invariance using confirmatory factor analysis. In R. H. Hoyle (Ed.), *Handbook of structural equation modeling* (2nd ed., in press). Guilford.
Winkens, L. H. H., van Strien, T., Barrada, J. R., Brouwer, I. A., Penninx, B. W. J. H., & Visser, M. (2018). The Mindful Eating Behavior Scale: Development and psychometric properties in a sample of Dutch adults aged 55 years and older. *Journal of the Academy of Nutrition and Dietetics*, *118*(7), 1277-1290. https://doi.org/10.1016/j.jand.2018.01.015

Wolf, E. J., Harrington, K. M., Clark, S. L., & Miller, M. W. (2013). Sample size requirements for structural equation models: An evaluation of power, bias, and solution propriety. *Educational and Psychological Measurement*, *73*, 913-934. https://doi.org/10.1177/0013164413495237

Worthington, R., & Whittaker, T. (2006). Scale development research: A content analysis and recommendations for best practice. *Counseling Psychologist*, *34*(6), 806-838. https://doi.org/10.1177/0011000006288127

Wu, Y., Alleva, J. M., & Mulkens, S. (2020). Factor analysis and psychometric properties of the Chinese translation of the Acceptance of Cosmetic Surgery Scale. *Body Image*, 33, 244-256. https://doi.org/10.1016/j.bodyim.2020.03.009

Xia, Y., & Yang, Y. (2019). RMSEA, CFI, and TLI in structural equation modeling with ordered categorical data: The story they tell depends on the estimation methods. *Behavior Research Methods*, *51*, 409-428. https://doi.org/10.3758/s13428-018-1055-2

Yu, C.-Y. (2002). *Evaluating cutoff criteria of model-fit indexes for latent variable models with binary and continuous outcomes* [unpublished doctoral dissertation]. University of California, Los Angeles, CA.

Yukhymenko, M. A., & Gilbert, W. D. (2021). Development and validation of the Coaching Athlete Purpose Scale (CAPS). *Psychology of Sport and Exercise*, *56*, 101960. https://doi.org/10.1016/j.psychsport.2021.101960

Table 1

A Summary of the Key Models Discussed in this Paper.

Model	Description
Exploratory factor analysis (EFA)	• Aims to estimate the smallest number of factors from multiple indicators (items) • All cross-loadings are freely estimated • Unable to incorporate or control for method effects (e.g., covariance between similarly worded items on an instrument) • Measurement invariance cannot be estimated (although it can be estimated using ESEM)
Confirmatory factor analysis (CFA)	• Aims to estimate a series of correlated factors (or a single factor) from multiple indicators (items) • Does not incorporate cross-loadings or correlated uniquenesses • Assumes that all indicators correspond to a single factor (i.e., assumes “pure” factors)
Exploratory structural equation modeling (ESEM)	• Overarching framework that connects EFA measurement with Structural Equation Modeling • Can be used in both exploratory and confirmatory ways • Used to add flexibility to an EFA measurement model (correlated uniquenesses, method factors, measurement invariance, etc.) • Can be used to test relations between EFA factors and additional latent or observed variables
Higher-order analyses	• Can be estimated with CFA or with ESEM • Assesses a series of first-order factors from multiple indicators (items) and then estimates one or more overarching factors from these first-order factors • Relies on an unrealistic proportionality constraint
Bifactor analyses	• Can be estimated with CFA or with ESEM • Estimates a global overarching construct (the G-factor) from the variance shared across all indicators (items), as well as a series of specific constructs (S-factors) from the variance shared among a subset of indicators but not explained by the global construct • Both the G- and S-factors are seen as meaningful

Table 2

Goodness-of-Fit Statistics for the Acceptance of Cosmetic Surgery Scale

Models	Nº	Description	χ^2	df	CFI	TLI	RMSEA	RMSEA 90% CI LB	RMSEA 90% CI UB	CM	$\Delta R\chi^2$	df	ΔCFI	ΔTLI	ΔRMSEA
CFA	1-1	CFA	817.853*	87	.931	.916	.081	.076	.086	-	-	-	-	-	-
ESEM	1-2	ESEM	325.645*	63	.975	.958	.057	.051	.063	-	-	-	-	-	-
	1-3	ESEM with CU	332.101*	60	.974	.955	.060	.053	.066	-	-	-	-	-	-
	1-4	ESEM with MF	329.464*	60	.974	.955	.059	.053	.066	-	-	-	-	-	-
B-CFA	1-5	B-CFA	458.943*	75	.964	.949	.063	.058	.069	-	-	-	-	-	-
B-ESEM	1-6	Bifactor-ESEM	207.360*	51	.985	.969	.049	.042	.056	-	-	-	-	-	-
	1-7	Bifactor-ESEM with CU	202.602*	48	.985	.968	.050	.043	.058	-	-	-	-	-	-
	1-8	Bifactor-ESEM with MF	201.798*	48	.985	.968	.050	.043	.057	-	-	-	-	-	-
ESEM: MI across gender	2-1	Configural invariance	399.796*	126	.972	.954	.058	.052	.065	-	-	-	-	-	-
	2-2	Weak invariance	434.458*	162	.973	.964	.051	.046	.057	2-1	37.19	36	+.001	+.010	-.007
	2-3	Strong invariance	471.705*	174	.970	.964	.052	.046	.057	2-2	38.66*	12	-.003	.000	+.001
	2-4	Strict invariance	594.054*	189	.959	.955	.058	.053	.063	2-3	90.90*	15	-.011	-.009	+.006
	2-5	Partial strict invariance	535.092*	187	.965	.961	.054	.049	.059	2-3	53.48*	13	-.005	-.003	+.002
	2-6	Variances-covariances invariance	621.341*	193	.957	.953	.059	.054	.064	2-5	91.15*	6	-.008	-.008	+.005
	2-7	Latent means invariance	798.614*	196	.939	.935	.069	.064	.074	2-6	252.80*	3	-.018	-.018	+.010
B-ESEM: MI across samples	3-1	Configural invariance	257.902*	102	.985	.970	.049	.042	.056	-	-	-	-	-	-
	3-2	Weak invariance	304.679*	146	.985	.979	.041	.035	.048	3-1	47.21	44	.000	+.009	-.008
	3-3	Strong invariance	315.906*	157	.985	.980	.040	.033	.046	3-2	8.92	11	.000	+.001	-.001
	3-4	Strict invariance	318.640*	172	.986	.983	.037	.030	.043	3-3	12.87	15	+.001	+.003	-.003
	3-5	Variances-covariances invariance	328.295*	182	.986	.984	.036	.029	.042	3-4	8.38	10	.000	+.001	-.001
	3-6	Latent means invariance	339.102*	186	.986	.984	.036	.030	.042	3-5	11.74	4	.000	.000	.000
ESEM: DIF (Age & BMI)	4-1	Null effects	480.006*	93	.966	.951	.057	.052	.062	-	-	-	-	-	-
	4-2	Saturated	335.486*	63	.976	.949	.058	.052	.064	4-1	140.38*	30	+.010	-.002	+.001
	4-3	Factors-only	419.773*	87	.971	.955	.055	.050	.060	4-1	67.81*	6	+.005	+.004	-.002
B-ESEM: DIF (Sample, gender, Sample x Gender)	5-1	Null effects	503.276*	96	.966	.946	.058	.053	.063	-	-	-	-	-	-
	5-2	Saturated	208.501*	51	.987	.961	.049	.042	.056	5-1	311.62*	45	+.021	+.015	-.009
	5-3	Factors-only	302.647*	84	.982	.967	.045	.040	.051	5-1	141.53*	12	+.016	+.021	-.013
ESEM: Hybrid DIF (Age, BMI)	6-1	Null effects	785.127*	253	.951	.948	.057	.053	.062	-	-	-	-	-	-
	6-2	Saturated	625.424*	193	.960	.944	.059	.054	.065	6-1	149.19*	60	+.009	-.004	+.002
	6-3	Factors-only	735.378*	241	.954	.949	.057	.052	.061	6-1	53.21*	12	-.007	+.001	-.002
	6-4	Factors-only - invariant	743.755*	247	.954	.950	.056	.052	.061	6-3	5.10	6	.000	+.001	-.001
B-ESEM: Hybrid DIF (Age, gender, BMI)	7-1	Null effects	736.492*	276	.962	.958	.051	.047	.056	-	-	-	-	-	-
	7-2	Saturated	335.752*	186	.988	.980	.036	.029	.042	7-1	444.37*	90	+.026	+.022	-.015
	7-3	Factors-only	466.644*	252	.982	.979	.037	.031	.042	7-1	321.28*	24	+.020	+.021	-.014
	7-4	Factors-only - invariant	479.884*	264	.982	.980	.036	.031	.041	7-3	11.42	12	.000	+.001	-.001

Notes. CFA= confirmatory factor analyses; B-CFA = bifactor CFA; ESEM = exploratory structural equation modeling; B-ESEM = bifactor exploratory structural equation modeling; CU = correlated uniqueness; MF = method factor; MI = measurement invariance; DIF = differential item functioning; χ^2 = robust maximum likelihood chi-square; df = degrees of freedom; CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation; 90% CI = 90% confidence interval of the RMSEA; LB = lower bound; UB = upper bound; $\Delta R\chi^2$ = robust chi-square difference tests (calculated from loglikelihoods for greater precision); Δ = change from the previous model. * $p \leq .01$

Table 3
Standardised Parameters Estimates from the Three-Factor Confirmatory Factor Analytic Representation of the Acceptance of Cosmetic Surgery Scale

Items	Intrapersonal (λ)	Social (λ)	Consider (λ)	δ
ACSS1	**.751**		_	.436
ACSS2	**.879**		_	.228
ACSS4	**.769**			.409
ACSS5	**.811**	_		.342
ACSS14	**.810**	_	_	.343
ACSS9		**.799**		.362
ACSS11		**.653**		.573
ACSS12		**.778**		.394
ACSS13	_	**.826**		.317
ACSS15	_	**.829**	_	.313
ACSS3			**.888**	.211
ACSS6			**.893**	.202
ACSS7	_		**.905**	.181
ACSS8			**.902**	.186
ACSS10			**.650**	.577
ω	.902	.885	.930	
Correlations				
Intrapersonal	**-**			
Social	.595	**-**		
Consider	.733	.699		

Notes. λ = factor loadings; δ = Uniquenesses; ω = McDonald's omega. Non-significant loadings and correlations are underlined and italicised.

Table 4
Standardised Parameters Estimates from the Bifactor Confirmatory Factor Analytic Representation of the Acceptance of Cosmetic Surgery Scale

Items	Intrapersonal (λ) S-factor	Social (λ) S-factor	Consider (λ) S-factor	G-factor	δ
ACSS1	**.370**			**.647**	.444
ACSS2	**.526**			**.700**	.234
ACSS4	**.427**			**.644**	.403
ACSS5	**.589**			**.597**	.296
ACSS14	**.438**			**.677**	.350
ACSS9		**.538**		**.596**	.356
ACSS11		**.187**		**.654**	.537
ACSS12		**.351**		**.676**	.420
ACSS13		**.806**		**.507**	.094
ACSS15		**.490**		**.648**	.341
ACSS3			**.211**	**.880**	.181
ACSS6			**.378**	**.806**	.207
ACSS7			**.482**	**.783**	.156
ACSS8			**.441**	**.793**	.176
ACSS10			**.329**	**.565**	.573
ω	.762	.763	.724	.956	

Notes. ACSS = Acceptance of Cosmetic Surgery Scale; λ = factor loadings; S -factor = specific factor; G-factor = global factor; δ = Uniquenesses; ω = McDonald's omega.

Table 5

Standardised Parameters Estimates from the Three-Factor Exploratory Structural Equation Modeling Representation of the Acceptance of Cosmetic Surgery Scale

Items	Intrapersonal (λ)	Social (λ)	Consider (λ)	δ
ACSS1	**.660**	-.092	.193	.431
ACSS2	**.897**	-.079	*.042*	.219
ACSS4	**.732**	.157	-.071	.391
ACSS5	**.909**	-.038	-.091	.315
ACSS14	**.738**	.112	*.001*	.347
ACSS9	-.102	**.801**	.111	.332
ACSS11	.178	**.417**	.155	.565
ACSS12	.097	**.628**	.105	.418
ACSS13	-.045	**.996**	-.185	.245
ACSS15	*.018*	**.776**	.060	.317
ACSS3	.186	.096	**.686**	.201
ACSS6	.045	.099	**.788**	.212
ACSS7	*-.026*	.045	**.896**	.176
ACSS8	-.066	*-.006*	**.967**	.158
ACSS10	*-.022*	-.087	**.729**	.561
ω	.901	.875	.927	
Intrapersonal	-			
Social	.569	-		
Consider	.702	.636		

Notes. ACSS = Acceptance of Cosmetic Surgery Scale; λ = factor loadings; S -factor = specific factor; G-factor = global factor; δ = Uniquenesses; ω = McDonald's omega; Non-significant loadings are underlined and italicised.

Table 6

Standardised Parameters Estimates from the Bifactor Exploratory Structural Equation Modeling Representation of the ACSS

Items	Intrapersonal (λ) S-factor	Social (λ) S-factor	Consider (λ) S-factor	G-factor	δ
ACSS1	**.440**	-.069	.156	**.588**	.432
ACSS2	**.581**	-.066	*.084*	**.657**	.220
ACSS4	**.447**	.058	*-.006*	**.637**	.391
ACSS5	**.594**	*-.033*	*.023*	**.579**	.310
ACSS14	**.459**	*.030*	*.040*	**.662**	.349
ACSS9	*-.036*	**.534**	.111	**.608**	.332
ACSS11	-.188	***-.082***	-.235	**.851**	.180
ACSS12	*-.052*	**.251**	*-.039*	**.739**	.387
ACSS13	*-.046*	**.718**	*-.094*	**.593**	.121
ACSS15	*.002*	**.462**	.052	**.667**	.340
ACSS3	.132	*.014*	**.377**	**.800**	.200
ACSS6	.094	.067	**.478**	**.741**	.208
ACSS7	.060	.043	**.539**	**.730**	.171
ACSS8	*.021*	*-.010*	**.550**	**.732**	.161
ACSS10	*.020*	-.075	**.401**	**.521**	.561
ω	.789	.723	.809	.959	

Notes. ACSS = Acceptance of Cosmetic Surgery Scale; λ = factor loadings; S -factor = specific factor; G-factor = global factor; δ = Uniquenesses; ω = McDonald's omega; Non-significant loadings are underlined and italicized.

Table 7

Results from the Final Bifactor-ESEM-Within-CFA Predictive Model

	Body appreciation		Symptoms of disordered eating		Self-esteem	
	b (SE)	*β*	*b* (SE)	*β*	*b* (SE)	*β*
G-factor	-.096 (.024)**	-.119	.184 (.021)**	.259	-.103 (.019)**	-.166
Intrapersonal	.007 (.026)	.009	-.101 (.023)**	-.142	.043 (.019)*	.069
Social	-.092 (.028)**	-.115	.155 (.025)**	.217	-.071 (.022)**	-.114
Consider	-.171 (.027)**	-.213	.087 (.023)**	.123	-.133 (.020)**	-.214

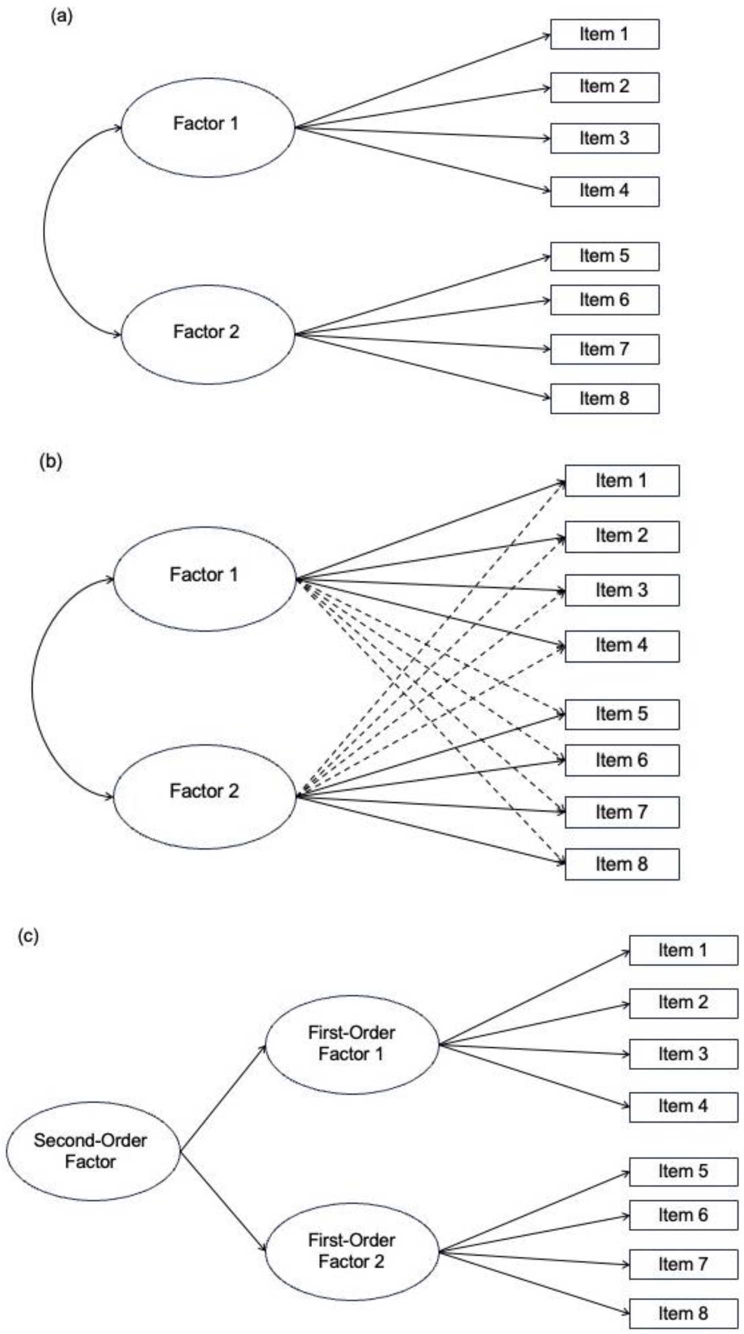
Notes. *b* = unstandardised regression coefficient; SE = standard error of the coefficient; β = sample-specific standardised regression coefficient; G-factor = global factor. * $p \leq .05$; ** $p \leq .01$

Table 8

Relations between the ACSS Latent Factors and the Predictors from the Bifactor Exploratory Structural Equation Modeling

		Subsample-specific standardised coefficients	
	b (SE)	*β* (First split-half sample)	*β* (Second split-half sample)
Age			
G-factor	-.053 (.035)	-.052	-.052
Intrapersonal	.046 (.040)	.046	.046
Social	.009 (.085)	.009	.009
Consider	-.204 (.033)**	-.188**	-.188**
Gender			
G-factor	.356 (.302)	.163	.159
Intrapersonal	.212 (.260)	.098	.096
Social	-.452 (.396)	-.203	-.199
Consider	.819 (.290)**	.349**	.342**
Body mass-index			
G-factor	-.021 (.067)	-.021	-.021
Intrapersonal	-.010 (.072)	-.010	-.010
Social	.100 (.032)**	.097**	.097**
Consider	.048 (.085)	.044	.044

Notes. ACSS = Acceptance of Cosmetic Surgery Scale; b = unstandardised regression coefficient taken from the factors-only models (6-4) invariant across samples; SE = standard error of the coefficient; β = sample-specific standardised regression coefficient (although some of the relations are invariant across samples, the standardised coefficients may still show some variation as a function of within-samples estimates of variability); G-factor = global factor. Because age and body mass index were standardised prior to these analyses and because the ACSS latent factors are estimated based on a model of latent variance-covariance invariance in which all latent factors have a SD of 1, all unstandardised coefficients can be directly interpreted is *SD* units. * $p \leq .05$; ** $p \leq .01$.


(a)
Factor 1
Factor 2
Item 1
Item 2
Item 3
Item 4
Item 5
Item 6
Item 7
Item 8
(b)
Factor 1
Factor 2
Item 1
Item 2
Item 3
Item 4
Item 5
Item 6
Item 7
Item 8
(c)
Second-Order Factor
First-Order Factor 1
First-Order Factor 2
Item 1
Item 2
Item 3
Item 4
Item 5
Item 6
Item 7
Item 8

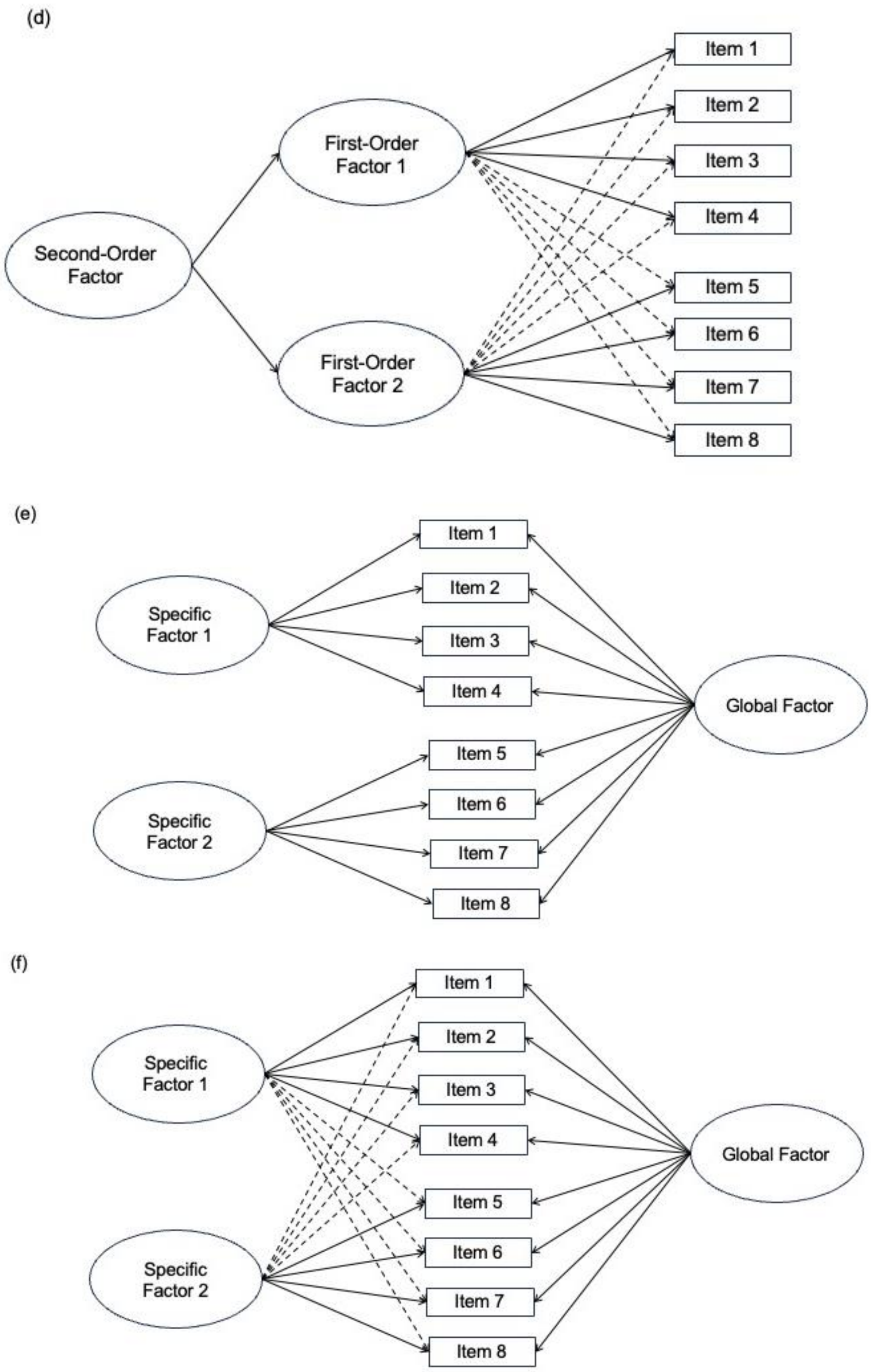


Figure 1. Abbreviated factor loading diagrams (error terms have been omitted). (a) Standard confirmatory factor analysis (CFA) model; (b) Standard exploratory structural equation modeling (ESEM) model; (c) Higher-order CFA model; (d) Higher-order ESEM model; (e) Bifactor-CFA model; (f) Bifactor-ESEM model

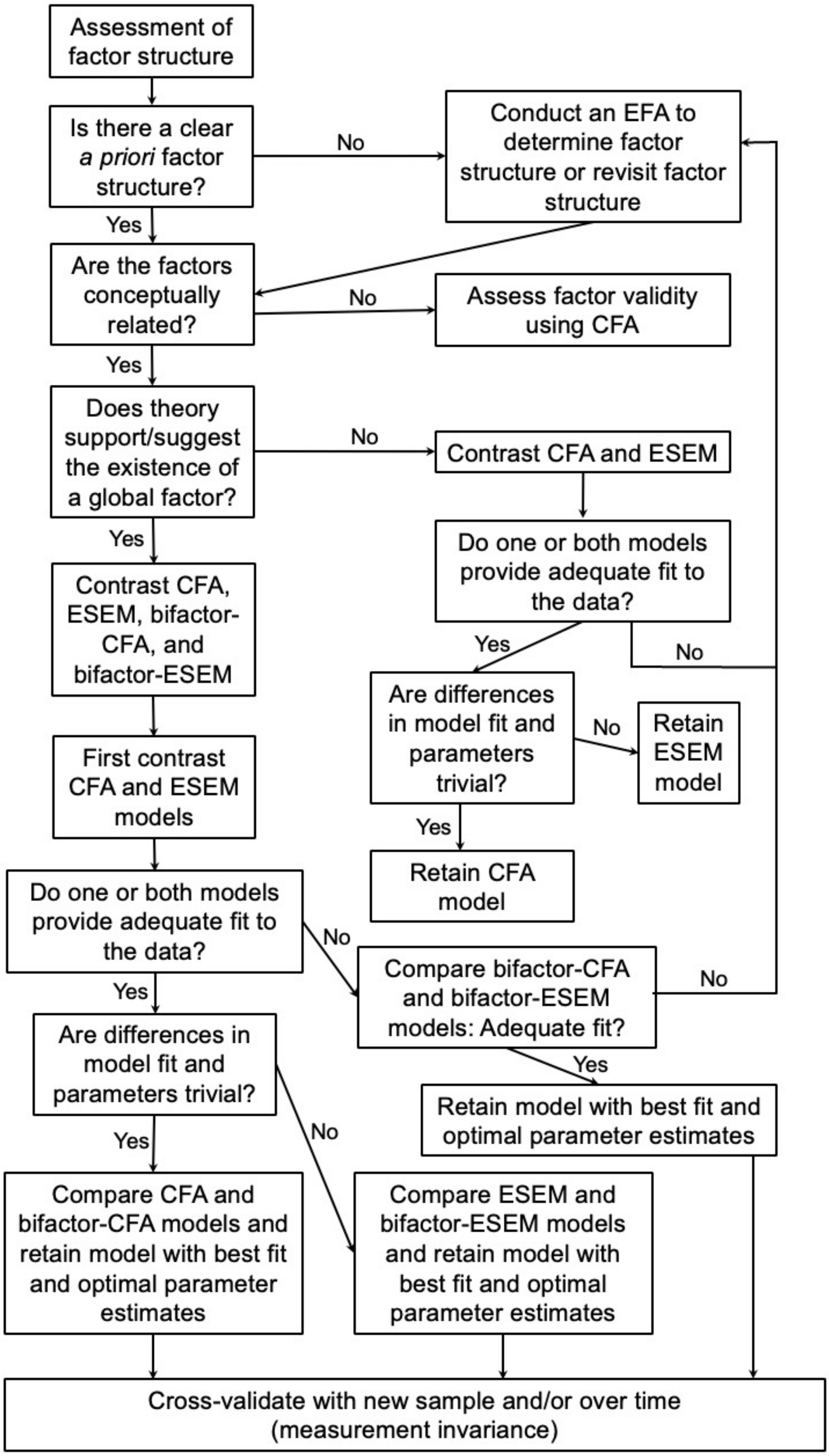


Figure 2. A decision tree for assistance in assessments of factor validity.

Technical Supplementary Materials for:

A Guide to Exploratory Structural Equation Modeling (ESEM) and Bifactor-ESEM in Body Image Research

Table of Contents

MEASUREMENT MODELS

CFA

```
!!! Mplus ignores annotations following !
!!! Each line of code (command) needs to end with ;
TITLE:   ACSS_CFA ;! Title of the input
  DATA:   FILE IS ACSS.dat; ! Name of the file

  VARIABLE:  ! Name of the variables in order of appearance in the file
  NAMES ARE sample age gender BMI acss1 acss2 acss3 acss4
  acss5 acss6 acss7 acss8 acss9 acss10 acss11 acss12 acss13
  acss14 acss15 BAS BISQ RSES;

  MISSING ARE ALL (-999); ! To identify the missing data in the file

! Recoded variables need to be added at the end of the USEVARIABLES list
  USEVARIABLES ARE acss1 acss2 acss3 acss4
  acss5 acss6 acss7 acss8 acss9 acss11 acss12 acss13
  acss14 acss15 acss10R;

  ANALYSIS:
  ESTIMATOR IS MLR; ! To identify the estimator used

  DEFINE: ! To modify variables; here it is to reverse-coded acss10
IF (acss10 EQ 1) THEN acss10R= 7;   IF (acss10 EQ 2) THEN acss10R= 6;   IF (acss10 EQ 3)
THEN acss10R= 5;   IF (acss10 EQ 4) THEN acss10R= 4;   IF (acss10 EQ 5) THEN acss10R= 3;
IF (acss10 EQ 6) THEN acss10R= 2;   IF (acss10 EQ 7) THEN acss10R= 1;

  MODEL:
! To define the 3 factors of the ACSS with the related indicators.
! The * is required to request the free estimation of the loading of the first indicator.
! For identification purposes, the factor variance is then fixed to 1 (@1).
  Intra BY acss1* acss2 acss4 acss5 acss14;

  Soc BY acss9* acss11 acss12 acss13 acss15;

  Cons BY acss3* acss6 acss7 acss8 acss10R;

  Intra@1;
  Soc@1;
  Cons@1;

  OUTPUT: ! To request specific output section, we recommend the following
SAMPSTAT STANDARDIZED CINTERVAL RESIDUAL SVALUES MODINDICES (6.0)
TECH1 TECH3 TECH4;
```

Bifactor-CFA

```
! We only report sections that differ from previous models.
MODEL:
! The ACSS G factor is defined using all indicators
  FG BY acss1* acss2 acss4 acss5 acss14
  acss9 acss11 acss12 acss13 acss15
  acss3 acss6 acss7 acss8 acss10R;

! The ACSS S-factors are defined as in the CFA model
  Intra BY acss1* acss2 acss4 acss5 acss14;
  Soc BY acss9* acss11 acss12 acss13 acss15;
  Cons BY acss3* acss6 acss7 acss8 acss10R;

! All ACSS factors are fixed to 1 for identification purposes
  FG@1;
  Intra@1;
  Soc@1;
  Cons@1;

! Correlations are fixed to be exactly 0 according to bifactor specifications
  FG WITH Intra@0 Soc@0 Cons@0;
  Intra WITH Soc@0 Cons@0;
  Soc WITH Cons@0;
```

ESEM with an Oblique GEOMIN (.5) Rotation

```
! We only report sections that differ from previous models.
  ANALYSIS:
! to request Geomin rotation (oblique by default)
  ROTATION=GEOMIN (.5);


  MODEL:
! This code is to request 3 ESEM factors (forming a single SET) defined from
! all indicators (with all loadings and cross-loadings free).
! ESEM factors are specified using (*1) at the end.
! Other Sets of factors would simply need to use a different number such as (*2)
  F1-F3 BY acss1 acss2 acss3 acss4
  acss5 acss6 acss7 acss8 acss9 acss11 acss12 acss13
  acss14 acss15 acss10R (*1);
```

Bifactor-ESEM with an Orthogonal GEOMIN (.5) Rotation

```
! We only report sections that differ from previous models.
  ANALYSIS:
! To request an orthogonal bifactor Geomin rotation
  ROTATION=BI-GEOMIN (ORTHOGONAL .5);

  MODEL:
! Relative to the ESEM model, the only change here is to add the request for a global factor
! F1-F4 would also work, as the BI-GEOMIN request automatically estimates the first factor as G
  FG F1-F3 BY acss1 acss2 acss3 acss4 acss5 acss6
 acss7 acss8 acss9 acss11 acss12 acss13
  acss14 acss15 acss10R (*1);
```

ESEM with a Target Rotation

```
! We only report sections that differ from previous models.
 ANALYSIS:
! To request a target rotation (oblique by default)
 ROTATION = TARGET;
 MODEL:
! With target rotation, factors are defined (and named) one at a time, but factors forming a Set
! are all defined by the same items.
! The set is identified as before with (*1) at the end of each factor.
! Main loadings are simply specified. Cross-loadings are given a target value of 0 using ~
 Intra BY acss1 acss2 acss4 acss5 acss14
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

 Soc BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9 acss11 acss12 acss13 acss15
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

  Cons BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3 acss6 acss7 acss8 acss10R (*t1);
```

Troubleshooting

When working with complex analytic models, some users may experience convergence difficulties: (a) The model fails to converge (i.e., no fit indices, standard errors, and tests of statistical significance are provided); (b) the model converges on an improper solution (standardised correlations ≥ 1, negative variance estimates, negative residual estimates, standardised loading higher than 1, etc.). Some of these problems can be solved by simply allowing the model a higher number of iterations. We then recommend adding the following to the ANALYSIS: section:

```
ITERATIONS = 10000;
H1ITERATIONS = 10000; ! this second one is related to the missing data handling procedure.
```

When this is not enough, it is possible to reduce the convergence criterion, which sometimes helps the model converge on a proper solution. The following then needs to be added, in addition to the previous addition, to the ANALYSIS: section:

```
CONVERGENCE = .0001;
H1CONVERGENCE = .0001;
```

When this is not enough, these values can be progressively decreased to .0005, then to .001, then to .005, then to .01, and then to .05 (do not skip a step).

Sometimes, rather than – or in addition to – adjusting the convergence criteria, it is possible to force the improper parameter estimates to take a proper value. However, sometimes, impossible (improper) parameter values only emerge when using one specific type of rotation. This is part of the rotational indeterminacy (all models with different rotations are equivalent) rather than a true problem with the model. It is possible to help the model converge on a proper solution (i.e., to guide the rotation to be result in the best statistically proper solution) using the MODEL CONSTRAINT section. However, if the solutions proposed here do not solve the problem, and this problem appears with other rotations, then this could be a true problem. Similar procedures can also be used in CFA (or in any type of models). In the present illustration, target rotation resulted in a standardised factor loading (associated with item ACSS13) higher than one. As one cannot label (and constraint) factor loadings in ESEM (as one can in CFA), the only way forward is to force the uniqueness of the item to take on a slightly higher value, as shown here:

```
! The uniqueness of the item is first assigned a unique label (here: res1).
  acss13 (res1);
! A MODEL CONSTRAINT section is added at the end of the model.
! The label is used to constrain the parameter to be higher or lower than a specific value.
! For the present problem:
  MODEL CONSTRAINT:
  res1 > 0.710;

! But had we wanted to handle a negative residual, we could have used:
  res1 > 0.01;
```

Similar procedures can be used to restrict correlations estimates to fall between 1.000 and -1.000. However, it is important to keep in mind that constraints can only be implemented on unstandardised estimates (i.e., covariances), rather than standardised ones (correlations). Thus, researchers would need to constrain covariances to take a value that results in a proper correlation, knowing that correlation = covariance / (standard deviation variable 1 * standard deviation variable y).

Bifactor-ESEM with an Orthogonal Target Rotation

```
! We only report sections that differ from previous models.
  ANALYSIS:
 ESTIMATOR IS MLR;
! To request a bifactor orthogonal target rotation
 ROTATION = TARGET (orthogonal);

 MODEL:
 ! Defined as in ESEM, with the addition of a G-factor including no target (all main loadings)
 FG BY acss1 acss2 acss4 acss5 acss14
 acss9 acss11 acss12 acss13 acss15
 acss3 acss6 acss7 acss8 acss10R (*t1);

 Intra BY acss1 acss2 acss4 acss5 acss14
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

 Soc BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9 acss11 acss12 acss13 acss15
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

 Cons BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3 acss6 acss7 acss8 acss10R (*t1);
```

CORRELATED UNIQUENESS AND METHOD FACTORS

ESEM with Correlated Uniquenesses

```
! We only report sections that differ from previous models.
 MODEL:
 Intra BY acss1 acss2 acss4 acss5 acss14
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

 Soc BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9 acss11 acss12 acss13 acss15
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

 Cons BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3 acss6 acss7 acss8 acss10R (*t1);

! To add correlated uniqueness
 acss15 WITH acss10R;
 acss5 WITH acss10R;
 acss15 WITH acss5;
```

ESEM with a Method Factor

```
! We only report sections that differ from previous models.
MODEL:
! To estimate a method factor (uncorrelated with the other factors)
 MF BY acss5* acss15 acss10R;
 MF@1;
 MF WITH Intra@0 Soc@0 Cons@0;

 Intra BY acss1 acss2 acss4 acss5 acss14
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

 Soc BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9 acss11 acss12 acss13 acss15
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

 Cons BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3 acss6 acss7 acss8 acss10R (*t1);
```

Bifactor-ESEM with Correlated Uniquenesses

```
! We only report sections that differing from previous models.
  MODEL:
  FG BY acss1 acss2 acss4 acss5 acss14
  acss9 acss11 acss12 acss13 acss15
  acss3 acss6 acss7 acss8 acss10R (*t1);

  Intra BY acss1 acss2 acss4 acss5 acss14
  acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
  acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

  Soc BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
  acss9 acss11 acss12 acss13 acss15
  acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

  Cons BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
  acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
  acss3 acss6 acss7 acss8 acss10R (*t1);

! To add correlated uniqueness
  acss15 WITH acss10R;
  acss5 WITH acss10R;
  acss15 WITH acss5;
```

Bifactor-ESEM with a Method Factor

```
! We only report sections that differ from previous models.
MODEL:
! To estimate a method factor (uncorrelated with the other factors)
  MF BY acss5* acss15 acss10R;
  MF@1;
  MF WITH FG@0 Intra@0 Soc@0 Cons@0;

  FG BY acss1 acss2 acss4 acss5 acss14
  acss9 acss11 acss12 acss13 acss15
  acss3 acss6 acss7 acss8 acss10R (*t1);

  Intra BY acss1 acss2 acss4 acss5 acss14
  acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
  acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

  Soc BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
  acss9 acss11 acss12 acss13 acss15
  acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

  Cons BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
  acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
  acss3 acss6 acss7 acss8 acss10R (*t1);
```

ESEM-WITHIN-CFA

```
! We only report sections that differ from previous models.
 ANALYSIS:
 ESTIMATOR IS MLR;
! This is no longer an ESEM solution, so there is no need for a rotation
! The ESEM-Within-CFA model is built from the final ESEM solution, using the unstandardized
! parameter estimates from this solution as start values. Start values are indicated by an * before
! the value. Fixed values are indicated by a @ before the value.
! When SVALUES are requested as part of the OUTPUT: section of the final ESEM solution, the
! values required for this set up will be provided in the model output section labelled "
! MODEL COMMAND WITH FINAL ESTIMATES USED AS STARTING VALUES"
! For each factor, one referent indicator is selected. It should ideally be an item with a high
! main loading and low cross-loadings, but any indicator will do. For this referent indicator, all
! cross-loadings are fixed to their ESEM values (@).
! Factor variances are also all fixed to 1.

 MODEL:
    intra BY acss1*1.43203;
    intra BY acss2*1.71045;
    intra BY acss4*1.35799;
    intra BY acss5*1.66550;
    intra BY acss14*1.42937;
    intra BY acss9*-0.17748;
    intra BY acss11*0.35441;
    intra BY acss12*0.19195;
    intra BY acss13@-0.07632; ! Referent indicator for Soc factor
    intra BY acss15*0.03492;
    intra BY acss3*0.39507;
    intra BY acss6*0.10193;
    intra BY acss7*-0.05908;
    intra BY acss8@-0.15394; ! Referent indicator for Cons factor
    intra BY acss10r*-0.04919;

    soc BY acss1*-0.20042;
    soc BY acss2*-0.15034;
    soc BY acss4*0.29114;
    soc BY acss5@-0.07012; ! Referent indicator for Intra factor
    soc BY acss14*0.21781;
    soc BY acss9*1.39505;
    soc BY acss11*0.82871;
    soc BY acss12*1.24284;
    soc BY acss13*1.69717;
    soc BY acss15*1.47664;
    soc BY acss3*0.20452;
    soc BY acss6*0.22270;
    soc BY acss7*0.10472;
    soc BY acss8@-0.01356; ! Referent indicator for Cons factor
    soc BY acss10r*-0.19625;

    cons BY acss1*0.41875;
    cons BY acss2*0.08018;
    cons BY acss4*-0.13089;
    cons BY acss5@-0.16687; ! Referent indicator for Intra factor
    cons BY acss14*0.00215;
```

```
      cons BY acss9*0.19381;
      cons BY acss11*0.30757;
      cons BY acss12*0.20718;
      cons BY acss13@-0.31551; ! Referent indicator for Soc factor
      cons BY acss15*0.11337;
      cons BY acss3*1.45748;
      cons BY acss6*1.76837;
      cons BY acss7*2.06492;
      cons BY acss8*2.25102;
      cons BY acss10r*1.64723;
      soc WITH intra*0.56897;
      cons WITH intra*0.70245;
      cons WITH soc*0.63633;
! Item intercepts
      [ acss1*4.28627 ];
      [ acss2*4.34824 ];
      [ acss3*3.27686 ];
      [ acss4*3.68314 ];
      [ acss5*4.69882 ];
      [ acss6*3.48392 ];
      [ acss7*3.68784 ];
      [ acss8*3.52706 ];
      [ acss9*2.18824 ];
      [ acss11*2.76941 ];
      [ acss12*2.80078 ];
      [ acss13*2.09647 ];
      [ acss14*4.13412 ];
      [ acss15*2.51843 ];
      [ acss10r*4.15843 ];
! Item uniquenesses
      acss1*2.02788;
      acss2*0.79462;
      acss3*0.90680;
      acss4*1.34856;
      acss5*1.05895;
      acss6*1.06513;
      acss7*0.93612;
      acss8*0.85496;
      acss9*1.00669;
      acss11*2.23441;
      acss12*1.63698;
      acss13*0.71009;
      acss14*1.30248;
      acss15*1.14723;
      acss10r*2.86117;

! Variances of ACSS factors are fixed (@) to 1
! To be able to keep them *1 (rather than @1) when the factors are endogenous, the main
! loading of the referent indicator should also be fixed (@)
    intra@1; soc@1; cons@1;
  OUTPUT:   SAMPSTAT STANDARDIZED CINTERVAL RESIDUAL SVALUES
MODINDICES (6.0) TECH1 TECH3 TECH4;
```

BIFACTOR-ESEM-WITHIN-CFA

```
! We only report sections that differ from previous models.
  ANALYSIS:
 ESTIMATOR IS MLR;
! This is no longer a bifactor ESEM solution, so there is no need for a rotation
! This model is set up as the previous one (ESEM-within-CFA). One referent indicator also needs
! to be selected for the G-factor, and all factor correlations need to be fixed to 0 (@0).
 MODEL:
    fg BY acss1*1.27466;
    fg BY acss2@1.25228; ! Referent indicator for Intra factor
    fg BY acss4*1.18214;
    fg BY acss5*1.06137;
    fg BY acss14*1.28156;
    fg BY acss9*1.05900;
    fg BY acss11*1.69114;
    fg BY acss12*1.46255;
    fg BY acss13@0.99653; ! Referent indicator for Soc factor
    fg BY acss15*1.26796;
    fg BY acss3*1.69946;
    fg BY acss6*1.66308;
    fg BY acss7@1.68231; ! Referent indicator for Cons factor
    fg BY acss8*1.70541;
    fg BY acss10r*1.17758;

    intra BY acss1*0.95349;
    intra BY acss2*1.10742;
    intra BY acss4*0.82938;
    intra BY acss5*1.08808;
    intra BY acss14*0.89000;
    intra BY acss9*-0.06188;
    intra BY acss11*-0.37323;
    intra BY acss12*-0.10224;
    intra BY acss13@-0.07649; ! Referent indicator for Soc factor
    intra BY acss15*0.00444;
    intra BY acss3*0.28106;
    intra BY acss6*0.21085;
    intra BY acss7@0.13809; ! Referent indicator for Cons factor
    intra BY acss8@0.04784; ! Referent indicator for G factor
    intra BY acss10r*0.04550;

    soc BY acss1*-0.14885;
    soc BY acss2@-0.12559; ! Referent indicator for Intra factor
    soc BY acss4*0.10857;
    soc BY acss5*-0.05988;
    soc BY acss14*0.05727;
    soc BY acss9*0.93001;
    soc BY acss11*-0.16328;
    soc BY acss12*0.49707;
    soc BY acss13*1.20634;
    soc BY acss15*0.87826;
    soc BY acss3*0.03014;
    soc BY acss6*0.15045;
    soc BY acss7@0.09863; ! Referent indicator for Cons factor
    soc BY acss8@-0.02380; ! Referent indicator for G factor
    soc BY acss10r*-0.16934;
    cons BY acss1*0.33739;
    cons BY acss2@0.15985; ! Referent indicator for Intra factor
    cons BY acss4*-0.01061;
    cons BY acss5*0.04130;
    cons BY acss14*0.07818;
    cons BY acss9*0.19293;
```

```
    cons BY acss11*-0.46634;
    cons BY acss12*-0.07797;
    cons BY acss13@-0.15812; ! Referent indicator for Soc factor
    cons BY acss15*0.09855;
    cons BY acss3*0.79999;
    cons BY acss6*1.07314;
    cons BY acss7*1.24152;
    cons BY acss8@1.28091; ! Referent indicator for G factor
    cons BY acss10r*0.90632;

! Factor correlations fixed to 0.
    intra WITH fg@0.00000;
    soc WITH fg@0.00000;
    soc WITH intra@0.00000;
    cons WITH fg@0.00000;
    cons WITH intra@0.00000;
    cons WITH soc@0.00000;

! Item intercepts
    [ acss1*4.28627 ];
    [ acss2*4.34824 ];
    [ acss3*3.27686 ];
    [ acss4*3.68314 ];
    [ acss5*4.69882 ];
    [ acss6*3.48392 ];
    [ acss7*3.68784 ];
    [ acss8*3.52706 ];
    [ acss9*2.18824 ];
    [ acss11*2.76941 ];
    [ acss12*2.80078 ];
    [ acss13*2.09647 ];
    [ acss14*4.13412 ];
    [ acss15*2.51843 ];
    [ acss10r*4.15843 ];

! Item uniquenesses
    acss1*2.03326;
    acss2*0.79811;
    acss3*0.90115;
    acss4*1.34904;
    acss5*1.04143;
    acss6*1.04792;
    acss7*0.91084;
    acss8*0.87058;
    acss9*1.00851;
    acss11*0.70970;
    acss12*1.51372;
    acss13*0.34209;
    acss14*1.30832;
    acss15*1.23027;
    acss10r*2.86230;
! Variances of ACSS factors (FG and S-factors) are fixed (@) to 1
! To be able to keep them *1 (rather than @1) when the factors are endogenous, the main
! loading of the referent indicator should also be fixed (@)
    fg@1; intra@1; soc@1; cons@1;
```

PREDICTIVE MODEL WITH BIFACTOR-ESEM-WITHIN-CFA
Predictors-to-Outcomes Paths Free for the G-Factor Only

```
TITLE:   ACSS_EwC_Bi-factor_ESEM_predictions_G&S-factors@0
DATA:   FILE IS ACSS.dat;
VARIABLE:
NAMES ARE sample age gender BMI acss1 acss2 acss3 acss4
acss5 acss6 acss7 acss8 acss9 acss10 acss11 acss12 acss13
acss14 acss15 BAS BISQ RSES;
MISSING ARE ALL (-999);
USEVARIABLES ARE acss1 acss2 acss3 acss4
acss5 acss6 acss7 acss8 acss9 acss11 acss12 acss13
acss14 acss15 BAS BISQ RSES acss10R;

 ANALYSIS:
ESTIMATOR IS MLR;
! The convergence criterion was reduced (.005) to help the model converge
! With missing data, the same should be done to the H1Convergence.
! Decreasing the convergence should be tried after having first increased the Iterations and
! H1Iterations to 10000;
convergence = .005;

MODEL:
   fg BY acss1*1.27466;
   fg BY acss2@1.25228; ! Referent indicator for Intra factor
   fg BY acss4*1.18214;
   fg BY acss5*1.06137;
   fg BY acss14*1.28156;
   fg BY acss9*1.05900;
   fg BY acss11*1.69114;
   fg BY acss12*1.46255;
   fg BY acss13@0.99653; ! Referent indicator for Soc factor
   fg BY acss15*1.26796;
   fg BY acss3*1.69946;
   fg BY acss6*1.66308;
   fg BY acss7@1.68231; ! Referent indicator for Cons factor
   fg BY acss8*1.70541;
   fg BY acss10r*1.17758;

   intra BY acss1*0.95349;
   intra BY acss2*1.10742;
   intra BY acss4*0.82938;
   intra BY acss5*1.08808;
   intra BY acss14*0.89000;
   intra BY acss9*-0.06188;
   intra BY acss11*-0.37323;
   intra BY acss12*-0.10224;
   intra BY acss13@-0.07649; ! Referent indicator for Soc factor
   intra BY acss15*0.00444;
   intra BY acss3*0.28106;
   intra BY acss6*0.21085;
   intra BY acss7@0.13809; ! Referent indicator for Cons factor
   intra BY acss8@0.04784; ! Referent indicator for FG factor
   intra BY acss10r*0.04550;
```

```
soc BY acss1*-0.14885;
soc BY acss2@-0.12559; ! Referent indicator for Intra factor
soc BY acss4*0.10857;
soc BY acss5*-0.05988;
soc BY acss14*0.05727;
soc BY acss9*0.93001;
soc BY acss11*-0.16328;
soc BY acss12*0.49707;
soc BY acss13*1.20634;
soc BY acss15*0.87826;
soc BY acss3*0.03014;
soc BY acss6*0.15045;
soc BY acss7@0.09863; ! Referent indicator for Cons factor
soc BY acss8@-0.02380; ! Referent indicator for FG factor
soc BY acss10r*-0.16934;
cons BY acss1*0.33739;
cons BY acss2@0.15985; ! Referent indicator for Intra factor
cons BY acss4*-0.01061;
cons BY acss5*0.04130;
cons BY acss14*0.07818;
cons BY acss9*0.19293;
cons BY acss11*-0.46634;
cons BY acss12*-0.07797;
cons BY acss13@-0.15812; ! Referent indicator for Soc factor
cons BY acss15*0.09855;
cons BY acss3*0.79999;
cons BY acss6*1.07314;
cons BY acss7*1.24152;
cons BY acss8@1.28091; ! Referent indicator for FG factor
cons BY acss10r*0.90632;

intra WITH fg@0.00000;
soc WITH fg@0.00000;
soc WITH intra@0.00000;
cons WITH fg@0.00000;
cons WITH intra@0.00000;
cons WITH soc@0.00000;

[ acss1*4.28627 ];
[ acss2*4.34824 ];
[ acss3*3.27686 ];
[ acss4*3.68314 ];
[ acss5*4.69882 ];
[ acss6*3.48392 ];
[ acss7*3.68784 ];
[ acss8*3.52706 ];
[ acss9*2.18824 ];
[ acss11*2.76941 ];
[ acss12*2.80078 ];
[ acss13*2.09647 ];
[ acss14*4.13412 ];
[ acss15*2.51843 ];
[ acss10r*4.15843 ];
```

```
    acss1*2.03326;
    acss2*0.79811;
    acss3*0.90115;
    acss4*1.34904;
    acss5*1.04143;
    acss6*1.04792;
    acss7*0.91084;
    acss8*0.87058;
    acss9*1.00851;
    acss11*0.70970;
    acss12*1.51372;
    acss13*0.34209;
    acss14*1.30832;
    acss15*1.23027;
    acss10r*2.86230;

! Variances of ACSS factors (FG and S-factors) are fixed (@) to 1
! If the G- and S- factors had been outcomes, then the variances should have been *1
! and the main loading of the referent indicator fixed (@).
    fg@1; intra@1; soc@1; cons@1;
! Predictions are indicated with ON. The outcome is specified before ON, the predictor after.
! Paths not estimated are fixed to 0 (@0).
    BAS BISQ RSES ON fg;
    BAS BISQ RSES ON intra@0;
    BAS BISQ RSES ON soc@0;
    BAS BISQ RSES ON cons@0;
```

Predictors-to-Outcomes Paths Free for the G- and S- Factors

```
! We only report sections that differ from previous models.
MODEL:
! Only the predictive section needs to be updated
    BAS BISQ RSES ON fg;
    BAS BISQ RSES ON intra;
    BAS BISQ RSES ON soc;
    BAS BISQ RSES ON cons;
```

GENDER INVARIANCE: ESEM

Configural Invariance

```
 TITLE:   M0-ESEM_Configural
 DATA:   FILE IS ACSS.dat;
 VARIABLE:
   NAMES ARE sample age gender BMI acss1 acss2 acss3 acss4
 acss5 acss6 acss7 acss8 acss9 acss10 acss11 acss12 acss13
 acss14 acss15 BAS BISQ RSES;
 MISSING ARE ALL (-999);
! Recoded variables need to be added at the end of the USEVARIABLES list
 USEVARIABLES ARE acss1 acss2 acss3 acss4
 acss5 acss6 acss7 acss8 acss9 acss11 acss12 acss13
 acss14 acss15 acss10R;
! The GROUPING command is used to identify the variable used to define the gender groups
! Each value of the grouping variable is given an arbitrary label (here men and women).
 GROUPING IS gender (1= men 2= women);
ANALYSIS:
 ESTIMATOR IS MLR;
 ROTATION = TARGET;

DEFINE:
IF (acss10 EQ 1) THEN acss10R= 7;   IF (acss10 EQ 2) THEN acss10R= 6;   IF (acss10 EQ 3)
THEN acss10R= 5;   IF (acss10 EQ 4) THEN acss10R= 4;   IF (acss10 EQ 5) THEN acss10R= 3;
IF (acss10 EQ 6) THEN acss10R= 2;   IF (acss10 EQ 7) THEN acss10R= 1;

! The MODEL section is used to define the parameters that apply to all groups.
! With ESEM, the scale of the factors is automatically set by allowing all of the loadings and
! cross-loadings to be freely identified and the factor variances to be fixed to 1.
! For consistency, we strongly recommend setting the scale of the mean structure in the same
! manner, by freely estimating all intercepts and fixing the factors means to be 0, leading to
! a complete standardized factors approach.
 MODEL:
! Factor loadings
 Intra BY acss1 acss2 acss4 acss5 acss14
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

 Soc BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9 acss11 acss12 acss13 acss15
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

   Cons BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3 acss6 acss7 acss8 acss10R (*t1);
! Factor variances
 Intra@1; Soc@1; Cons@1;
! Factor means
 [Intra@0]; [Soc@0]; [Cons@0];
! Item intercepts
 [acss1 -acss10R];
! Item uniquenesses
 acss1-acss10R;
```

```
! The MODEL WOMEN section is then used to define how the parameters differ, or not,
! across gender. One specific section fewer than the total number of groups is usually needed,
! and this section cannot be the one referring to the first group.
! In the configural model, all parameters are free (the previous syntax is repeated here)
MODEL WOMEN:
 Intra BY acss1 acss2 acss4 acss5 acss14
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

 Soc BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9 acss11 acss12 acss13 acss15
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

  Cons BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3 acss6 acss7 acss8 acss10R (*t1);

 Intra@1;   Soc@1;   Cons@1;
 [Intra@0];   [Soc@0];   [Cons@0];
 [acss1-acss10R];
 acss1-acss10R;

 OUTPUT: SAMPSTAT STANDARDIZED CINTERVAL RESIDUAL SVALUES
MODINDICES (6.0) TECH1 TECH3 TECH4;
```

Weak Invariance

```
! We only report sections that differ from previous models.
  MODEL:
  Intra BY acss1 acss2 acss4 acss5 acss14
  acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
  acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

  Soc BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
  acss9 acss11 acss12 acss13 acss15
  acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

    Cons BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
  acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
  acss3 acss6 acss7 acss8 acss10R (*t1);

  Intra@1;   Soc@1;   Cons@1;
  [Intra@0];   [Soc@0];   [Cons@0];
  [acss1 -acss10R];
  acss1-acss10R;

  MODEL women:
! By default, factor loadings are set up to be equal across groups in Mplus.
! So, for tests of weak invariance, the women-specific mention of ACSS factor loadings should
! simply be taken out. By constraining the loadings to equality across gender groups, the variance
! now needs to be freed in all but the first group.
  Intra*;   Soc*;   Cons*;
  [Intra@0];   [Soc@0];   [Cons@0];
  [acss1-acss10R];
  acss1-acss10R;
```

Strong Invariance

```
! We only report sections that differ from previous models.
  MODEL:
 Intra BY acss1 acss2 acss4 acss5 acss14
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

 Soc BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9 acss11 acss12 acss13 acss15
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

  Cons BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3 acss6 acss7 acss8 acss10R (*t1);

 Intra@1;   Soc@1;   Cons@1;
 [Intra@0];   [Soc@0];   [Cons@0];
! Intercepts can be constrained to equality across groups by using identical labels (in
! parentheses) in all gender groups. We recommend using alphanumeric labels where the letter
! is linked to the type of parameter being estimated (e.g., i for intercept). Labels need to be
! uniquely associated with a single parameter.
 [acss1-acss10R] (i1-i15);
 acss1-acss10R;

 MODEL women:
! Once intercepts are invariant, factor means need to be freed in in all but the first group.
 Intra*;   Soc*;   Cons*;
 [Intra*];  [Soc*];  [Cons*];
 [acss1-acss10R] (i1-i15);
 acss1-acss10R;
```

Strict Invariance

```
! We only report sections that differ from previous models
 MODEL:
 Intra BY acss1 acss2 acss4 acss5 acss14
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

 Soc BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9 acss11 acss12 acss13 acss15
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

  Cons BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3 acss6 acss7 acss8 acss10R (*t1);

 Intra@1;   Soc@1;   Cons@1;
 [Intra@0];   [Soc@0];   [Cons@0];
 [acss1-acss10R] (i1-i15);
! To set the ACSS item uniquenesses (e.g., u for uniquenesses) to be equal across gender groups
 acss1-acss10R (u1-u15);

 MODEL women:
 Intra*;   Soc*;   Cons*;
 [Intra*];   [Soc*];   [Cons*];
 [acss1-acss10R] (i1-i15);
 acss1-acss10R (u1-u15);
```

Partial Strict Invariance

```
! We only report sections that differ from previous models
  MODEL:
  Intra BY acss1 acss2 acss4 acss5 acss14
  acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
  acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

  Soc BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
  acss9 acss11 acss12 acss13 acss15
  acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

   Cons BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
  acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
  acss3 acss6 acss7 acss8 acss10R (*t1);

  Intra@1;   Soc@1;   Cons@1;
  [Intra@0];   [Soc@0];   [Cons@0];
  [acss1-acss10R] (i1-i15);

  acss1 (u1);   acss2 (u2);   acss3 (u3);   acss4 (u4);   acss5 (u5);   acss6 (u6);   acss7 (u7);
  acss8 (u8);    acss9 (u9);
! To request the free estimation of the non-invariant uniqueness, remove the label.
acss11*;
 acss12 (u11);    acss13 (u12);   acss14 (u13);
! To request the free estimation of the non-invariant uniqueness, remove the label.
acss15*;
  acss10R (u15);

  MODEL women:
  Intra*;   Soc*;   Cons*;
  [Intra*];   [Soc*];   [Cons*];
  [acss1-acss10R] (i1-i15);

  acss1 (u1);   acss2 (u2);   acss3 (u3);   acss4 (u4);   acss5 (u5);   acss6 (u6);   acss7 (u7);
  acss8 (u8);    acss9 (u9);
! To request the free estimation of the non-invariant uniqueness, remove the label.
acss11*;
 acss12 (u11);    acss13 (u12);   acss14 (u13);
! To request the free estimation of the non-invariant uniqueness, remove the label.
acss15*;
  acss10R (u15);
```

Latent Variances and Covariances Invariance

```
! We only report sections that differ from previous models
 MODEL:
 Intra BY acss1 acss2 acss4 acss5 acss14
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

 Soc BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9 acss11 acss12 acss13 acss15
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

  Cons BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3 acss6 acss7 acss8 acss10R (*t1);

! ACSS factor variances need to be fixed back to 1 in all groups.
! In doing so, ACSS factor covariances need to be specified and set to equality across groups.
 Intra@1;   Soc@1;   Cons@1;
 Intra WITH Soc (cov1);
 Intra WITH Cons (cov2);
 Soc WITH Cons (cov3);

 [Intra@0];   [Soc@0];   [Cons@0];
 [acss1-acss10R] (i1-i15);
 acss1 (u1);   acss2 (u2);   acss3 (u3);   acss4 (u4);   acss5 (u5);   acss6 (u6);   acss7 (u7);
 acss8 (u8);    acss9 (u9);
acss11*;
 acss12 (u11);    acss13 (u12);   acss14 (u13);
acss15*;
 acss10R (u15);

 MODEL women:
! ACSS factor variances need to be fixed back to 1 in all groups.
! In doing so, ACSS factor covariances need to be specified and set to equality across groups.
 Intra@1;   Soc@1;   Cons@1;
 Intra WITH Soc (cov1);
 Intra WITH Cons (cov2);
 Soc WITH Cons (cov3);

 [Intra*];   [Soc*];   [Cons*];
 [acss1-acss10R] (i1-i15);

 acss1 (u1);   acss2 (u2);   acss3 (u3);   acss4 (u4);   acss5 (u5);   acss6 (u6);   acss7 (u7);
 acss8 (u8);    acss9 (u9);
acss11*;
 acss12 (u11);    acss13 (u12);   acss14 (u13);
acss15*;
 acss10R (u15);
```

Latent Means Invariance

```
! We only report sections that differ from previous models
  MODEL:
  Intra BY acss1 acss2 acss4 acss5 acss14
  acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
  acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

  Soc BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
  acss9 acss11 acss12 acss13 acss15
  acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

    Cons BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
  acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
  acss3 acss6 acss7 acss8 acss10R (*t1);

  Intra@1;   Soc@1;   Cons@1;
  Intra WITH Soc (cov1);
  Intra WITH Cons (cov2);
  Soc WITH Cons (cov3);
! ACSS factor means need to be fixed back to 0 in all groups.
  [Intra@0];   [Soc@0];   [Cons@0];

  [acss1-acss10R] (i1-i15);
  acss1 (u1);   acss2 (u2);   acss3 (u3);   acss4 (u4);   acss5 (u5);   acss6 (u6);   acss7 (u7);
  acss8 (u8);    acss9 (u9);
acss11*;
 acss12 (u11);    acss13 (u12);   acss14 (u13);
acss15*;
  acss10R (u15);

  MODEL women:
  Intra@1;   Soc@1;   Cons@1;
  Intra WITH Soc (cov1);
  Intra WITH Cons (cov2);
  Soc WITH Cons (cov3);
! ACSS factor means need to be fixed back to 0 in all groups.
  [Intra@0];   [Soc@0];   [Cons@0];

  [acss1-acss10R] (i1-i15);
  acss1 (u1);   acss2 (u2);   acss3 (u3);   acss4 (u4);   acss5 (u5);   acss6 (u6);   acss7 (u7);
  acss8 (u8);    acss9 (u9);
acss11*;
 acss12 (u11);    acss13 (u12);   acss14 (u13);
acss15*;
  acss10R (u15);
```

SAMPLE INVARIANCE: BIFACTOR-ESEM

Configural Invariance

```
  TITLE:   M0-BESEM_Configural
  DATA:  FILE IS ACSS.dat;
  VARIABLE:
  NAMES ARE sample age gender BMI acss1 acss2 acss3 acss4
  acss5 acss6 acss7 acss8 acss9 acss10 acss11 acss12 acss13
  acss14 acss15 BAS BISQ RSES;
  MISSING ARE ALL (-999);
! Recoded variables need to be added at the end of the USEVARIABLES list
  USEVARIABLES ARE acss1 acss2 acss3 acss4
acss5 acss6 acss7 acss8 acss9  acss11 acss12 acss13
acss14 acss15 acss10R;
! The GROUPING command is used to identify the variable used to define the samples
! Each value of the grouping variable is given an arbitrary label (here sample1 and sample2).
  GROUPING IS sample (1= sample1 2= sample2);
ANALYSIS:
  ESTIMATOR IS MLR;
  ROTATION = TARGET (orthogonal);

DEFINE:
IF (acss10 EQ 1) THEN acss10R= 7;   IF (acss10 EQ 2) THEN acss10R= 6;   IF (acss10 EQ 3)
THEN acss10R= 5;   IF (acss10 EQ 4) THEN acss10R= 4;   IF (acss10 EQ 5) THEN acss10R= 3;
IF (acss10 EQ 6) THEN acss10R= 2;   IF (acss10 EQ 7) THEN acss10R= 1;

! The MODEL section is used to define the parameters that apply to all groups.
! With Bifactor-ESEM, the scale of the factors is automatically set by allowing all loadings and
! cross-loadings to be freely identified and the factor variances to be fixed to 1.
! For consistency, we strongly recommend setting the scale of the mean structure in the same
! manner, by freely estimating all intercepts and fixing the factors means to be 0, leading to
! a complete standardized factors approach.
! Factor correlations are automatically rotated to 0 with an orthogonal rotation.
  MODEL:
! Factor loadings
  FG BY acss1 acss2 acss4 acss5 acss14
  acss9 acss11 acss12 acss13 acss15
  acss3 acss6 acss7 acss8 acss10R (*t1);

  Intra BY acss1 acss2 acss4 acss5 acss14
  acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
  acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

  Soc BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
  acss9 acss11 acss12 acss13 acss15
  acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

   Cons BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
  acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
  acss3 acss6 acss7 acss8 acss10R (*t1);

! Factor variances
  FG@1;   Intra@1;   Soc@1;   Cons@1;
```

```
! Factor means
 [FG@0];   [Intra@0];   [Soc@0];   [Cons@0];
! Item intercepts
 [acss1-acss10R];
! Item uniquenesses
 acss1-acss10R;

! The MODEL SAMPLE2 section is then used to define how the parameters differ, or not,
! across samples. One specific section fewer than the total number of groups is usually needed.
! In the configural model, all parameters are free (the previous syntax is repeated here)
 MODEL SAMPLE2:
 FG BY acss1 acss2 acss4 acss5 acss14
 acss9 acss11 acss12 acss13 acss15
 acss3 acss6 acss7 acss8 acss10R (*t1);

 Intra BY acss1 acss2 acss4 acss5 acss14
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

 Soc BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9 acss11 acss12 acss13 acss15
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

  Cons BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3 acss6 acss7 acss8 acss10R (*t1);

 FG@1;   Intra@1;   Soc@1;   Cons@1;
 [FG@0];   [Intra@0];   [Soc@0];   [Cons@0];
 [acss1-acss10R];
 acss1-acss10R;
```

Weak Invariance

```
! We only report sections that differ from previous models
 MODEL:
 FG BY acss1 acss2 acss4 acss5 acss14
 acss9 acss11 acss12 acss13 acss15
 acss3 acss6 acss7 acss8 acss10R (*t1);

 Intra BY acss1 acss2 acss4 acss5 acss14
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

 Soc BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9 acss11 acss12 acss13 acss15
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

  Cons BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3 acss6 acss7 acss8 acss10R (*t1);

 FG@1;   Intra@1;   Soc@1;   Cons@1;
 [FG@0];   [Intra@0];   [Soc@0];   [Cons@0];
 [acss1-acss10R];
 acss1-acss10R;

 MODEL sample2:
! By default, factor loadings are set up to be equal across groups in Mplus.
! So, for tests of weak invariance, the sample-specific mention of ACSS factor loadings need to be
! simply be taken out. By constraining the loadings to equality across subsamples, the variance
! now need to be freed in all but the first group.
 FG*;   Intra*;   Soc*;   Cons*;
 [FG@0];   [Intra@0];   [Soc@0];   [Cons@0];
 [acss1-acss10R];
 acss1-acss10R;
```

Strong Invariance

```
! We only report sections that differ from previous models
 MODEL:
 FG BY acss1 acss2 acss4 acss5 acss14
 acss9 acss11 acss12 acss13 acss15
 acss3 acss6 acss7 acss8 acss10R (*t1);

 Intra BY acss1 acss2 acss4 acss5 acss14
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

 Soc BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9 acss11 acss12 acss13 acss15
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

  Cons BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3 acss6 acss7 acss8 acss10R (*t1);

 FG@1;   Intra@1;   Soc@1;   Cons@1;
 [FG@0];   [Intra@0];   [Soc@0];   [Cons@0];
! Intercepts can be constrained to equality across groups by using identical labels (in
! parentheses) in all gender groups. We recommend using alphanumeric labels where the letter
! is linked to the type of parameter being estimated (e.g., i for intercept). Labels need to be
! uniquely associated with a single parameter.
 [acss1-acss10R] (i1-i15);
 acss1-acss10R;

 MODEL sample2:
 FG*;   Intra*;   Soc*;   Cons*;
! Once intercepts are invariant, factor means need to be freed in in all but the first group.
 [FG*];   [Intra*];   [Soc*];   [Cons*];
[acss1-acss10R] (i1-i15);
  acss1-acss10R;
```

Strict Invariance

```
! We only report sections that differ from previous models
 MODEL:
 FG BY acss1 acss2 acss4 acss5 acss14
 acss9 acss11 acss12 acss13 acss15
 acss3 acss6 acss7 acss8 acss10R (*t1);

 Intra BY acss1 acss2 acss4 acss5 acss14
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

 Soc BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9 acss11 acss12 acss13 acss15
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

  Cons BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3 acss6 acss7 acss8 acss10R (*t1);

 FG@1;   Intra@1;   Soc@1;   Cons@1;
 [FG@0];   [Intra@0];   [Soc@0];   [Cons@0];
 [acss1-acss10R] (i1-i15);
! Set the item uniquenesses (e.g., u for uniquenesses) to be equal across samples
 acss1-acss10R (u1-u15);

 MODEL sample2:
 FG*;   Intra*;   Soc*;   Cons*;
 [FG*];   [Intra*];   [Soc*];   [Cons*];
 [acss1-acss10R] (i1-i15);
 acss1-acss10R (u1-u15);
```

Latent Variances and Covariances Invariance

```
! We only report sections that differ from previous models
 MODEL:
 FG BY acss1 acss2 acss4 acss5 acss14
 acss9 acss11 acss12 acss13 acss15
 acss3 acss6 acss7 acss8 acss10R (*t1);

 Intra BY acss1 acss2 acss4 acss5 acss14
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

 Soc BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9 acss11 acss12 acss13 acss15
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

  Cons BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3 acss6 acss7 acss8 acss10R (*t1);

! ACSS factor variances need to be fixed back to 1 in all groups.
! In doing so, ACSS factor covariances need to be specified and set to equality across groups.
! (even if they are rotated to be 0)
 FG@1;  Intra@1;  Soc@1;  Cons@1;
 FG WITH Intra (cov1);
 FG WITH Soc (cov2);
 FG WITH Cons (cov3);
 Intra WITH Soc (cov4);
 Intra WITH Cons (cov5);
 Soc WITH Cons (cov6);
 [FG@0];  [Intra@0];  [Soc@0];  [Cons@0];
 [acss1-acss10R] (i1-i15);
 acss1-acss10R (u1-u15);

 MODEL sample2:
! ACSS factor variances need to be fixed back to 1 in all groups.
! In doing so, ACSS factor covariances need to be specified and set to equality across groups
! (even if they are rotated to be 0)
 FG@1;  Intra@1;  Soc@1;  Cons@1;
 FG WITH Intra (cov1);
 FG WITH Soc (cov2);
 FG WITH Cons (cov3);
 Intra WITH Soc (cov4);
 Intra WITH Cons (cov5);
 Soc WITH Cons (cov6);
 [FG*];  [Intra*]; [Soc*];  [Cons*];
 [acss1-acss10R] (i1-i15);
 acss1-acss10R (u1-u15);
```

Latent Means Invariance

```
! We only report sections that differ from previous models
 MODEL:
 FG BY acss1 acss2 acss4 acss5 acss14
 acss9 acss11 acss12 acss13 acss15
 acss3 acss6 acss7 acss8 acss10R (*t1);

 Intra BY acss1 acss2 acss4 acss5 acss14
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

 Soc BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9 acss11 acss12 acss13 acss15
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

  Cons BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3 acss6 acss7 acss8 acss10R (*t1);

 FG@1;   Intra@1;   Soc@1;   Cons@1;
 FG WITH Intra (cov1);
 FG WITH Soc (cov2);
 FG WITH Cons (cov3);
 Intra WITH Soc (cov4);
 Intra WITH Cons (cov5);
 Soc WITH Cons (cov6);
! ACSS factor means need to be fixed back to 0 in all groups.
 [FG@0];   [Intra@0];   [Soc@0];   [Cons@0];
 [acss1-acss10R] (i1-i15);
 acss1-acss10R (u1-u15);

 MODEL sample2:
 FG@1;   Intra@1;   Soc@1;   Cons@1;
 FG WITH Intra (cov1);
 FG WITH Soc (cov2);
 FG WITH Cons (cov3);
 Intra WITH Soc (cov4);
 Intra WITH Cons (cov5);
 Soc WITH Cons (cov6);
! ACSS factor means need to be fixed back to 0 in all groups.
 [FG@0];   [Intra@0];   [Soc@0];   [Cons@0];
 [acss1-acss10R] (i1-i15);
 acss1-acss10R (u1-u15);
```

TEST OF DIFFERENTIAL ITEM FUNCTIONING (DIF)

ESEM with Age and Body Mass Index as Predictors: Null Effects Model

```
  TITLE:   M1-ESEM-DIF_null-effects
  DATA:   FILE IS ACSS.dat;

  VARIABLE:
  NAMES ARE sample age gender BMI acss1 acss2 acss3 acss4
  acss5 acss6 acss7 acss8 acss9 acss10 acss11 acss12 acss13
  acss14 acss15 BAS BISQ RSES;

  MISSING ARE ALL (-999);

! The predictors need to be added to the USEVARIABLES list
! Recoded variables need to be added at the end of the USEVARIABLES list
  USEVARIABLES ARE acss1 acss2 acss3 acss4
  acss5 acss6 acss7 acss8 acss9 acss11 acss12 acss13
  acss14 acss15 age BMI acss10R;

  ANALYSIS:
  ESTIMATOR IS MLR;
  ROTATION = TARGET;

  DEFINE:
IF (acss10 EQ 1) THEN acss10R= 7;  IF (acss10 EQ 2) THEN acss10R= 6;   IF (acss10 EQ 3)
THEN acss10R= 5;   IF (acss10 EQ 4) THEN acss10R= 4;   IF (acss10 EQ 5) THEN acss10R= 3;
IF (acss10 EQ 6) THEN acss10R= 2;   IF (acss10 EQ 7) THEN acss10R= 1;
! To standardize the predictors
  Standardize age BMI;

  MODEL:
! The ACSS factors are defined as in ESEM
  Intra BY acss1 acss2 acss4 acss5 acss14
  acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
  acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

  Soc BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
  acss9 acss11 acss12 acss13 acss15
  acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

   Cons BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
  acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
  acss3 acss6 acss7 acss8 acss10R (*t1);

! The ACSS factors and items are regressed on the predictors
! All predictions are fixed to 0 (@0).
  Intra-Cons ON age@0 BMI@0;
  acss1-acss15 ON age@0 BMI@0;
  acss10R ON age@0 BMI@0;

  OUTPUT:   SAMPSTAT STANDARDIZED CINTERVAL RESIDUAL SVALUES
MODINDICES (6.0) TECH1 TECH3 TECH4;
```

ESEM with Age and Body Mass Index as Predictors: Saturated Model

```
! We only report sections that differ from previous models
 MODEL:
 Intra BY acss1 acss2 acss4 acss5 acss14
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

 Soc BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9 acss11 acss12 acss13 acss15
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

  Cons BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3 acss6 acss7 acss8 acss10R (*t1);
! The ACSS factors and items are regressed on the predictors.
! The effects of the predictors on the factors remain fixed to 0 (@0).
! The effects of the predictors on the items are freely estimated.
 Intra-Cons ON age@0 BMI@0;
 acss1-acss15 ON age BMI;
 acss10R ON age BMI;
```

ESEM with Age and Body Mass Index as Predictors: Factors-Only Model

```
! We only report sections that differ from previous models
 MODEL:
 Intra BY acss1 acss2 acss4 acss5 acss14
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

 Soc BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9 acss11 acss12 acss13 acss15
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

  Cons BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3 acss6 acss7 acss8 acss10R (*t1);
! The ACSS factors and items are regressed on the predictors.
! The effects of the predictors on the items remain fixed to 0 (@0).
! The effects of the predictors on the factors are freely estimated.
 Intra-Cons ON age BMI;
 acss1-acss15 ON age@0 BMI@0;
 acss10R ON age@0 BMI@0;
```

Bifactor-ESEM with Sample, Gender and Sample x Gender as Predictors: Null Effects Model

```
  TITLE:   M1-BESEM-MIMIC_null-effects
  DATA:   FILE IS ACSS.dat;
  VARIABLE:
  NAMES ARE sample age gender BMI acss1 acss2 acss3 acss4
  acss5 acss6 acss7 acss8 acss9 acss10 acss11 acss12 acss13
  acss14 acss15 BAS BISQ RSES;
  MISSING ARE ALL (-999);
! The predictors need to be added to the USEVARIABLES list
! Recoded variables need to be added at the end of the USEVARIABLES list
 USEVARIABLES ARE acss1 acss2 acss3 acss4 acss5 acss6 acss7
 acss8 acss9 acss11 acss12 acss13 acss14 acss15 acss10R
sampleR genderR SamXGen;
  ANALYSIS:
  ESTIMATOR IS MLR;
  ROTATION = TARGET (orthogonal);

  DEFINE:
IF (acss10 EQ 1) THEN acss10R= 7;  IF (acss10 EQ 2) THEN acss10R= 6;   IF (acss10 EQ 3)
THEN acss10R= 5;   IF (acss10 EQ 4) THEN acss10R= 4;   IF (acss10 EQ 5) THEN acss10R= 3;
IF (acss10 EQ 6) THEN acss10R= 2;   IF (acss10 EQ 7) THEN acss10R= 1;
! To recode sample as a dummy variable. Sample1 was recoded 0 and sample2 was recoded 1
 IF (sample EQ 1) THEN sampleR = 0;
 IF (sample EQ 2) THEN sampleR = 1;
! To recode gender as a dummy variable. Men was recoded 0 and women was recoded 1
 IF (gender EQ 1) THEN genderR = 0;
 IF (gender EQ 2) THEN genderR = 1;
! To compute the interaction between sample and gender
  SamXGen = sampleR*genderR;

  MODEL:
! The ACSS factors are defined as in Bifactor-ESEM
  FG BY acss1 acss2 acss4 acss5 acss14
  acss9 acss11 acss12 acss13 acss15
  acss3 acss6 acss7 acss8 acss10R (*t1);

  Intra BY acss1 acss2 acss4 acss5 acss14
  acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
  acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

  Soc BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
  acss9 acss11 acss12 acss13 acss15
  acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

   Cons BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
  acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
  acss3 acss6 acss7 acss8 acss10R (*t1);

! The ACSS factors and items are regressed on the predictors
! All predictions are fixed to 0 (@0).
  FG-Cons ON sampleR@0 genderR@0 SamXGen@0;
  acss1-acss10R ON sampleR@0 genderR@0 SamXGen@0;
```

Bifactor-ESEM with Sample, Gender and Sample x Gender as Predictors: Saturated Model

```
! We only report sections that differ from previous models
 MODEL:
 FG BY acss1 acss2 acss4 acss5 acss14
 acss9 acss11 acss12 acss13 acss15
 acss3 acss6 acss7 acss8 acss10R (*t1);

 Intra BY acss1 acss2 acss4 acss5 acss14
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

 Soc BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9 acss11 acss12 acss13 acss15
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

  Cons BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3 acss6 acss7 acss8 acss10R (*t1);

! The ACSS factors and items are regressed on the predictors.
! The effects of the predictors on the factors remain fixed to 0 (@0).
! The effects of the predictors on the items are freely estimated.
 FG-Cons ON sampleR@0 genderR@0 SamXGen@0;
 acss1-acss10R ON sampleR genderR SamXGen;
```

Bifactor-ESEM with Sample, Gender and Sample x Gender as Predictors: Factors-Only Model

```
! We only report sections that differ from previous models
 MODEL:
 FG BY acss1 acss2 acss4 acss5 acss14
 acss9 acss11 acss12 acss13 acss15
 acss3 acss6 acss7 acss8 acss10R (*t1);

 Intra BY acss1 acss2 acss4 acss5 acss14
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

 Soc BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9 acss11 acss12 acss13 acss15
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

  Cons BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3 acss6 acss7 acss8 acss10R (*t1);

The ACSS factors and items are regressed on the predictors.
! The effects of the predictors on the items remain fixed to 0 (@0).
! The effects of the predictors on the factors are freely estimated.
 FG-Cons ON sampleR genderR SamXGen;
 acss1-acss10R ON sampleR@0 genderR@0 SamXGen@0;
```

HYBRID DIF WITH AGE AND BODY MASS INDEX – ESEM

Null Effects Model

```
! The starting model is the most invariant ESEM Solution (Latent Variances and Covariances
Invariance, see p. T22)
  TITLE: M41-ESEM-Hybrid-DIF_null-effects
  DATA: FILE IS ACSS.dat;
  VARIABLE:
  NAMES ARE sample age gender BMI acss1 acss2 acss3 acss4 acss5 acss6 acss7 acss8 acss9
acss10 acss11 acss12 acss13 acss14 acss15 BAS BISQ RSES;
  MISSING ARE ALL (-999);
! The predictors need to be added to the USEVARIABLES list
  USEVARIABLES ARE acss1 acss2 acss3 acss4 acss5 acss6 acss7 acss8 acss9  acss11 acss12
acss13   acss14 acss15 age BMI acss10R;
  GROUPING IS gender (1= men 2= women);
  ANALYSIS:
  ESTIMATOR IS MLR;
  ROTATION = TARGET;

  DEFINE:
 IF (acss10 EQ 1) THEN acss10R= 7;   IF (acss10 EQ 2) THEN acss10R= 6;   IF (acss10 EQ 3)
 THEN acss10R= 5;   IF (acss10 EQ 4) THEN acss10R= 4;   IF (acss10 EQ 5) THEN acss10R=
3;   IF (acss10 EQ 6) THEN acss10R= 2;   IF (acss10 EQ 7) THEN acss10R= 1;
! To standardize the predictors
  Standardize age BMI;

  MODEL:
  Intra BY acss1 acss2 acss4 acss5 acss14
  acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
  acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

  Soc BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
  acss9 acss11 acss12 acss13 acss15
  acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

   Cons BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
  acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
  acss3 acss6 acss7 acss8 acss10R (*t1);

  Intra@1;   Soc@1;   Cons@1;
  [Intra@0];   [Soc@0];   [Cons@0];
  [acss1] (i1);   [acss2] (i2);   [acss3] (i3);   [acss4] (i4);   [acss5] (i5);   [acss6] (i6);   [acss7] (i7);
[acss8] (i8);   [acss9] (i9);  [acss11] (i10);   [acss12] (i11);   [acss13] (i12);  [acss14] (i13);
[acss15] (i14);  [acss10R] (i15);
acss1 (u1);   acss2 (u2);   acss3 (u3);   acss4 (u4);   acss5 (u5); acss6 (u6); acss7 (u7); acss8 (u8);
  acss9 (u9); acss11 ;   acss12 (u11);   acss13 (u12);   acss14 (u13);  acss15 ; acss10R (u15);
  Intra WITH Soc (cov1);   Intra WITH Cons (cov2);   Soc WITH Cons (cov3);

! The factors and items are regressed on the predictors, with all predictions fixed to 0 (@0) in
! both groups.
  Intra-Cons ON age@0 BMI@0;
  acss1-acss15 ON age@0 BMI@0;
  acss10R ON age@0 BMI@0;
```

```
  MODEL women:
  Intra@1;   Soc@1;   Cons@1;
  [Intra*];   [Soc*];   [Cons*];
  [acss1-acss10R] (i1-i15);
  acss1 (u1);   acss2 (u2);   acss3 (u3);   acss4 (u4);   acss5 (u5); acss6 (u6); acss7 (u7); acss8 (u8);
  acss9 (u9); acss11 ;   acss12 (u11);   acss13 (u12);   acss14 (u13);  acss15 ; acss10R (u15);
  Intra WITH Soc (cov1);   Intra WITH Cons (cov2);   Soc WITH Cons (cov3);

! The factors and items are regressed on the predictors, with all predictions fixed to 0 (@0) in
! both groups.
  Intra-Cons ON age@0 BMI@0;
  acss1-acss15 ON age@0 BMI@0;
  acss10R ON age@0 BMI@0;

  OUTPUT:   SAMPSTAT STANDARDIZED CINTERVAL RESIDUAL SVALUES
MODINDICES (6.0) TECH1 TECH3 TECH4;
```

Saturated Model

```
! We only report sections that differ from previous models
 MODEL:
 Intra BY acss1 acss2 acss4 acss5 acss14
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

 Soc BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9 acss11 acss12 acss13 acss15
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

   Cons BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3 acss6 acss7 acss8 acss10R (*t1);

 Intra@1;   Soc@1;   Cons@1;
 [Intra@0];   [Soc@0];   [Cons@0];
 [acss1-acss10R] (i1-i15);
 acss1 (u1);   acss2 (u2);   acss3 (u3);   acss4 (u4);   acss5 (u5); acss6 (u6); acss7 (u7); acss8 (u8);
 acss9 (u9); acss11 ;   acss12 (u11);   acss13 (u12);   acss14 (u13);  acss15 ; acss10R (u15);
 Intra WITH Soc (cov1);   Intra WITH Cons (cov2);   Soc WITH Cons (cov3);
! The ACSS factors and items are regressed on the predictors.
! The effects of the predictors on the ACSS factors remain fixed to 0 (@0) in both groups.
! The effects of the predictors on the ACSS items are freely estimated in both groups.
 Intra-Cons ON age@0 BMI@0;
 acss1-acss15 ON age BMI;
 acss10R ON age BMI;

 MODEL women:
 Intra@1;   Soc@1;   Cons@1;
 [Intra*];   [Soc*];   [Cons*];
 [acss1-acss10R] (i1-i15);
 acss1 (u1);   acss2 (u2);   acss3 (u3);   acss4 (u4);   acss5 (u5); acss6 (u6); acss7 (u7); acss8 (u8);
 acss9 (u9); acss11 ;   acss12 (u11);   acss13 (u12);   acss14 (u13);  acss15 ; acss10R (u15);
 Intra WITH Soc (cov1);   Intra WITH Cons (cov2);   Soc WITH Cons (cov3);
! The ACSS factors and items are regressed on the predictors.
! The effects of the predictors on the ACSS factors remain fixed to 0 (@0) in both groups.
! The effects of the predictors on the ACSS items are freely estimated in both groups.
 Intra-Cons ON age@0 BMI@0;
 acss1-acss15 ON age BMI;
 acss10R ON age BMI;
```

Factors-Only Model

```
! We only report sections that differ from previous models
 MODEL:
 Intra BY acss1 acss2 acss4 acss5 acss14
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

 Soc BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9 acss11 acss12 acss13 acss15
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

  Cons BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3 acss6 acss7 acss8 acss10R (*t1);
 Intra@1;   Soc@1;   Cons@1;
 [Intra@0];   [Soc@0];   [Cons@0];
 [acss1-acss10R] (i1-i15);
 acss1 (u1);   acss2 (u2);   acss3 (u3);   acss4 (u4);   acss5 (u5); acss6 (u6); acss7 (u7); acss8 (u8);
 acss9 (u9); acss11 ;   acss12 (u11);   acss13 (u12);   acss14 (u13);  acss15 ; acss10R (u15);
 Intra WITH Soc (cov1);   Intra WITH Cons (cov2);   Soc WITH Cons (cov3);
! The ACSS factors and items are regressed on the predictors.
! The effects of the predictors on the ACSS items remain fixed to 0 (@0) in both groups.
! The effects of the predictors on the ACSS factors are freely estimated in both groups.
 Intra-Cons ON age BMI;
 acss1-acss15 ON age@0 BMI@0;
 acss10R ON age@0 BMI@0;

 MODEL women:
 Intra@1;   Soc@1;   Cons@1;
 [Intra*];   [Soc*];   [Cons*];
 [acss1-acss10R] (i1-i15);
 acss1 (u1);   acss2 (u2);   acss3 (u3);   acss4 (u4);   acss5 (u5); acss6 (u6); acss7 (u7); acss8 (u8);
 acss9 (u9); acss11 ;   acss12 (u11);   acss13 (u12);   acss14 (u13);  acss15 ; acss10R (u15);
 Intra WITH Soc (cov1);   Intra WITH Cons (cov2);   Soc WITH Cons (cov3);
! The ACSS factors and items are regressed on the predictors.
! The effects of the predictors on the ACSS items remain fixed to 0 (@0) in both groups.
! The effects of the predictors on the ACSS factors are freely estimated in both groups.
 Intra-Cons ON age BMI;
 acss1-acss15 ON age@0 BMI@0;
 acss10R ON age@0 BMI@0;
```

Factors-Only Invariant Model

```
! We only report sections that differ from previous models
 MODEL:
 Intra BY acss1 acss2 acss4 acss5 acss14
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

 Soc BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9 acss11 acss12 acss13 acss15
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

  Cons BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3 acss6 acss7 acss8 acss10R (*t1);

 Intra@1;   Soc@1;   Cons@1;
 [Intra@0];   [Soc@0];   [Cons@0];
 [acss1-acss10R] (i1-i15);
 acss1 (u1);   acss2 (u2);   acss3 (u3);   acss4 (u4);   acss5 (u5); acss6 (u6); acss7 (u7); acss8 (u8);
 acss9 (u9); acss11 ;   acss12 (u11);   acss13 (u12);   acss14 (u13);  acss15 ; acss10R (u15);
 Intra WITH Soc (cov1);   Intra WITH Cons (cov2);   Soc WITH Cons (cov3);

! The ACSS factors and items are regressed on the predictors.
! The effects of the predictors on the ACSS items remain fixed to 0 (@0) in both groups.
! The effects of the predictors on the ACSS factors are free but equal across groups.
 Intra-Cons ON age BMI (FO1-FO6);
 acss1-acss15 ON age@0 BMI@0;
 acss10R ON age@0 BMI@0;

 MODEL women:
 Intra@1;   Soc@1;   Cons@1;
 [Intra*];   [Soc*];   [Cons*];
 [acss1-acss10R] (i1-i15);
 acss1 (u1);   acss2 (u2);   acss3 (u3);   acss4 (u4);   acss5 (u5); acss6 (u6); acss7 (u7); acss8 (u8);
 acss9 (u9); acss11 ;   acss12 (u11);   acss13 (u12);   acss14 (u13);  acss15 ; acss10R (u15);
 Intra WITH Soc (cov1);   Intra WITH Cons (cov2);   Soc WITH Cons (cov3);

! The ACSS factors and items are regressed on the predictors.
! The effects of the predictors on the ACSS items remain fixed to 0 (@0) in both groups.
! The effects of the predictors on the ACSS factors are free but equal across groups.
 Intra-Cons ON age BMI (FO1-FO6);
 acss1-acss15 ON age@0 BMI@0;
 acss10R ON age@0 BMI@0;
```

HYBRID DIF WITH AGE, GENDER AND BODY MASS INDEX – BIFACTOR-ESEM

Null Effects Model

```
! The starting model is the most invariant bifactor-ESEM solution (Latent Means Invariance, see
! p T30)
  TITLE:   M51-BESEM-Hybrid-MIMIC_null-effects
  DATA: FILE IS ACSS.dat;
  VARIABLE:
  NAMES ARE sample age gender BMI acss1 acss2 acss3 acss4 acss5 acss6 acss7 acss8 acss9
acss10 acss11 acss12 acss13 acss14 acss15 BAS BISQ RSES;
  MISSING ARE ALL (-999);
! The predictors need to be added to the USEVARIABLES list
  USEVARIABLES ARE acss1 acss2 acss3 acss4   acss5 acss6 acss7 acss8 acss9  acss11 acss12
acss13   acss14 acss15 Age BMI acss10R genderR;
  DEFINE:
 IF (acss10 EQ 1) THEN acss10R= 7;   IF (acss10 EQ 2) THEN acss10R= 6;   IF (acss10 EQ 3)
 THEN acss10R= 5;   IF (acss10 EQ 4) THEN acss10R= 4;   IF (acss10 EQ 5) THEN acss10R=
3;   IF (acss10 EQ 6) THEN acss10R= 2;   IF (acss10 EQ 7) THEN acss10R= 1;
! To recode gender as a dummy variable. Men was recoded 0 and women was recoded 1
IF (gender EQ 1) THEN genderR = 0;
IF (gender EQ 2) THEN genderR = 1;
! To standardize the predictors
  Standardize age BMI;

  MODEL:
  FG BY acss1 acss2 acss4 acss5 acss14
  acss9 acss11 acss12 acss13 acss15
  acss3 acss6 acss7 acss8 acss10R (*t1);

  Intra BY acss1 acss2 acss4 acss5 acss14
  acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
  acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

  Soc BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
  acss9 acss11 acss12 acss13 acss15
  acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

   Cons BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
  acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
  acss3 acss6 acss7 acss8 acss10R (*t1);

  FG@1;   Intra@1;   Soc@1;   Cons@1;
  [FG@0];   [Intra@0];   [Soc@0];   [Cons@0];
  [acss1] (i1);   [acss2] (i2);   [acss3] (i3);   [acss4] (i4);   [acss5] (i5);   [acss6] (i6);   [acss7] (i7);
[acss8] (i8);   [acss9] (i9);  [acss11] (i10);   [acss12] (i11);   [acss13] (i12);  [acss14] (i13);
[acss15] (i14);  [acss10R] (i15);
  acss1-acss15(u1-u14);
  acss10R (u15);
  FG WITH Intra (cov1);   FG WITH Soc (cov2);   FG WITH Cons (cov3);   Intra WITH Soc
(cov4);   Intra WITH Cons (cov5);   Soc WITH Cons (cov6);
```

```
! The ACSS factors and items are regressed on the predictors.
! All predictions are fixed to 0 (@0) in both groups.
  FG-Cons ON age@0 genderR@0 BMI@0;
  acss1-acss15 ON age@0 genderR@0 BMI@0;
  acss10R ON age@0 genderR@0 BMI@0;

  MODEL sample2:
  FG@1;   Intra@1;   Soc@1;   Cons@1;
  [FG@0];   [Intra@0];   [Soc@0];   [Cons@0];
  [acss1] (i1);   [acss2] (i2);   [acss3] (i3);   [acss4] (i4);   [acss5] (i5);   [acss6] (i6);   [acss7] (i7);
[acss8] (i8);   [acss9] (i9);  [acss11] (i10);   [acss12] (i11);   [acss13] (i12);  [acss14] (i13);
[acss15] (i14);  [acss10R] (i15);
  acss1-acss15(u1-u14);
  acss10R (u15);
  FG WITH Intra (cov1);   FG WITH Soc (cov2);   FG WITH Cons (cov3);   Intra WITH Soc
(cov4);   Intra WITH Cons (cov5);   Soc WITH Cons (cov6);
! The ACSS factors and items are regressed on the predictors.
! All predictions are fixed to 0 (@0) in both groups.
  FG-Cons ON age@0 genderR@0 BMI@0;
  acss1-acss15 ON age@0 genderR@0 BMI@0;
  acss10R ON age@0 genderR@0 BMI@0;

  OUTPUT:   SAMPSTAT STANDARDIZED CINTERVAL RESIDUAL SVALUES
MODINDICES (6.0) TECH1 TECH3 TECH4;
```

Saturated Model

```
! We only report sections that differ from previous models
  MODEL:
  FG BY acss1 acss2 acss4 acss5 acss14
  acss9 acss11 acss12 acss13 acss15
  acss3 acss6 acss7 acss8 acss10R (*t1);

  Intra BY acss1 acss2 acss4 acss5 acss14
  acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
  acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

  Soc BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
  acss9 acss11 acss12 acss13 acss15
  acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

   Cons BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
  acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
  acss3 acss6 acss7 acss8 acss10R (*t1);

  FG@1;   Intra@1;   Soc@1;   Cons@1;
  [FG@0];   [Intra@0];   [Soc@0];   [Cons@0];
  [acss1] (i1);   [acss2] (i2);   [acss3] (i3);   [acss4] (i4);   [acss5] (i5);   [acss6] (i6);   [acss7] (i7);
  [acss8] (i8);   [acss9] (i9);  [acss11] (i10);   [acss12] (i11);   [acss13] (i12);  [acss14] (i13);
  [acss15] (i14);  [acss10R] (i15);
  acss1-acss15(u1-u14);
  acss10R (u15);
  FG WITH Intra (cov1);   FG WITH Soc (cov2);   FG WITH Cons (cov3);   Intra WITH Soc
(cov4);   Intra WITH Cons (cov5);   Soc WITH Cons (cov6);
! The ACSS factors and items are regressed on the predictors.
! The effects of the predictors on the ACSS factors remain fixed to 0 (@0) in both groups.
! The effects of the predictors on the ACSS items are freely estimated in both groups.
  FG-Cons ON age@0 genderR@0 BMI@0;
  acss1-acss15 ON age genderR BMI;
  acss10R ON age genderR BMI;

  MODEL sample2:
  FG@1;   Intra@1;   Soc@1;   Cons@1;
  [FG@0];   [Intra@0];   [Soc@0];   [Cons@0];
  [acss1] (i1);   [acss2] (i2);   [acss3] (i3);   [acss4] (i4);   [acss5] (i5);   [acss6] (i6);   [acss7] (i7);
  [acss8] (i8);   [acss9] (i9);  [acss11] (i10);   [acss12] (i11);   [acss13] (i12);  [acss14] (i13);
 [acss15] (i14);  [acss10R] (i15);
  acss1-acss15(u1-u14);
  acss10R (u15);
  FG WITH Intra (cov1);   FG WITH Soc (cov2);   FG WITH Cons (cov3);   Intra WITH Soc
(cov4);   Intra WITH Cons (cov5);   Soc WITH Cons (cov6);

! The ACSS factors and items are regressed on the predictors.
! The effects of the predictors on the ACSS factors remain fixed to 0 (@0) in both groups.
! The effects of the predictors on the ACSS items are freely estimated in both groups.
  FG-Cons ON age@0 genderR@0 BMI@0;
  acss1-acss15 ON age genderR BMI;
  acss10R ON age genderR BMI;
```

Factors-Only Model

```
! We only report sections that differ from previous models
 MODEL:
 FG BY acss1 acss2 acss4 acss5 acss14
 acss9 acss11 acss12 acss13 acss15
 acss3 acss6 acss7 acss8 acss10R (*t1);

 Intra BY acss1 acss2 acss4 acss5 acss14
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

 Soc BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9 acss11 acss12 acss13 acss15
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

  Cons BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3 acss6 acss7 acss8 acss10R (*t1);

 FG@1;  Intra@1;  Soc@1;  Cons@1;
 [FG@0];  [Intra@0];  [Soc@0];  [Cons@0];
 [acss1] (i1);  [acss2] (i2);  [acss3] (i3);  [acss4] (i4);  [acss5] (i5);  [acss6] (i6);  [acss7] (i7);
 [acss8] (i8);  [acss9] (i9);  [acss11] (i10);  [acss12] (i11);  [acss13] (i12);  [acss14] (i13);
 [acss15] (i14);  [acss10R] (i15);
 acss1-acss15(u1-u14);
 acss10R (u15);
 FG WITH Intra (cov1);  FG WITH Soc (cov2);  FG WITH Cons (cov3);  Intra WITH Soc
(cov4);  Intra WITH Cons (cov5);  Soc WITH Cons (cov6);

! The ACSS factors and items are regressed on the predictors.
! The effects of the predictors on the ACSS items remain fixed to 0 (@0) in both groups.
! The effects of the predictors on the ACSS factors are freely estimated in both groups.
 FG-Cons ON age genderR BMI;
 acss1-acss15 ON age@0 genderR@0 BMI@0;
 acss10R ON age@0 genderR@0 BMI@0;

 MODEL sample2:
 FG@1;  Intra@1;  Soc@1;  Cons@1;
 [FG@0];  [Intra@0];  [Soc@0];  [Cons@0];
 [acss1] (i1);  [acss2] (i2);  [acss3] (i3);  [acss4] (i4);  [acss5] (i5);  [acss6] (i6);  [acss7] (i7);
 [acss8] (i8);  [acss9] (i9);  [acss11] (i10);  [acss12] (i11);  [acss13] (i12);  [acss14] (i13);
[acss15] (i14);  [acss10R] (i15);
 acss1-acss15(u1-u14);
 acss10R (u15);
 FG WITH Intra (cov1);  FG WITH Soc (cov2);  FG WITH Cons (cov3);  Intra WITH Soc
(cov4);  Intra WITH Cons (cov5);  Soc WITH Cons (cov6);

! The ACSS factors and items are regressed on the predictors.
! The effects of the predictors on the ACSS items remain fixed to 0 (@0) in both groups.
! The effects of the predictors on the ACSS factors are freely estimated in both groups.
 FG-Cons ON age genderR BMI;
 acss1-acss15 ON age@0 genderR@0 BMI@0;
 acss10R ON age@0 genderR@0 BMI@0;
```

Factors-Only Invariant Model

```
! We only report sections that differ from previous models
 MODEL:
 FG BY acss1 acss2 acss4 acss5 acss14
 acss9 acss11 acss12 acss13 acss15
 acss3 acss6 acss7 acss8 acss10R (*t1);

 Intra BY acss1 acss2 acss4 acss5 acss14
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

 Soc BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9 acss11 acss12 acss13 acss15
 acss3~0 acss6~0 acss7~0 acss8~0 acss10R~0 (*t1);

  Cons BY acss1~0 acss2~0 acss4~0 acss5~0 acss14~0
 acss9~0 acss11~0 acss12~0 acss13~0 acss15~0
 acss3 acss6 acss7 acss8 acss10R (*t1);

 FG@1;  Intra@1;  Soc@1;  Cons@1;
 [FG@0];  [Intra@0];  [Soc@0];  [Cons@0];
 [acss1] (i1);  [acss2] (i2);  [acss3] (i3);  [acss4] (i4);  [acss5] (i5);  [acss6] (i6);  [acss7] (i7);
 [acss8] (i8);  [acss9] (i9); [acss11] (i10);  [acss12] (i11);  [acss13] (i12); [acss14] (i13);
 [acss15] (i14); [acss10R] (i15);
 acss1-acss15(u1-u14);
 acss10R (u15);
 FG WITH Intra (cov1);  FG WITH Soc (cov2);  FG WITH Cons (cov3);  Intra WITH Soc
(cov4);  Intra WITH Cons (cov5);  Soc WITH Cons (cov6);

! The ACSS factors and items are regressed on the predictors.
! The effects of the predictors on the ACSS items remain fixed to 0 (@0) in both groups.
! The effects of the predictors on the ACSS factors are free and equal across groups.
 FG-Cons ON age genderR BMI (FO1-FO12);
 acss1-acss15 ON age@0 genderR@0 BMI@0;
 acss10R ON age@0 genderR@0 BMI@0;

 MODEL sample2:
 FG@1;  Intra@1;  Soc@1;  Cons@1;
 [FG@0];  [Intra@0];  [Soc@0];  [Cons@0];
 [acss1] (i1);  [acss2] (i2);  [acss3] (i3);  [acss4] (i4);  [acss5] (i5);  [acss6] (i6);  [acss7] (i7);
 [acss8] (i8);  [acss9] (i9); [acss11] (i10);  [acss12] (i11);  [acss13] (i12); [acss14] (i13);
[acss15] (i14); [acss10R] (i15);
 acss1-acss15(u1-u14);
 acss10R (u15);
 FG WITH Intra (cov1);  FG WITH Soc (cov2);  FG WITH Cons (cov3);  Intra WITH Soc
(cov4);  Intra WITH Cons (cov5);  Soc WITH Cons (cov6);

! The ACSS factors and items are regressed on the predictors.
! The effects of the predictors on the ACSS items remain fixed to 0 (@0) in both groups.
! The effects of the predictors on the ACSS factors are free and equal across groups.
 FG-Cons ON age genderR BMI (FO1-FO12);
 acss1-acss15 ON age@0 genderR@0 BMI@0;
 acss10R ON age@0 genderR@0 BMI@0;
```