INVARIANCE TESTING IN DIAGNOSTIC CLASSIFICATION MODELS

by

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(Under the Direction of Jonathan Templin)

ABSTRACT

This study examined the invariance of items (based on sex of individuals) on a diagnostic classification screener, Body Image Rating Scale (BIRS), for Body Dysmorphic Disorder (BDD). The purpose of this study was to develop a method for testing invariance in diagnostic classification models (DCMs). The development of a diagnostic classification model for BDD was vital; specifically, using MPlus, a loglinear cognitive diagnostic model (LCDM) was created. The investigation to construct a method for testing invariance in DCMs began using a method for testing invariance for confirmatory factor analysis (CFA), which was already established. Adapting the syntax for invariance testing for CFA to work for DCMs was based on the how CFA models are similar to DCMs in comparing the type of data and latent variable appropriate for the model. Using MPlus, syntax was created to perform invariance testing for the LCDM for BDD.

INDEX WORDS: INVARIANCE TESTING, DIAGNOSTIC CLASSIFICATION MODEL, CONFIRMATORY FACTOR ANALYSIS, BODY DYSMORPHIC DISORDER

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DEDICATION

I would like to dedicate my thesis to my wonderful husband, David. Thank you for all the encouragement and support. Without your help, I would not have stayed sane enough to finish. I love you.

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I would like to thank my advisor, Dr. Jonathan Templin, for his continuous support and encouragement throughout my course of study. Without his guidance, I would have not acquired all the skills and knowledge necessary for this thesis. Thank you for challenging me to go further than the classroom. Thank you for investing your time and energy into my education. I will always be grateful for all the help and guidance you provided for me during the past two years.

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INTRODUCTION

The purpose of this paper was to develop a method of testing invariance in diagnostic classification models (DCMs), specifically the loglinear cognitive diagnostic model (LCDM). This paper investigates DCMs and relates item response theory (IRT) and confirmatory factor analysis (CFA) to DCMs in an effort to demonstrate how the use of the LCDM can be expanded, in terms of the type of data and latent variables. This paper uses the diagnostic assessment Body Image Rating Scale (BIRS) for Body Dysmorphic Disorder (BDD) for all applications.

In the first chapter, DCMs are defined and the uses of DCMs are described. The diagnostic assessment used in this paper, the BIRS, is introduced after the uses of DCMs section. The BIRS is introduced early on in the paper to allow for applications for the models presented later in the paper. To show a transition from models where invariance testing (or differential item functioning) methods are well known, item response theory and confirmatory factor analysis and how they relate to each other are described next. Following the sections on IRT and CFA, historical DCMs are characterized, leading to the LCDM. The chapter concludes with an application of the LCDM with the BIRS dataset. In Chapter 2, invariance testing is explored, first using CFA. Once invariance testing methods are defined in CFA, in order to bridge the types of invariance tests in CFA and DCMs, another application with the BIRS dataset is performed with and without a marker variable. Chapter 3 brings the LCDM mentioned in Chapter 1 and invariance testing mentioned in Chapter 2 together for the final application with the BIRS dataset. Chapter 3 applies the methods developed for invariance testing in DCMs.

Currently, methods for invariance testing in DCMs do not exist. Invariance of items is essential for any type of interpretation and comparison made between the groups being tested. Since DCMs classify individuals, invariance of diagnostic assessments is vital. This paper defines a method for testing invariance using the LCDM with the intention to be able to generalize the method for LCDM to other DCMs.

CHAPTER 1

DIAGNOSTIC CLASSIFICATION MODELS

What are Diagnostic Classification Models

Diagnostic Classification Models (DCMs) are a subset of psychometric models that classify individuals based on multiple categorical latent variables. The foundations of classifications made with DCMs are the observed response data collected with a diagnostic assessment. DCMs offer mechanisms for assessing the importance of the data gathered. If classifications support important understandings about individual unobserved characteristics, then using DCMs may provide potentially useful practical analyses (Rupp, Templin, & Henson, 2010). The following section of this paper describes DCMs in depth, specifically the uses for DCMs and the historical DCMs. In addition to DCMs, several other models are explored, item response theory (IRT) and confirmatory factor analysis (CFA). IRT and CFA are described to lead into the discussion of log-linear cognitive diagnosis model (LCDM), a type of DCM that will be used for the analyses in this paper.

DCMs provide tools for analyses concerning types of individuals' behavior dependent on data patterns with various weights (Rupp et al., 2010). Yet, the selection of how the behavioral patterns are developed (deciding which attributes to represent, what information to extract, how to code extracted information as input for a statistical model), is solely the discretion of the diagnostic assessment developer. Attributes in DCMs represent constructs such as knowledge, psychological, or disease conditions, and classifications of respondents are made based on these

attributes. Attributes are derived from categorical latent variables; therefore, it is necessary that the classification be statistically deduced from the observable data from respondents. DCMs provide the statistical association (Rupp et al., 2010).

Rupp and Templin (2008) list nine essential characteristics that can be used to compare DCMs to other latent variable models. Of those nine, the following characteristics will be described further: (1) their multidimensional nature, (2) their confirmatory nature, (3) the complexity of the typical loading structure used in DCM applications, and (4) the diagnostic nature of their interpretations. DCMs include multiple latent variables, each variable representing one attribute in the diagnostic assessment, similar to multidimensional Confirmatory Factor Analysis (CFA) models and multidimensional Item Response Theory (IRT) models. The Q-matrix, a loading structure for a DCM, characterizes the confirmatory nature of DCMs by representing which latent variables are measured by each item by a pattern of zeros and ones. A zero in the Q-matrix represents that the item is not measured by the latent variable. CFA and IRT models are typically used when tests have simpler loading structures (i.e., each item loads on to only one dimension), but DCMs have more complex loading structures which usually requires several integral abilities for each item (Rupp & Templin, 2008).

Under DCMs, a hypothesized latent continuum is split into two separate categories where interpretations such as “mastery” vs. “nonmastery” appear in the educational field or “has disorder” vs. “does not have disorder” appear in the field of clinical psychology (Rupp & Templin, 2008). Probabilities notably higher than 0.50 are considered evidence of a “positive” diagnosis (i.e., mastery), and probabilities considerably lower than 0.50 are judged as evidence of a “negative” diagnosis (i.e., nonmastery) for each attribute (Rupp et al., 2010). Probabilities close to 0.50 suggest that the observable variables did not give sufficient information to offer an

unequivocal diagnosis, making classification extremely ambiguous (Rupp et al., 2010). Diagnosis is the main purpose of DCMs, making the application of DCMs to data from a diagnostic assessment different from the application of CFA or IRT models to data from an evaluation for placement, admission, or certification (Rupp & Templin, 2008).

Uses of Diagnostic Classification Models

Domains such as clinical, cognitive, and standard-based diagnosis are all appropriate for the use of DCMs (Rupp et al., 2010). Interpretations and decisions formed from the diagnostic assessment ought to guide the use and application of DCMs. In the domain of clinical psychology, in order to be diagnosed with many varying disorders, an individual must meet a set of criteria established in the *Diagnostic and Statistical Manual of Mental Disorders* (text revision [DSM-IV-TR]) (American Psychiatric Association, 2000). The DSM-IV-TR (2000) states how many of the criteria must be met to receive the diagnosis of a certain disorder. An example of DCMs utilized in the clinical domain, Templin and Henson (2006) built a diagnostic assessment that could be applied to screen individuals for pathological gambling. The DSM-IV-TR (2000) text revision lists 10 diagnostic criteria (attributes), symbolized by 10 latent variables, that are utilized to classify an individual as a pathological gambler. According to the DSM-IV-TR, an individual must have 5 of the 10 criteria to be classified as a pathological gambler (American Psychiatric Association, 2000).

Templin and Henson (2006) used the Gambling Research Instrument developed by Feasel, Henson, and Jones (2004) which has 41 Likert-type items of varying complexity with respect to the number of criteria measured by each. Using DCMs, Templin and Henson (2006) were able to estimate the proportion of individuals, who had met certain criteria and would answer positively to the item related to the criterion; knowing which criteria an individual meets,

provides more information to assist in the creation of preventative measures to decrease the likelihood of a person becoming a pathological gambler.

Within education, cognitive diagnosis models evaluate the cognitive processes thought to be fundamental to assessment responses by individuals (Rupp et al., 2010). Cognitive diagnostic assessments aim to diagnose the cognitive attributes required for the individual to have to be capable of answering the item correctly (Rupp et al., 2010). Such assessments "seek to provide more fine-grained interpretations to support instruction and learning" (Rupp et al., 2010, p. 65). Tatsuoka's (1990) study on fraction subtraction provides an example of a standard cognitively diagnostic modeling of attributes. The 20-item diagnostic assessment of fractions was created to be a brief technique for establishing the topic of study teachers and students need to accentuate when learning fraction subtraction (Rupp et al., 2010).

To demonstrate the types of cognitive assessments used in DCMs, we highlight one used by de la Torre and Douglas (2004). The authors used the data from Tatsuoka (1990) study and listed eight main cognitive attributes necessary to obtain in order to answer the items correctly listed in Table 1.1. For example, Item 13 measures Attribute 2, 4, 5, and 7 to be able to answer the item, and Item 6 only measures Attribute 7 (de la Torre and Douglas, 2004). Much time and work goes into creating the assessment design specifications and associated Q-matrix for cognitive diagnostic assessments. Therefore, with a cognitive diagnostic assessment using the fraction subtraction data, if an individual has not mastered the subtracting numerators attribute (for instance, as measured in part by Item 6), the teacher would know to focus on teaching subtracting numerators. The cognitive diagnostic assessments are suitable for teachers, parents, and educational administrators who want to learn how much information an individual has mastered at the cognitive level (Rupp et al., 2010).

Table 1.1

Eight Cognitive Attributes for Fraction Subtraction

1. Convert a whole number to a fraction.
2. Separate a whole number from a fraction.
3. Simplify before subtracting.
4. Find a common denominator.
5. Borrow from a whole number part.
6. Borrow across columns to subtract the second numerator from the first.
7. Subtract numerators.
8. Reduce answers to simplest form.

Body Dysmorphic Disorder

Body Dysmorphic Disorder (BDD) is classified as a somatoform disorder (physical symptoms cannot be completely justified by a physical disorder). The DSM-IV-TR states three criteria an individual must meet to be diagnosed with BDD. Table 1.2 lists the three criteria mentioned in the DSM-IV-TR (American Psychiatric Association, 2000). BDD was formally recognized in the DSM-IV (in the late 1980s), but Phillips (1996) states the concept behind BDD has been throughout the literature since the 1880s when it was recognized as *dysmorphophobia*. The onset of BDD, which can be gradual or immediate, often occurs during adolescence, but could easily go undiagnosed for several years due to individuals being ashamed to reveal their symptoms (DSM-IV-TR, American Psychiatric Association, 2000). Research has shown that women who have BDD are more worried about their weight, hips, and lower-body issues, and

men who have BDD are more worried about their hair, upper-body, muscle mass, and genitals (Mayville, Katz, Gipson, & Cabral, 1999; Phillips & Diaz, 1997).

Table 1.2

Diagnostic Criteria for Body Dysmorphic Disorder

A. Preoccupation with an imagined defect in appearance. If a slight physical anomaly is present, the person's concern is markedly excessive.
B. The preoccupation causes clinically significant distress or impairment in social, occupational, or other important areas of functioning.
C. The preoccupation is not better accounted for by another mental disorder (e.g., dissatisfaction with body shape and size in Anorexia Nervosa).

The Body Image Rating Scale (BIRS) is a diagnostic assessment used for diagnosing BDD (Mayville, Gipson, & Katz, 1998). BIRS consists of 14 nine-point Likert-type items that focus on cognitive, affective, and behavioral characteristics of BDD (Wester, 2003). Table 1.3 lists the 14 items. The BIRS was intended to measure the prevalence of BDD by means of items that correspond to DSM-IV-TR criteria for BDD (Wester, 2003). The internal consistency of the BIRS was strong ($N = 150$, $\alpha = 0.92$), and the temporal reliability (over a two-week period) was satisfactory ($N = 56$, $r = 0.86$) (Mayville et al., 1998). The reading level for the BIRS is considered to be at an 8.4 grade level (Mayville et al., 1998). Mayville et al. (1998), however, did not establish a cutoff score for determining what scores on the BIRS would likely indicate a person has BDD. In the field of clinical psychology, a cutoff score is a score that determines if an

individual possesses enough characteristics of a disorder to be classified as having the disorder; more specifically, if an individual has more characteristics than the number represented by the cutoff score, then the individual can be classified as having the disorder.

This paper uses data obtained from Wester's (2003) dissertation, in which she implemented the BIRS. The data were gathered during the summer of 2002 from current undergraduate and graduate students (men and women) enrolled at a mid-size state university in Ohio. The entire population of students enrolled during the summer of 2002 were selected to avoid any sampling error (n=5,858). Around 39% of the population participated in the study. Females represent the majority of the sample (n=1702, approximately 75%) and males represent approximately 25% (n=589) of the sample.

Of the sample, 89% were Caucasian, 5.5% African American, 2.0% Asian/Pacific Islander, 1.1% Hispanic/Latino, and 2.1% said they were "other or bi/multiracial." Most of the sample represented undergraduate students (n=1877, approximately 82%). The age range was 17 to 57 years old in the sample, with the average age being 23.5 years (SD=6.91). The average height for females was 5 feet 4 inches (SD=2.78 inches), and 5 feet 9 inches (SD=2.86 inches) for males. Table 1.4 summarizes the demographics for the sample.

The survey (BIRS being a part of the survey) was dispersed to students by way of a campus-wide email that was obtained by every student who was presently registered in courses and had an active email address during the summer of 2002. Wester (2003) decided the cutoff score for the BIRS would be a score of 98. A cutoff score of 98 would require an individual to answer most of the items at the high end of the scale (above 7) to be diagnosed with BDD. The BIRS dataset will be used to describe CFA and continuous LCDM. In the next section, item

response theory (IRT) is discussed to provide the statistical connection between CFA and LCDM.

Table 1.3

BIRS items

1) I _____ that other people may be noticing my physical appearance.
   1…….2…….3…….4…….5…..…..6…..…..7…..…..8…..…..9
   don't worry sometimes worry worry

2) It _____ when I think that I am in a situation where others are evaluating my physical appearance.
   1…….2…….3…….4…….5…..…..6…..…..7…..…..8…..…..9
   does not bother me makes me feel a little uneasy frightens me

3) During the day, I _____ as the result of a specific aspect of my physical appearance.
   1…….2…….3…….4…….5…..…..6…..…..7…..…..8…..…..9
   rarely or never seek out or avoid mirrors sometimes seek out or avoid mirrors seek out or avoid mirrors

4) I _____ find myself touching/physically inspecting a certain part of my physical appearance.
   1…….2…….3…….4…….5…..…..6…..…..7…..…..8…..…..9
   rarely if ever sometimes very often

5) I _____ articles of clothing and/or makeup to mask part of my physical appearance.
   1…….2…….3…….4…….5…..…..6…..…..7…..…..8…..…..9
   never find myself using sometimes find myself using often find myself using

6) I spend _____ deciding how I can best conceal a certain aspect of my physical appearance.
   1…….2…….3…….4…….5…..…..6…..…..7…..…..8…..…..9
   a minimal amount of time a lot of time

Table 1.3 continued.

BIRS Item

7) If I could change a certain aspect of my physical appearance, my overall quality of life would _____.
1…….2…….3…….4…….5…..…..6…..…..7…..…..8…..…..9
remain the same improve somewhat greatly improve

8) Most people _____ about my physical appearance.

1…….2…….3…….4…….5…..…..6…..…..7…..…..8…..…..9
have felt the same as I feel don't know what it is like to feel as bad as I feel

9) Discussing my physical appearance with others _____.
1…….2…….3…….4…….5…..…..6…..…..7…..…..8…..…..9
does not bother me makes me feel slightly self conscious makes me feel very uncomfortable

10) If I never thought about my physical appearance, things in life would be _____.
1…….2…….3…….4…….5…..…..6…..…..7…..…..8…..…..9
no different about the same much improved

11) I _____ because of a specific aspect of my physical appearance.
1…….2…….3…….4…….5…..…..6…..…..7…..…..8…..…..9
never avoid things that I love doing rarely avoid things I love doing often avoid things that I love doing

12) When I am engaged in a conversation with someone, I _____.
1…….2…….3…….4…….5…..…..6…..…..7…..…..8…..…..9
don't hide any part of physical appearance from them shield part of my physical appearance from their view

13) When I think of my physical appearance the word(s) that best corresponds to my thoughts is/are _____.
1…….2…….3…….4…….5…..…..6…..…..7…..…..8…..…..9
beautiful/handsome not bad ugly

14) If I ran naked through the street, people would _____.
1…….2…….3…….4…….5…..…..6…..…..7…..…..8…..…..9
act disgusted, but secretly admire God's masterpiece be shocked, but wouldn't necessarily study my entire physical appearance notice a defect in my physical appearance

Table 1.4

Demographics

Variable	Frequency	Percentage
Student Status		
Undergraduate	1877	81.9%
Graduate	414	18.1%
Sex		
Male	589	25.7%
Female	1702	74.3%
Ethnicity		
Caucasian	2046	89.3%
African American	126	5.5%
Asian/Pacific Islander	46	2.0%
Hispanic/Latino	26	1.1%
Other	47	2.1%

Item Response Theory

Item response theory (IRT) is based on two fundamental claims: (1) individual's performance on a test item can be predicted by a group of factors (traits or abilities), and (2) the association between the individual's item performance and the group of factors essential to item performance can be illustrated by an item characteristic function or item characteristic curve (ICC), a monotonically increasing function (Hambleton, Swaminathan, & Rogers, 1991). The ICC indicates that the probability of an accurate answer to an item increases as the level of the ability increases. IRT is used with discrete (categorical) data and uses continuous latent variables. There are many IRT models; all models include one or more parameters depicting the item and one or more parameters depicting the individual (Hambleton et al., 1991).

Each IRT model calculates the probability that an individual will give a specific answer to a particular item. Individuals can have varying levels of ability, and the difficulty of items can

vary. Defined here for dichotomous items (to enable the researcher to investigate the different levels of ability and items varying in difficulty), probability is denoted as P which is a function of the ability of an individual, or θ_j (Hambleton et al., 1991). Three unidimensional IRT models are often used for discrete items having one, two, or three parameters that characterize the relationship between continuous ability and the probability of a correct response to an item X_{ij}, where *i* symbolizes the item and *j* the individual. The two-parameter IRT model will be the focus of this paper because of its association to CFA and DCMs.

The two-parameter IRT model (also known as the two-parameter logistic model) adds an item parameter, a_i, to ability θ_j and the item parameter b_i to calculate the probability of an accurate answer to a test item (Hambleton et al., 1991). The item parameter added (a_i) is known as the discrimination parameter, which represents the slope. An item offers more information on ability when discrimination is high, and the information is heavily focused on item difficulty (Hambleton et al., 1991). Less information is given with low discrimination parameters, and the information is spread out throughout the length of the ability span. The two-parameter model can be defined as:

$$P_{ij}\left(X_i = 1|\theta_j\right) = \frac{\exp[a_i(\theta_j - b_i)]}{1+\exp[a_i(\theta_j - b_i)]}. \quad (1)$$

The CFA model and LCDM do not look like the previously defined two-parameter model. In order to clearly show how these models can be connected, some rewriting of the two parameter model needs to be done. Multiplying the item parameter a_i through, the two-parameter model can be defined as:

$$P_{ij}\left(X_i = 1|\theta_j\right) = \frac{exp\,(a_i\theta_j - a_i b_i)}{1+exp\,(a_i\theta_j - a_i b_i)}. \quad (2)$$

The expression being raised in Equation 2 can be rewritten further to define the two-parameter model as:

$$P_{ij}\left(X_i = 1|\theta_j\right) = \frac{exp\left(-a_i b_i + a_i\theta_j\right)}{1+\exp\left(-a_i b_i + a_i\theta_j\right)} \quad (3)$$

where $-a_i b_i$ can be represented as the intercept (λ_{i0}) and $a_i\theta_j$ can be represented as the slope ($\lambda_i\theta_j$), which helps to provide a notational link to CFA.

Having a unidimensional latent structure (one latent construct measured by all the items of a test) represents one main assumption underlying the IRT models mentioned above. Estimation of item parameters and respondents abilities could be seriously influenced in many ways when the assumption of unidimensional latent structure is not satisfied (Finch, 2010). For instance, when the assumption is violated, and items assess numerous latent qualities, the compensatory multidimensional IRT (MIRT) model could be a suitable instrument for connecting the latent quality with an item response. The MIRT can be defined as:

$$P\left(X_{ij} = 1|\theta_j\right) = \frac{e^{\lambda_{i0}+\sum\lambda_{i1a}\theta_{ja}}}{1+e^{\lambda_{i0}+\sum\lambda_{i1a}\theta_{ja}}}, \quad (4)$$

where the parameters in MIRT (θ, λ) represent the same entities as the symbols in the IRT models, except that they are displayed in slope-intercept form (as in Equation 3) and that the symbols in MIRT have an extra subscript *a* signifying which latent trait.

Confirmatory Factor Analysis

Confirmatory Factor Analysis (CFA) is a measurement model that investigates whether a particular group of constructs is affecting responses in a predicted manner. As with IRT, CFA features continuous latent variables, but instead of categorical data, CFA is used for continuous

data. DeCoster (1998) mentioned six functions in which an individual would want to perform CFA. One reason an individual would decide to implement CFA would be to determine the validity of a one-factor model. Evaluating the capability of two different models to explain the same set of data provides another reason for using CFA. CFA also has the ability to investigate the meaning of a particular factor loading and to examine the association among two or more factor loadings. Analyzing whether a group of factors are correlated or uncorrelated and calculating the convergent and discriminate validity of a group of measures are two other situations in which CFA would work.

Standard CFA models have three characteristics. First, each item is a continuous variable characterized as including two sources: variability due to the factor(s) of the item is believed to measure (common factors) and every other unique source of variability symbolized by the error term (residuals). Second, the factors are independent of the measurement errors, as well as the measurement errors being independent of each other (a psychometric convention ensuring the latent trait is measured by the items of a test). Third, all relations among the factors are not examined, and, therefore, the relations between the factors are unknown. Factor loadings (λ), also known as pattern coefficients, are statistical estimates of direct effects. Factor loadings are deciphered as regression coefficients (unstandardized or standardized form) that approximate the direct effect of the factors on the indicators. Effect (reflective) indicators, are indicators believed to be caused by essential factors (Kline, 2005).

The unidimensional CFA model can be defined as:

$$X_{ij} = \mu_i + \lambda_{i1}F_{j1} + \lambda_{i2}F_{j2} + \ldots + \lambda_{iA}F_{jA} + e_{ij} \quad (5)$$

where X_{ij} symbolizes the response to the observable variable *i* by person *j*, μ_i represents the mean of the item, λ_i indicates factor loading for the item, F_{ja} symbolizes latent variable value for individual *j* and latent variable *a* (for a test measuring *A* attributes), and e_{ij} represents the uniqueness (of the individual) for observed indicator variables (residuals); the subscript *i* signifies the item number (McDonald, 1999). The mean (μ_i) is a constant that represents the item difficulty. The factor loading (λ_i) is a measure of the capability of an item to distinguish between individuals with high and low amounts of the attribute. A relatively large factor loading for an item denotes a better indicator of the attribute than a relatively smaller factor loading for an item. A zero factor loading represents an item that does not measure the attribute at all. Factor loadings can be regarded as the *discriminating power* of an item. The positive or negative direction that X_i shifts from the projected level of response to the attribute is symbolized by e_i (McDonald, 1999).

Since CFA and IRT models analyze continuous latent variables, the IRT model can be transformed into the CFA model. The item parameter estimates for an IRT model can be acquired by transforming the factor loadings and threshold values (McDonald, 1999). The item discrimination parameter can be defined in terms of the factor loadings as:

$$a_i = \frac{\lambda_i}{\sqrt{1-\lambda_i^{'}\varphi\lambda_i}} \tag{6}$$

where the factor loading vector for item *i* is symbolized as λ_i, and φ signifies the covariance matrix of factors. The item difficulty can be expressed as:

$$b_i = \frac{-\tau_i}{\sqrt{1-\lambda_i^{'}\varphi\lambda_i}} \tag{7}$$

where τ symbolizes the threshold, a constant, for item *i*. When an individual possesses a value of the attribute being measured that is more than or equivalent to the threshold, the individual will answer the item correctly (Finch, 2010). When the response method is less than the threshold, the individual will answer the item incorrectly (Finch, 2010). With these simple transformations, it is feasible to employ generally obtainable CFA methods to acquire estimates of MIRT item parameters for discrete or continuous data (Finch, 2010).

To better understand CFA, a one-group, two-factor analysis of the BIRS data is included. The overall model fit is poor (47 free parameters; RMSEA = 0.092). Table 1.5 summarizes the factor loadings for the model. Items 3, 4, and 6 have relatively large factor loadings for both attributes and are therefore better indicators of the attributes than the other items with relatively small factor loadings. However, since the factor is continuous in nature for CFA, CFA cannot be used for diagnosis without having to use additional methods to determine factor-score cut points.

Table 1.5

Factor Loadings for CFA BIRS Dataset

Item	Factor Loadings for F1	Factor Loadings for F2
1	1.737	
2	1.544	
3	-5.225	6.438
4	-9.533	10.572
5	1.738	
6	-3.116	4.866
7		1.799
8	1.257	
9		1.673
10		1.738
11		1.649
12	-0.997	2.654
13	1.336	
14	1.344	

Historical Diagnostic Classification Models

Many different DCMs exist in literature and in practice. To compare and contrast many DCMs, three kinds of variables will be examined: dichotomous or polytomous response variables, dichotomous or polytomous latent variables, and the compensatory or non-compensatory grouping of latent attribute variables. Compensatory models permit that insufficiency in one attribute to be *compensated* for by an excess in a different attribute, and noncompensatory models demand that every attribute be there in order to generate an accurate answer (Rupp & Templin, 2008).

Noncompensatory models can be furthered classified as conjunctive or disjunctive. Conjunctive models do not let an individual "make up" for attributes not mastered through other attributes mastered (Henson, Templin, & Willse, 2009). The "opposite" of conjunctive models, disjunctive models describe the likelihood of an accurate answer such that mastery a subset of attributes is adequate to have a high likelihood of a correct response; an individual who has mastered the subset of attributes needed and an individual who has mastered all of the attributes needed should perform alike (Henson et al., 2009).

Deciding between a more intricate model and a simpler option is not an easy choice. Implementing a model that is too intricate for the specified data from a study may cause over fitting, meaning the model does not decrease the intricacy of the data structure adequately to affirm its function as a significant explanatory device. Still, though structurally simpler models may be appealing from estimation and interpretation viewpoints, their ease also has disadvantages, specifically that simpler models are less probable to fit an actual data set (Rupp et al., 2010).

Many DCMs are appropriate for dichotomous observed response variables as well as dichotomous latent predictor variables. Representing simpler core DCMs as "special cases" in more adaptable DCM structures (particularly the Loglinear Cognitive Diagnosis Model (LCDM), is the present trend in literature (Rupp et al., 2010). The LCDM is used to model observed categorical item responses and unobserved categorical latent attribute variables. LCDMs provide the conditional probability that a given individual's attribute profile gives an accurate response to an item (Rupp et al., 2010). LCDMs classify an entire range of models that can be conveyed as spanning from completely disjunctive models (i.e., the DINO model) to completely conjunctive models (i.e., the DINA model) (Henson et al., 2009).

The LCDM can also be written as an equation using a logit link function. Representing the LCDM as a logit link function parallels the representational structure for the item response theory models mentioned on pages 13 and 14.The link function is used to make model-predicted probabilities between zero and one (Rupp et al., 2010). The LCDM can be defined as:

$$P\left(X_{ij}=1|\alpha_j\right)=\frac{e^{\boldsymbol{\lambda_{i0}}+\boldsymbol{\lambda_i^T h}\left(\boldsymbol{q_i},\boldsymbol{\alpha_j}\right)}}{1+e^{\boldsymbol{\lambda_{i0}}+\boldsymbol{\lambda_i^T h}\left(\boldsymbol{q_i},\boldsymbol{\alpha_j}\right)}} \quad (8)$$

where the vector $\boldsymbol{\lambda}_i$ symbolizes a 1 x $(2^K - 1)$ vector of weights (main effect and interaction parameters) for item *i*, $\mathbf{h}(\boldsymbol{\alpha}_j, \mathbf{q}_i)$ denotes a group of linear combinations of the $\boldsymbol{\alpha}_j$ and $\mathbf{q}_i$ (the Q-matrix entries for item *i*), and logit(λ_{i0}) represents the reference group (Henson et al., 2009). For the LCDM, $\mathbf{h}(\boldsymbol{\alpha}_j, \mathbf{q}_i)$ is described as the collection of every main effect and interaction parameter incorporated in the complete model with K latent dichotomous attributes. Via the LCDM, $\boldsymbol{\lambda_i^T h}\left(\boldsymbol{q_i},\boldsymbol{\alpha_j}\right)$ can be expressed as:

$$\lambda_i^T h\left(q_i,\alpha_j\right)=\sum_{u=1}^{K}\lambda_{iu}\left(\alpha_u q_{iu}\right)+\sum_{u=1}^{K}\sum_{v>u}\lambda_{iuv}\left(\alpha_u\alpha_v q_{iu}q_{iv}\right)+\ldots \quad (9)$$

where the conditional association between mastery or nonmastery of attribute *u* for item *i* is associated to λ_{iu}, and λ_{iuv} represents the degree the conditional association of attribute *u* and the item, which is contingent on the second attribute *v* for item *i* (Henson et al., 2009). Henson et al. (2009) provides a LCDM for the probability of a correct answer for an item that needs two attributes as:

$$P(X_{ij} = 1 \mid \alpha) = \frac{e^{\lambda_{i0}+\lambda_{i1}\alpha_1+\lambda_{i2}\alpha_2+\lambda_{i12}\alpha_1\alpha_2}}{1+e^{\lambda_{i0}+\lambda_{i1}\alpha_1+\lambda_{i2}\alpha_2+\lambda_{i12}\alpha_1\alpha_2}}. \quad (10)$$

The specification of the Q-matrix, monotonicity, and that attributes and Q-matrix entries are defined as 0/1 demonstrate many of the constraints integrated to guarantee the identifiability of the LCDMs (Henson et al., 2009). Attributes could change in their meaning without a Q-matrix. Monotonicity is "the property such that for any individual who masters additional skills his or her probability of a correct response must be equal to or greater than the probability of a correct response prior to learning the additional skills" (Henson et al., 2009, p. 198). The definition of monotonicity symbolized is:

$$P(X_{ij} = 1 \mid \alpha_j^w) \geq P(X_{ij} = 1 \mid \alpha_j) \text{ for all } w \quad (11)$$

where

$$\alpha_{jk}^w = \begin{cases} \alpha_{jk}, & \text{where } w \neq k \\ 1 & \text{otherwise.} \end{cases}$$

Requiring the attributes and Q-matrix entries to be defined as 0/1 provides a reference group, which represents individuals who have mastered none of the necessary attributes for an item (Henson et al., 2009).

The LCDM can be considered a particular type of a linear model, and therefore is similar to a multiple way-ANOVA (Rupp et al., 2010). The LCDM and multiple way-ANOVA model responses similarly (Rupp et al., 2010). The attributes in a LCDM are equivalent to the factors in ANOVA and the mastery states of each attribute are the levels of the factors in the ANOVA (Rupp et al., 2010). A strength of the LCDM is that the LCDM can be utilized to find an appropriate DCM by inserting parameter limitations within a very broad model (Rupp et al., 2010). Within a certain study, this strength permits for an easy assessment of the relative and absolute fit for each of the DCMs being contemplated (Rupp et al., 2010).

Some other models can be represented in terms of the LCDM. The C-RUM (Hartz, 2002) shows the most straightforward relationship to LCDM by being considered as a "reduced version of the LCDM" by setting λ_{i12} to equal zero (Henson et al., 2009, p.199). Henson et al. (2009) describes the DINA model (Haertel, 1989; Junker & Sijstma, 2001), DINO model (Templin & Henson, 2006), and the reduced RUM (Hartz, 2002) in terms of the LCDM. The parameterization of the LCDM permits for an account of the variation for every model, as well as allowing for more intricate data structures (Henson et al., 2009).

Changing the LCDM into a continuous model is done by taking the part of the model in Equation 10 (p. 20) that is raised by the exponent and adding an error term (e_i). The continuous LCDM can be defined as:

$$X_{ij} = \lambda_{i0} + \lambda_{i1}\alpha_1 + \lambda_{i2}\alpha_2 + \lambda_{i12}\alpha_1\alpha_2 + e_i. \quad (12)$$

An analysis was performed with this data set via Mplus using the loglinear cognitive diagnostic model (LCDM) for continuous data. The syntax of Mplus can be found in Appendix A. The data set consists of a 14-item test measuring two attributes. Of the 14 items, 10 measure

only one attribute, and four items measure both attributes. The Q-matrix for the dataset is shown in Table 1.6. Every item has an intercept parameter. Items that measure one attribute only have one main effect parameter, and items that measure both attributes have two main effect parameters and a two-way interaction.

Table 1.6

Q-matrix

Item	Attribute 1	Attribute 2	Item	Attribute 1	Attribute 2
1	1	0	8	1	0
2	1	0	9	0	1
3	1	1	10	0	1
4	1	1	11	0	1
5	1	0	12	1	1
6	1	1	13	1	0
7	0	1	14	1	0

The parameter estimates from Mplus, which are very important to estimating and standardizing a diagnostic classification model (DCM) since it includes the estimates for every LCDM model parameter, are listed in Table 1.7. The parameters have the format: L[*i*]_[*e*][*a1,…*], where [*i*] is the item number, [*e*] is the type of effect (intercepts, main effects, interactions), and [*a1, …*] represents the list of attributes to which the effect applies (Rupp et al., 2010). The type of effects [*e*] takes the following values: intercepts = 0, main effects = 1, two-way interactions = 2, etc.

To demonstrate how the LCDM functions, we examine the results for a single item – Item 2. Item 2 measures only Attribute 1, preoccupation of a perceived defect in appearance. The intercept for Item 2 is denoted as L2_0 (also symbolized as $\lambda_{2,0}$), with an estimate of 3.759. The LCDM estimate 3.759 means that an individual that does not meet this criterion has an average correct response of 3.759. The main effect for Item 2 for Attribute 1(denoted as L2_11) has an estimate of 2.572 meaning that an individual who has met the criterion for Attribute 1 has an average correct response of 6.331 (3.759 + 2.572).

In contrast, Item12 measures both Attribute 1, preoccupation of a perceived defect in appearance, and Attribute 2, preoccupation causes clinically significant distress or impairment. The intercept for Item 12, L12_0 has an LCDM estimate of 2.149. Therefore, an individual who does not possess either Attribute 1 or Attribute 2 has an average response of 2.149 on the nine-point Likert-type scale. If the individual has met only the criterion for Attribute 1, then the individual has an average response score of 2.302. If the individual has met the criterion for only Attribute 2, then the individual has an average response score of 3.729. If the individual has met both criteria, Attribute 1 and Attribute 2, then the individual has an average response of 5.349 (2.149 + 0.153 + 1.58 + 1.467). Figure 1.2 presents a graphical representation of Item 12.However, since the model fit is so poor, item parameters should not be interpreted. In the next chapter, invariance testing is discussed in the context of CFA where invariance testing methods are well known. We highlight testing under two types of identifiability conditions: with both a marker variable and without a marker variable. Invariance is typically assumed. However, when the invariance assumption is violated, valid comparisons between groups may be hindered. It is crucial to test for invariance if group comparisons are going to be made.

Table 1.7

Parameter Estimates

Parameter	**Estimate**	**Standard Error**
L1_0	3.900	0.067
L1_11	3.016	0.073
L2_0	3.759	0.058
L2_11	2.572	0.063
L3_0	2.702	0.061
L3_12	1.026	0.218
L3_11	0.000	0.000
L3_212	1.293	0.223
L4_0	3.888	0.069
L4_12	1.405	0.219
L4_11	0.000	0.000
L4_212	0.653	0.220
L5_0	3.788	0.078
L5_11	3.160	0.087
L6_0	2.360	0.055
L6_12	1.403	0.199
L6_11	2.196	0.498
L6_212	-0.240	0.539
L7_0	3.193	0.068
L7_12	3.275	0.077
L8_0	2.736	0.052
L8_11	2.170	0.090
L9_0	2.548	0.054
L9_12	2.912	0.086
L10_0	3.697	0.078
L10_12	3.118	0.074
L11_0	2.104	0.049
L11_12	2.942	0.083
L12_0	2.149	0.048
L12_12	1.580	0.190
L12_11	0.153	0.290
L12_212	1.467	0.365
L13_0	3.578	0.046
L13_11	2.242	0.075
L14_0	4.337	0.048
L14_11	2.393	0.084

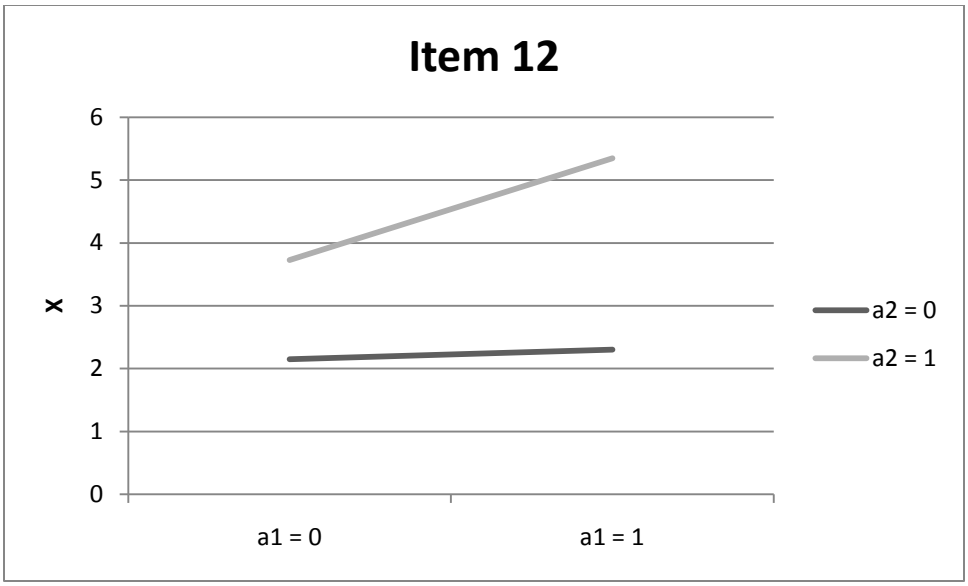

Figure 1.2. Item 12 parameter estimates

CHAPTER 2

TESTING FOR INVARIANCE IN STRUCTURAL EQUATION MODELS

Invariance Testing

The methods in Chapter 1 work for homogenous groups. However, sometimes the factor structure changes as a function of the group under study. When the factor structure changes, the methods in Chapter 1 break down, and invariance testing methods need to be performed. Invariance of items of a diagnostic assessment is vital since diagnostic assessments are used to classify individuals. If items are non-invariant, then classifications between groups (i.e. males and females) could potentially be biased. For any inferences concerning group associated differences, the validity of that supposition is essential. Little (1997) asserts that unless this statement is correct, a researcher cannot declare that the separate groups have identical constructs. Steinmetz, Schmidt, Tina-Booh, Wieczorek, and Schwartz (2009) states that testing for measurement invariance in confirmatory factor analysis (CFA) focuses on four questions:

> 1) Are the measurement parameters (factor loadings, measurement errors, etc.) the same across groups? 2) Are there pronounced response biases in a particular group? 3) Can one unambiguously interpret observed mean differences as latent mean differences? 4) Is the same construct measured in all groups? (p. 600).

In CFA there are two kinds of invariance: measurement invariance (invariance of item intercepts, factor loadings, and error variance) and structural invariance (invariance of the variances and covariances of the latent variables) (Steinmetz et al., 2009). Measurement

invariance has to do with how the items assess the latent construct across groups or over time. Four tests are involved with testing measurement invariance: test for configural invariance, metric invariance, scalar invariance, and residual variance invariance (Steinmetz et al., 2009).

Figure 2.1 (based on Figure 1 in Gregorich, 2006) illustrates a two-group measurement model with labels along the top defining each part of the model examined during the testing for invariance. The circles symbolize common factors, squares symbolize items, and diamonds symbolize means and intercepts. Arrows with a single-head symbolize values of regression parameters such as factor loadings (λ_{11}, λ_{12}, λ_{21}…), common factor means (κ_{11}, κ_{12} …), and intercepts (τ_{11}, τ_{12}…). Arrows with a double-head symbolize common factor variances (φ_{11}, φ_{12}...), covariances ($\varphi_{(1, 2)1}$, $\varphi_{(1, 2)2}$…), and item residual variances (θ_{11}, θ_{12}…). The first subscript indicates the common factor or item, and the second subscript indicates the group membership for every parameter.

For this thesis, Thompson and Green's (2006) approach to invariance is used. Configural invariance is the "prerequisite" for metric, scalar, and residual invariance testing (Steinmetz et al., 2009). Testing for configural invariance does not enforce any constraints and investigates whether the groups have the same factor structure (Gregorich, 2006). Configural invariance is concerned with the same number of factors and the same pattern of free/0 loadings in the groups. Configural invariance allows all the model parameters to be free, in which this estimated model becomes the baseline for more testing.

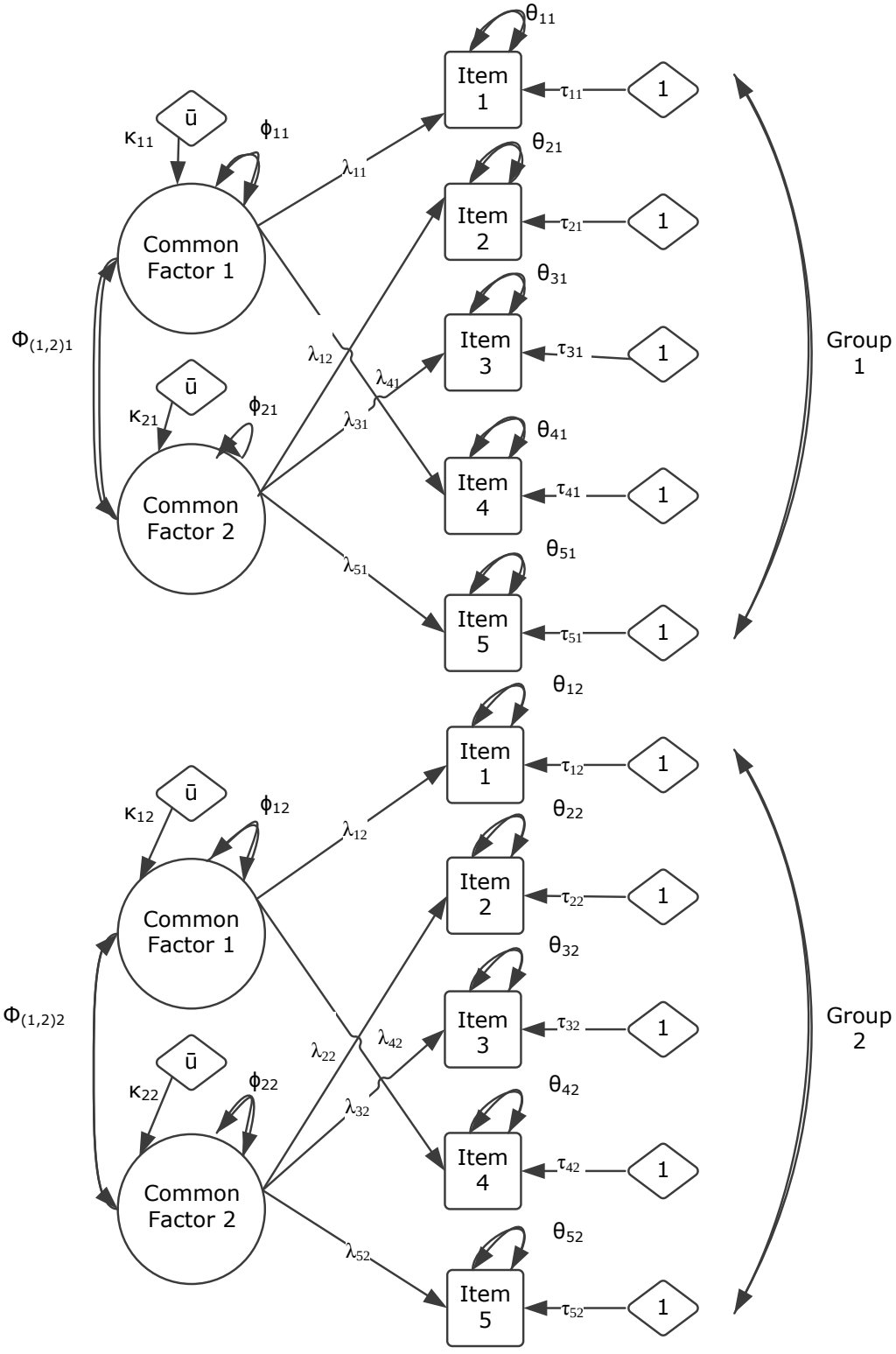

Figure 2.1. Two-group measurement model

For metric invariance, the question analyzed is if the two groups have the "same factor loadings". Testing metric invariance keeps the factor loadings ($\lambda_{11} = \lambda_{12} = \lambda_{21}\ldots$) for the groups equal (Steinmetz et al., 2009). Using a single item X, the factor loading is in bold:

$$X_{11} = \mu_{11} + \boldsymbol{\lambda_{11}}F_{11} + e_{11}. \quad (12)$$

Constraining the factor loadings to be equal across the groups investigates whether the groups "calibrate" their measures in equivalent ways (Steinmetz et al., 2009). Metric invariance testing offers indication that equivalent common factors have identical implication across groups (Gregorich, 2006). Quantitative group comparisons of estimated factor variances and covariances are justifiable if metric invariance holds (Gregorich, 2006).

Scalar invariance testing examines the question of whether the two groups have the "same item intercepts" by holding factor loadings and item intercepts equal in both groups($\lambda_{11} = \lambda_{12} = \lambda_{21}\ldots$, $\tau_{11} = \tau_{12}\ldots$) (Steinmetz et al., 2009). When examining if item intercepts are equal in both groups, the observed mean (μ) for the item is tested. Using a single item X, the part of the model tested for scalar invariance is in bold:

$$X_{11} = \boldsymbol{\mu_{11}} + \lambda_{11}F_{11} + e_{11}. \quad (13)$$

Scalar invariance concerns differential additive response bias (Gregorich, 2006). Influences not connected to the common factors (i.e. cultural customs) may methodically cause "higher-or-lower-valued item response in one population group compared with another" (Gregorich, 2006, p.S82). Item intercepts indicate these methodical additive weights on responses to the items (Gregorich, 2006). Implications that group variations in estimated factor means will be impartial and group variations in observed item means will be clearly linked to group variations in factor means and will not be tainted by "differential additive response bias" can be confirmed when

matching factor loadings and item intercepts are invariant across groups (Gregorich, 2006, p.S82).

Residual variance invariance testing explores the question if the two groups have the "same item residual variances" by restraining the factor loadings, item intercepts, and residual variances all equal in both groups ($\lambda_{11} = \lambda_{12} = \lambda_{21}\ldots$, $\tau_{11} = \tau_{12}\ldots$, $\theta_{11} = \theta_{12}\ldots$) (Steinmetz et al., 2009). Testing for residual invariance, θ_{ij} is symbolized as e_{ij}; below in bold shows the part of a model for a single item X that is examined during residual invariance testing:

$$X_{11} = \mu_{11} + \lambda_{11}F_{11} + \mathbf{e_{11}}. \quad (14)$$

Residual variance is the last step in testing for measurement invariance. Residual invariance does not provide evidence for significant assessments of group means (Gregorich, 2006). However, for a valid assessment across groups of the observed mean and variance estimates, verification of residual invariance must be acquired (Gregorich, 2006).

The previous descriptions of testing for measurement invariance have been given in terms of *full* measurement invariance (all corresponding components are invariant across groups). For group comparisons, full metric invariance is recognized as a condition that may be overly stringent and impractical (Steinmetz et al., 2009). Byrne, Shavelson, and Muthen (1989) presented the idea of partial invariance – where only part of the group of parameters has to be invariant instead of all parameters. Byrne et al. (1989) gave the criteria that two or more parameters need to be invariant to assure significance of group comparisons. Only the items that are invariant while testing for metric, scalar, or residual invariance are utilized to assess related group variations (Gregorich, 2006). The subset of items that are found to be invariant after metric invariance testing are used for testing scalar invariance; the subset of items found to still

be invariant after testing for scalar invariance are used for testing residual invariance. A significant p-value means that we do not have invariance and further testing of items will be necessary to decide if the measure has partial invariance or none at all.

Measurement Invariance With Marker Variable

To provide an example, the 14 BIRS items and two groups are used to explain testing measurement invariance with a marker variable. A marker variable represents a variable that is set to equal 1 for identification and is presumed invariant. Table 2.1 provides a list of equations representing what is being tested for configural invariance (same factor structure). The factor mean (μ_{ij}) is fixed to zero for now. The "1" in front of F_{11} and F_{12} for Item 1, and F_{21} and F_{22} for Item 7, signifies the marker variables."F" represents the factors, "λ" denotes the factor loadings, and "e" symbolizes residual (error) variances.

Table 2.1

Configural Invariance Model

Group 1 (last subscript = 1)	Group 2 (last subscript = 2)
$X_{11} = \mu_{11} + 1F_{11} + e_{11}$	$X_{12} = \mu_{12} + 1F_{12} + e_{12}$
$X_{21} = \mu_{21} + \lambda_{211}F_{11} + e_{21}$	$X_{22} = \mu_{22} + \lambda_{212}F_{12} + e_{22}$
$X_{31} = \mu_{31} + \lambda_{311}F_{11} + \lambda_{321}F_{21} + e_{31}$	$X_{32} = \mu_{32} + \lambda_{312}F_{12} + \lambda_{322}F_{22} + e_{32}$
$X_{41} = \mu_{41} + \lambda_{411}F_{11} + \lambda_{421}F_{21} + e_{41}$	$X_{42} = \mu_{42} + \lambda_{412}F_{12} + \lambda_{422}F_{22} + e_{42}$
$X_{51} = \mu_{51} + \lambda_{511}F_{11} + e_{51}$	$X_{52} = \mu_{52} + \lambda_{512}F_{12} + e_{52}$
$X_{61} = \mu_{61} + \lambda_{611}F_{11} + \lambda_{621}F_{21} + e_{61}$	$X_{62} = \mu_{62} + \lambda_{612}F_{12} + \lambda_{622}F_{22} + e_{62}$
$X_{71} = \mu_{71} + 1F_{21} + e_{71}$	$X_{72} = \mu_{72} + 1F_{22} + e_{72}$
$X_{81} = \mu_{81} + \lambda_{811}F_{11} + e_{81}$	$X_{82} = \mu_{82} + \lambda_{812}F_{12} + e_{82}$
$X_{91} = \mu_{91} + \lambda_{921}F_{21} + e_{91}$	$X_{92} = \mu_{92} + \lambda_{922}F_{22} + e_{92}$
$X_{101} = \mu_{101} + \lambda_{1021}F_{21} + e_{101}$	$X_{102} = \mu_{102} + \lambda_{1022}F_{22} + e_{102}$
$X_{111} = \mu_{111} + \lambda_{1121}F_{12} + e_{111}$	$X_{112} = \mu_{112} + \lambda_{1122}F_{12} + e_{112}$
$X_{121} = \mu_{121} + \lambda_{1211}F_{11} + \lambda_{1221}F_{21} + e_{121}$	$X_{122} = \mu_{122} + \lambda_{1212}F_{12} + \lambda_{1222}F_{22} + e_{122}$
$X_{131} = \mu_{131} + \lambda_{1311}F_{11} + e_{131}$	$X_{132} = \mu_{132} + \lambda_{1312}F_{12} + e_{132}$
$X_{141} = \mu_{141} + \lambda_{1411}F_{11} + e_{141}$	$X_{142} = \mu_{142} + \lambda_{1412}F_{12} + e_{142}$

If configural invariance is present, this model's X^2 and degrees of freedom will be compared to the metric invariance test. Metric invariance testing is assessing factor loadings, still keeping the factor mean fixed to zero. Using a marker variable, the factor loadings of Item 1 and Item 7 in both groups from Table 2.2 are not tested because they are assumed to be invariant. Table 2.2 provides the equations that represent the model for metric invariance with the part being tested (factor loadings) in bold. If metric invariance does not hold, retest the model to find which factor loadings need to vary between groups; this is done by testing one item at a time (Thompson & Green, 2006). If at least some items are invariant, partial metric invariance can be stated.

Table 2.2

Metric Invariance Model

Group 1 (last subscript = 1)	Group 2 (last subscript = 2)
$X_{11} = \mu_{11} + 1F_{11} + e_{11}$	$X_{12} = \mu_{12} + 1F_{12} + e_{12}$
$X_{21} = \mu_{21} + \boldsymbol{\lambda_{211}}F_{11} + e_{21}$	$X_{22} = \mu_{22} + \boldsymbol{\lambda_{212}}F_{12} + e_{22}$
$X_{31} = \mu_{31} + \boldsymbol{\lambda_{311}}F_{11} + \boldsymbol{\lambda_{321}}F_{21} + e_{31}$	$X_{32} = \mu_{32} + \boldsymbol{\lambda_{312}}F_{12} + \boldsymbol{\lambda_{322}}F_{22} + e_{32}$
$X_{41} = \mu_{41} + \boldsymbol{\lambda_{411}}F_{11} + \boldsymbol{\lambda_{421}}F_{21} + e_{41}$	$X_{42} = \mu_{42} + \boldsymbol{\lambda_{412}}F_{12} + \boldsymbol{\lambda_{422}}F_{22} + e_{42}$
$X_{51} = \mu_{51} + \boldsymbol{\lambda_{511}}F_{11} + e_{51}$	$X_{52} = \mu_{52} + \boldsymbol{\lambda_{512}}F_{12} + e_{52}$
$X_{61} = \mu_{61} + \boldsymbol{\lambda_{611}}F_{11} + \boldsymbol{\lambda_{621}}F_{21} + e_{61}$	$X_{62} = \mu_{62} + \boldsymbol{\lambda_{612}}F_{12} + \boldsymbol{\lambda_{622}}F_{22} + e_{62}$
$X_{71} = \mu_{71} + \mathbf{1}F_{21} + e_{71}$	$X_{72} = \mu_{72} + \mathbf{1}F_{22} + e_{72}$
$X_{81} = \mu_{81} + \boldsymbol{\lambda_{811}}F_{11} + e_{81}$	$X_{82} = \mu_{82} + \boldsymbol{\lambda_{812}}F_{12} + e_{82}$
$X_{91} = \mu_{91} + \boldsymbol{\lambda_{921}}F_{21} + e_{91}$	$X_{92} = \mu_{92} + \boldsymbol{\lambda_{922}}F_{22} + e_{92}$
$X_{101} = \mu_{101} + \boldsymbol{\lambda_{1021}}F_{21} + e_{101}$	$X_{102} = \mu_{102} + \boldsymbol{\lambda_{1022}}F_{22} + e_{102}$
$X_{111} = \mu_{111} + \boldsymbol{\lambda_{1121}}F_{12} + e_{111}$	$X_{112} = \mu_{112} + \boldsymbol{\lambda_{1122}}F_{12} + e_{112}$
$X_{121} = \mu_{121} + \boldsymbol{\lambda_{1211}}F_{11} + \boldsymbol{\lambda_{1221}}F_{21} + e_{121}$	$X_{122} = \mu_{122} + \boldsymbol{\lambda_{1212}}F_{12} + \boldsymbol{\lambda_{1222}}F_{22} + e_{122}$
$X_{131} = \mu_{131} + \boldsymbol{\lambda_{1311}}F_{11} + e_{131}$	$X_{132} = \mu_{132} + \boldsymbol{\lambda_{1312}}F_{12} + e_{132}$
$X_{141} = \mu_{141} + \boldsymbol{\lambda_{1411}}F_{11} + e_{141}$	$X_{142} = \mu_{142} + \boldsymbol{\lambda_{1412}}F_{12} + e_{142}$

For the Body Image Rating Scale dataset mentioned in Chapter 1 (p. 8), Table 2.3 provides a summary of the metric invariance test with degrees of freedom abbreviated as "df". In Table 2.3, Item 1 and Item 7 are not listed because they are the marker variables. As stated previously, marker variables are not tested, but assumed invariant. Using the cutoff p-value of 0.05, Items 2, 4, 6, 8, and 10 are significant, meaning they are non-invariant, and require different factor loadings for males and females. These five items will not be subject to testing further for scalar, or residual invariance. All other items will continue to the next level of testing: scalar invariance.

Table 2.3

BIRS Dataset Metric Invariance Test Summary Table

Item	Configural Loadings for F1		Configural Loadings for F2		Full Metric Model		Partial Metric Model		Change		P-Value
	Male	Female	Male	Female	Chi Square	df	Chi Square	df	Chi Square	df	
2	0.87	0.945			1567.076	160	1562.696	159	4.38	1	0.036363
3	-2.482	-3.597	2.949	4	1567.076	160	1565.371	158	1.705	2	0.426348
4	-6.095	-4.433	6.166	4.744	1567.076	160	1553.178	158	13.898	2	0.00096
5	0.927	1.024			1567.076	160	1563.291	159	3.785	1	0.051714
6	-1.772	-1.901	2.579	2.585	1567.076	160	1555.391	158	11.685	2	0.002902
8	0.773	0.638			1567.076	160	1557.319	159	9.757	1	0.001786
9			0.911	0.895	1567.076	160	1566.899	159	0.177	1	0.673964
10			0.913	0.996	1567.076	160	1562.6	159	4.476	1	0.034374
11			0.9	0.902	1567.076	160	1567.068	159	0.008	1	0.92873
12	-0.363	-0.86	1.245	1.658	1567.076	160	1565.337	158	1.739	2	0.419161
13	0.793	0.803			1567.076	160	1567.054	159	0.022	1	0.882087
14	0.807	0.8			1567.076	160	1566.954	159	0.122	1	0.726875

Scalar invariance testing occurs for the items that result as invariant from the metric invariance test. The factor mean for Group 1 is fixed to zero (creating a reference group), while

the factor mean for Group 2 is free (allowed to vary). This represents the factor mean difference. Table 2.4 shows a generic Scalar Invariance Model with the part of the equation being tested in bold. To decide if items are scalar invariant, the model fit of the metric invariance model is compared to the model fit of the scalar invariance model. If the criterion for full scalar invariance is not met, retest the model by fixing one intercept at a time to see if partial scalar invariance exists (Thompson & Green, 2006).

Table 2.4

Scalar Invariance Model

Group 1 (last subscript = 1)	Group 2 (last subscript = 2)
$X_{11} = \mathbf{\mu_{11}} + 1F_{11} + e_{11}$	$X_{12} = \mathbf{\mu_{12}} + 1F_{12} + e_{12}$
$X_{21} = \mathbf{\mu_{21}} + \lambda_{211}F_{11} + e_{21}$	$X_{22} = \mathbf{\mu_{22}} + \lambda_{212}F_{12} + e_{22}$
$X_{31} = \mathbf{\mu_{31}} + \lambda_{311}F_{11} + \lambda_{321}F_{21} + e_{31}$	$X_{32} = \mathbf{\mu_{32}} + \lambda_{312}F_{12} + \lambda_{322}F_{22} + e_{32}$
$X_{41} = \mathbf{\mu_{41}} + \lambda_{411}F_{11} + \lambda_{421}F_{21} + e_{41}$	$X_{42} = \mathbf{\mu_{42}} + \lambda_{412}F_{12} + \lambda_{422}F_{22} + e_{42}$
$X_{51} = \mathbf{\mu_{51}} + \lambda_{511}F_{11} + e_{51}$	$X_{52} = \mathbf{\mu_{52}} + \lambda_{512}F_{12} + e_{52}$
$X_{61} = \mathbf{\mu_{61}} + \lambda_{611}F_{11} + \lambda_{621}F_{21} + e_{61}$	$X_{62} = \mathbf{\mu_{62}} + \lambda_{612}F_{12} + \lambda_{622}F_{22} + e_{62}$
$X_{71} = \mathbf{\mu_{71}} + 1F_{21} + e_{71}$	$X_{72} = \mathbf{\mu_{72}} + 1F_{22} + e_{72}$
$X_{81} = \mathbf{\mu_{81}} + \lambda_{811}F_{11} + e_{81}$	$X_{82} = \mathbf{\mu_{82}} + \lambda_{812}F_{12} + e_{82}$
$X_{91} = \mathbf{\mu_{91}} + \lambda_{921}F_{21} + e_{91}$	$X_{92} = \mathbf{\mu_{92}} + \lambda_{922}F_{22} + e_{92}$
$X_{101} = \mathbf{\mu_{101}} + \lambda_{1021}F_{21} + e_{101}$	$X_{102} = \mathbf{\mu_{102}} + \lambda_{1022}F_{22} + e_{102}$
$X_{111} = \mathbf{\mu_{111}} + \lambda_{1121}F_{12} + e_{111}$	$X_{112} = \mathbf{\mu_{112}} + \lambda_{1122}F_{12} + e_{112}$
$X_{121} = \mathbf{\mu_{121}} + \lambda_{1211}F_{11} + \lambda_{1221}F_{21} + e_{121}$	$X_{122} = \mathbf{\mu_{122}} + \lambda_{1212}F_{12} + \lambda_{1222}F_{22} + e_{122}$
$X_{131} = \mathbf{\mu_{131}} + \lambda_{1311}F_{11} + e_{131}$	$X_{132} = \mathbf{\mu_{132}} + \lambda_{1312}F_{12} + e_{132}$
$X_{141} = \mathbf{\mu_{141}} + \lambda_{1411}F_{11} + e_{141}$	$X_{142} = \mathbf{\mu_{142}} + \lambda_{1412}F_{12} + e_{142}$

For the Body Image Rating Scale dataset, Table 2.5 provides a summary of the scalar invariance test. Items 2, 4, 6, 8, and 10 are not tested, resulting in N/A (not applicable) next to those items in Table 2.5.Using the cutoff p-value of 0.05, Items 3, 5, 13, and 14 are significant, therefore, are non-invariant and require different item intercepts for males and females. These four items will not be subject to testing further for residual invariance.

Items that are scalar invariant are further tested for residual variance invariance. Residual variance invariance testing occurs by constraining the residual variances for the same item to equal in both groups (Steinmetz et al., 2009). Table 2.6 depicts a generic Residual Variance Invariance Model with the variable in the model being tested in bold. To determine if items are residual variance invariant, the model fit of the scalar invariance model is compared to the model fit of the residual variance invariance model. If the criterion for full scalar invariance is not achieved, retest the model by fixing one residual variance at a time to see if partial residual variance invariance exists. Table 2.7 shows a summary of the residual variance invariance test for the BIRS dataset. Using a cutoff score of 0.05, Item 12 is significant (non-invariant), and requires different residual variances for males and females. Items 9 and 11 remain invariant for males and females.

Table 2.5

BIRS Dataset Scalar Invariance Test Summary Table

Item	Significant Item Intercept		Full Scalar Model		Partial Scalar Model		Change from Full to Partial Model		P-value
	Male	Female	Chi Square	df	Chi Square	df	Chi Square	df	
2	5.008	4.019	1890.401	165	N/A	N/A	N/A	N/A	N/A
3	3.832	3.104	1890.401	165	1884.666	164	5.735	1	0.016630069
4	4.876	4.44	1890.401	165	N/A	N/A	N/A	N/A	N/A
5	5.511	3.562	1890.401	165	1720.887	164	169.514	1	9.44745E-39
6	4.13	2.659	1890.401	165	N/A	N/A	N/A	N/A	N/A
8	3.715	3.175	1890.401	165	N/A	N/A	N/A	N/A	N/A
9	4.059	3.28	1890.401	165	1890.241	164	0.16	1	0.689156517
10	5.359	4.353	1890.401	165	N/A	N/A	N/A	N/A	N/A
11	3.605	2.917	1890.401	165	1888.943	164	1.458	1	0.227248726
12	3.684	2.83	1890.401	165	1886.843	164	3.558	1	0.059259107
13	4.565	4.102	1890.401	165	1836.201	164	54.2	1	1.81087E-13
14	5.363	4.973	1890.401	165	1834.965	164	55.436	1	9.65519E-14

Table 2.6

Residual Variance Invariance Model

Group 1 (last subscript = 1)	Group 2 (last subscript = 2)
$X_{11} = \mu_{11} + 1F_{11} + \mathbf{e_{11}}$	$X_{12} = \mu_{12} + 1F_{12} + \mathbf{e_{12}}$
$X_{21} = \mu_{21} + \lambda_{211}F_{11} + \mathbf{e_{21}}$	$X_{22} = \mu_{22} + \lambda_{212}F_{12} + \mathbf{e_{22}}$
$X_{31} = \mu_{31} + \lambda_{311}F_{11} + \lambda_{321}F_{21} + \mathbf{e_{31}}$	$X_{32} = \mu_{32} + \lambda_{312}F_{12} + \lambda_{322}F_{22} + \mathbf{e_{32}}$
$X_{41} = \mu_{41} + \lambda_{411}F_{11} + \lambda_{421}F_{21} + \mathbf{e_{41}}$	$X_{42} = \mu_{42} + \lambda_{412}F_{12} + \lambda_{422}F_{22} + \mathbf{e_{42}}$
$X_{51} = \mu_{51} + \lambda_{511}F_{11} + \mathbf{e_{51}}$	$X_{52} = \mu_{52} + \lambda_{512}F_{12} + \mathbf{e_{52}}$
$X_{61} = \mu_{61} + \lambda_{611}F_{11} + \lambda_{621}F_{21} + \mathbf{e_{61}}$	$X_{62} = \mu_{62} + \lambda_{612}F_{12} + \lambda_{622}F_{22} + \mathbf{e_{62}}$
$X_{71} = \mu_{71} + 1F_{21} + \mathbf{e_{71}}$	$X_{72} = \mu_{72} + 1F_{22} + \mathbf{e_{72}}$
$X_{81} = \mu_{81} + \lambda_{811}F_{11} + \mathbf{e_{81}}$	$X_{82} = \mu_{82} + \lambda_{812}F_{12} + \mathbf{e_{82}}$
$X_{91} = \mu_{91} + \lambda_{921}F_{21} + \mathbf{e_{91}}$	$X_{92} = \mu_{92} + \lambda_{922}F_{22} + \mathbf{e_{92}}$
$X_{101} = \mu_{101} + \lambda_{1021}F_{21} + \mathbf{e_{101}}$	$X_{102} = \mu_{102} + \lambda_{1022}F_{22} + \mathbf{e_{102}}$
$X_{111} = \mu_{111} + \lambda_{1121}F_{12} + \mathbf{e_{111}}$	$X_{112} = \mu_{112} + \lambda_{1122}F_{12} + \mathbf{e_{112}}$
$X_{121} = \mu_{121} + \lambda_{1211}F_{11} + \lambda_{1221}F_{21} + \mathbf{e_{121}}$	$X_{122} = \mu_{122} + \lambda_{1212}F_{12} + \lambda_{1222}F_{22} + \mathbf{e_{122}}$
$X_{131} = \mu_{131} + \lambda_{1311}F_{11} + \mathbf{e_{131}}$	$X_{132} = \mu_{132} + \lambda_{1312}F_{12} + \mathbf{e_{132}}$
$X_{141} = \mu_{141} + \lambda_{1411}F_{11} + \mathbf{e_{141}}$	$X_{142} = \mu_{142} + \lambda_{1412}F_{12} + \mathbf{e_{142}}$

Table 2.7

BIRS Dataset Residual Variance Invariance Test Summary Table

Item	Residual Error Variance		Residual Model		Partial Model		Change from Full to Partial Model		P-value
	Male	Female	Chi Square	df	Chi Square	df	Chi Square	df	
2	1.227	1.17	1568.524	161	N/A	N/A	N/A	N/A	N/A
3	3.224	3.117	1568.524	161	N/A	N/A	N/A	N/A	N/A
4	2.441	2.821	1568.524	161	N/A	N/A	N/A	N/A	N/A
5	2.772	2.4	1568.524	161	N/A	N/A	N/A	N/A	N/A
6	1.795	1.812	1568.524	161	N/A	N/A	N/A	N/A	N/A
8	2.698	2.305	1568.524	161	N/A	N/A	N/A	N/A	N/A
9	2.261	2.096	1568.524	161	1567.551	160	0.973	1	0.323933
10	2.177	2.134	1568.524	161	N/A	N/A	N/A	N/A	N/A
11	2.128	2.021	1568.524	161	1568.153	160	0.371	1	0.54246
12	2.317	1.985	1568.524	161	1550.566	159	17.958	2	0.000126
13	1.446	1.279	1568.524	161	N/A	N/A	N/A	N/A	N/A
14	1.881	1.867	1568.524	161	N/A	N/A	N/A	N/A	N/A

Measurement Invariance Without a Marker Variable

Since the marker variable is fixed to one for identification purposes, it cannot be tested for invariance, and is therefore assumed invariant. If the marker variable is truly not invariant, assessments of loadings and/or intercepts may be distorted. An alternative condition of fixing the factor variance(s) to 1 in the reference group only, but estimating all factor loadings solves the dilemma with using a marker variable unknown to be invariant. The procedure for configural invariance testing does not change when testing without a marker variable. However, metric, scalar, and residual variance invariance testing does change.

Testing for metric invariance without a marker variable assesses every factor loading by fixing the factor variance(s) to 1 in the reference group but keeping them free in the other group. Table 2.8 displays a general metric invariance model without a marker variable. The parameter in bold represents what is being tested for invariance. As depicted, every equation in the model has a factor loading instead of factor loading(s) being fixed to 1. However, what is not shown is that the factor variance(s) are also fixed to 1 in the reference group (Group 1). Just like with a marker variable, the model fit of the metric invariance is compared to the model fit of the configural invariance to assess if there is invariance. If there is evidence (modification indices) that some factor loadings want to vary, retest the model by releasing one loading at a time to assess for partial metric invariance.

Table 2.8

Metric Invariance Model without Marker Variable

Group 1 (last subscript = 1)	Group 2 (last subscript = 2)
$X_{11} = \mu_{11} + \boldsymbol{\lambda_{111}}F_{11} + e_{11}$	$X_{12} = \mu_{12} + \boldsymbol{\lambda_{211}}F_{12} + e_{12}$
$X_{21} = \mu_{21} + \boldsymbol{\lambda_{211}}F_{11} + e_{21}$	$X_{22} = \mu_{22} + \boldsymbol{\lambda_{212}}F_{12} + e_{22}$
$X_{31} = \mu_{31} + \boldsymbol{\lambda_{311}}F_{11} + \boldsymbol{\lambda_{321}}F_{21} + e_{31}$	$X_{32} = \mu_{32} + \boldsymbol{\lambda_{312}}F_{12} + \boldsymbol{\lambda_{322}}F_{22} + e_{32}$
$X_{41} = \mu_{41} + \boldsymbol{\lambda_{411}}F_{11} + \boldsymbol{\lambda_{421}}F_{21} + e_{41}$	$X_{42} = \mu_{42} + \boldsymbol{\lambda_{412}}F_{12} + \boldsymbol{\lambda_{422}}F_{22} + e_{42}$
$X_{51} = \mu_{51} + \boldsymbol{\lambda_{511}}F_{11} + e_{51}$	$X_{52} = \mu_{52} + \boldsymbol{\lambda_{512}}F_{12} + e_{52}$
$X_{61} = \mu_{61} + \boldsymbol{\lambda_{611}}F_{11} + \boldsymbol{\lambda_{621}}F_{21} + e_{61}$	$X_{62} = \mu_{62} + \boldsymbol{\lambda_{612}}F_{12} + \boldsymbol{\lambda_{622}}F_{22} + e_{62}$
$X_{71} = \mu_{71} + \boldsymbol{\lambda_{721}}F_{21} + e_{71}$	$X_{72} = \mu_{72} + \boldsymbol{\lambda_{722}}F_{22} + e_{72}$
$X_{81} = \mu_{81} + \boldsymbol{\lambda_{811}}F_{11} + e_{81}$	$X_{82} = \mu_{82} + \boldsymbol{\lambda_{812}}F_{12} + e_{82}$
$X_{91} = \mu_{91} + \boldsymbol{\lambda_{921}}F_{21} + e_{91}$	$X_{92} = \mu_{92} + \boldsymbol{\lambda_{922}}F_{22} + e_{92}$
$X_{101} = \mu_{101} + \boldsymbol{\lambda_{1021}}F_{21} + e_{101}$	$X_{102} = \mu_{102} + \boldsymbol{\lambda_{1022}}F_{22} + e_{102}$
$X_{111} = \mu_{111} + \boldsymbol{\lambda_{1121}}F_{12} + e_{111}$	$X_{112} = \mu_{112} + \boldsymbol{\lambda_{1122}}F_{12} + e_{112}$
$X_{121} = \mu_{121} + \boldsymbol{\lambda_{1211}}F_{11} + \boldsymbol{\lambda_{1221}}F_{21} + e_{121}$	$X_{122} = \mu_{122} + \boldsymbol{\lambda_{1212}}F_{12} + \boldsymbol{\lambda_{1222}}F_{22} + e_{122}$
$X_{131} = \mu_{131} + \boldsymbol{\lambda_{1311}}F_{11} + e_{131}$	$X_{132} = \mu_{132} + \boldsymbol{\lambda_{1312}}F_{12} + e_{132}$
$X_{141} = \mu_{141} + \boldsymbol{\lambda_{1411}}F_{11} + e_{141}$	$X_{142} = \mu_{142} + \boldsymbol{\lambda_{1412}}F_{12} + e_{142}$

For the Body Image Rating Scale dataset Table 2.9 provides a summary of the metric invariance test without a marker variable. Table 2.9 is practically identical to Table 2.3 with the only differences being that Item 1 and Item 7 are listed. Other than Item 1 and Item 7 being in the table, all other parts are identical to Table 2.3. This happens when the marker variables are truly invariant (as shown in the table with Item 1 and Item 7). The same items (2, 4, 6, 8, and 10) are significant using the cutoff p-value of 0.05, and will not proceed to testing for scalar invariance.

Table 2.9

BIRS Dataset Metric Invariance Test Summary Table Without Marker Variable

Item	Configural Loadings for F1		Configural Loadings for F2		Full Metric Model		Partial Metric Model		Change		P-Value
	Male	Female	Male	Female	Chi Square	df	Chi Square	df	Chi Square	df	
1	1.682	1.636			1567.076	160	1566.813	159	0.263	1	0.608067
2	1.463	1.545			1567.076	160	1562.696	159	4.38	1	0.036363
3	-4.174	-5.884	5.421	6.821	1567.076	160	1565.371	158	1.705	2	0.426348
4	-10.25	-7.252	11.332	8.089	1567.076	160	1553.178	158	13.898	2	0.00096
5	1.56	1.675			1567.076	160	1563.291	159	3.785	1	0.051714
6	-2.979	-3.11	4.739	4.408	1567.076	160	1555.391	158	11.685	2	0.002902
7			1.838	1.705	1567.076	160	1567.074	159	0.002	1	0.964329
8	1.3	1.044			1567.076	160	1557.319	159	9.757	1	0.001786
9			1.675	1.527	1567.076	160	1566.899	159	0.177	1	0.673964
10			1.678	1.698	1567.076	160	1562.6	159	4.476	1	0.034374
11			1.654	1.539	1567.076	160	1567.068	159	0.008	1	0.92873
12	-0.611	-1.406	2.288	2.826	1567.076	160	1565.337	158	1.739	2	0.419161
13	1.334	1.313			1567.076	160	1567.054	159	0.022	1	0.882087
14	1.358	1.309			1567.076	160	1566.954	159	0.122	1	0.726875

Scalar and residual variance invariance testing without a marker variable is basically the same as with a marker variable in the sense of what parameter is being examined. The only difference lies within the model: each item has a factor loading (none are fixed), and factor variance(s) remains fixed in reference group to equal 1 but free in the other group. Assessing scalar invariance and residual variance invariance occurs the same way as with a marker variable by comparing the model fit from the previous invariance test. Table 2.10 shows a generic scalar invariance model with the parameter subject to testing bolded.

Table 2.10

Scalar Invariance Model without Marker Variable

Group 1 (last subscript = 1)	Group 2 (last subscript = 2)
$X_{11} = \boldsymbol{\mu_{11}} + \lambda_{\mathbf{111}}F_{11} + e_{11}$	$X_{12} = \boldsymbol{\mu_{12}} + \lambda_{\mathbf{112}}F_{12} + e_{12}$
$X_{21} = \boldsymbol{\mu_{21}} + \lambda_{211}F_{11} + e_{21}$	$X_{22} = \boldsymbol{\mu_{22}} + \lambda_{212}F_{12} + e_{22}$
$X_{31} = \boldsymbol{\mu_{31}} + \lambda_{311}F_{11} + \lambda_{321}F_{21} + e_{31}$	$X_{32} = \boldsymbol{\mu_{32}} + \lambda_{312}F_{12} + \lambda_{322}F_{22} + e_{32}$
$X_{41} = \boldsymbol{\mu_{41}} + \lambda_{411}F_{11} + \lambda_{421}F_{21} + e_{41}$	$X_{42} = \boldsymbol{\mu_{42}} + \lambda_{412}F_{12} + \lambda_{422}F_{22} + e_{42}$
$X_{51} = \boldsymbol{\mu_{51}} + \lambda_{511}F_{11} + e_{51}$	$X_{52} = \boldsymbol{\mu_{52}} + \lambda_{512}F_{12} + e_{52}$
$X_{61} = \boldsymbol{\mu_{61}} + \lambda_{611}F_{11} + \lambda_{621}F_{21} + e_{61}$	$X_{62} = \boldsymbol{\mu_{62}} + \lambda_{612}F_{12} + \lambda_{622}F_{22} + e_{62}$
$X_{71} = \boldsymbol{\mu_{71}} + \lambda_{721}F_{21} + e_{71}$	$X_{72} = \boldsymbol{\mu_{72}} + \lambda_{722}F_{22} + e_{72}$
$X_{81} = \boldsymbol{\mu_{81}} + \lambda_{811}F_{11} + e_{81}$	$X_{82} = \boldsymbol{\mu_{82}} + \lambda_{812}F_{12} + e_{82}$
$X_{91} = \boldsymbol{\mu_{91}} + \lambda_{921}F_{21} + e_{91}$	$X_{92} = \boldsymbol{\mu_{92}} + \lambda_{922}F_{22} + e_{92}$
$X_{101} = \boldsymbol{\mu_{101}} + \lambda_{1021}F_{21} + e_{101}$	$X_{102} = \boldsymbol{\mu_{102}} + \lambda_{1022}F_{22} + e_{102}$
$X_{111} = \boldsymbol{\mu_{111}} + \lambda_{1121}F_{12} + e_{111}$	$X_{112} = \boldsymbol{\mu_{112}} + \lambda_{1122}F_{12} + e_{112}$
$X_{121} = \boldsymbol{\mu_{121}} + \lambda_{1211}F_{11} + \lambda_{1221}F_{21} + e_{121}$	$X_{122} = \boldsymbol{\mu_{122}} + \lambda_{1212}F_{12} + \lambda_{1222}F_{22} + e_{122}$
$X_{131} = \boldsymbol{\mu_{131}} + \lambda_{1311}F_{11} + e_{131}$	$X_{132} = \boldsymbol{\mu_{132}} + \lambda_{1312}F_{12} + e_{132}$
$X_{141} = \boldsymbol{\mu_{141}} + \lambda_{1411}F_{11} + e_{141}$	$X_{142} = \boldsymbol{\mu_{142}} + \lambda_{1412}F_{12} + e_{142}$

If need, retesting the model to see if intercepts or residual variances need to vary is done the same way as with a marker variable. For the Body Image Rating Scale dataset, Table 2.11 provides a summary of the scalar invariance test. Items 2, 4, 6, 8, and 10 are not tested, resulting in N/A (not applicable) next to those items in Table 2.11 (identical to Table 2.6 with the addition of Item 1).Using the cutoff p-value of 0.05, Items 3, 5, 7, 13, and 14 are found non-invariant because of a significant p-value.

Table 2.11

BIRS Dataset Scalar Invariance Test Summary Table Without Marker Variable

Item	Significant Item Intercept		Full Scalar Model		Partial Scalar Model		Change from Full to Partial Model		P-value
	Male	Female	Chi Square	df	Chi Square	df	Chi Square	df	
1	5.344	4.268	1890.401	165	1890.036	164	0.365	1	0.545742392
2	5.008	4.019	1890.401	165	N/A	N/A	N/A	N/A	N/A
3	3.832	3.104	1890.401	165	1884.666	164	5.735	1	0.016630069
4	4.876	4.44	1890.401	165	N/A	N/A	N/A	N/A	N/A
5	5.511	3.562	1890.401	165	1720.887	164	169.514	1	9.44745E-39
6	4.13	2.659	1890.401	165	N/A	N/A	N/A	N/A	N/A
7	4.787	4.323	1890.401	165	1840.089	164	50.312	1	1.31145E-12
8	3.715	3.175	1890.401	165	N/A	N/A	N/A	N/A	N/A
9	4.059	3.28	1890.401	165	1890.241	164	0.16	1	0.689156517
10	5.359	4.353	1890.401	165	N/A	N/A	N/A	N/A	N/A
11	3.605	2.917	1890.401	165	1888.943	164	1.458	1	0.227248726
12	3.684	2.83	1890.401	165	1886.843	164	3.558	1	0.059259107
13	4.565	4.102	1890.401	165	1836.201	164	54.2	1	1.81087E-13
14	5.363	4.973	1890.401	165	1834.965	164	55.436	1	9.65519E-14

Items 1, 9, 11, and 12 remain for testing residual variance invariance. Table 2.12 displays the residual variance invariance model with the corresponding parameter tested in bold. Table 2.13 shows the summary of the residual variance invariance test. Using a cutoff of 0.05, Item 12 is significant (non-invariant) and needs different residual variances for males and females. Items 1, 9, and 11 remain invariant for males and females.

Table 2.12

Residual Variance Invariance Model without Marker Variable

Group 1 (last subscript = 1)	Group 2 (last subscript = 2)
$X_{11} = \mu_{11} + \lambda_{\mathbf{111}}F_{11} + \mathbf{e_{11}}$	$X_{12} = \mu_{12} + \lambda_{\mathbf{112}}F_{12} + \mathbf{e_{12}}$
$X_{21} = \mu_{21} + \lambda_{211}F_{11} + \mathbf{e_{21}}$	$X_{22} = \mu_{22} + \lambda_{212}F_{12} + \mathbf{e_{22}}$
$X_{31} = \mu_{31} + \lambda_{311}F_{11} + \lambda_{321}F_{21} + \mathbf{e_{31}}$	$X_{32} = \mu_{32} + \lambda_{312}F_{12} + \lambda_{322}F_{22} + \mathbf{e_{32}}$
$X_{41} = \mu_{41} + \lambda_{411}F_{11} + \lambda_{421}F_{21} + \mathbf{e_{41}}$	$X_{42} = \mu_{42} + \lambda_{412}F_{12} + \lambda_{422}F_{22} + \mathbf{e_{42}}$
$X_{51} = \mu_{51} + \lambda_{511}F_{11} + \mathbf{e_{51}}$	$X_{52} = \mu_{52} + \lambda_{512}F_{12} + \mathbf{e_{52}}$
$X_{61} = \mu_{61} + \lambda_{611}F_{11} + \lambda_{621}F_{21} + \mathbf{e_{61}}$	$X_{62} = \mu_{62} + \lambda_{612}F_{12} + \lambda_{622}F_{22} + \mathbf{e_{62}}$
$X_{71} = \mu_{71} + \lambda_{721}F_{21} + \mathbf{e_{71}}$	$X_{72} = \mu_{72} + \lambda_{722}F_{22} + \mathbf{e_{72}}$
$X_{81} = \mu_{81} + \lambda_{811}F_{11} + \mathbf{e_{81}}$	$X_{82} = \mu_{82} + \lambda_{812}F_{12} + \mathbf{e_{82}}$
$X_{91} = \mu_{91} + \lambda_{921}F_{21} + \mathbf{e_{91}}$	$X_{92} = \mu_{92} + \lambda_{922}F_{22} + \mathbf{e_{92}}$
$X_{101} = \mu_{101} + \lambda_{1021}F_{21} + \mathbf{e_{101}}$	$X_{\mathbf{102}} = \mu_{102} + \lambda_{1022}F_{22} + \mathbf{e_{102}}$
$X_{111} = \mu_{111} + \lambda_{1121}F_{12} + \mathbf{e_{111}}$	$X_{112} = \mu_{112} + \lambda_{1122}F_{12} + \mathbf{e_{112}}$
$X_{121} = \mu_{121} + \lambda_{1211}F_{11} + \lambda_{1221}F_{21} + \mathbf{e_{121}}$	$X_{122} = \mu_{122} + \lambda_{1212}F_{12} + \lambda_{1222}F_{22} + \mathbf{e_{122}}$
$X_{131} = \mu_{131} + \lambda_{1311}F_{11} + \mathbf{e_{131}}$	$X_{132} = \mu_{132} + \lambda_{1312}F_{12} + \mathbf{e_{132}}$
$X_{141} = \mu_{141} + \lambda_{1411}F_{11} + \mathbf{e_{141}}$	$X_{142} = \mu_{142} + \lambda_{1412}F_{12} + \mathbf{e_{142}}$

Table 2.13

BIRS Dataset Residual Variance Invariance Test Summary Table Without Marker Variable

Item	Residual Error Variance		Residual Model		Partial Model		Change from Full to Partial Model		P-value
	Male	Female	Chi Square	df	Chi Square	df	Chi Square	df	
1	1.659	1.784	1546.976	159	1546.198	158	0.778	1	0.377754
2	1.22	1.159	1546.976	159	N/A	N/A	N/A	N/A	N/A
3	3.211	3.178	1546.976	159	N/A	N/A	N/A	N/A	N/A
4	2.599	2.935	1546.976	159	N/A	N/A	N/A	N/A	N/A
5	2.775	2.426	1546.976	159	N/A	N/A	N/A	N/A	N/A
6	1.789	1.771	1546.976	159	N/A	N/A	N/A	N/A	N/A
7	2.174	2.307	1546.976	159	N/A	N/A	N/A	N/A	N/A
8	2.698	2.307	1546.976	159	N/A	N/A	N/A	N/A	N/A
9	2.264	2.091	1546.976	159	1545.863	158	1.113	1	0.291431
10	2.175	2.136	1546.976	159	N/A	N/A	N/A	N/A	N/A
11	2.132	2.031	1546.976	159	1546.64	158	0.336	1	0.562147
12	2.313	1.958	1546.976	159	1542.087	158	4.889	1	0.027028
13	1.442	1.27	1546.976	159	N/A	N/A	N/A	N/A	N/A
14	1.875	1.852	1546.976	159	N/A	N/A	N/A	N/A	N/A

Structural Invariance Testing

Structural invariance concerns the invariance of factor variances, factor covariances, and latent means (Steinmetz et al., 2009). Testing for structural invariance concerns the entire test, not only the items found invariant through measurement invariant testing. When groups have the similar variances in their relevant latent variables, invariance of factor variance is present (Steinmetz et al., 2009). Factor variance is symbolized by the double arrows with ϕ_{11}, ϕ_{12}, ϕ_{21}, and ϕ_{22} in Figure 2.1. Examining factor variance invariance evaluates potential variation in homogeneity of the latent variables across groups.

Similarity of the relationships between the latent variables across groups refers to factor covariance invariance (Steinmetz et al., 2009). The double arrows with $\phi_{(1,2)1}$ and $\phi_{(1,2)2}$ in Figure 2.1 signifies factor covariance. Covariances between constructs have connotations for the constructs' validity; disparate covariances create concerns about uniformity of construct meanings (Steinmetz et al., 2009).Testing latent means invariance requires similarity of factor loadings and item intercepts (Steinmetz et al., 2009). In Figure 2.1, κ_{11}, κ_{12}, κ_{21}, and κ_{22} represent latent means.

Table 2.14 shows the results of the structural invariance test for factor variance and covariance for both marker and non-marker CFA. Structural invariance for factor variance and covariance was not met for the marker CFA, but was for the non-marker CFA. Table 2.15 summarizes the structural invariance test for factor means. Since factor variances and covariances were not invariant for the marker CFA, the marker CFA did not undergo testing for structural factor mean invariance. Structural factor mean invariance, however, was not met for the non-marker CFA.

Table 2.14

Structural Invariance for Factor Variance and Covariance

Test	Residual Comparison Model		Structural Model		Change		P-Value
	Chi Square	df	Chi Square	df	Chi Square	df	
Factor Variance and Covariance Marker	1564.371	160	1583.347	163	18.976	3	0.000277
Factor Variance and Covariance Non-marker	1542.087	158	1544.019	159	1.932	1	0.16454

Table 2.15

Structural Invariance for Factor Means

Test	Structural Factor Variance and Covariance Comparison Model		Structural Model		Change		P-Value
	Chi Square	df	Chi Square	df	Chi Square	df	
Factor Mean Non-marker	1544.019	159	1653.415	161	109.396	2	1.76E-24

The items that were found to be metric non-invariant (Items 2, 4, 6, 8, and 10) were the same for both marker and non-marker CFA invariance testing; this confirms that the marker items (Item 1 and Item 7) were truly invariant (as assumed when held to equal 1 during the invariance testing). However, items found to be scalar non-invariant were slightly different for the marker and non-marker CFA invariance testing. Items 3, 5, 13, and 14 were scalar non-invariant for both marker and non-marker invariance testing, but Item 7 was also found non-invariant for the non-marker invariance testing. This shows that Item 7 was not truly invariant when held to equal 1 in the marker variable CFA invariance testing.

For residual variance, Item 12 was found non-invariant for both the marker and non-marker CFA invariance testing. Item 1 remained invariant throughout the non-marker invariance testing, validating the assumption that Item 1 is invariant and not tested in marker variable invariance testing. Item 7 did not remain invariant; results attained by holding Item 7 equal to 1 could potentially be biased. Item 9 and Item 11 remained invariant in both marker and non-marker CFA invariance testing.

In the next chapter, invariance testing methods described in this chapter for CFA are applied to DCMs, specifically the continuous LCDM, for the BIRS. There will not be any use of marker variables in invariance testing in the continuous LCDM. The continuous LCDM model parameters were estimated using Mplus (Muthen & Muthen, 1998-2009). Syntax for invariance testing in continuous LCDM can be found in Appendix D.

CHAPTER 3

APPLICATION

Invariance Testing in DCMs

Currently, there is very little research about invariance testing in DCMs. Li's (2008) dissertation focuses on developing a differential item functioning (DIF) analysis for the DINA model (a noncompensatory conjunctive DCM). DIF of an item exists if individuals from each group have different probabilities of getting the item correct provided the individuals have similar ability (Pine, 1977). The reference group and a focus group (focus of concern) are generally the two groups compared in DIF analysis (Li, 2008).

Other than Li's (2008) dissertation, hardly any other research has been performed for invariance testing in DCMs. This paper aims to add to the body of research how to test for invariance for the continuous LCDM. The continuous LCDM was defined at the end of Chapter 1 (p. 21). Taking the continuous LCDM, a series of equations were developed to test for configural, metric, scalar, and residual variance invariance to measure measurement invariance, and equations were developed to test for structural invariance.

The motivation for this study was to test the item invariance for the Body Image Rating Scale between males and females for diagnostic classification models (DCMs). The continuous LCDM was implemented in this study because of its adaptable structure (described in Chapter 1). More than half ($p = 0.5821$) of the males were classified in the group as having neither Attribute 1, preoccupation with an imagined defect in appearance, or Attribute 2, preoccupation

causes clinically significant distress or impairment; for females, almost half (p = 0.5108) were classified as having neither Attribute 1 or 2. Only 5.7% (p = 0.0572) of males and 2% (p = 0.0199) of females were classified as having only Attribute 1. Around 4% (p = 0.0404) of males and 9% (p = 0.0928) of females were classified as having Attribute 2. Approximately 32% (p = 0.3203) of males and 38% (p = 0.3765) of females were classified as having both Attribute 1 and Attribute 2.

The process of how to test from configural to metric, metric to scalar, and scalar to residual variance is the same as for the CFA model in Chapter 2. The equations used to test for invariance for the continuous LCDM do not have marker variables. The other difference from the equations used for invariance testing in CFA is the continuous LCDM equations have interaction terms (λ_{i12j}) whereas CFA did not include interaction terms. The *i* represents the item, *1* the first attribute, *2* the second attribute, and *j* the group. Table 3.1 lists the equations representing what is tested for configural invariance (same factor structure).

Table 3.1

Configural LCDM Invariance Model

Group 1 (last subscript = 1)	Group 2 (last subscript = 2)
$X_{11} = \lambda_{101} + \lambda_{111}\alpha_{11} + e_{11}$	$X_{12} = \lambda_{102} + \lambda_{112}\alpha_{12} + e_{12}$
$X_{21} = \lambda_{201} + \lambda_{211}\alpha_{11} + e_{21}$	$X_{22} = \lambda_{202} + \lambda_{212}\alpha_{12} + e_{22}$
$X_{31} = \lambda_{301} + \lambda_{311}\alpha_{11} + \lambda_{321}\alpha_{21} + \lambda_{3121}\alpha_{11}\alpha_{21} + e_{31}$	$X_{32} = \lambda_{302} + \lambda_{312}\alpha_{12} + \lambda_{322}\alpha_{22} + \lambda_{3122}\alpha_{12}\alpha_{22} + e_{32}$
$X_{41} = \lambda_{401} + \lambda_{411}\alpha_{11} + \lambda_{421}\alpha_{21} + \lambda_{4121}\alpha_{11}\alpha_{21} + e_{41}$	$X_{42} = \lambda_{402} + \lambda_{412}\alpha_{12} + \lambda_{422}\alpha_{22} + \lambda_{4122}\alpha_{12}\alpha_{22} + e_{42}$
$X_{51} = \lambda_{501} + \lambda_{511}\alpha_{11} + e_{51}$	$X_{52} = \lambda_{502} + \lambda_{512}\alpha_{12} + e_{52}$
$X_{61} = \lambda_{601} + \lambda_{611}\alpha_{11} + \lambda_{621}\alpha_{21} + \lambda_{6121}\alpha_{11}\alpha_{21} + e_{61}$	$X_{62} = \lambda_{602} + \lambda_{612}\alpha_{12} + \lambda_{622}\alpha_{22} + \lambda_{6122}\alpha_{12}\alpha_{22} + e_{62}$
$X_{71} = \lambda_{701} + \lambda_{721}\alpha_{21} + e_{71}$	$X_{72} = \lambda_{702} + \lambda_{722}\alpha_{22} + e_{72}$
$X_{81} = \lambda_{801} + \lambda_{811}\alpha_{11} + e_{81}$	$X_{82} = \lambda_{802} + \lambda_{812}\alpha_{12} + e_{82}$
$X_{91} = \lambda_{901} + \lambda_{921}\alpha_{21} + e_{91}$	$X_{92} = \lambda_{902} + \lambda_{922}\alpha_{22} + e_{92}$
$X_{101} = \lambda_{1001} + \lambda_{1021}\alpha_{21} + e_{101}$	$X_{102} = \lambda_{1002} + \lambda_{1022}\alpha_{22} + e_{102}$
$X_{111} = \lambda_{1101} + \lambda_{1121}\alpha_{12} + e_{111}$	$X_{112} = \lambda_{1102} + \lambda_{1122}\alpha_{12} + e_{112}$
$X_{121} = \lambda_{1201} + \lambda_{1211}\alpha_{11} + \lambda_{1221}\alpha_{21} + \lambda_{12121}\alpha_{11}\alpha_{21} + e_{121}$	$X_{122} = \lambda_{1202} + \lambda_{1212}\alpha_{12} + \lambda_{1222}\alpha_{22} + \lambda_{12122}\alpha_{12}\alpha_{22} + e_{122}$
$X_{131} = \lambda_{1301} + \lambda_{1311}\alpha_{11} + e_{131}$	$X_{132} = \lambda_{1302} + \lambda_{1312}\alpha_{12} + e_{132}$
$X_{141} = \lambda_{1401} + \lambda_{1411}\alpha_{11} + e_{141}$	$X_{142} = \lambda_{1402} + \lambda_{1412}\alpha_{12} + e_{142}$

If configural invariance exists, metric invariance is tested. Full metric is evaluated first; if full metric criterion is not met, partial metric invariance testing occurs by testing each item at a time. Just as in CFA, factor loadings are tested for invariance. The difference from CFA, in continuous LCDM there is another factor loading for items that measure multiple attributes (the interaction). The factor loadings are constrained to be equal in both groups. Table 3.2 provides the equations with the factor loadings in bold showing the part of each equation being tested.

Table 3.2

Metric LCDM Invariance Model

Group 1 (last subscript = 1)	Group 2 (last subscript = 2)
$X_{11} = \lambda_{101} + \boldsymbol{\lambda_{111}}\, \alpha_{11} + e_{11}$	$X_{12} = \lambda_{102} + \boldsymbol{\lambda_{112}}\, \alpha_{12} + e_{12}$
$X_{21} = \lambda_{201} + \boldsymbol{\lambda_{211}}\, \alpha_{11} + e_{21}$	$X_{22} = \lambda_{202} + \boldsymbol{\lambda_{212}}\, \alpha_{12} + e_{22}$
$X_{31} = \lambda_{301} + \boldsymbol{\lambda_{311}}\, \alpha_{11} + \boldsymbol{\lambda_{321}}\, \alpha_{21} + \boldsymbol{\lambda_{3121}}\, \alpha_{11}\, \alpha_{21} + e_{31}$	$X_{32} = \lambda_{302} + \boldsymbol{\lambda_{312}}\, \alpha_{12} + \boldsymbol{\lambda_{322}}\, \alpha_{22} + \boldsymbol{\lambda_{3122}}\, \alpha_{12}\, \alpha_{22} + e_{32}$
$X_{41} = \lambda_{401} + \boldsymbol{\lambda_{411}}\, \alpha_{11} + \boldsymbol{\lambda_{421}}\, \alpha_{21} + \boldsymbol{\lambda_{4121}}\, \alpha_{11}\, \alpha_{21} + e_{41}$	$X_{42} = \lambda_{402} + \boldsymbol{\lambda_{412}}\, \alpha_{12} + \boldsymbol{\lambda_{422}}\, \alpha_{22} + \boldsymbol{\lambda_{4122}}\, \alpha_{12}\, \alpha_{22} + e_{42}$
$X_{51} = \lambda_{501} + \boldsymbol{\lambda_{511}}\, \alpha_{11} + e_{51}$	$X_{52} = \lambda_{502} + \boldsymbol{\lambda_{512}}\, \alpha_{12} + e_{52}$
$X_{61} = \lambda_{601} + \boldsymbol{\lambda_{611}}\, \alpha_{11} + \boldsymbol{\lambda_{621}}\, \alpha_{21} + \boldsymbol{\lambda_{6121}}\, \alpha_{11}\, \alpha_{21} + e_{61}$	$X_{62} = \lambda_{602} + \boldsymbol{\lambda_{612}}\, \alpha_{12} + \boldsymbol{\lambda_{622}}\, \alpha_{22} + \boldsymbol{\lambda_{6122}}\, \alpha_{122} + e_{62}$
$X_{71} = \lambda_{701} + \boldsymbol{\lambda_{721}}\, \alpha_{21} + e_{71}$	$X_{72} = \lambda_{702} + \boldsymbol{\lambda_{722}}\, \alpha_{22} + e_{72}$
$X_{81} = \lambda_{801} + \boldsymbol{\lambda_{811}}\, \alpha_{11} + e_{81}$	$X_{82} = \lambda_{802} + \boldsymbol{\lambda_{812}}\, \alpha_{12} + e_{82}$
$X_{91} = \lambda_{901} + \boldsymbol{\lambda_{921}}\, \alpha_{21} + e_{91}$	$X_{92} = \lambda_{902} + \boldsymbol{\lambda_{922}}\, \alpha_{22} + e_{92}$
$X_{101} = \lambda_{1001} + \boldsymbol{\lambda_{1021}}\, \alpha_{21} + e_{101}$	$X_{102} = \lambda_{1002} + \boldsymbol{\lambda_{1022}}\, \alpha_{22} + e_{102}$
$X_{111} = \lambda_{1101} + \boldsymbol{\lambda_{1121}}\, \alpha_{12} + e_{111}$	$X_{112} = \lambda_{1102} + \boldsymbol{\lambda_{1122}}\, \alpha_{12} + e_{112}$
$X_{121} = \lambda_{1201} + \boldsymbol{\lambda_{1211}}\, \alpha_{11} + \boldsymbol{\lambda_{1221}}\, \alpha_{21} + \boldsymbol{\lambda_{12121}}\, \alpha_{11}\, \alpha_{21} + e_{121}$	$X_{122} = \lambda_{1202} + \boldsymbol{\lambda_{1212}}\, \alpha_{12} + \boldsymbol{\lambda_{1222}}\, \alpha_{22} + \boldsymbol{\lambda_{12122}}\, \alpha_{12}\, \alpha_{22} + e_{122}$
$X_{131} = \lambda_{1301} + \boldsymbol{\lambda_{1311}}\, \alpha_{11} + e_{131}$	$X_{132} = \lambda_{1302} + \boldsymbol{\lambda_{1312}}\, \alpha_{12} + e_{132}$
$X_{141} = \lambda_{1401} + \boldsymbol{\lambda_{1411}}\, \alpha_{11} + e_{141}$	$X_{142} = \lambda_{1402} + \boldsymbol{\lambda_{1412}}\, \alpha_{12} + e_{142}$

Configural invariance test provides the baseline model for further comparisons. The configural invariance test produced 107 free parameters and $\chi^2 = 129898.978$. Using a cutoff p-value of 0.05, full metric invariance criteria was not satisfied since the difference in chi-square values was significant ($\chi^2 = 129972.082$, number of free parameters = 85, p-value = 2.13E-7).

Therefore, partial metric invariance was explored. Table 3.3 summarizes the results for partial metric invariance testing. Items 3, 5, 6, 8, and 12 were significant, therefore considered non-invariant, and not subject to further testing. All remaining items were tested for scalar invariance.

Since Item 3 (which measures both attributes) is non-invariant, it requires different factor loadings, intercepts, and residual variance for males and females. A male that does not have Attribute 1, preoccupation with an imagined defect in appearance, or Attribute 2, preoccupation causes clinically significant distress or impairment, has an average response of 2.438. A female that does not have Attribute 1 or Attribute 2 has an average response of 2.797. For Attribute 1, a male has an average response of 2.697 on the nine-point Likert-type scale. A female who has Attribute 1 has an average response score of 4.628. A male who has Attribute 2 has an average response score of 3.363. For Attribute 2, a female has an average response score of 3.909. A male who has both Attribute 1 and Attribute 2, has an average response score of 4.373. A female who has both Attribute 1 and Attribute 2, has an average response score of 5.178. Figure 3.1 and Figure 3.2 depict Item 3 for males and females graphically.

For only the items found to be invariant after testing for metric invariance, scalar invariance testing is performed. As with scalar invariance testing for CFA, testing for scalar invariance for the continuous LCDM evaluates whether the item intercepts are the same in both groups for each item. The item intercepts are constrained as well as keeping the factor loadings constrained to be equal for both groups. The factor mean for the reference group is held to zero and the factor mean in the focus group is free. Table 3.4 lists the equations with the factor mean in bold. The model fit of the metric invariance model is compared to the model fit of the scalar invariance model to decide if items are scalar invariant. If full scalar invariance is not met, partial scalar invariance testing occurs by testing only one item at a time.

Table 3.3

LCDM Metric Invariance Test Summary Table

Item	Configural Loadings						Metric Loadings		
	Attribute One		Attribute Two		Interaction		Attribute One	Attribute Two	Interaction
	Male	Female	Male	Female	Male	Female			
1	2.911	2.914					2.913		
2	2.558	2.427					2.457		
3	0.171	1.78	0.936	1.114	0.813	-0.507	0.962	1.056	0.253
4	0.817	2.075	1.592	1.588	-0.566	-1.521	1.428	1.565	-0.931
5	3.242	2.837					2.952		
6	1.195	3.31	0.497	1.56	0.92	-1.487	2.189	1.29	-0.314
7			3.266	3.345				3.326	
8	1.771	2.21					2.082		
9			2.843	2.893				2.88	
10			3.131	2.972				3.01	
11			3.009	2.926				2.947	
12	0.66	0.354	1.159	1.68	0.906	1.264	0.641	1.564	0.933
13	2.135	2.264					2.23		
14	2.236	2.491					2.428		

Table 3.3 continued.

LCDM Metric Invariance Test Summary Table

Item	Configural Chi Square	Configural Degrees of Freedom	Metric Partial Model		Change from Full Configural to Partial Metric		P-value
			Chi Square	Df	Chi Square	Df	
1	129898.978	107	129898.978	106	0	1	1
2	129898.978	107	129899.774	106	0.796	1	0.372292003
3	129898.978	107	129909.224	104	10.246	3	0.016586728*
4	129898.978	107	129904.092	104	5.114	3	0.163637299
5	129898.978	107	129904.24	106	5.262	1	0.021795961*
6	129898.978	107	129935.114	104	36.136	3	7.00862E-08*
7	129898.978	107	129899.178	106	0.2	1	0.654720846
8	129898.978	107	129905.464	106	6.486	1	0.010872736*
9	129898.978	107	129899.058	106	0.08	1	0.777297411
10	129898.978	107	129899.818	106	0.84	1	0.359396774
11	129898.978	107	129899.216	106	0.238	1	0.625654367
12	129898.978	107	129910.532	104	11.554	3	0.00907812*
13	129898.978	107	129899.768	106	0.79	1	0.374100128
14	129898.978	107	129901.546	106	2.568	1	0.109045547

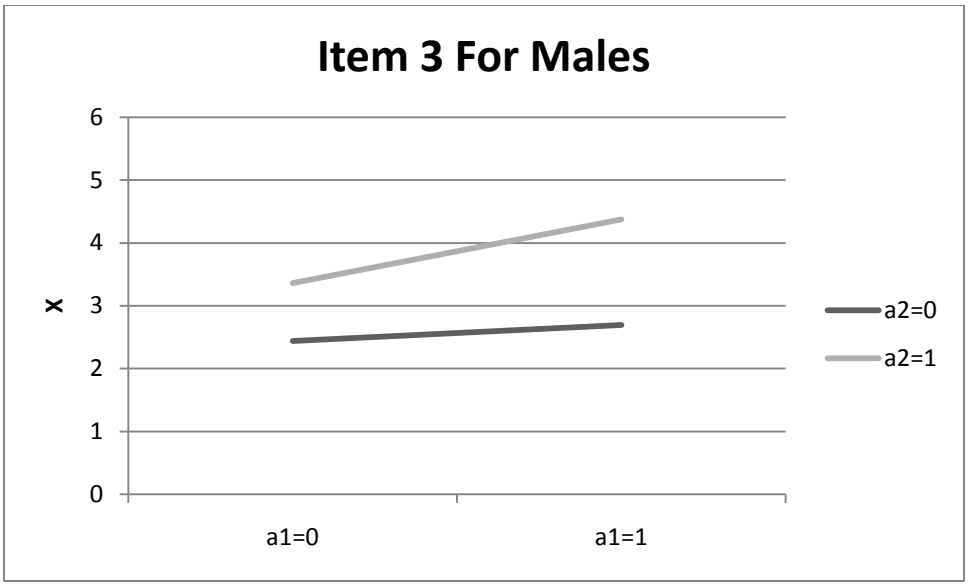

Figure 3.1. Item 3 for males

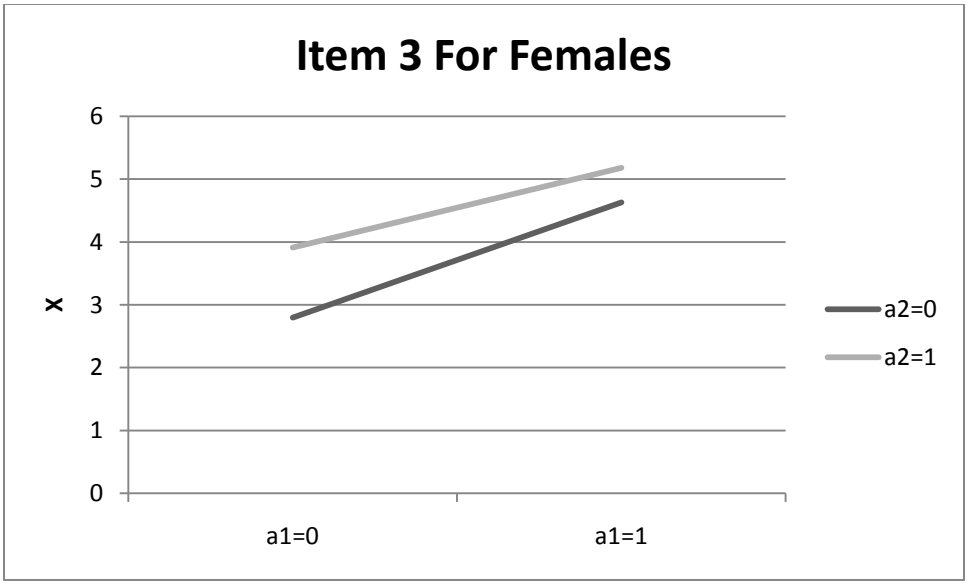

Figure 3.2. Item 3 for females

Table 3.4

Scalar LCDM Invariance Model

Group 1 (last subscript = 1)	Group 2 (last subscript = 2)
$X_{11} = \boldsymbol{\lambda_{101}} + \lambda_{111}\,\alpha_{11} + e_{11}$	$X_{12} = \boldsymbol{\lambda_{102}} + \lambda_{112}\,\alpha_{12} + e_{12}$
$X_{21} = \boldsymbol{\lambda_{201}} + \lambda_{211}\,\alpha_{11} + e_{21}$	$X_{22} = \boldsymbol{\lambda_{202}} + \lambda_{212}\,\alpha_{12} + e_{22}$
$X_{31} = \boldsymbol{\lambda_{301}} + \lambda_{311}\,\alpha_{11} + \lambda_{321}\,\alpha_{21} + \lambda_{3121}\,\alpha_{11}\,\alpha_{21} + e_{31}$	$X_{32} = \boldsymbol{\lambda_{302}} + \lambda_{312}\,\alpha_{12} + \lambda_{322}\,\alpha_{22} + \lambda_{3122}\,\alpha_{12}\,\alpha_{22} + e_{32}$
$X_{41} = \boldsymbol{\lambda_{401}} + \lambda_{411}\,\alpha_{11} + \lambda_{421}\,\alpha_{21} + \lambda_{4121}\,\alpha_{11}\,\alpha_{21} + e_{41}$	$X_{42} = \boldsymbol{\lambda_{402}} + \lambda_{412}\,\alpha_{12} + \lambda_{422}\,\alpha_{22} + \lambda_{4122}\,\alpha_{12}\,\alpha_{22} + e_{42}$
$X_{51} = \boldsymbol{\lambda_{501}} + \lambda_{511}\,\alpha_{11} + e_{51}$	$X_{52} = \boldsymbol{\lambda_{502}} + \lambda_{512}\,\alpha_{12} + e_{52}$
$X_{61} = \boldsymbol{\lambda_{601}} + \lambda_{611}\,\alpha_{11} + \lambda_{621}\,\alpha_{21} + \lambda_{6121}\,\alpha_{11}\,\alpha_{21} + e_{61}$	$X_{62} = \boldsymbol{\lambda_{602}} + \lambda_{612}\,\alpha_{12} + \lambda_{622}\,\alpha_{22} + \lambda_{6122}\,\alpha_{12}\,\alpha_{22} + e_{62}$
$X_{71} = \boldsymbol{\lambda_{701}} + \lambda_{721}\,\alpha_{21} + e_{71}$	$X_{72} = \boldsymbol{\lambda_{702}} + \lambda_{722}\,\alpha_{22} + e_{72}$
$X_{81} = \boldsymbol{\lambda_{801}} + \lambda_{811}\,\alpha_{11} + e_{81}$	$X_{82} = \boldsymbol{\lambda_{802}} + \lambda_{812}\,\alpha_{12} + e_{82}$
$X_{91} = \boldsymbol{\lambda_{901}} + \lambda_{921}\,\alpha_{21} + e_{91}$	$X_{92} = \boldsymbol{\lambda_{902}} + \lambda_{922}\,\alpha_{22} + e_{92}$
$X_{101} = \boldsymbol{\lambda_{1001}} + \lambda_{1021}\,\alpha_{21} + e_{101}$	$X_{102} = \boldsymbol{\lambda_{1002}} + \lambda_{1022}\,\alpha_{22} + e_{102}$
$X_{111} = \boldsymbol{\lambda_{1101}} + \lambda_{1121}\,\alpha_{12} + e_{111}$	$X_{112} = \boldsymbol{\lambda_{1102}} + \lambda_{1122}\,\alpha_{12} + e_{112}$
$X_{121} = \boldsymbol{\lambda_{1201}} + \lambda_{1211}\,\alpha_{11} + \lambda_{1221}\,\alpha_{21} + \lambda_{12121}\,\alpha_{11}\,\alpha_{21} + e_{121}$	$X_{122} = \boldsymbol{\lambda_{1202}} + \lambda_{1212}\,\alpha_{12} + \lambda_{1222}\,\alpha_{22} + \lambda_{12122}\,\alpha_{12}\,\alpha_{22} + e_{122}$
$X_{131} = \boldsymbol{\lambda_{1301}} + \lambda_{1311}\,\alpha_{11} + e_{131}$	$X_{132} = \boldsymbol{\lambda_{1302}} + \lambda_{1312}\,\alpha_{12} + e_{132}$
$X_{141} = \boldsymbol{\lambda_{1401}} + \lambda_{1411}\,\alpha_{11} + e_{141}$	$X_{142} = \boldsymbol{\lambda_{1402}} + \lambda_{1412}\,\alpha_{12} + e_{142}$

Table 3.5 summarizes the results for partial scalar invariance testing. Of the nine items tested for scalar invariant, all were significant except for Item 7, which states "If I could change a certain aspect of my physical appearance, my overall quality of life would _____." Item 7 may have remained invariant because quality of life may improve similarly for males and females if the particular part of their physical appearance changed.

Item 4 was metric invariant (same factor loadings), but was found to be scalar non-invariant and needs separate item intercepts for male and female. A male with neither Attribute 1, preoccupation with an imagined defect in appearance, nor Attribute 2, preoccupation causes clinically significant distress or impairment, has an average response of 3.644 on the nine-point Likert-type scale. A female with neither Attribute 1 nor Attribute 2 has an average response score of 3.923. For Attribute 1, a male with Attribute 1 has an average response score of 5.072. A female with Attribute 1 has an average response score of 5.351. For Attribute 2, a male has an

average response score of 5.202, and a female has an average response score of 5.481. A male who has both Attribute 1 and Attribute 2 has an average response score of 5.707. A female who has both Attribute 1 and Attribute 2 has an average response score of 5.986. Figure 3.3 and Figure 3.4 show Item 4 for males and females graphically.

Table 3.5

LCDM Scalar Invariance Test Summary Table

Item	**Significant Intercept**		**Comparison Model**		**Scalar Partial Model**		**Change**		**P-value**
	Male	**Female**	**Chi Square**	**df**	**Chi Square**	**df**	**Chi Square**	**df**	
1	3.179	4.185	129910.03	96	130034.19	95	124.16	1	7.76E-29*
2	3.1	4.03	129910.03	96	130045.59	95	135.57	1	2.48E-31*
3	2.438	2.796	129910.03	96	N/A	N/A	N/A	N/A	N/A
4	3.639	3.926	129910.03	96	129918.73	95	8.69	1	0.003185*
5	2.348	4.382	129910.03	96	N/A	N/A	N/A	N/A	N/A
6	1.734	2.649	129910.03	96	N/A	N/A	N/A	N/A	N/A
7	3.124	3.228	129910.03	96	129911.30	95	1.27	1	0.259017
8	2.51	2.835	129910.03	96	N/A	N/A	N/A	N/A	N/A
9	2.242	2.709	129910.03	96	129937.73	95	27.69	1	1.42E-07*
10	3.269	3.949	129910.03	96	129964.13	95	54.10	1	1.90E-13*
11	1.855	2.225	129910.03	96	129928.48	95	18.45	1	1.75E-05*
12	1.875	2.281	129910.03	96	N/A	N/A	N/A	N/A	N/A
13	3.268	3.677	129910.03	96	129939.65	95	29.61	1	5.26E-08*
14	4.064	4.396	129910.03	96	129926.26	95	16.23	1	5.60E-05*

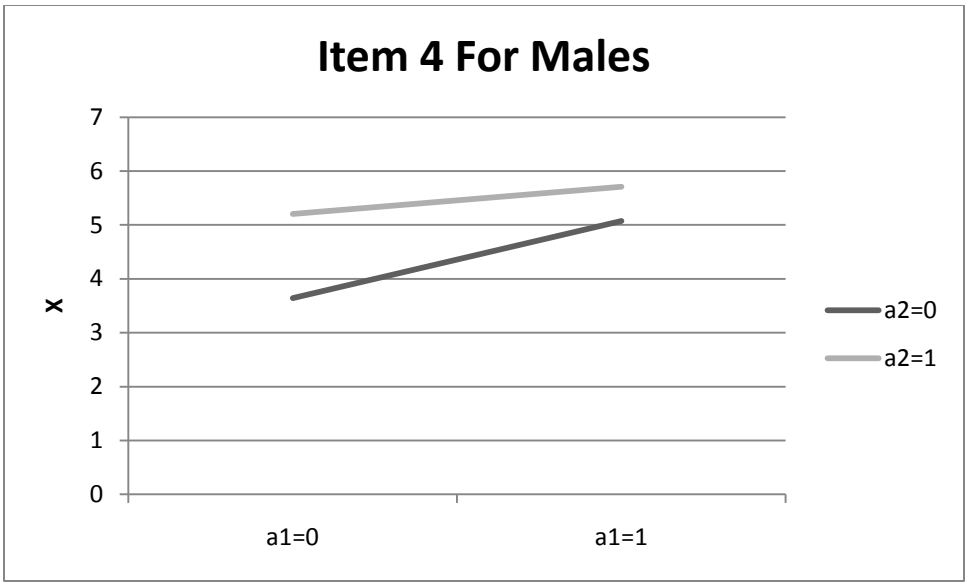

Figure 3.3. Item 4 for males

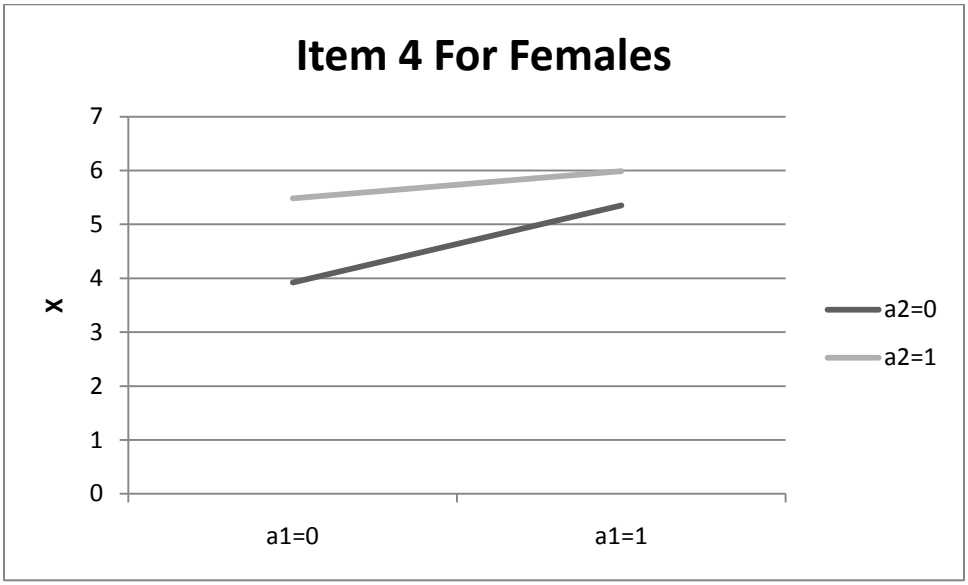

Figure 3.4. Item 4 for females

Any items found scalar invariant are tested further for residual variance invariance, by restraining the residual variances in addition to the factor loading and item intercepts. Table 3.6 shows the equation for each item with the part tested for residual variance invariance in bold. The model fit of the residual variance invariance model is compared to the model fit of the scalar invariance model; if full residual variance invariance criterion is not satisfied, then partial residual variance invariance testing occurs by testing one item at a time.

Item 7 was tested for residual invariance and found invariant. Table 3.7 summarizes these results. Since Item 7 was found invariant for metric, scalar, and residual, the factor loadings, item intercepts, and residual variance are all the same for both male and female. For a male or female, the average response score without having Attribute 1, preoccupation with an imagined defect in appearance, is 3.198. The average response score for a male or female with only Attribute 1 is 3.333. Figure 3.5 depicts Item 7 graphically.

Table 3.6

Residual LCDM Invariance Model

Group 1 (last subscript = 1)	Group 2 (last subscript = 2)
$X_{11} = \lambda_{101} + \lambda_{111}\alpha_{11} + \mathbf{e_{11}}$	$X_{12} = \lambda_{102} + \lambda_{112}\alpha_{12} + \mathbf{e_{12}}$
$X_{21} = \lambda_{201} + \lambda_{211}\alpha_{11} + \mathbf{e_{21}}$	$X_{22} = \lambda_{202} + \lambda_{212}\alpha_{12} + \mathbf{e_{22}}$
$X_{31} = \lambda_{301} + \lambda_{311}\alpha_{11} + \lambda_{321}\alpha_{21} + \lambda_{3121}\alpha_{11}\alpha_{21} + \mathbf{e_{31}}$	$X_{32} = \lambda_{302} + \lambda_{312}\alpha_{12} + \lambda_{322}\alpha_{22} + \lambda_{3122}\alpha_{12}\alpha_{22} + \mathbf{e_{32}}$
$X_{41} = \lambda_{401} + \lambda_{411}\alpha_{11} + \lambda_{421}\alpha_{21} + \lambda_{4121}\alpha_{11}\alpha_{21} + \mathbf{e_{41}}$	$X_{42} = \lambda_{402} + \lambda_{412}\alpha_{12} + \lambda_{422}\alpha_{22} + \lambda_{4122}\alpha_{12}\alpha_{22} + \mathbf{e_{42}}$
$X_{51} = \lambda_{501} + \lambda_{511}\alpha_{11} + \mathbf{e_{51}}$	$X_{52} = \lambda_{502} + \lambda_{512}\alpha_{12} + \mathbf{e_{52}}$
$X_{61} = \lambda_{601} + \lambda_{611}\alpha_{11} + \lambda_{621}\alpha_{21} + \lambda_{6121}\alpha_{11}\alpha_{21} + \mathbf{e_{61}}$	$X_{62} = \lambda_{602} + \lambda_{612}\alpha_{12} + \lambda_{622}\alpha_{22} + \lambda_{6122}\alpha_{12}\alpha_{22} + \mathbf{e_{62}}$
$X_{71} = \lambda_{701} + \lambda_{721}\alpha_{21} + \mathbf{e_{71}}$	$X_{72} = \lambda_{702} + \lambda_{722}\alpha_{22} + \mathbf{e_{72}}$
$X_{81} = \lambda_{801} + \lambda_{811}\alpha_{11} + \mathbf{e_{81}}$	$X_{82} = \lambda_{802} + \lambda_{812}\alpha_{12} + \mathbf{e_{82}}$
$X_{91} = \lambda_{901} + \lambda_{921}\alpha_{21} + \mathbf{e_{91}}$	$X_{92} = \lambda_{902} + \lambda_{922}\alpha_{22} + \mathbf{e_{92}}$
$X_{101} = \lambda_{1001} + \lambda_{1021}\alpha_{21} + \mathbf{e_{101}}$	$X_{102} = \lambda_{1002} + \lambda_{1022}\alpha_{22} + \mathbf{e_{102}}$
$X_{111} = \lambda_{1011} + \lambda_{1121}\alpha_{12} + \mathbf{e_{111}}$	$X_{112} = \lambda_{1102} + \lambda_{1122}\alpha_{12} + \mathbf{e_{112}}$
$X_{121} = \lambda_{1201} + \lambda_{1211}\alpha_{11} + \lambda_{1221}\alpha_{21} + \lambda_{12121}\alpha_{11}\alpha_{21} + \mathbf{e_{121}}$	$X_{122} = \lambda_{1202} + \lambda_{1212}\alpha_{12} + \lambda_{1222}\alpha_{22} + \lambda_{12122}\alpha_{12}\alpha_{22} + \mathbf{e_{122}}$
$X_{131} = \lambda_{1301} + \lambda_{1311}\alpha_{11} + \mathbf{e_{131}}$	$X_{132} = \lambda_{1302} + \lambda_{1312}\alpha_{12} + \mathbf{e_{132}}$
$X_{141} = \lambda_{1401} + \lambda_{1411}\alpha_{11} + \mathbf{e_{141}}$	$X_{142} = \lambda_{1402} + \lambda_{1412}\alpha_{12} + \mathbf{e_{142}}$

Table 3.7

LCDM Residual Invariance Testing Summary Table

Item	Residual Error Variance		Comparison Chi Square	Comparison Degrees of Freedom	Residual Partial Model		Change		P-value
	Male	Female			Chi Square	df	Chi Square	df	
7	2.771	2.77	129911.306	95	129911.31	94	0	1	1

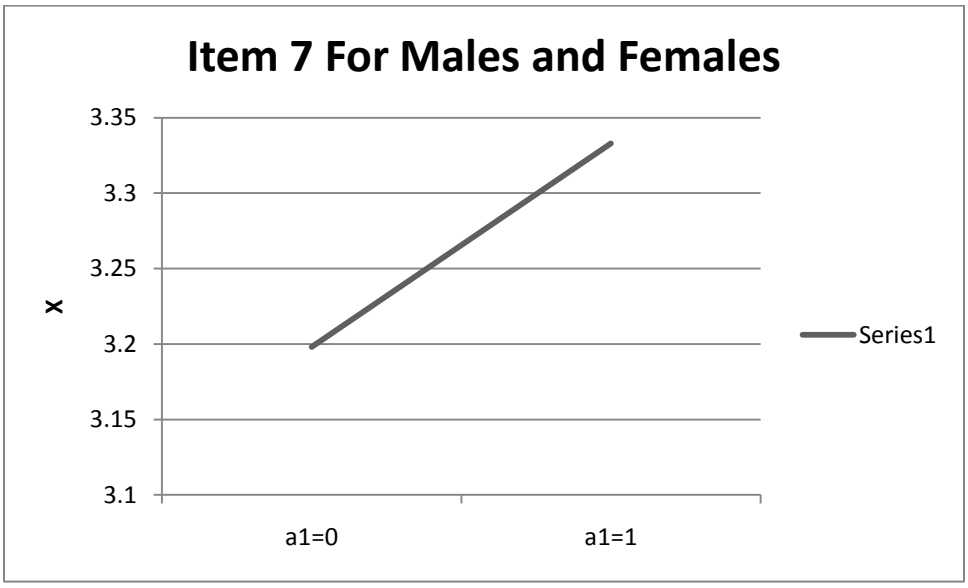

Figure 3.5. Item 7 for males and females

Structural invariance testing was performed using the BIRS dataset. Testing for structural invariance implements the data as a whole, not an item-by-item analysis. Structural invariance was not met (χ^2 difference = 24.594, degrees of freedom = 3, p-value = 1.88E-05).

Discussion

This study has discussed invariance testing in diagnostic classification models (DCMs) through adapting methods of invariance testing in confirmatory factor analysis (CFA) models. There are other approaches for invariance testing than the one implemented in this paper. The results of the analyses demonstrate the importance of testing for item invariance on tests that are used for classification purposes. Specifically, this study has analyzed the validity of comparisons for groups based on sex (male and female). The findings of this study should not be generalized to other groups.

After performing the measurement invariance tests on the Body Image Rating Scale (BIRS) dataset, only Item 7 remained completely invariant. However, with CFA for marker variables, Item 9 and Item 11 remained invariant. Item 1, Item 9, and Item 11 remained invariant in CFA without marker variables.

Items 3, 5, 6, 8, and 12 were non-invariant for metric invariant for LCDM, they cannot be used for further comparisons between male and females. In CFA for marker variables, Items 2, 4, 6, 8, and 10 were non-invariant for metric. The same items for CFA marker variables were non-invariant for metric when no marker variables were used. These items do not have the same validity coefficients for males and females and raises the question of whether the constructs are the same in both groups, and any interpretations of the differences in factor loadings of these items for males and females need to be made vigilantly.

Items 1, 2, 4, 9, 10, 11, 13, and 14 were non-invariant for scalar invariance for LCDM. In CFA for marker variables, Items 3, 5, 13, and 14 were non-invariant for scalar invariance, and Items 3, 5, 7, 13, and 14 were non-invariant for scalar invariance in CFA without marker

variables. These items do not have similar systematic response bias for males and females. Any interpretations of disparity among the latent means of these items when comparing males and females must be done cautiously.

The only item left for measurement invariance testing in LCDM is Item 7. Item 7 remained invariant after testing for residual invariance and therefore can be interpreted to have similar indicator reliability between males and females. In CFA with marker variables, Items 9, 11, and 12 were tested for residual variance invariance, but only Items 9 and 11 remained invariant. In CFA without marker variables, Items 1, 9, 11, and 12 were tested for residual variance invariance, and all were invariant except Item 12.

For CFA marker variable and LCDM, structural invariance for factor variance and covariance did not hold for the BIRS, and therefore, structural invariance testing for factor means did not occur. The criteria profile patterns are not the same for males and females. For the non-marker CFA factor variance and covariance was found invariant, however factor means were non-invariant.

Why the findings between LCDM and CFA with marker and without marker variables do not show similar results throughout invariance testing needs to be investigated further. Research in invariance testing for DCMs should continue further and branch out into other screeners and assessments for disorders. Assessments that are truly invariant will provide the most accurate interpretations for comparisons for sex, ethnicities, socio-economic classes, and other group comparisons. Measurement invariance testing should become required for assessments that are used for any type of comparison to make sure the comparisons are valid.

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APPENDIX A

MPLUS CODE FOR LOG-LINEAR COGNITIVE DIAGNOSTIC MODEL

```
TITLE:          Body Dysmorphic Disorder Items
DATA:           FILE IS bodydataitems.csv;
VARIABLE:
        NAMES = x1-x14;
         CLASSES = c(4);
ANALYSIS:
        TYPE=MIXTURE;
        STARTs=0;
MODEL:
%OVERALL%
[C#1] (m1);
[C#2] (m2);
[C#3] (m3);

%c#1%
[x1] (t1_1);
[x2] (t2_1);
[x3] (t3_1);
[x4] (t4_1);
[x5] (t5_1);
[x6] (t6_1);
[x7] (t7_1);
[x8] (t8_1);
[x9] (t9_1);
[x10] (t10_1);
[x11] (t11_1);
[x12] (t12_1);
[x13] (t13_1);
[x14] (t14_1);

%c#2%
[x1] (t1_1);
[x2] (t2_1);
[x3] (t3_2);
[x4] (t4_2);
[x5] (t5_1);
[x6] (t6_2);
[x7] (t7_2);
```

[x8] (t8_1);
[x9] (t9_2);
[x10] (t10_2);
[x11] (t11_2);
[x12] (t12_2);
[x13] (t13_1);
[x14] (t14_1);

%c#3%
[x1] (t1_2);
[x2] (t2_2);
[x3] (t3_3);
[x4] (t4_3);
[x5] (t5_2);
[x6] (t6_3);
[x7] (t7_1);
[x8] (t8_2);
[x9] (t9_1);
[x10] (t10_1);
[x11] (t11_1);
[x12] (t12_3);
[x13] (t13_2);
[x14] (t14_2);

%c#4%
[x1] (t1_2);
[x2] (t2_2);
[x3] (t3_4);
[x4] (t4_4);
[x5] (t5_2);
[x6] (t6_4);
[x7] (t7_2);
[x8] (t8_2);
[x9] (t9_2);
[x10] (t10_2);
[x11] (t11_2);
[x12] (t12_4);
[x13] (t13_2);
[x14] (t14_2);

MODEL CONSTRAINT:
!ITEM 1:
NEW (l1_0 l1_11);
t1_1=l1_0-l1_11;
t1_2=l1_0+l1_11;
l1_11>0;

```
!ITEM 2:
NEW (l2_0 l2_11);
t2_1=l2_0-l2_11;
t2_2=l2_0+l2_11;
l2_11>0;

!ITEM 3:
NEW (l3_0 l3_12 l3_11 l3_212);
t3_1=l3_0-l3_12-l3_11+l3_212;
t3_2=l3_0+l3_12-l3_11-l3_212;
t3_3=l3_0-l3_11+l3_11-l3_212;
t3_4=l3_0+l3_12+l3_11+l3_212;
l3_11>0;
l3_12>0;
l3_212>-l3_11;
l3_212>-l3_12;

!ITEM 4:
NEW (l4_0 l4_12 l4_11 l4_212);
t4_1=l4_0-l4_12-l4_11+l4_212;
t4_2=l4_0+l4_12-l4_11-l4_212;
t4_3=l4_0-l4_12+l4_11-l4_212;
t4_4=l4_0+l4_12+l4_11+l4_212;
l4_11>0;
l4_12>0;
l4_212>-l4_11;
l4_212>-l4_12;

!ITEM 5:
NEW (l5_0 l5_11);
t5_1=l5_0-l5_11;
t5_2=l5_0+l5_11;
l5_11>0;

!ITEM 6:
NEW (l6_0 l6_12 l6_11 l6_212);
t6_1=l6_0-l6_12-l6_11+l6_212;
t6_2=l6_0+l6_12-l6_11-l6_212;
t6_3=l6_0-l6_12+l6_11-l6_212;
t6_4=l6_0+l6_12+l6_11+l6_212;
l6_11>0;
l6_12>0;
l6_212>-l6_11;
l6_212>-l6_12;
```

```
!ITEM 7:
NEW (l7_0 l7_12);
t7_1=l7_0-l7_12;
t7_2=l7_0+l7_12;
l7_12>0;

!ITEM 8:
NEW (l8_0 l8_11);
t8_1=l8_0-l8_11;
t8_2=l8_0+l8_11;
l8_11>0;

!ITEM 9:
NEW (l9_0 l9_12);
t9_1=l9_0-l9_12;
t9_2=l9_0+l9_12;
l9_12>0;

!ITEM 10:
NEW (l10_0 l10_12);
t10_1=l10_0-l10_12;
t10_2=l10_0+l10_12;
l10_12>0;

!ITEM 11:
NEW (l11_0 l11_12);
t11_1=l11_0-l11_12;
t11_2=l11_0+l11_12;
l11_12>0;

!ITEM 12:
NEW (l12_0 l12_12 l12_11 l12_212);
t12_1=l12_0-l12_12-l12_11+l12_212;
t12_2=l12_0+l12_12-l12_11-l12_212;
t12_3=l12_0-l12_12+l12_11-l12_212;
t12_4=l12_0+l12_12+l12_11+l12_212;
l12_11>0;
l12_12>0;
l12_212>-l12_11;
l12_212>-l12_12;

!ITEM 13:
NEW (l13_0 l13_11);
t13_1=l13_0-l13_11;
t13_2=l13_0+l13_11;
l13_11>0;
```

```
!ITEM 14:
NEW (l14_0 l14_11);
t14_1=l14_0-l14_11;
t14_2=l14_0+l14_11;
l14_11>0;

OUTPUT:
        TECH1          TECH5          TECH8 TECH10;

SAVEDATA:
        FORMAT IS f10.5;
        FILE IS respondent.dat;
        SAVE = CPROBABILITIES;
```

APPENDIX B

MPLUS CODE FOR TWO-GROUP CONFIRMATORY FACTOR ANALYSIS

```
TITLE:          Body Dysmorphic Disorder Items
DATA:           FILE IS bodydataitems.csv;
VARIABLE:
      NAMES = x1-x14;
MODEL:
f1 by x1* x2 x3 x4 x5 x6 x8 x12 x13 x14;
f2 by x3* x4 x6 x7 x9 x10 x11 x12;
f1@1;
f2@1;
```

APPENDIX C

MPLUS CODE FOR INVARIANCE TESTING IN CONFIRMATORY FACTOR ANALYSIS WITH MARKER VARIABLE FOR CONFIGURAL

```
TITLE:  Body Dysmorphic Disorder Items
DATA:   FILE IS itemsandsex.csv;
        FORMAT IS free;
        TYPE IS INDIVIDUAL;
VARIABLE:   NAMES ARE x1-x14 g;
            USEVARIABLES ARE x1-x14;
            GROUPING IS g (0=f 1=m);
ANALYSIS:   TYPE IS GENERAL;
            ESTIMATOR IS ML;

! reference group (female) configural model
MODEL:
   ! factor loadings (1=marker, rest free)
   f1 by
      x1@1  (L1_1)
      x2*   (L1_2)
      x3*   (L1_3)
      x4*   (L1_4)
      x5*   (L1_5)
      x6*   (L1_6)
      x8*   (L1_8)
```

```
x12*  (L1_12)
    x13*  (L1_13)
    x14*  (L1_14);
 f2 by
    x3*   (L2_3)
    x4*   (L2_4)
    x6*   (L2_6)
    x7@1  (L2_7)
    x9*   (L2_9)
    x10*  (L2_10)
    x11*  (L2_11)
    x12*  (L2_12);
 !item intercepts (all free)
 [x1*]   (I1); [x2*]   (I2);   [x3*] (I3);   [x4*] (I4);
 [x5*]   (I5); [x6*]   (I6);   [x7*] (I7);   [x8*] (I8);
 [x9*]   (I9); [x10*] (I10); [x11*] (I11); [x12*] (I12);
 [x13*] (I13); [x14*] (I14);
 !Residual variances (all free)
 x1*   (E1); x2*   (E2); x3* (E3); x4*   (E4); x5*   (E5);   x6* (E6);
 x7*   (E7); x8*   (E8); x9* (E9); x10* (E10); x11* (E11); x12* (E12);
 x13* (E13); x14* (E14);
 !factor variance (free in configural model)
 f1* (F1); f2* (F2);
 !factor covariance (free in configural model)
 f1 with f2* (F12);
 !factor mean is 0
 [f1@0] (FM1); [f2@0] (FM2);
```

```
! model 1: configural model for men
MODEL m:
   !factor loadings (1=marker, rest free)
   f1 by x1@1 x2* x3* x4* x5* x6* x8* x12* x13* x14*;
   f2 by x3* x4* x6* x7@1 x9* x10* x11* x12*;
   !item intercepts (all free)
   [x1-x14*];
   !residual variances (all free)
   x1-x14*;
   !factor variance (ALWAYS FREE)
   f1*; f2*;
   !factor covariance (free in configural model)
   f1 with f2;
   !factor mean is still 0
   [f1@0]; [f2@0];

OUTPUT:    SAMPSTAT
           MODINDICES
           STDYX
           RESIDUAL;
```

APPENDIX D

MPLUS CODE FOR INVARIANCE TESTING IN CONFIRMATORY FACTOR ANALYSIS WITH MARKER VARIABLE FOR METRIC

```
TITLE:  Body Dysmorphic Disorder Items
DATA:   FILE IS itemsandsex.csv;
        FORMAT IS free;
        TYPE IS INDIVIDUAL;
VARIABLE:   NAMES ARE x1-x14 g;
          USEVARIABLES ARE x1-x14;
          GROUPING IS g (0=f 1=m);
ANALYSIS:   TYPE IS GENERAL;
          ESTIMATOR IS ML;

! reference group (female) configural model
MODEL:
    ! factor loadings (1=marker, rest free)
    f1 by
       x1@1  (L1_1)
       x2*   (L1_2)
       x3*   (L1_3)
       x4*   (L1_4)
       x5*   (L1_5)
       x6*   (L1_6)
       x8*   (L1_8)
```

```
   x12*  (L1_12)
   x13*  (L1_13)
   x14*  (L1_14);
f2 by
   x3*   (L2_3)
   x4*   (L2_4)
   x6*   (L2_6)
   x7@1  (L2_7)
   x9*   (L2_9)
   x10*  (L2_10)
   x11*  (L2_11)
   x12*  (L2_12);
!item intercepts (all free)
[x1*]   (I1); [x2*]   (I2);   [x3*] (I3);   [x4*] (I4);
[x5*]   (I5); [x6*]   (I6);   [x7*] (I7);   [x8*] (I8);
[x9*]   (I9); [x10*] (I10); [x11*] (I11); [x12*] (I12);
[x13*] (I13); [x14*] (I14);
!Residual variances (all free)
x1*   (E1); x2*   (E2); x3* (E3); x4*   (E4); x5*   (E5);   x6* (E6);
x7*   (E7); x8*   (E8); x9* (E9); x10* (E10); x11* (E11); x12* (E12);
x13* (E13); x14* (E14);
!factor variance (free in configural model)
f1* (F1); f2* (F2);
!factor covariance (free in configural model)
f1 with f2* (F12);
!factor mean is 0
[f1@0] (FM1); [f2@0] (FM2);
```

```
! model 1: configural model for men
MODEL m:
   !factor loadings (1=marker, NOW all same as women)
   f1 by
      x1@1  (L1_1)
      x2*   (L1_2)
      x3*   (L1_3)
      x4*   (L1_4)
      x5*   (L1_5)
      x6*   (L1_6)
      x8*   (L1_8)
      x12*  (L1_12)
      x13*  (L1_13)
      x14*  (L1_14);
   f2 by
      x3*   (L2_3)
      x4*   (L2_4)
      x6*   (L2_6)
      x7@1  (L2_7)
      x9*   (L2_9)
      x10*  (L2_10)
      x11*  (L2_11)
      x12*  (L2_12);
   !item intercepts (all free)
   [x1-x14*];
   !residual variances (all free)
```

```
    x1-x14*;
    !factor variance (ALWAYS FREE)
    f1*; f2*;
    !factor covariance (free in configural model)
    f1 with f2;
    !factor mean is still 0
    [f1@0]; [f2@0];

OUTPUT:     SAMPSTAT
            MODINDICES
            STDYX
            RESIDUAL;
```

APPENDIX E

MPLUS CODE FOR INVARIANCE TESTING IN CONFIRMATORY FACTOR ANALYSIS WITH MARKER VARIABLE FOR SCALAR

```
TITLE:  Body Dysmorphic Disorder Items
DATA:   FILE IS itemsandsex.csv;
        FORMAT IS free;
        TYPE IS INDIVIDUAL;
VARIABLE:   NAMES ARE x1-x14 g;
          USEVARIABLES ARE x1-x14;
          GROUPING IS g (0=f 1=m);
ANALYSIS:   TYPE IS GENERAL;
          ESTIMATOR IS ML;

! reference group (female) configural model
MODEL:
    ! factor loadings (1=marker, rest free)
    f1 by
       x1@1  (L1_1)
       x2*   (L1_2)
       x3*   (L1_3)
       x4*   (L1_4)
       x5*   (L1_5)
       x6*   (L1_6)
       x8*   (L1_8)
```

```
   x12*  (L1_12)
   x13*  (L1_13)
   x14*  (L1_14);
f2 by
   x3*   (L2_3)
   x4*   (L2_4)
   x6*   (L2_6)
   x7@1  (L2_7)
   x9*   (L2_9)
   x10*  (L2_10)
   x11*  (L2_11)
   x12*  (L2_12);
!item intercepts (all free)
[x1*]   (I1); [x2*]   (I2);   [x3*] (I3);   [x4*] (I4);
[x5*]   (I5); [x6*]   (I6);   [x7*] (I7);   [x8*] (I8);
[x9*]   (I9); [x10*] (I10); [x11*] (I11); [x12*] (I12);
[x13*] (I13); [x14*] (I14);
!Residual variances (all free)
x1*   (E1); x2*   (E2); x3* (E3); x4*   (E4); x5*   (E5);   x6* (E6);
x7*   (E7); x8*   (E8); x9* (E9); x10* (E10); x11* (E11); x12* (E12);
x13* (E13); x14* (E14);
!factor variance (free in configural model)
f1* (F1); f2* (F2);
!factor covariance (free in configural model)
f1 with f2* (F12);
!factor mean is 0
[f1@0] (FM1); [f2@0] (FM2);
```

```
! model 1: configural model for men
MODEL m:
   !factor loadings (1=marker, still same as women)
   f1 by
      x1@1  (L1_1)
      x2*   (L1_2)
      x3*   (L1_3)
      x4*   (L1_4)
      x5*   (L1_5)
      x6*   (L1_6)
      x8*   (L1_8)
      x12*  (L1_12)
      x13*  (L1_13)
      x14*  (L1_14);
   f2 by
      x3*   (L2_3)
      x4*   (L2_4)
      x6*   (L2_6)
      x7@1  (L2_7)
      x9*   (L2_9)
      x10*  (L2_10)
      x11*  (L2_11)
      x12*  (L2_12);
   !item intercepts (NOW same as women)
   [x1*]   (I1); [x2*]   (I2);   [x3*] (I3);   [x4*] (I4);
   [x5*]   (I5); [x6*]   (I6);   [x7*] (I7);   [x8*] (I8);
```

```
[x9*]   (I9); [x10*] (I10); [x11*] (I11); [x12*] (I12);
[x13*] (I13); [x14*] (I14);
!residual variances (all free)
x1-x14*;
!factor variance (ALWAYS FREE)
f1*; f2*;
!factor covariance (free in configural model)
f1 with f2;
!factor mean is NOW freed
[f1]; [f2];

OUTPUT:     SAMPSTAT
            MODINDICES
            STDYX
            RESIDUAL;
```

APPENDIX F

MPLUS CODE FOR INVARIANCE TESTING IN CONFIRMATORY FACTOR ANALYSIS WITH MARKER VARIABLE FOR RESIDUAL VARIANCE

```
TITLE:  Body Dysmorphic Disorder Items
DATA:   FILE IS itemsandsex.csv;
        FORMAT IS free;
        TYPE IS INDIVIDUAL;
VARIABLE:   NAMES ARE x1-x14 g;
          USEVARIABLES ARE x1-x14;
          GROUPING IS g (0=f 1=m);
ANALYSIS:   TYPE IS GENERAL;
          ESTIMATOR IS ML;

! reference group (female) configural model
MODEL:
   ! factor loadings (1=marker, rest free)
   f1 by
      x1@1  (L1_1)
      x2*   (L1_2)
      x3*   (L1_3)
      x4*   (L1_4)
      x5*   (L1_5)
      x6*   (L1_6)
      x8*   (L1_8)
```

```
   x12*  (L1_12)
   x13*  (L1_13)
   x14*  (L1_14);
f2 by
   x3*   (L2_3)
   x4*   (L2_4)
   x6*   (L2_6)
   x7@1  (L2_7)
   x9*   (L2_9)
   x10*  (L2_10)
   x11*  (L2_11)
   x12*  (L2_12);
!item intercepts (all free)
[x1*]   (I1); [x2*]   (I2);   [x3*] (I3);   [x4*] (I4);
[x5*]   (I5); [x6*]   (I6);   [x7*] (I7);   [x8*] (I8);
[x9*]   (I9); [x10*] (I10); [x11*] (I11); [x12*] (I12);
[x13*] (I13); [x14*] (I14);
!Residual variances (all free)
x1*   (E1); x2*   (E2); x3* (E3); x4*   (E4); x5*   (E5);   x6* (E6);
x7*   (E7); x8*   (E8); x9* (E9); x10* (E10); x11* (E11); x12* (E12);
x13* (E13); x14* (E14);
!factor variance (free in configural model)
f1* (F1); f2* (F2);
!factor covariance (free in configural model)
f1 with f2* (F12);
!factor mean is 0
[f1@0] (FM1); [f2@0] (FM2);
```

```
! model 1: configural model for men
MODEL m:
   !factor loadings (1=marker, still same as women)
   f1 by
      x1@1  (L1_1)
      x2*   (L1_2)
      x3*   (L1_3)
      x4*   (L1_4)
      x5*   (L1_5)
      x6*   (L1_6)
      x8*   (L1_8)
      x12*  (L1_12)
      x13*  (L1_13)
      x14*  (L1_14);
   f2 by
      x3*   (L2_3)
      x4*   (L2_4)
      x6*   (L2_6)
      x7@1  (L2_7)
      x9*   (L2_9)
      x10*  (L2_10)
      x11*  (L2_11)
      x12*  (L2_12);
   !item intercepts (still same as women)
   [x1*]   (I1); [x2*]   (I2);   [x3*] (I3);   [x4*] (I4);
   [x5*]   (I5); [x6*]   (I6);   [x7*] (I7);   [x8*] (I8);
```

```
[x9*]   (I9); [x10*] (I10); [x11*] (I11); [x12*] (I12);
[x13*] (I13); [x14*] (I14);
!residual variances (NOW same as women)
x1*   (E1); x2*   (E2); x3* (E3); x4*   (E4); x5*   (E5);   x6* (E6);
x7*   (E7); x8*   (E8); x9* (E9); x10* (E10); x11* (E11); x12* (E12);
x13* (E13); x14* (E14)
!factor variance (ALWAYS FREE)
f1*; f2*;
!factor covariance (free in configural model)
f1 with f2;
!factor mean is still free
[f1]; [f2];

OUTPUT:     SAMPSTAT
            MODINDICES
            STDYX
            RESIDUAL;
```

APPENDIX G

MPLUS CODE FOR STRUCTURAL INVARIANCE TESTING IN CONFIRMATORY FACTOR ANALYSIS WITH MARKER VARIABLE FOR FACTOR VARIANCE AND COVARIANCE

```
TITLE:  Body Dysmorphic Disorder Items
DATA:   FILE IS itemsandsex.csv;
        FORMAT IS free;
        TYPE IS INDIVIDUAL;
VARIABLE:   NAMES ARE x1-x14 g;
           USEVARIABLES ARE x1-x14;
           GROUPING IS g (0=f 1=m);
ANALYSIS:   TYPE IS GENERAL;
           ESTIMATOR IS ML;

! reference group (female) configural model
MODEL:
   ! factor loadings (1=marker, rest free)
   f1 by
      x1@1  (L1_1)
      x2*   (L1_2)
      x3*   (L1_3)
      x4*   (L1_4)
      x5*   (L1_5)
      x6*   (L1_6)
      x8*   (L1_8)
      x12*  (L1_12)
```

```
   x13*  (L1_13)
   x14*  (L1_14);
f2 by
   x3*   (L2_3)
   x4*   (L2_4)
   x6*   (L2_6)
   x7@1  (L2_7)
   x9*   (L2_9)
   x10*  (L2_10)
   x11*  (L2_11)
   x12*  (L2_12);
!item intercepts (all free)
[x1*]   (I1); [x2*]   (I2);   [x3*] (I3);   [x4*] (I4);
[x5*]   (I5); [x6*]   (I6);   [x7*] (I7);   [x8*] (I8);
[x9*]   (I9); [x10*] (I10); [x11*] (I11); [x12*] (I12);
[x13*] (I13); [x14*] (I14);
!Residual variances (all free)
x1*   (E1); x2*   (E2); x3* (E3); x4*   (E4); x5*   (E5);   x6* (E6);
x7*   (E7); x8*   (E8); x9* (E9); x10* (E10); x11* (E11); x12* (E12);
x13* (E13); x14* (E14);
!factor variance (free in configural model)
f1* (F1); f2* (F2);
!factor covariance (free in configural model)
f1 with f2* (F12);
!factor mean is 0
[f1@0] (FM1); [f2@0] (FM2);
```

```
! model 1: configural model for men
MODEL m:
   !factor loadings (1=marker, still same as women)
   f1 by
      x1@1  (L1_1)
      x2*   (L1_2)
      x3*   (L1_3)
      x4*   (L1_4)
      x5*   (L1_5)
      x6*   (L1_6)
      x8*   (L1_8)
      x12*  (L1_12)
      x13*  (L1_13)
      x14*  (L1_14);
   f2 by
      x3*   (L2_3)
      x4*   (L2_4)
      x6*   (L2_6)
      x7@1  (L2_7)
      x9*   (L2_9)
      x10*  (L2_10)
      x11*  (L2_11)
      x12*  (L2_12);
   !item intercepts (still same as women)
   [x1*]   (I1); [x2*]   (I2);   [x3*] (I3);   [x4*] (I4);
   [x5*]   (I5); [x6*]   (I6);   [x7*] (I7);   [x8*] (I8);
   [x9*]   (I9); [x10*] (I10); [x11*] (I11); [x12*] (I12);
```

```
    [x13*] (I13); [x14*] (I14);
    !residual variances (still same as women)
    x1*   (E1); x2*   (E2); x3* (E3); x4*   (E4); x5*   (E5);   x6* (E6);
    x7*   (E7); x8*   (E8); x9* (E9); x10* (E10); x11* (E11); x12* (E12);
    x13* (E13); x14* (E14)
    !factor variance (NOW equal to women)
    f1* (F1); f2* (F2);
    !factor covariance (NOW equal to women)
    f1 with f2* (F12);
    !factor means are still free
    [f1]; [f2];

OUTPUT:     SAMPSTAT
            MODINDICES
            STDYX
            RESIDUAL;
```

APPENDIX H

MPLUS CODE FOR STRUCTURAL INVARIANCE TESTING IN CONFIRMATORY FACTOR ANALYSIS WITH MARKER VARIABLE FOR FACTOR MEAN

```
TITLE:  Body Dysmorphic Disorder Items

DATA:   FILE IS itemsandsex.csv;

        FORMAT IS free;

        TYPE IS INDIVIDUAL;

VARIABLE:   NAMES ARE x1-x14 g;

          USEVARIABLES ARE x1-x14;

          GROUPING IS g (0=f 1=m);

ANALYSIS:   TYPE IS GENERAL;

          ESTIMATOR IS ML;


! reference group (female) configural model

MODEL:

   ! factor loadings (1=marker, rest free)

   f1 by

      x1@1  (L1_1)

      x2*   (L1_2)

      x3*   (L1_3)

      x4*   (L1_4)

      x5*   (L1_5)

      x6*   (L1_6)

      x8*   (L1_8)

      x12*  (L1_12)
```

```
    x13*  (L1_13)
    x14*  (L1_14);
 f2 by
    x3*   (L2_3)
    x4*   (L2_4)
    x6*   (L2_6)
    x7@1  (L2_7)
    x9*   (L2_9)
    x10*  (L2_10)
    x11*  (L2_11)
    x12*  (L2_12);
 !item intercepts (all free)
 [x1*]   (I1); [x2*]   (I2);   [x3*] (I3);   [x4*] (I4);
 [x5*]   (I5); [x6*]   (I6);   [x7*] (I7);   [x8*] (I8);
 [x9*]   (I9); [x10*] (I10); [x11*] (I11); [x12*] (I12);
 [x13*] (I13); [x14*] (I14);
 !Residual variances (all free)
 x1*   (E1); x2*   (E2); x3* (E3); x4*   (E4); x5*   (E5);   x6* (E6);
 x7*   (E7); x8*   (E8); x9* (E9); x10* (E10); x11* (E11); x12* (E12);
 x13* (E13); x14* (E14);
 !factor variance (free in configural model)
f1* (F1); f2* (F2);
 !factor covariance (free in configural model)
 f1 with f2* (F12);
 !factor mean is 0
 [f1@0] (FM1); [f2@0] (FM2);
```

```
! model 1: configural model for men
MODEL m:
   !factor loadings (1=marker, still same as women)
   f1 by
      x1@1  (L1_1)
      x2*   (L1_2)
      x3*   (L1_3)
      x4*   (L1_4)
      x5*   (L1_5)
      x6*   (L1_6)
      x8*   (L1_8)
      x12*  (L1_12)
      x13*  (L1_13)
      x14*  (L1_14);
   f2 by
      x3*   (L2_3)
      x4*   (L2_4)
      x6*   (L2_6)
      x7@1  (L2_7)
      x9*   (L2_9)
      x10*  (L2_10)
      x11*  (L2_11)
      x12*  (L2_12);
   !item intercepts (still same as women)
   [x1*]   (I1); [x2*]   (I2);   [x3*] (I3);   [x4*] (I4);
   [x5*]   (I5); [x6*]   (I6);   [x7*] (I7);   [x8*] (I8);
   [x9*]   (I9); [x10*] (I10); [x11*] (I11); [x12*] (I12);
```

```
    [x13*] (I13); [x14*] (I14);
    !residual variances (still same as women)
    x1*   (E1); x2*   (E2); x3* (E3); x4*   (E4); x5*   (E5);   x6* (E6);
    x7*   (E7); x8*   (E8); x9* (E9); x10* (E10); x11* (E11); x12* (E12);
    x13* (E13); x14* (E14)
    !factor variance (still equal to women)
    f1* (F1); f2* (F2);
    !factor covariance (still equal to women)
    f1 with f2* (F12);
    !factor mean is NOW 0
    [f1@0]; [f2@0];

OUTPUT:     SAMPSTAT
            MODINDICES
            STDYX
            RESIDUAL;
```

APPENDIX I

MPLUS CODE FOR INVARIANCE TESTING IN CONFIRMATORY FACTOR ANALYSIS WITHOUT MARKER VARIABLE FOR CONFIGURAL

```
TITLE:  Body Dysmorphic Disorder Items
DATA:   FILE IS itemsandsex.csv;
        FORMAT IS free;
        TYPE IS INDIVIDUAL;
VARIABLE:   NAMES ARE x1-x14 g;
            USEVARIABLES ARE x1-x14;
           GROUPING IS g (0=f 1=m);
ANALYSIS:   TYPE IS GENERAL;
            ESTIMATOR IS ML;
            ITERATIONS = 100000;

! reference group (female) configural model
MODEL:
   ! factor loadings (all free)
   f1 by
      x1*  (L1_1)
      x2*   (L1_2)
      x3*   (L1_3)
      x4*   (L1_4)
      x5*   (L1_5)
      x6*   (L1_6)
```

```
   x8*   (L1_8)
   x12*  (L1_12)
   x13*  (L1_13)
   x14*  (L1_14);
f2 by
   x3*   (L2_3)
   x4*   (L2_4)
   x6*   (L2_6)
   x7*   (L2_7)
   x9*   (L2_9)
   x10*  (L2_10)
   x11*  (L2_11)
   x12*  (L2_12);
!item intercepts (all free)
[x1*]   (I1); [x2*]   (I2);   [x3*] (I3);   [x4*] (I4);
[x5*]   (I5); [x6*]   (I6);   [x7*] (I7);   [x8*] (I8);
[x9*]   (I9); [x10*] (I10); [x11*] (I11); [x12*] (I12);
[x13*] (I13); [x14*] (I14);
!Residual variances (all free)
x1*   (E1); x2*   (E2); x3* (E3); x4*   (E4); x5*   (E5);   x6* (E6);
x7*   (E7); x8*   (E8); x9* (E9); x10* (E10); x11* (E11); x12* (E12);
x13* (E13); x14* (E14);
!factor variance (always fixed)
f1@1; f2@1;
!factor covariance (free in configural model)
f1 with f2*;
!factor mean is 0
```

```
    [f1@0]; [f2@0];


! model 1: configural model for men
MODEL m:
    !factor loadings (all free)
    f1 by x1* x2* x3* x4* x5* x6* x8* x12* x13* x14*;
    f2 by x3* x4* x6* x7* x9* x10* x11* x12*;
    !item intercepts (all free)
    [x1-x14*];
    !residual variances (all free)
    x1-x14*;
    !factor variance (ALWAYS fixed)
    f1@1; f2@1;
    !factor covariance (free in configural model)
    f1 with f2;
    !factor mean is still 0
    [f1@0]; [f2@0];

OUTPUT:     SAMPSTAT
                MODINDICES
                STDYX
                RESIDUAL;
```

APPENDIX J

MPLUS CODE FOR INVARIANCE TESTING IN CONFIRMATORY FACTOR ANALYSIS WITHOUT MARKER VARIABLE FOR METRIC

```
TITLE:  Body Dysmorphic Disorder Items
DATA:   FILE IS itemsandsex.csv;
        FORMAT IS free;
       TYPE IS INDIVIDUAL;
VARIABLE:   NAMES ARE x1-x14 g;
           USEVARIABLES ARE x1-x14;
           GROUPING IS g (0=f 1=m);
ANALYSIS:   TYPE IS GENERAL;
           ESTIMATOR IS ML;
           ITERATIONS = 100000;

! reference group (female) configural model
MODEL:
   ! factor loadings (all free)
   f1 by
      x1*  (L1_1)
      x2*   (L1_2)
      x3*   (L1_3)
      x4*   (L1_4)
      x5*   (L1_5)
      x6*   (L1_6)
```

```
    x8*   (L1_8)
    x12*  (L1_12)
    x13*  (L1_13)
    x14*  (L1_14);
  f2 by
    x3*   (L2_3)
    x4*   (L2_4)
    x6*   (L2_6)
    x7*   (L2_7)
    x9*   (L2_9)
    x10*  (L2_10)
    x11*  (L2_11)
    x12*  (L2_12);
 !item intercepts (all free)
  [x1*]   (I1); [x2*]   (I2);   [x3*] (I3);   [x4*] (I4);
  [x5*]   (I5); [x6*]   (I6);   [x7*] (I7);   [x8*] (I8);
  [x9*]   (I9); [x10*] (I10); [x11*] (I11); [x12*] (I12);
  [x13*] (I13); [x14*] (I14);
  !Residual variances (all free)
  x1*   (E1); x2*   (E2); x3* (E3); x4*   (E4); x5*   (E5);   x6* (E6);
  x7*   (E7); x8*   (E8); x9* (E9); x10* (E10); x11* (E11); x12* (E12);
  x13* (E13); x14* (E14);
  !factor variance (always fixed)
  f1@1 (F1); f2@1 (F2);
  !factor covariance (free in configural model)
  f1 with f2* (F12);
  !factor mean is 0
```

```
   [f1@0] (FM1); [f2@0] (FM2);


! model 1: configural model for men
MODEL m:
   !factor loadings (Now all equal to women)
   f1 by
      x1*  (L1_1)
      x2*   (L1_2)
      x3*   (L1_3)
      x4*   (L1_4)
      x5*   (L1_5)
      x6*   (L1_6)
      x8*   (L1_8)
      x12*  (L1_12)
      x13*  (L1_13)
      x14*  (L1_14);
   f2 by
      x3*   (L2_3)
      x4*   (L2_4)
      x6*   (L2_6)
      x7*   (L2_7)
      x9*   (L2_9)
      x10*  (L2_10)
      x11*  (L2_11)
      x12*  (L2_12);
   !item intercepts (all free)
   [x1-x14*];
```

```
    !residual variances (all free)
    x1-x14*;
    !factor variance (Freed to put on differing scales)
    f1; f2;
    !factor covariance (free in configural model)
    f1 with f2;
    !factor mean is still 0
    [f1@0]; [f2@0];

OUTPUT:     SAMPSTAT
            MODINDICES
            STDYX
            RESIDUAL;
```

APPENDIX K

MPLUS CODE FOR INVARIANCE TESTING IN CONFIRMATORY FACTOR ANALYSIS WITHOUT MARKER VARIABLE FOR SCALAR

```
TITLE:  Body Dysmorphic Disorder Items
DATA:   FILE IS itemsandsex.csv;
        FORMAT IS free;
        TYPE IS INDIVIDUAL;
VARIABLE:   NAMES ARE x1-x14 g;
           USEVARIABLES ARE x1-x14;
           GROUPING IS g (0=f 1=m);
ANALYSIS:   TYPE IS GENERAL;
           ESTIMATOR IS ML;
           ITERATIONS = 100000;

! reference group (female) configural model
MODEL:
   ! factor loadings (all free)
   f1 by
      x1*  (L1_1)
      x2*   (L1_2)
      x3*   (L1_3)
      x4*   (L1_4)
      x5*   (L1_5)
      x6*   (L1_6)
```

```
    x8*   (L1_8)
   x12*  (L1_12)
   x13*  (L1_13)
   x14*  (L1_14);
f2 by
   x3*   (L2_3)
   x4*   (L2_4)
   x6*   (L2_6)
   x7*   (L2_7)
   x9*   (L2_9)
   x10*  (L2_10)
   x11*  (L2_11)
   x12*  (L2_12);
!item intercepts (all free)
[x1*]   (I1); [x2*]   (I2);   [x3*] (I3);   [x4*] (I4);
[x5*]   (I5); [x6*]   (I6);   [x7*] (I7);   [x8*] (I8);
[x9*]   (I9); [x10*] (I10); [x11*] (I11); [x12*] (I12);
[x13*] (I13); [x14*] (I14);
!Residual variances (all free)
x1*   (E1); x2*   (E2); x3* (E3); x4*   (E4); x5*   (E5);   x6* (E6);
x7*   (E7); x8*   (E8); x9* (E9); x10* (E10); x11* (E11); x12* (E12);
x13* (E13); x14* (E14);
!factor variance (always fixed)
f1@1 (F1); f2@1 (F2);
!factor covariance (free in configural model)
f1 with f2* (F12);
!factor mean is 0
```

```
   [f1@0] (FM1); [f2@0] (FM2);


! model 1: configural model for men
MODEL m:
   !factor loadings (still all equal to women)
   f1 by
      x1*  (L1_1)
      x2*   (L1_2)
      x3*   (L1_3)
      x4*   (L1_4)
      x5*   (L1_5)
      x6*   (L1_6)
      x8*   (L1_8)
      x12*  (L1_12)
      x13*  (L1_13)
      x14*  (L1_14);
   f2 by
      x3*   (L2_3)
      x4*   (L2_4)
      x6*   (L2_6)
      x7*   (L2_7)
      x9*   (L2_9)
      x10*  (L2_10)
      x11*  (L2_11)
      x12*  (L2_12);
   !item intercepts (NOW all equal to women)
   [x1*]   (I1); [x2*]   (I2);   [x3*] (I3);   [x4*] (I4);
```

```
   [x5*]   (I5); [x6*]   (I6);   [x7*] (I7);   [x8*] (I8);
   [x9*]   (I9); [x10*] (I10); [x11*] (I11); [x12*] (I12);
   [x13*] (I13); [x14*] (I14);
  !residual variances (all free)
   x1-x14*;
   !factor variance (Freed to put on differing scales)
   f1; f2;
   !factor covariance (free in configural model)
   f1 with f2;
   !factor mean NOW free
   [f1]; [f2];

OUTPUT:    SAMPSTAT
           MODINDICES
           STDYX
           RESIDUAL;
```

APPENDIX L

MPLUS CODE FOR INVARIANCE TESTING IN CONFIRMATORY FACTOR ANALYSIS WITHOUT MARKER VARIABLE FOR RESIDUAL VARIANCE

```
TITLE:  Body Dysmorphic Disorder Items

DATA:   FILE IS itemsandsex.csv;

        FORMAT IS free;

        TYPE IS INDIVIDUAL;

VARIABLE:   NAMES ARE x1-x14 g;

           USEVARIABLES ARE x1-x14;

           GROUPING IS g (0=f 1=m);

ANALYSIS:   TYPE IS GENERAL;

           ESTIMATOR IS ML;

           ITERATIONS = 100000;


! reference group (female) configural model

MODEL:

   ! factor loadings (all free)

   f1 by

      x1*  (L1_1)

      x2*   (L1_2)

      x3*   (L1_3)

      x4*   (L1_4)

      x5*   (L1_5)

      x6*   (L1_6)

      x8*   (L1_8)
```

```
   x12*  (L1_12)
   x13*  (L1_13)
   x14*  (L1_14);
f2 by
   x3*   (L2_3)
   x4*   (L2_4)
   x6*   (L2_6)
   x7*   (L2_7)
   x9*   (L2_9)
   x10*  (L2_10)
   x11*  (L2_11)
   x12*  (L2_12);
!item intercepts (all free)
[x1*]   (I1); [x2*]   (I2);   [x3*] (I3);   [x4*] (I4);
[x5*]   (I5); [x6*]   (I6);   [x7*] (I7);   [x8*] (I8);
[x9*]   (I9); [x10*] (I10); [x11*] (I11); [x12*] (I12);
[x13*] (I13); [x14*] (I14);
!Residual variances (all free)
x1*   (E1); x2*   (E2); x3* (E3); x4*   (E4); x5*   (E5);   x6* (E6);
x7*   (E7); x8*   (E8); x9* (E9); x10* (E10); x11* (E11); x12* (E12);
x13* (E13); x14* (E14);
!factor variance (always fixed)
f1@1 (F1); f2@1 (F2);
!factor covariance (free in configural model)
f1 with f2* (F12);
!factor mean is 0
[f1@0] (FM1); [f2@0] (FM2);
```

```
! model 1: configural model for men
MODEL m:
   !factor loadings (still all equal to women)
   f1 by
      x1*  (L1_1)
      x2*
      x3*   (L1_3)
      x4*
      x5*   (L1_5)
      x6*
      x8*
      x12*  (L1_12)
      x13*  (L1_13)
      x14*  (L1_14);
   f2 by
      x3*   (L2_3)
      x4*
      x6*
      x7*   (L2_7)
      x9*   (L2_9)
      x10*
      x11*  (L2_11)
      x12*  (L2_12);
   !item intercepts (still all equal to women)
   [x1*]   (I1); [x2*];   [x3*];   [x4*];
   [x5*]; [x6*];   [x7*];   [x8*];
```

```
[x9*]   (I9); [x10*]; [x11*] (I11); [x12*] (I12);
[x13*]; [x14*];
!residual variances (now all equal to women)
x1*   (E1); x2*; x3*; x4*; x5*;   x6*;
x7*; x8*; x9* (E9); x10*; x11* (E11); x12* (E12);
x13*; x14*;
!factor variance (Freed to put on differing scales)
f1; f2;
!factor covariance (free in configural model)
f1 with f2;
!factor means are still free
[f1]; [f2];

OUTPUT:     SAMPSTAT
            MODINDICES
            STDYX
            RESIDUAL;
```

APPENDIX M

MPLUS CODE FOR STRUCTURAL INVARIANCE TESTING IN CONFIRMATORY FACTOR ANALYSIS WITHOUT MARKER VARIABLE FOR FACTOR VARIANCE AND COVARIANCE

```
TITLE:  Body Dysmorphic Disorder Items
DATA:   FILE IS itemsandsex.csv;
        FORMAT IS free;
        TYPE IS INDIVIDUAL;
VARIABLE:   NAMES ARE x1-x14 g;
           USEVARIABLES ARE x1-x14;
           GROUPING IS g (0=f 1=m);
ANALYSIS:   TYPE IS GENERAL;
           ESTIMATOR IS ML;
           ITERATIONS = 100000;

! reference group (female) configural model
MODEL:
   ! factor loadings (all free)
   f1 by
      x1*  (L1_1)
      x2*   (L1_2)
      x3*   (L1_3)
      x4*   (L1_4)
      x5*   (L1_5)
      x6*   (L1_6)
      x8*   (L1_8)
```

```
  x12*  (L1_12)
   x13*  (L1_13)
   x14*  (L1_14);
f2 by
   x3*   (L2_3)
   x4*   (L2_4)
   x6*   (L2_6)
   x7*   (L2_7)
   x9*   (L2_9)
   x10*  (L2_10)
   x11*  (L2_11)
   x12*  (L2_12);
!item intercepts (all free)
[x1*]   (I1); [x2*]   (I2);   [x3*] (I3);   [x4*] (I4);
[x5*]   (I5); [x6*]   (I6);   [x7*] (I7);   [x8*] (I8);
[x9*]   (I9); [x10*] (I10); [x11*] (I11); [x12*] (I12);
[x13*] (I13); [x14*] (I14);
!Residual variances (all free)
x1*   (E1); x2*   (E2); x3* (E3); x4*   (E4); x5*   (E5);   x6* (E6);
x7*   (E7); x8*   (E8); x9* (E9); x10* (E10); x11* (E11); x12* (E12);
x13* (E13); x14* (E14);
!factor variance (always fixed)
f1@1 (F1); f2@1 (F2);
!factor covariance (free in configural model)
f1 with f2* (F12);
!factor mean is 0
[f1@0] (FM1); [f2@0] (FM2);
```

```
! model 1: configural model for men
MODEL m:
   !factor loadings (still all equal to women)
   f1 by
      x1*  (L1_1)
      x2*   (L1_2)
      x3*   (L1_3)
      x4*   (L1_4)
      x5*   (L1_5)
      x6*   (L1_6)
      x8*   (L1_8)
      x12*  (L1_12)
      x13*  (L1_13)
      x14*  (L1_14);
   f2 by
      x3*   (L2_3)
      x4*   (L2_4)
      x6*   (L2_6)
      x7*   (L2_7)
      x9*   (L2_9)
      x10*  (L2_10)
      x11*  (L2_11)
      x12*  (L2_12);
   !item intercepts (still all equal to women)
   [x1*]   (I1); [x2*]   (I2);   [x3*] (I3);   [x4*] (I4);
   [x5*]   (I5); [x6*]   (I6);   [x7*] (I7);   [x8*] (I8);
```

```
[x9*]   (I9); [x10*] (I10); [x11*] (I11); [x12*] (I12);
[x13*] (I13); [x14*] (I14);
!residual variances (still all equal to women)
x1*   (E1); x2*   (E2); x3* (E3); x4*   (E4); x5*   (E5);   x6* (E6);
x7*   (E7); x8*   (E8); x9* (E9); x10* (E10); x11* (E11); x12* (E12);
x13* (E13); x14* (E14);
!factor variance (now equal to women)
f1@1 (F1); f2@1 (F2);
!factor covariance (now equal to women)
f1 with f2* (F12);
!factor mean are still free
[f1]; [f2];

OUTPUT:     SAMPSTAT
            MODINDICES
            STDYX
            RESIDUAL;
```

APPENDIX N

MPLUS CODE FOR STRUCTURAL INVARIANCE TESTING IN CONFIRMATORY FACTOR ANALYSIS WITHOUT MARKER VARIABLE FOR FACTOR MEAN

```
TITLE:  Body Dysmorphic Disorder Items

DATA:   FILE IS itemsandsex.csv;

        FORMAT IS free;

        TYPE IS INDIVIDUAL;

VARIABLE:   NAMES ARE x1-x14 g;

            USEVARIABLES ARE x1-x14;

            GROUPING IS g (0=f 1=m);

ANALYSIS:   TYPE IS GENERAL;

            ESTIMATOR IS ML;

            ITERATIONS = 100000;


! reference group (female) configural model

MODEL:

   ! factor loadings (all free)

   f1 by

      x1*  (L1_1)

      x2*   (L1_2)

      x3*   (L1_3)

      x4*   (L1_4)

      x5*   (L1_5)

      x6*   (L1_6)

      x8*   (L1_8)
```

```
   x12*  (L1_12)
   x13*  (L1_13)
   x14*  (L1_14);
f2 by
   x3*   (L2_3)
   x4*   (L2_4)
   x6*   (L2_6)
   x7*   (L2_7)
   x9*   (L2_9)
   x10*  (L2_10)
   x11*  (L2_11)
   x12*  (L2_12);
!item intercepts (all free)
[x1*]   (I1); [x2*]   (I2);   [x3*] (I3);   [x4*] (I4);
[x5*]   (I5); [x6*]   (I6);   [x7*] (I7);   [x8*] (I8);
[x9*]   (I9); [x10*] (I10); [x11*] (I11); [x12*] (I12);
[x13*] (I13); [x14*] (I14);
!Residual variances (all free)
x1*   (E1); x2*   (E2); x3* (E3); x4*   (E4); x5*   (E5);   x6* (E6);
x7*   (E7); x8*   (E8); x9* (E9); x10* (E10); x11* (E11); x12* (E12);
x13* (E13); x14* (E14);
!factor variance (always fixed)
f1@1 (F1); f2@1 (F2);
!factor covariance (free in configural model)
f1 with f2* (F12);
!factor mean is 0
[f1@0] (FM1); [f2@0] (FM2);
```

```
! model 1: configural model for men
MODEL m:
   !factor loadings (still all equal to women)
   f1 by
      x1*  (L1_1)
      x2*   (L1_2)
      x3*   (L1_3)
      x4*   (L1_4)
      x5*   (L1_5)
      x6*   (L1_6)
      x8*   (L1_8)
      x12*  (L1_12)
      x13*  (L1_13)
      x14*  (L1_14);
   f2 by
      x3*   (L2_3)
      x4*   (L2_4)
      x6*   (L2_6)
      x7*   (L2_7)
      x9*   (L2_9)
      x10*  (L2_10)
      x11*  (L2_11)
      x12*  (L2_12);
   !item intercepts (still all equal to women)
   [x1*]   (I1); [x2*]   (I2);   [x3*] (I3);   [x4*] (I4);
   [x5*]   (I5); [x6*]   (I6);   [x7*] (I7);   [x8*] (I8);
```

```
[x9*]   (I9); [x10*] (I10); [x11*] (I11); [x12*] (I12);
[x13*] (I13); [x14*] (I14);
!residual variances (still all equal to women)
x1*   (E1); x2*   (E2); x3* (E3); x4*   (E4); x5*   (E5);   x6* (E6);
x7*   (E7); x8*   (E8); x9* (E9); x10* (E10); x11* (E11); x12* (E12);
x13* (E13); x14* (E14);
!factor variance (still equal to women)
f1@1 (F1); f2@1 (F2);
!factor covariance (still equal to women)
f1 with f2* (F12);
!factor mean are now zero
[f1@0]; [f2@0];

OUTPUT:     SAMPSTAT
            MODINDICES
            STDYX
            RESIDUAL;
```

APPENDIX O

MPLUS CODE FOR CONFIGURAL INVARIANCE TESTING FOR LOG-LINEAR COGNITIVE DIAGNOSTIC MODEL

```
TITLE:          Body Dysmorphic Disorder Items

DATA:           FILE IS itemsandsex.csv;

VARIABLE:

        NAMES = x1-x14 g;

   CLASSES =  c(4) gender(2);

   KNOWNCLASS = gender (g=0 g=1);

ANALYSIS:

        TYPE=MIXTURE;

        STARTS=0;

MODEL:

%OVERALL%
gender on c;

%c#1.gender#1%

[x1] (t1_10);
x1* (e1_0);

[x2] (t2_10);
x2* (e2_0);

[x3] (t3_10);
x3* (e3_0);

[x4] (t4_10);
x4* (e4_0);

[x5] (t5_10);
x5* (e5_0);

[x6] (t6_10);
x6* (e6_0);
```

[x7] (t7_10);
x7* (e7_0);

[x8] (t8_10);
x8* (e8_0);

[x9] (t9_10);
x9* (e9_0);

[x10] (t10_10);
x10* (e10_0);

[x11] (t11_10);
x11* (e11_0);

[x12] (t12_10);
x12* (e12_0)

[x13] (t13_10);
x13* (e13_0);

[x14] (t14_10);
x14* (e14_0);

%c#2.gender#1%

[x1] (t1_10);
x1* (e1_0);

[x2] (t2_10);
x2* (e2_0);

[x3] (t3_20);
x3* (e3_0);

[x4] (t4_20);
x4* (e4_0);

[x5] (t5_10);
x5* (e5_0);

[x6] (t6_20);
x6* (e6_0);

[x7] (t7_20);
x7* (e7_0);

[x8] (t8_10);
x8* (e8_0);

[x9] (t9_20);
x9* (e9_0);

[x10] (t10_20);
x10* (e10_0);

[x11] (t11_20);
x11* (e11_0);

[x12] (t12_20);
x12* (e12_0);

[x13] (t13_10);
x13* (e13_0);

[x14] (t14_10);
x14* (e14_0);

%c#3.gender#1%

[x1] (t1_20);
x1* (e1_0);

[x2] (t2_20);
x2* (e2_0);

[x3] (t3_30);
x3* (e3_0);

[x4] (t4_30);
x4* (e4_0);

[x5] (t5_20);
x5* (e5_0);

[x6] (t6_30);
x6* (e6_0);

[x7] (t7_10);
x7* (e7_0);

[x8] (t8_20);
x8* (e8_0);

[x9] (t9_10);
x9* (e9_0);

[x10] (t10_10);
x10* (e10_0);

[x11] (t11_10);
x11* (e11_0);

[x12] (t12_30);
x12* (e12_0);

[x13] (t13_20);
x13* (e13_0);

[x14] (t14_20);
x14* (e14_0);

%c#4.gender#1%

[x1] (t1_20);
x1* (e1_0);

[x2] (t2_20);
x2* (e2_0);

[x3] (t3_40);
x3* (e3_0);

[x4] (t4_40);
x4* (e4_0);

[x5] (t5_20);
x5* (e5_0);

[x6] (t6_40);
x6* (e6_0);

[x7] (t7_20);
x7* (e7_0);

[x8] (t8_20);
x8* (e8_0);

[x9] (t9_20);
x9* (e9_0);

[x10] (t10_20);
x10* (e10_0);

[x11] (t11_20);
x11* (e11_0);

[x12] (t12_40);
x12* (e12_0);

[x13] (t13_20);
x13* (e13_0);

[x14] (t14_20);
x14* (e14_0);

%c#1.gender#2%

[x1] (t1_11);
x1* (e1_1);

[x2] (t2_11);
x2* (e2_1);

[x3] (t3_11);
x3* (e3_1);

[x4] (t4_11);
x4* (e4_1);

[x5] (t5_11);
x5* (e5_1);

[x6] (t6_11);
x6* (e6_1);

[x7] (t7_11);
x7* (e7_1);

[x8] (t8_11);
x8* (e8_1);

[x9] (t9_11);
x9* (e9_1);

[x10] (t10_11);
x10* (e10_1);

[x11] (t11_11);
x11* (e11_1);

[x12] (t12_11);
x12* (e12_1)

[x13] (t13_11);
x13* (e13_1);

[x14] (t14_11);
x14* (e14_1);

```
%c#2.gender#2%

[x1] (t1_11);
x1* (e1_1);

[x2] (t2_11);
x2* (e2_1);

[x3] (t3_21);
x3* (e3_1);

[x4] (t4_21);
x4* (e4_1);

[x5] (t5_11);
x5* (e5_1);

[x6] (t6_21);
x6* (e6_1);

[x7] (t7_21);
x7* (e7_1);

[x8] (t8_11);
x8* (e8_1);

[x9] (t9_21);
x9* (e9_1);

[x10] (t10_21);
x10* (e10_1);

[x11] (t11_21);
x11* (e11_1);

[x12] (t12_21);
x12* (e12_1);

[x13] (t13_11);
x13* (e13_1);

[x14] (t14_11);
x14* (e14_1);


%c#3.gender#2%

[x1] (t1_21);
x1* (e1_1);
```

[x2] (t2_21);
x2* (e2_1);

[x3] (t3_31);
x3* (e3_1);

[x4] (t4_31);
x4* (e4_1);

[x5] (t5_21);
x5* (e5_1);

[x6] (t6_31);
x6* (e6_1);

[x7] (t7_11);
x7* (e7_1);

[x8] (t8_21);
x8* (e8_1);

[x9] (t9_11);
x9* (e9_1);

[x10] (t10_11);
x10* (e10_1);

[x11] (t11_11);
x11* (e11_1);

[x12] (t12_31);
x12* (e12_1);

[x13] (t13_21);
x13* (e13_1);

[x14] (t14_21);
x14* (e14_1);

%c#4.gender#2%

[x1] (t1_21);
x1* (e1_1);

[x2] (t2_21);
x2* (e2_1);

[x3] (t3_41);
x3* (e3_1);

[x4] (t4_41);
x4* (e4_1);

[x5] (t5_21);
x5* (e5_1);

[x6] (t6_41);
x6* (e6_1);

[x7] (t7_21);
x7* (e7_1);

[x8] (t8_21);
x8* (e8_1);

[x9] (t9_21);
x9* (e9_1);

[x10] (t10_21);
x10* (e10_1);

[x11] (t11_21);
x11* (e11_1);

[x12] (t12_41);
x12* (e12_1);

[x13] (t13_21);
x13* (e13_1);

[x14] (t14_21);
x14* (e14_1);

MODEL CONSTRAINT:

!ITEM 1:
NEW (l1_0_0*5 l1_0_1*5 l1_11_0*2 l1_11_1*2 u1_0 u1_1);
t1_10=l1_0_0;
t1_11=l1_0_1;
t1_20=l1_0_0+l1_11_0;
t1_21=l1_0_1+l1_11_1;
e1_0 = u1_0;
e1_1 = u1_1;

!ITEM 2:
NEW (l2_0_0*5 l2_0_1*5 l2_11_0*2 l2_11_1*2 u2_0 u2_1);
t2_10=l2_0_0;
t2_11=l2_0_1;

```
t2_20=l2_0_0+l2_11_0;
t2_21=l2_0_1+l2_11_1;
e2_0 = u2_0;
e2_1 = u2_1;


!ITEM 3:
NEW (l3_0_0*5 l3_0_1*5 l3_11_0*2 l3_11_1*2);
NEW (l3_12_0*2 l3_12_1*2 l3_2120*0 l3_2121*0 u3_0 u3_1);
t3_10=l3_0_0;
t3_20=l3_0_0+l3_12_0;
t3_30=l3_0_0+l3_11_0;
t3_40=l3_0_0+l3_12_0+l3_11_0+l3_2120;
t3_11=l3_0_1;
t3_21=l3_0_1+l3_12_1;
t3_31=l3_0_1+l3_11_1;
t3_41=l3_0_1+l3_12_1+l3_11_1+l3_2121;
e3_0 = u3_0;
e3_1 = u3_1;


!ITEM 4:

NEW (l4_0_0*5 l4_0_1*5 l4_11_0*2 l4_11_1*2);
NEW (l4_12_0*2 l4_12_1*2 l4_2120*0 l4_2121*0 u4_0 u4_1);
t4_10=l4_0_0;
t4_20=l4_0_0+l4_12_0;
t4_30=l4_0_0+l4_11_0;
t4_40=l4_0_0+l4_12_0+l4_11_0+l4_2120;
t4_11=l4_0_1;
t4_21=l4_0_1+l4_12_1;
t4_31=l4_0_1+l4_11_1;
t4_41=l4_0_1+l4_12_1+l4_11_1+l4_2121;
e4_0 = u4_0;
e4_1 = u4_1;


!ITEM 5:

NEW (l5_0_0*5 l5_0_1*5 l5_11_0*2 l5_11_1*2 u5_0 u5_1);
t5_10=l5_0_0;
t5_11=l5_0_1;
t5_20=l5_0_0+l5_11_0;
t5_21=l5_0_1+l5_11_1;
e5_0 = u5_0;
e5_1 = u5_1;
```

```
!ITEM 6:
NEW (l6_0_0*5 l6_0_1*5 l6_11_0*2 l6_11_1*2);
NEW (l6_12_0*2 l6_12_1*2 l6_2120*0 l6_2121*0 u6_0 u6_1);
t6_10=l6_0_0;
t6_20=l6_0_0+l6_12_0;
t6_30=l6_0_0+l6_11_0;
t6_40=l6_0_0+l6_12_0+l6_11_0+l6_2120;
t6_11=l6_0_1;
t6_21=l6_0_1+l6_12_1;
t6_31=l6_0_1+l6_11_1;
t6_41=l6_0_1+l6_12_1+l6_11_1+l6_2121;
e6_0 = u6_0;
e6_1 = u6_1;


!ITEM 7:
NEW (l7_0_0*5 l7_0_1*5 l7_12_0*2 l7_12_1*2 u7_0 u7_1);
t7_10=l7_0_0;
t7_11=l7_0_1;
t7_20=l7_0_0+l7_12_0;
t7_21=l7_0_1+l7_12_1;
e7_0 = u7_0;
e7_1 = u7_1;


!ITEM 8:
NEW (l8_0_0*5 l8_0_1*5 l8_11_0*2 l8_11_1*2 u8_0 u8_1);
t8_10=l8_0_0;
t8_11=l8_0_1;
t8_20=l8_0_0+l8_11_0;
t8_21=l8_0_1+l8_11_1;
e8_0 = u8_0;
e8_1 = u8_1;


!ITEM 9:
NEW (l9_0_0*5 l9_0_1*5 l9_12_0*2 l9_12_1*2 u9_0 u9_1);
t9_10=l9_0_0;
t9_11=l9_0_1;
t9_20=l9_0_0+l9_12_0;
t9_21=l9_0_1+l9_12_1;
e9_0 = u9_0;
e9_1 = u9_1;
```

```
!ITEM 10:
NEW (l10_0_0*5 l10_0_1*5 l10_12_0*2 l10_12_1*2 u10_0 u10_1);
t10_10=l10_0_0;
t10_11=l10_0_1;
t10_20=l10_0_0+l10_12_0;
t10_21=l10_0_1+l10_12_1;
e10_0 = u10_0;
e10_1 = u10_1;


!ITEM 11:
NEW (l11_0_0*5 l11_0_1*5 l11_12_0*2 l11_12_1*2 u11_0 u11_1);
t11_10=l11_0_0;
t11_11=l11_0_1;
t11_20=l11_0_0+l11_12_0;
t11_21=l11_0_1+l11_12_1;
e11_0 = u11_0;
e11_1 = u11_1;


!ITEM 12:
NEW (l12_0_0*5 l12_0_1*5 l12_11_0*2 l12_11_1*2);
NEW (l12_12_0*2 l12_12_1*2 l12_2120*0 l12_2121*0 u12_0 u12_1);
t12_10=l12_0_0;
t12_20=l12_0_0+l12_12_0;
t12_30=l12_0_0+l12_11_0;
t12_40=l12_0_0+l12_12_0+l12_11_0+l12_2120;
t12_11=l12_0_1;
t12_21=l12_0_1+l12_12_1;
t12_31=l12_0_1+l12_11_1;
t12_41=l12_0_1+l12_12_1+l12_11_1+l12_2121;
e12_0 = u12_0;
e12_1 = u12_1;


!ITEM 13:
NEW (l13_0_0*5 l13_0_1*5 l13_11_0*2 l13_11_1*2 u13_0 u13_1);
t13_10=l13_0_0;
t13_11=l13_0_1;
t13_20=l13_0_0+l13_11_0;
t13_21=l13_0_1+l13_11_1;
e13_0 = u13_0;
e13_1 = u13_1;
```

```
!ITEM 14:
NEW (l14_0_0*5 l14_0_1*5 l14_11_0*2 l14_11_1*2 u14_0 u14_1);
t14_10=l14_0_0;
t14_11=l14_0_1;
t14_20=l14_0_0+l14_11_0;
t14_21=l14_0_1+l14_11_1;
e14_0 = u14_0;
e14_1 = u14_1;
```

APPENDIX P

MPLUS CODE FOR METRIC INVARIANCE TESTING FOR LOG-LINEAR COGNITIVE DIAGNOSTIC MODEL

P.1 FULL METRIC INVARIANCE TESTING SYNTAX

```
TITLE:          Body Dysmorphic Disorder Items

DATA:           FILE IS itemsandsex.csv;

VARIABLE:

        NAMES = x1-x14 g;

   CLASSES =  c(4) gender(2);

   KNOWNCLASS = gender (g=0 g=1);

ANALYSIS:

        TYPE=MIXTURE;

        STARTS=0;

MODEL:

%OVERALL%
gender on c;

%c#1.gender#1%

[x1] (t1_10);
x1* (e1_0);

[x2] (t2_10);
x2* (e2_0);

[x3] (t3_10);
x3* (e3_0);

[x4] (t4_10);
x4* (e4_0);

[x5] (t5_10);
x5* (e5_0);
```

[x6] (t6_10);
x6* (e6_0);

[x7] (t7_10);
x7* (e7_0);

[x8] (t8_10);
x8* (e8_0);

[x9] (t9_10);
x9* (e9_0);

[x10] (t10_10);
x10* (e10_0);

[x11] (t11_10);
x11* (e11_0);

[x12] (t12_10);
x12* (e12_0)

[x13] (t13_10);
x13* (e13_0);

[x14] (t14_10);
x14* (e14_0);

%c#2.gender#1%

[x1] (t1_10);
x1* (e1_0);

[x2] (t2_10);
x2* (e2_0);

[x3] (t3_20);
x3* (e3_0);

[x4] (t4_20);
x4* (e4_0);

[x5] (t5_10);
x5* (e5_0);

[x6] (t6_20);
x6* (e6_0);

[x7] (t7_20);
x7* (e7_0);

[x8] (t8_10);
x8* (e8_0);

[x9] (t9_20);
x9* (e9_0);

[x10] (t10_20);
x10* (e10_0);

[x11] (t11_20);
x11* (e11_0);

[x12] (t12_20);
x12* (e12_0);

[x13] (t13_10);
x13* (e13_0);

[x14] (t14_10);
x14* (e14_0);

%c#3.gender#1%

[x1] (t1_20);
x1* (e1_0);

[x2] (t2_20);
x2* (e2_0);

[x3] (t3_30);
x3* (e3_0);

[x4] (t4_30);
x4* (e4_0);

[x5] (t5_20);
x5* (e5_0);

[x6] (t6_30);
x6* (e6_0);

[x7] (t7_10);
x7* (e7_0);

[x8] (t8_20);
x8* (e8_0);

[x9] (t9_10);
x9* (e9_0);

[x10] (t10_10);
x10* (e10_0);

[x11] (t11_10);
x11* (e11_0);

[x12] (t12_30);
x12* (e12_0);

[x13] (t13_20);
x13* (e13_0);

[x14] (t14_20);
x14* (e14_0);

%c#4.gender#1%

[x1] (t1_20);
x1* (e1_0);

[x2] (t2_20);
x2* (e2_0);

[x3] (t3_40);
x3* (e3_0);

[x4] (t4_40);
x4* (e4_0);

[x5] (t5_20);
x5* (e5_0);

[x6] (t6_40);
x6* (e6_0);

[x7] (t7_20);
x7* (e7_0);

[x8] (t8_20);
x8* (e8_0);

[x9] (t9_20);
x9* (e9_0);

[x10] (t10_20);
x10* (e10_0);

[x11] (t11_20);
x11* (e11_0);

[x12] (t12_40);
x12* (e12_0);

[x13] (t13_20);
x13* (e13_0);

[x14] (t14_20);
x14* (e14_0);

%c#1.gender#2%

[x1] (t1_11);
x1* (e1_1);

[x2] (t2_11);
x2* (e2_1);

[x3] (t3_11);
x3* (e3_1);

[x4] (t4_11);
x4* (e4_1);

[x5] (t5_11);
x5* (e5_1);

[x6] (t6_11);
x6* (e6_1);

[x7] (t7_11);
x7* (e7_1);

[x8] (t8_11);
x8* (e8_1);

[x9] (t9_11);
x9* (e9_1);

[x10] (t10_11);
x10* (e10_1);

[x11] (t11_11);
x11* (e11_1);

[x12] (t12_11);
x12* (e12_1)

[x13] (t13_11);
x13* (e13_1);

[x14] (t14_11);
x14* (e14_1);

%c#2.gender#2%

[x1] (t1_11);
x1* (e1_1);

[x2] (t2_11);
x2* (e2_1);

[x3] (t3_21);
x3* (e3_1);

[x4] (t4_21);
x4* (e4_1);

[x5] (t5_11);
x5* (e5_1);

[x6] (t6_21);
x6* (e6_1);

[x7] (t7_21);
x7* (e7_1);

[x8] (t8_11);
x8* (e8_1);

[x9] (t9_21);
x9* (e9_1);

[x10] (t10_21);
x10* (e10_1);

[x11] (t11_21);
x11* (e11_1);

[x12] (t12_21);
x12* (e12_1);

[x13] (t13_11);
x13* (e13_1);

[x14] (t14_11);
x14* (e14_1);

```
%c#3.gender#2%

[x1] (t1_21);
x1* (e1_1);

[x2] (t2_21);
x2* (e2_1);

[x3] (t3_31);
x3* (e3_1);

[x4] (t4_31);
x4* (e4_1);

[x5] (t5_21);
x5* (e5_1);

[x6] (t6_31);
x6* (e6_1);

[x7] (t7_11);
x7* (e7_1);

[x8] (t8_21);
x8* (e8_1);

[x9] (t9_11);
x9* (e9_1);

[x10] (t10_11);
x10* (e10_1);

[x11] (t11_11);
x11* (e11_1);

[x12] (t12_31);
x12* (e12_1);

[x13] (t13_21);
x13* (e13_1);

[x14] (t14_21);
x14* (e14_1);


%c#4.gender#2%

[x1] (t1_21);
x1* (e1_1);
```

[x2] (t2_21);
x2* (e2_1);

[x3] (t3_41);
x3* (e3_1);

[x4] (t4_41);
x4* (e4_1);

[x5] (t5_21);
x5* (e5_1);

[x6] (t6_41);
x6* (e6_1);

[x7] (t7_21);
x7* (e7_1);

[x8] (t8_21);
x8* (e8_1);

[x9] (t9_21);
x9* (e9_1);

[x10] (t10_21);
x10* (e10_1);

[x11] (t11_21);
x11* (e11_1);

[x12] (t12_41);
x12* (e12_1);

[x13] (t13_21);
x13* (e13_1);

[x14] (t14_21);
x14* (e14_1);

MODEL CONSTRAINT:

!ITEM 1:
NEW (l1_0_0*5 l1_0_1*5 l1_11*2 u1_0 u1_1);
t1_10=l1_0_0;
t1_11=l1_0_1;
t1_20=l1_0_0+l1_11;
t1_21=l1_0_1+l1_11;
e1_0 = u1_0;
e1_1 = u1_1;

```
!ITEM 2:
NEW (l2_0_0*5 l2_0_1*5 l2_11*2 u2_0 u2_1);
t2_10=l2_0_0;
t2_11=l2_0_1;
t2_20=l2_0_0+l2_11;
t2_21=l2_0_1+l2_11;
e2_0 = u2_0;
e2_1 = u2_1;

!ITEM 3:
NEW (l3_0_0*5 l3_0_1*5 l3_11*2);
NEW (l3_12*2 l3_212*0 u3_0 u3_1);
t3_10=l3_0_0;
t3_20=l3_0_0+l3_12;
t3_30=l3_0_0+l3_11;
t3_40=l3_0_0+l3_12+l3_11+l3_212;
t3_11=l3_0_1;
t3_21=l3_0_1+l3_12;
t3_31=l3_0_1+l3_11;
t3_41=l3_0_1+l3_12+l3_11+l3_212;
e3_0 = u3_0;
e3_1 = u3_1;

!ITEM 4:
NEW (l4_0_0*5 l4_0_1*5 l4_11*2);
NEW (l4_12*2 l4_212*0 u4_0 u4_1);
t4_10=l4_0_0;
t4_20=l4_0_0+l4_12;
t4_30=l4_0_0+l4_11;
t4_40=l4_0_0+l4_12+l4_11+l4_212;
t4_11=l4_0_1;
t4_21=l4_0_1+l4_12;
t4_31=l4_0_1+l4_11;
t4_41=l4_0_1+l4_12+l4_11+l4_212;
e4_0 = u4_0;
e4_1 = u4_1;

!ITEM 5:
NEW (l5_0_0*5 l5_0_1*5 l5_11*2 u5_0 u5_1);
t5_10=l5_0_0;
t5_11=l5_0_1;
t5_20=l5_0_0+l5_11;
t5_21=l5_0_1+l5_11;
e5_0 = u5_0;
e5_1 = u5_1;

!ITEM 6:
NEW (l6_0_0*5 l6_0_1*5 l6_11*2);
```

```
NEW (l6_12*2 l6_212*0 u6_0 u6_1);
t6_10=l6_0_0;
t6_20=l6_0_0+l6_12;
t6_30=l6_0_0+l6_11;
t6_40=l6_0_0+l6_12+l6_11+l6_212;
t6_11=l6_0_1;
t6_21=l6_0_1+l6_12;
t6_31=l6_0_1+l6_11;
t6_41=l6_0_1+l6_12+l6_11+l6_212;
e6_0 = u6_0;
e6_1 = u6_1;

!ITEM 7:
NEW (l7_0_0*5 l7_0_1*5 l7_12*2 u7_0 u7_1);
t7_10=l7_0_0;
t7_11=l7_0_1;
t7_20=l7_0_0+l7_12;
t7_21=l7_0_1+l7_12;
e7_0 = u7_0;
e7_1 = u7_1;

!ITEM 8:
NEW (l8_0_0*5 l8_0_1*5 l8_11*2 u8_0 u8_1);
t8_10=l8_0_0;
t8_11=l8_0_1;
t8_20=l8_0_0+l8_11;
t8_21=l8_0_1+l8_11;
e8_0 = u8_0;
e8_1 = u8_1;

!ITEM 9:
NEW (l9_0_0*5 l9_0_1*5 l9_12*2 u9_0 u9_1);
t9_10=l9_0_0;
t9_11=l9_0_1;
t9_20=l9_0_0+l9_12;
t9_21=l9_0_1+l9_12;
e9_0 = u9_0;
e9_1 = u9_1;

!ITEM 10:
NEW (l10_0_0*5 l10_0_1*5 l10_12*2 u10_0 u10_1);
t10_10=l10_0_0;
t10_11=l10_0_1;
t10_20=l10_0_0+l10_12;
t10_21=l10_0_1+l10_12;
e10_0 = u10_0;
e10_1 = u10_1;
```

```
!ITEM 11:
NEW (l11_0_0*5 l11_0_1*5 l11_12*2 u11_0 u11_1);
t11_10=l11_0_0;
t11_11=l11_0_1;
t11_20=l11_0_0+l11_12;
t11_21=l11_0_1+l11_12;
e11_0 = u11_0;
e11_1 = u11_1;

!ITEM 12:
NEW (l12_0_0*5 l12_0_1*5 l12_11*2);
NEW (l12_12*2 l12_212*0 u12_0 u12_1);
t12_10=l12_0_0;
t12_20=l12_0_0+l12_12;
t12_30=l12_0_0+l12_11;
t12_40=l12_0_0+l12_12+l12_11+l12_212;
t12_11=l12_0_1;
t12_21=l12_0_1+l12_12;
t12_31=l12_0_1+l12_11;
t12_41=l12_0_1+l12_12+l12_11+l12_212;
e12_0 = u12_0;
e12_1 = u12_1;

!ITEM 13:
NEW (l13_0_0*5 l13_0_1*5 l13_11*2 u13_0 u13_1);
t13_10=l13_0_0;
t13_11=l13_0_1;
t13_20=l13_0_0+l13_11;
t13_21=l13_0_1+l13_11;
e13_0 = u13_0;
e13_1 = u13_1;

!ITEM 14:
NEW (l14_0_0*5 l14_0_1*5 l14_11*2 u14_0 u14_1);
t14_10=l14_0_0;
t14_11=l14_0_1;
t14_20=l14_0_0+l14_11;
t14_21=l14_0_1+l14_11;
e14_0 = u14_0;
e14_1 = u14_1;
```

P.2 PARTIAL METRIC INVARIANCE MODEL CONSTRAINT SYNTAX (FOR ITEM 1)

MODEL CONSTRAINT:

```
!ITEM 1:
NEW (l1_0_0*5 l1_0_1*5 l1_11*2 u1_0 u1_1);
t1_10=l1_0_0;
t1_11=l1_0_1;
t1_20=l1_0_0+l1_11;
t1_21=l1_0_1+l1_11;
e1_0 = u1_0;
e1_1 = u1_1;


!ITEM 2:
NEW (l2_0_0*5 l2_0_1*5 l2_11_0*2 l2_11_1*2 u2_0 u2_1);
t2_10=l2_0_0;
t2_11=l2_0_1;
t2_20=l2_0_0+l2_11_0;
t2_21=l2_0_1+l2_11_1;
e2_0 = u2_0;
e2_1 = u2_1;


!ITEM 3:
NEW (l3_0_0*5 l3_0_1*5 l3_11_0*2 l3_11_1*2);
NEW (l3_12_0*2 l3_12_1*2 l3_2120*0 l3_2121*0 u3_0 u3_1);
t3_10=l3_0_0;
t3_20=l3_0_0+l3_12_0;
t3_30=l3_0_0+l3_11_0;
t3_40=l3_0_0+l3_12_0+l3_11_0+l3_2120;
t3_11=l3_0_1;
t3_21=l3_0_1+l3_12_1;
t3_31=l3_0_1+l3_11_1;
t3_41=l3_0_1+l3_12_1+l3_11_1+l3_2121;
e3_0 = u3_0;
e3_1 = u3_1;


!ITEM 4:
NEW (l4_0_0*5 l4_0_1*5 l4_11_0*2 l4_11_1*2);
NEW (l4_12_0*2 l4_12_1*2 l4_2120*0 l4_2121*0 u4_0 u4_1);
t4_10=l4_0_0;
t4_20=l4_0_0+l4_12_0;
t4_30=l4_0_0+l4_11_0;
t4_40=l4_0_0+l4_12_0+l4_11_0+l4_2120;
```

```
t4_11=l4_0_1;
t4_21=l4_0_1+l4_12_1;
t4_31=l4_0_1+l4_11_1;
t4_41=l4_0_1+l4_12_1+l4_11_1+l4_2121;
e4_0 = u4_0;
e4_1 = u4_1;

!ITEM 5:
NEW (l5_0_0*5 l5_0_1*5 l5_11_0*2 l5_11_1*2 u5_0 u5_1);
t5_10=l5_0_0;
t5_11=l5_0_1;
t5_20=l5_0_0+l5_11_0;
t5_21=l5_0_1+l5_11_1;
e5_0 = u5_0;
e5_1 = u5_1;


!ITEM 6:
NEW (l6_0_0*5 l6_0_1*5 l6_11_0*2 l6_11_1*2);
NEW (l6_12_0*2 l6_12_1*2 l6_2120*0 l6_2121*0 u6_0 u6_1);
t6_10=l6_0_0;
t6_20=l6_0_0+l6_12_0;
t6_30=l6_0_0+l6_11_0;
t6_40=l6_0_0+l6_12_0+l6_11_0+l6_2120;
t6_11=l6_0_1;
t6_21=l6_0_1+l6_12_1;
t6_31=l6_0_1+l6_11_1;
t6_41=l6_0_1+l6_12_1+l6_11_1+l6_2121;
e6_0 = u6_0;
e6_1 = u6_1;



!ITEM 7:
NEW (l7_0_0*5 l7_0_1*5 l7_12_0*2 l7_12_1*2 u7_0 u7_1);
t7_10=l7_0_0;
t7_11=l7_0_1;
t7_20=l7_0_0+l7_12_0;
t7_21=l7_0_1+l7_12_1;
e7_0 = u7_0;
e7_1 = u7_1;



!ITEM 8:
NEW (l8_0_0*5 l8_0_1*5 l8_11_0*2 l8_11_1*2 u8_0 u8_1);
t8_10=l8_0_0;
t8_11=l8_0_1;
```

```
t8_20=l8_0_0+l8_11_0;
t8_21=l8_0_1+l8_11_1;
e8_0 = u8_0;
e8_1 = u8_1;


!ITEM 9:
NEW (l9_0_0*5 l9_0_1*5 l9_12_0*2 l9_12_1*2 u9_0 u9_1);
t9_10=l9_0_0;
t9_11=l9_0_1;
t9_20=l9_0_0+l9_12_0;
t9_21=l9_0_1+l9_12_1;
e9_0 = u9_0;
e9_1 = u9_1;


!ITEM 10:
NEW (l10_0_0*5 l10_0_1*5 l10_12_0*2 l10_12_1*2 u10_0 u10_1);
t10_10=l10_0_0;
t10_11=l10_0_1;
t10_20=l10_0_0+l10_12_0;
t10_21=l10_0_1+l10_12_1;
e10_0 = u10_0;
e10_1 = u10_1;


!ITEM 11:
NEW (l11_0_0*5 l11_0_1*5 l11_12_0*2 l11_12_1*2 u11_0 u11_1);
t11_10=l11_0_0;
t11_11=l11_0_1;
t11_20=l11_0_0+l11_12_0;
t11_21=l11_0_1+l11_12_1;
e11_0 = u11_0;
e11_1 = u11_1;


!ITEM 12:
NEW (l12_0_0*5 l12_0_1*5 l12_11_0*2 l12_11_1*2);
NEW (l12_12_0*2 l12_12_1*2 l12_2120*0 l12_2121*0 u12_0 u12_1);
t12_10=l12_0_0;
t12_20=l12_0_0+l12_12_0;
t12_30=l12_0_0+l12_11_0;
t12_40=l12_0_0+l12_12_0+l12_11_0+l12_2120;
t12_11=l12_0_1;
t12_21=l12_0_1+l12_12_1;
```

```
t12_31=l12_0_1+l12_11_1;
t12_41=l12_0_1+l12_12_1+l12_11_1+l12_2121;
e12_0 = u12_0;
e12_1 = u12_1;


!ITEM 13:
NEW (l13_0_0*5 l13_0_1*5 l13_11_0*2 l13_11_1*2 u13_0 u13_1);
t13_10=l13_0_0;
t13_11=l13_0_1;
t13_20=l13_0_0+l13_11_0;
t13_21=l13_0_1+l13_11_1;
e13_0 = u13_0;
e13_1 = u13_1;


!ITEM 14:
NEW (l14_0_0*5 l14_0_1*5 l14_11_0*2 l14_11_1*2 u14_0 u14_1);
t14_10=l14_0_0;
t14_11=l14_0_1;
t14_20=l14_0_0+l14_11_0;
t14_21=l14_0_1+l14_11_1;
e14_0 = u14_0;
e14_1 = u14_1;
```

APPENDIX Q

MPLUS CODE FOR SCALAR INVARIANCE TESTING FOR LOG-LINEAR COGNITIVE DIAGNOSTIC MODEL

Q.1 FULL SCALAR INVARIANCE TESTING SYNTAX

```
TITLE:          Body Dysmorphic Disorder Items

DATA:           FILE IS itemsandsex.csv;

VARIABLE:

        NAMES = x1-x14 g;

   CLASSES =  c(4) gender(2);

   KNOWNCLASS = gender (g=0 g=1);

ANALYSIS:

        TYPE=MIXTURE;

        STARTS=0;

MODEL:

%OVERALL%

gender on c;


%c#1.gender#1%

[x1] (t1_10);
x1* (e1_0);

[x2] (t2_10);
x2* (e2_0);

[x3] (t3_10);
x3* (e3_0);

[x4] (t4_10);
x4* (e4_0);
```

[x5] (t5_10);
x5* (e5_0);

[x6] (t6_10);
x6* (e6_0);

[x7] (t7_10);
x7* (e7_0);

[x8] (t8_10);
x8* (e8_0);

[x9] (t9_10);
x9* (e9_0);

[x10] (t10_10);
x10* (e10_0);

[x11] (t11_10);
x11* (e11_0);

[x12] (t12_10);
x12* (e12_0)

[x13] (t13_10);
x13* (e13_0);

[x14] (t14_10);
x14* (e14_0);

%c#2.gender#1%

[x1] (t1_10);
x1* (e1_0);

[x2] (t2_10);
x2* (e2_0);

[x3] (t3_20);
x3* (e3_0);

[x4] (t4_20);
x4* (e4_0);

[x5] (t5_10);
x5* (e5_0);

[x6] (t6_20);
x6* (e6_0);

[x7] (t7_20);
x7* (e7_0);

[x8] (t8_10);
x8* (e8_0);

[x9] (t9_20);
x9* (e9_0);

[x10] (t10_20);
x10* (e10_0);

[x11] (t11_20);
x11* (e11_0);

[x12] (t12_20);
x12* (e12_0);

[x13] (t13_10);
x13* (e13_0);

[x14] (t14_10);
x14* (e14_0);

%c#3.gender#1%

[x1] (t1_20);
x1* (e1_0);

[x2] (t2_20);
x2* (e2_0);

[x3] (t3_30);
x3* (e3_0);

[x4] (t4_30);
x4* (e4_0);

[x5] (t5_20);
x5* (e5_0);

[x6] (t6_30);
x6* (e6_0);

[x7] (t7_10);
x7* (e7_0);

[x8] (t8_20);
x8* (e8_0);

[x9] (t9_10);
x9* (e9_0);

[x10] (t10_10);
x10* (e10_0);

[x11] (t11_10);
x11* (e11_0);

[x12] (t12_30);
x12* (e12_0);

[x13] (t13_20);
x13* (e13_0);

[x14] (t14_20);
x14* (e14_0);

%c#4.gender#1%

[x1] (t1_20);
x1* (e1_0);

[x2] (t2_20);
x2* (e2_0);

[x3] (t3_40);
x3* (e3_0);

[x4] (t4_40);
x4* (e4_0);

[x5] (t5_20);
x5* (e5_0);

[x6] (t6_40);
x6* (e6_0);

[x7] (t7_20);
x7* (e7_0);

[x8] (t8_20);
x8* (e8_0);

[x9] (t9_20);
x9* (e9_0);

[x10] (t10_20);
x10* (e10_0);

[x11] (t11_20);
x11* (e11_0);

[x12] (t12_40);
x12* (e12_0);

[x13] (t13_20);
x13* (e13_0);

[x14] (t14_20);
x14* (e14_0);

%c#1.gender#2%

[x1] (t1_11);
x1* (e1_1);

[x2] (t2_11);
x2* (e2_1);

[x3] (t3_11);
x3* (e3_1);

[x4] (t4_11);
x4* (e4_1);

[x5] (t5_11);
x5* (e5_1);

[x6] (t6_11);
x6* (e6_1);

[x7] (t7_11);
x7* (e7_1);

[x8] (t8_11);
x8* (e8_1);

[x9] (t9_11);
x9* (e9_1);

[x10] (t10_11);
x10* (e10_1);

[x11] (t11_11);
x11* (e11_1);

[x12] (t12_11);
x12* (e12_1)

[x13] (t13_11);
x13* (e13_1);

[x14] (t14_11);
x14* (e14_1);

%c#2.gender#2%

[x1] (t1_11);
x1* (e1_1);

[x2] (t2_11);
x2* (e2_1);

[x3] (t3_21);
x3* (e3_1);

[x4] (t4_21);
x4* (e4_1);

[x5] (t5_11);
x5* (e5_1);

[x6] (t6_21);
x6* (e6_1);

[x7] (t7_21);
x7* (e7_1);

[x8] (t8_11);
x8* (e8_1);

[x9] (t9_21);
x9* (e9_1);

[x10] (t10_21);
x10* (e10_1);

[x11] (t11_21);
x11* (e11_1);

[x12] (t12_21);
x12* (e12_1);

[x13] (t13_11);
x13* (e13_1);

[x14] (t14_11);
x14* (e14_1);

```
%c#3.gender#2%

[x1] (t1_21);
x1* (e1_1);

[x2] (t2_21);
x2* (e2_1);

[x3] (t3_31);
x3* (e3_1);

[x4] (t4_31);
x4* (e4_1);

[x5] (t5_21);
x5* (e5_1);

[x6] (t6_31);
x6* (e6_1);

[x7] (t7_11);
x7* (e7_1);

[x8] (t8_21);
x8* (e8_1);

[x9] (t9_11);
x9* (e9_1);

[x10] (t10_11);
x10* (e10_1);

[x11] (t11_11);
x11* (e11_1);

[x12] (t12_31);
x12* (e12_1);

[x13] (t13_21);
x13* (e13_1);

[x14] (t14_21);
x14* (e14_1);


%c#4.gender#2%

[x1] (t1_21);
x1* (e1_1);
```

[x2] (t2_21);
x2* (e2_1);

[x3] (t3_41);
x3* (e3_1);

[x4] (t4_41);
x4* (e4_1);

[x5] (t5_21);
x5* (e5_1);

[x6] (t6_41);
x6* (e6_1);

[x7] (t7_21);
x7* (e7_1);

[x8] (t8_21);
x8* (e8_1);

[x9] (t9_21);
x9* (e9_1);

[x10] (t10_21);
x10* (e10_1);

[x11] (t11_21);
x11* (e11_1);

[x12] (t12_41);
x12* (e12_1);

[x13] (t13_21);
x13* (e13_1);

[x14] (t14_21);
x14* (e14_1);

MODEL CONSTRAINT:

!ITEM 1:
NEW (l1_0*5 l1_11*2 u1_0 u1_1);
t1_10=l1_0;
t1_11=l1_0;
t1_20=l1_0+l1_11;
t1_21=l1_0+l1_11;
e1_0 = u1_0;
e1_1 = u1_1;

```
!ITEM 2:
NEW (l2_0*5 l2_11*2 u2_0 u2_1);
t2_10=l2_0;
t2_11=l2_0;
t2_20=l2_0+l2_11;
t2_21=l2_0+l2_11;
e2_0 = u2_0;
e2_1 = u2_1;


!ITEM 3:
NEW (l3_0*5 l3_11*2);
NEW (l3_12*2 l3_212*0 u3_0 u3_1);
t3_10=l3_0;
t3_20=l3_0+l3_12;
t3_30=l3_0+l3_11;
t3_40=l3_0+l3_12+l3_11+l3_212;
t3_11=l3_0;
t3_21=l3_0+l3_12;
t3_31=l3_0+l3_11;
t3_41=l3_0+l3_12+l3_11+l3_212;
e3_0 = u3_0;
e3_1 = u3_1;


!ITEM 4:
NEW (l4_0*5 l4_11*2);
NEW (l4_12*2 l4_212*0 u4_0 u4_1);
t4_10=l4_0;
t4_20=l4_0+l4_12;
t4_30=l4_0+l4_11;
t4_40=l4_0+l4_12+l4_11+l4_212;
t4_11=l4_0;
t4_21=l4_0+l4_12;
t4_31=l4_0+l4_11;
t4_41=l4_0+l4_12+l4_11+l4_212;
e4_0 = u4_0;
e4_1 = u4_1;


!ITEM 5:
NEW (l5_0*5 l5_11*2 u5_0 u5_1);
t5_10=l5_0;
t5_11=l5_0;
t5_20=l5_0+l5_11;
```

```
t5_21=l5_0+l5_11;
e5_0 = u5_0;
e5_1 = u5_1;


!ITEM 6:
NEW (l6_0*5 l6_11*2);
NEW (l6_12*2 l6_212*0 u6_0 u6_1);
t6_10=l6_0;
t6_20=l6_0+l6_12;
t6_30=l6_0+l6_11;
t6_40=l6_0+l6_12+l6_11+l6_212;
t6_11=l6_0;
t6_21=l6_0+l6_12;
t6_31=l6_0+l6_11;
t6_41=l6_0+l6_12+l6_11+l6_212;
e6_0 = u6_0;
e6_1 = u6_1;


!ITEM 7:
NEW (l7_0*5 l7_12*2 u7_0 u7_1);
t7_10=l7_0;
t7_11=l7_0;
t7_20=l7_0+l7_12;
t7_21=l7_0+l7_12;
e7_0 = u7_0;
e7_1 = u7_1;


!ITEM 8:
NEW (l8_0*5 l8_11*2 u8_0 u8_1);
t8_10=l8_0;
t8_11=l8_0;
t8_20=l8_0+l8_11;
t8_21=l8_0+l8_11;
e8_0 = u8_0;
e8_1 = u8_1;


!ITEM 9:
NEW (l9_0*5 l9_12*2 u9_0 u9_1);
t9_10=l9_0;
t9_11=l9_0;
t9_20=l9_0+l9_12;
```

```
t9_21=l9_0+l9_12;
e9_0 = u9_0;
e9_1 = u9_1;


!ITEM 10:
NEW (l10_0*5 l10_12*2 u10_0 u10_1);
t10_10=l10_0;
t10_11=l10_0;
t10_20=l10_0+l10_12;
t10_21=l10_0+l10_12;
e10_0 = u10_0;
e10_1 = u10_1;


!ITEM 11:
NEW (l11_0*5 l11_12*2 u11_0 u11_1);
t11_10=l11_0;
t11_11=l11_0;
t11_20=l11_0+l11_12;
t11_21=l11_0+l11_12;
e11_0 = u11_0;
e11_1 = u11_1;


!ITEM 12:
NEW (l12_0*5 l12_11*2);
NEW (l12_12*2 l12_212*0 u12_0 u12_1);
t12_10=l12_0;
t12_20=l12_0+l12_12;
t12_30=l12_0+l12_11;
t12_40=l12_0+l12_12+l12_11+l12_212;
t12_11=l12_0;
t12_21=l12_0+l12_12;
t12_31=l12_0+l12_11;
t12_41=l12_0+l12_12+l12_11+l12_212;
e12_0 = u12_0;
e12_1 = u12_1;


!ITEM 13:
NEW (l13_0*5 l13_11*2 u13_0 u13_1);
t13_10=l13_0;
t13_11=l13_0;
t13_20=l13_0+l13_11;
```

```
t13_21=l13_0+l13_11;
e13_0 = u13_0;
e13_1 = u13_1;


!ITEM 14:
NEW (l14_0*5 l14_11*2 u14_0 u14_1);
t14_10=l14_0;
t14_11=l14_0;
t14_20=l14_0+l14_11;
t14_21=l14_0+l14_11;
e14_0 = u14_0;
e14_1 = u14_1;
```

Q.2 PARTIAL SCALAR INVARIANCE MODEL CONSTRAINT SYNTAX (FOR ITEM 1)

MODEL CONSTRAINT:

```
!ITEM 1:
NEW (l1_0*5 l1_11*2 u1_0 u1_1);
t1_10=l1_0;
t1_11=l1_0;
t1_20=l1_0+l1_11;
t1_21=l1_0+l1_11;
e1_0 = u1_0;
e1_1 = u1_1;


!ITEM 2:
NEW (l2_0_0*5 l2_0_1*5 l2_11*2 u2_0 u2_1);
t2_10=l2_0_0;
t2_11=l2_0_1;
t2_20=l2_0_0+l2_11;
t2_21=l2_0_1+l2_11;
e2_0 = u2_0;
e2_1 = u2_1;


!ITEM 3:
NEW (l3_0_0*5 l3_0_1*5 l3_11_0*2 l3_11_1*2);
NEW (l3_12_0*2 l3_12_1*2 l3_2120*0 l3_2121*0 u3_0 u3_1);
t3_10=l3_0_0;
t3_20=l3_0_0+l3_12_0;
t3_30=l3_0_0+l3_11_0;
```

```
t3_40=l3_0_0+l3_12_0+l3_11_0+l3_2120;
t3_11=l3_0_1;
t3_21=l3_0_1+l3_12_1;
t3_31=l3_0_1+l3_11_1;
t3_41=l3_0_1+l3_12_1+l3_11_1+l3_2121;
e3_0 = u3_0;
e3_1 = u3_1;


!ITEM 4:
NEW (l4_0_0*5 l4_0_1*5 l4_11*2);
NEW (l4_12*2 l4_212*0 u4_0 u4_1);
t4_10=l4_0_0;
t4_20=l4_0_0+l4_12;
t4_30=l4_0_0+l4_11;
t4_40=l4_0_0+l4_12+l4_11+l4_212;
t4_11=l4_0_1;
t4_21=l4_0_1+l4_12;
t4_31=l4_0_1+l4_11;
t4_41=l4_0_1+l4_12+l4_11+l4_212;
e4_0 = u4_0;
e4_1 = u4_1;


!ITEM 5:
NEW (l5_0_0*5 l5_0_1*5 l5_11_0*2 l5_11_1*2 u5_0 u5_1);
t5_10=l5_0_0;
t5_11=l5_0_1;
t5_20=l5_0_0+l5_11_0;
t5_21=l5_0_1+l5_11_1;
e5_0 = u5_0;
e5_1 = u5_1;


!ITEM 6:
NEW (l6_0_0*5 l6_0_1*5 l6_11_0*2 l6_11_1*2);
NEW (l6_12_0*2 l6_12_1*2 l6_2120*0 l6_2121*0 u6_0 u6_1);
t6_10=l6_0_0;
t6_20=l6_0_0+l6_12_0;
t6_30=l6_0_0+l6_11_0;
t6_40=l6_0_0+l6_12_0+l6_11_0+l6_2120;
t6_11=l6_0_1;
t6_21=l6_0_1+l6_12_1;
t6_31=l6_0_1+l6_11_1;
t6_41=l6_0_1+l6_12_1+l6_11_1+l6_2121;
```

```
e6_0 = u6_0;
e6_1 = u6_1;


!ITEM 7:
NEW (l7_0_0*5 l7_0_1*5 l7_12*2 u7_0 u7_1);
t7_10=l7_0_0;
t7_11=l7_0_1;
t7_20=l7_0_0+l7_12;
t7_21=l7_0_1+l7_12;
e7_0 = u7_0;
e7_1 = u7_1;


!ITEM 8:
NEW (l8_0_0*5 l8_0_1*5 l8_11_0*2 l8_11_1*2 u8_0 u8_1);
t8_10=l8_0_0;
t8_11=l8_0_1;
t8_20=l8_0_0+l8_11_0;
t8_21=l8_0_1+l8_11_1;
e8_0 = u8_0;
e8_1 = u8_1;


!ITEM 9:
NEW (l9_0_0*5 l9_0_1*5 l9_12*2 u9_0 u9_1);
t9_10=l9_0_0;
t9_11=l9_0_1;
t9_20=l9_0_0+l9_12;
t9_21=l9_0_1+l9_12;
e9_0 = u9_0;
e9_1 = u9_1;


!ITEM 10:
NEW (l10_0_0*5 l10_0_1*5 l10_12*2 u10_0 u10_1);
t10_10=l10_0_0;
t10_11=l10_0_1;
t10_20=l10_0_0+l10_12;
t10_21=l10_0_1+l10_12;
e10_0 = u10_0;
e10_1 = u10_1;
```

```
!ITEM 11:
NEW (l11_0_0*5 l11_0_1*5 l11_12*2 u11_0 u11_1);
t11_10=l11_0_0;
t11_11=l11_0_1;
t11_20=l11_0_0+l11_12;
t11_21=l11_0_1+l11_12;
e11_0 = u11_0;
e11_1 = u11_1;


!ITEM 12:
NEW (l12_0_0*5 l12_0_1*5 l12_11_0*2 l12_11_1*2);
NEW (l12_12_0*2 l12_12_1*2 l12_2120*0 l12_2121*0 u12_0 u12_1);
t12_10=l12_0_0;
t12_20=l12_0_0+l12_12_0;
t12_30=l12_0_0+l12_11_0;
t12_40=l12_0_0+l12_12_0+l12_11_0+l12_2120;
t12_11=l12_0_1;
t12_21=l12_0_1+l12_12_1;
t12_31=l12_0_1+l12_11_1;
t12_41=l12_0_1+l12_12_1+l12_11_1+l12_2121;
e12_0 = u12_0;
e12_1 = u12_1;


!ITEM 13:
NEW (l13_0_0*5 l13_0_1*5 l13_11*2 u13_0 u13_1);
t13_10=l13_0_0;
t13_11=l13_0_1;
t13_20=l13_0_0+l13_11;
t13_21=l13_0_1+l13_11;
e13_0 = u13_0;
e13_1 = u13_1;


!ITEM 14:
NEW (l14_0_0*5 l14_0_1*5 l14_11*2 u14_0 u14_1);
t14_10=l14_0_0;
t14_11=l14_0_1;
t14_20=l14_0_0+l14_11;
t14_21=l14_0_1+l14_11;
e14_0 = u14_0;
e14_1 = u14_1;
```

APPENDIX R

MPLUS CODE FOR RESIDUAL INVARIANCE TESTING FOR LOG-LINEAR COGNITIVE DIAGNOSTIC MODEL

R.1 FULL RESIDUAL INVARIANCE TESTING SYNTAX

```
TITLE:          Body Dysmorphic Disorder Items

DATA:           FILE IS itemsandsex.csv;

VARIABLE:

        NAMES = x1-x14 g;

   CLASSES =  c(4) gender(2);

   KNOWNCLASS = gender (g=0 g=1);

ANALYSIS:

        TYPE=MIXTURE;

        STARTS=0;

MODEL:

%OVERALL%

gender on c;

%c#1.gender#1%

[x1] (t1_10);
x1* (e1_0);

[x2] (t2_10);
x2* (e2_0);

[x3] (t3_10);
x3* (e3_0);

[x4] (t4_10);
x4* (e4_0);
```

[x5] (t5_10);
x5* (e5_0);

[x6] (t6_10);
x6* (e6_0);

[x7] (t7_10);
x7* (e7_0);

[x8] (t8_10);
x8* (e8_0);

[x9] (t9_10);
x9* (e9_0);

[x10] (t10_10);
x10* (e10_0);

[x11] (t11_10);
x11* (e11_0);

[x12] (t12_10);
x12* (e12_0)

[x13] (t13_10);
x13* (e13_0);

[x14] (t14_10);
x14* (e14_0);

%c#2.gender#1%

[x1] (t1_10);
x1* (e1_0);

[x2] (t2_10);
x2* (e2_0);

[x3] (t3_20);
x3* (e3_0);

[x4] (t4_20);
x4* (e4_0);

[x5] (t5_10);
x5* (e5_0);

[x6] (t6_20);
x6* (e6_0);

[x7] (t7_20);
x7* (e7_0);

[x8] (t8_10);
x8* (e8_0);

[x9] (t9_20);
x9* (e9_0);

[x10] (t10_20);
x10* (e10_0);

[x11] (t11_20);
x11* (e11_0);

[x12] (t12_20);
x12* (e12_0);

[x13] (t13_10);
x13* (e13_0);

[x14] (t14_10);
x14* (e14_0);

%c#3.gender#1%

[x1] (t1_20);
x1* (e1_0);

[x2] (t2_20);
x2* (e2_0);

[x3] (t3_30);
x3* (e3_0);

[x4] (t4_30);
x4* (e4_0);

[x5] (t5_20);
x5* (e5_0);

[x6] (t6_30);
x6* (e6_0);

[x7] (t7_10);
x7* (e7_0);

[x8] (t8_20);
x8* (e8_0);

[x9] (t9_10);
x9* (e9_0);

[x10] (t10_10);
x10* (e10_0);

[x11] (t11_10);
x11* (e11_0);

[x12] (t12_30);
x12* (e12_0);

[x13] (t13_20);
x13* (e13_0);

[x14] (t14_20);
x14* (e14_0);

%c#4.gender#1%

[x1] (t1_20);
x1* (e1_0);

[x2] (t2_20);
x2* (e2_0);

[x3] (t3_40);
x3* (e3_0);

[x4] (t4_40);
x4* (e4_0);

[x5] (t5_20);
x5* (e5_0);

[x6] (t6_40);
x6* (e6_0);

[x7] (t7_20);
x7* (e7_0);

[x8] (t8_20);
x8* (e8_0);

[x9] (t9_20);
x9* (e9_0);

[x10] (t10_20);
x10* (e10_0);

[x11] (t11_20);
x11* (e11_0);

[x12] (t12_40);
x12* (e12_0);

[x13] (t13_20);
x13* (e13_0);

[x14] (t14_20);
x14* (e14_0);

%c#1.gender#2%

[x1] (t1_11);
x1* (e1_1);

[x2] (t2_11);
x2* (e2_1);

[x3] (t3_11);
x3* (e3_1);

[x4] (t4_11);
x4* (e4_1);

[x5] (t5_11);
x5* (e5_1);

[x6] (t6_11);
x6* (e6_1);

[x7] (t7_11);
x7* (e7_1);

[x8] (t8_11);
x8* (e8_1);

[x9] (t9_11);
x9* (e9_1);

[x10] (t10_11);
x10* (e10_1);

[x11] (t11_11);
x11* (e11_1);

[x12] (t12_11);
x12* (e12_1)

[x13] (t13_11);
x13* (e13_1);

[x14] (t14_11);
x14* (e14_1);

%c#2.gender#2%

[x1] (t1_11);
x1* (e1_1);

[x2] (t2_11);
x2* (e2_1);

[x3] (t3_21);
x3* (e3_1);

[x4] (t4_21);
x4* (e4_1);

[x5] (t5_11);
x5* (e5_1);

[x6] (t6_21);
x6* (e6_1);

[x7] (t7_21);
x7* (e7_1);

[x8] (t8_11);
x8* (e8_1);

[x9] (t9_21);
x9* (e9_1);

[x10] (t10_21);
x10* (e10_1);

[x11] (t11_21);
x11* (e11_1);

[x12] (t12_21);
x12* (e12_1);

[x13] (t13_11);
x13* (e13_1);

[x14] (t14_11);
x14* (e14_1);

```
%c#3.gender#2%

[x1] (t1_21);
x1* (e1_1);

[x2] (t2_21);
x2* (e2_1);

[x3] (t3_31);
x3* (e3_1);

[x4] (t4_31);
x4* (e4_1);

[x5] (t5_21);
x5* (e5_1);

[x6] (t6_31);
x6* (e6_1);

[x7] (t7_11);
x7* (e7_1);

[x8] (t8_21);
x8* (e8_1);

[x9] (t9_11);
x9* (e9_1);

[x10] (t10_11);
x10* (e10_1);

[x11] (t11_11);
x11* (e11_1);

[x12] (t12_31);
x12* (e12_1);

[x13] (t13_21);
x13* (e13_1);

[x14] (t14_21);
x14* (e14_1);


%c#4.gender#2%

[x1] (t1_21);
x1* (e1_1);
```

[x2] (t2_21);
x2* (e2_1);

[x3] (t3_41);
x3* (e3_1);

[x4] (t4_41);
x4* (e4_1);

[x5] (t5_21);
x5* (e5_1);

[x6] (t6_41);
x6* (e6_1);

[x7] (t7_21);
x7* (e7_1);

[x8] (t8_21);
x8* (e8_1);

[x9] (t9_21);
x9* (e9_1);

[x10] (t10_21);
x10* (e10_1);

[x11] (t11_21);
x11* (e11_1);

[x12] (t12_41);
x12* (e12_1);

[x13] (t13_21);
x13* (e13_1);

[x14] (t14_21);
x14* (e14_1);

MODEL CONSTRAINT:

!ITEM 1:
NEW (l1_0*5 l1_11*2 u1);
t1_10=l1_0;
t1_11=l1_0;
t1_20=l1_0+l1_11;
t1_21=l1_0+l1_11;
e1_0 = u1;
e1_1 = u1;

```
!ITEM 2:
NEW (l2_0*5 l2_11*2 u2);
t2_10=l2_0;
t2_11=l2_0;
t2_20=l2_0+l2_11;
t2_21=l2_0+l2_11;
e2_0 = u2;
e2_1 = u2;


!ITEM 3:
NEW (l3_0*5 l3_11*2);
NEW (l3_12*2 l3_212*0 u3);
t3_10=l3_0;
t3_20=l3_0+l3_12;
t3_30=l3_0+l3_11;
t3_40=l3_0+l3_12+l3_11+l3_212;
t3_11=l3_0;
t3_21=l3_0+l3_12;
t3_31=l3_0+l3_11;
t3_41=l3_0+l3_12+l3_11+l3_212;
e3_0 = u3;
e3_1 = u3;


!ITEM 4:
NEW (l4_0*5 l4_11*2);
NEW (l4_12*2 l4_212*0 u4);
t4_10=l4_0;
t4_20=l4_0+l4_12;
t4_30=l4_0+l4_11;
t4_40=l4_0+l4_12+l4_11+l4_212;
t4_11=l4_0;
t4_21=l4_0+l4_12;
t4_31=l4_0+l4_11;
t4_41=l4_0+l4_12+l4_11+l4_212;
e4_0 = u4;
e4_1 = u4;


!ITEM 5:
NEW (l5_0*5 l5_11*2 u5);
t5_10=l5_0;
t5_11=l5_0;
t5_20=l5_0+l5_11;
```

```
t5_21=l5_0+l5_11;
e5_0 = u5;
e5_1 = u5;


!ITEM 6:
NEW (l6_0*5 l6_11*2);
NEW (l6_12*2 l6_212*0 u6);
t6_10=l6_0;
t6_20=l6_0+l6_12;
t6_30=l6_0+l6_11;
t6_40=l6_0+l6_12+l6_11+l6_212;
t6_11=l6_0;
t6_21=l6_0+l6_12;
t6_31=l6_0+l6_11;
t6_41=l6_0+l6_12+l6_11+l6_212;
e6_0 = u6;
e6_1 = u6;


!ITEM 7:
NEW (l7_0*5 l7_12*2 u7);
t7_10=l7_0;
t7_11=l7_0;
t7_20=l7_0+l7_12;
t7_21=l7_0+l7_12;
e7_0 = u7;
e7_1 = u7;


!ITEM 8:
NEW (l8_0*5 l8_11*2 u8);
t8_10=l8_0;
t8_11=l8_0;
t8_20=l8_0+l8_11;
t8_21=l8_0+l8_11;
e8_0 = u8;
e8_1 = u8;


!ITEM 9:
NEW (l9_0*5 l9_12*2 u9);
t9_10=l9_0;
t9_11=l9_0;
t9_20=l9_0+l9_12;
```

```
t9_21=l9_0+l9_12;
e9_0 = u9;
e9_1 = u9;


!ITEM 10:
NEW (l10_0*5 l10_12*2 u10);
t10_10=l10_0;
t10_11=l10_0;
t10_20=l10_0+l10_12;
t10_21=l10_0+l10_12;
e10_0 = u10;
e10_1 = u10;


!ITEM 11:
NEW (l11_0*5 l11_12*2 u11);
t11_10=l11_0;
t11_11=l11_0;
t11_20=l11_0+l11_12;
t11_21=l11_0+l11_12;
e11_0 = u11;
e11_1 = u11;


!ITEM 12:
NEW (l12_0*5 l12_11*2);
NEW (l12_12*2 l12_212*0 u12);
t12_10=l12_0;
t12_20=l12_0+l12_12;
t12_30=l12_0+l12_11;
t12_40=l12_0+l12_12+l12_11+l12_212;
t12_11=l12_0;
t12_21=l12_0+l12_12;
t12_31=l12_0+l12_11;
t12_41=l12_0+l12_12+l12_11+l12_212;
e12_0 = u12;
e12_1 = u12;


!ITEM 13:
NEW (l13_0*5 l13_11*2 u13);
t13_10=l13_0;
t13_11=l13_0;
t13_20=l13_0+l13_11;
```

```
t13_21=l13_0+l13_11;
e13_0 = u13;
e13_1 = u13;


!ITEM 14:
NEW (l14_0*5 l14_11*2 u14);
t14_10=l14_0;
t14_11=l14_0;
t14_20=l14_0+l14_11;
t14_21=l14_0+l14_11;
e14_0 = u14;
e14_1 = u14;
```

R.2 PARTIAL RESIDUAL INVARIANCE MODEL CONSTRAINT SYNTAX (FOR ITEM 7)

MODEL CONSTRAINT:

```
!ITEM 1:
NEW (l1_0_0*5 l1_0_1*5 l1_11*2 u1_0 u1_1);
t1_10=l1_0_0;
t1_11=l1_0_1;
t1_20=l1_0_0+l1_11;
t1_21=l1_0_1+l1_11;
e1_0 = u1_0;
e1_1 = u1_1;


!ITEM 2:
NEW (l2_0_0*5 l2_0_1*5 l2_11*2 u2_0 u2_1);
t2_10=l2_0_0;
t2_11=l2_0_1;
t2_20=l2_0_0+l2_11;
t2_21=l2_0_1+l2_11;
e2_0 = u2_0;
e2_1 = u2_1;


!ITEM 3:
NEW (l3_0_0*5 l3_0_1*5 l3_11_0*2 l3_11_1*2);
NEW (l3_12_0*2 l3_12_1*2 l3_2120*0 l3_2121*0 u3_0 u3_1);
t3_10=l3_0_0;
t3_20=l3_0_0+l3_12_0;
t3_30=l3_0_0+l3_11_0;
```

```
t3_40=l3_0_0+l3_12_0+l3_11_0+l3_2120;
t3_11=l3_0_1;
t3_21=l3_0_1+l3_12_1;
t3_31=l3_0_1+l3_11_1;
t3_41=l3_0_1+l3_12_1+l3_11_1+l3_2121;
e3_0 = u3_0;
e3_1 = u3_1;


!ITEM 4:
NEW (l4_0_0*5 l4_0_1*5 l4_11*2);
NEW (l4_12*2 l4_212*0 u4_0 u4_1);
t4_10=l4_0_0;
t4_20=l4_0_0+l4_12;
t4_30=l4_0_0+l4_11;
t4_40=l4_0_0+l4_12+l4_11+l4_212;
t4_11=l4_0_1;
t4_21=l4_0_1+l4_12;
t4_31=l4_0_1+l4_11;
t4_41=l4_0_1+l4_12+l4_11+l4_212;
e4_0 = u4_0;
e4_1 = u4_1;


!ITEM 5:
NEW (l5_0_0*5 l5_0_1*5 l5_11_0*2 l5_11_1*2 u5_0 u5_1);
t5_10=l5_0_0;
t5_11=l5_0_1;
t5_20=l5_0_0+l5_11_0;
t5_21=l5_0_1+l5_11_1;
e5_0 = u5_0;
e5_1 = u5_1;


!ITEM 6:
NEW (l6_0_0*5 l6_0_1*5 l6_11_0*2 l6_11_1*2);
NEW (l6_12_0*2 l6_12_1*2 l6_2120*0 l6_2121*0 u6_0 u6_1);
t6_10=l6_0_0;
t6_20=l6_0_0+l6_12_0;
t6_30=l6_0_0+l6_11_0;
t6_40=l6_0_0+l6_12_0+l6_11_0+l6_2120;
t6_11=l6_0_1;
t6_21=l6_0_1+l6_12_1;
t6_31=l6_0_1+l6_11_1;
t6_41=l6_0_1+l6_12_1+l6_11_1+l6_2121;
```

```
e6_0 = u6_0;
e6_1 = u6_1;


!ITEM 7:
NEW (l7_0*5 l7_12*2 u7);
t7_10=l7_0;
t7_11=l7_0;
t7_20=l7_0+l7_12;
t7_21=l7_0+l7_12;
e7_0 = u7;
e7_1 = u7;


!ITEM 8:
NEW (l8_0_0*5 l8_0_1*5 l8_11_0*2 l8_11_1*2 u8_0 u8_1);
t8_10=l8_0_0;
t8_11=l8_0_1;
t8_20=l8_0_0+l8_11_0;
t8_21=l8_0_1+l8_11_1;
e8_0 = u8_0;
e8_1 = u8_1;


!ITEM 9:
NEW (l9_0_0*5 l9_0_1*5 l9_12*2 u9_0 u9_1);
t9_10=l9_0_0;
t9_11=l9_0_1;
t9_20=l9_0_0+l9_12;
t9_21=l9_0_1+l9_12;
e9_0 = u9_0;
e9_1 = u9_1;


!ITEM 10:
NEW (l10_0_0*5 l10_0_1*5 l10_12*2 u10_0 u10_1);
t10_10=l10_0_0;
t10_11=l10_0_1;
t10_20=l10_0_0+l10_12;
t10_21=l10_0_1+l10_12;
e10_0 = u10_0;
e10_1 = u10_1;
```

```
!ITEM 11:
NEW (l11_0_0*5 l11_0_1*5 l11_12*2 u11_0 u11_1);
t11_10=l11_0_0;
t11_11=l11_0_1;
t11_20=l11_0_0+l11_12;
t11_21=l11_0_1+l11_12;
e11_0 = u11_0;
e11_1 = u11_1;


!ITEM 12:
NEW (l12_0_0*5 l12_0_1*5 l12_11_0*2 l12_11_1*2);
NEW (l12_12_0*2 l12_12_1*2 l12_2120*0 l12_2121*0 u12_0 u12_1);
t12_10=l12_0_0;
t12_20=l12_0_0+l12_12_0;
t12_30=l12_0_0+l12_11_0;
t12_40=l12_0_0+l12_12_0+l12_11_0+l12_2120;
t12_11=l12_0_1;
t12_21=l12_0_1+l12_12_1;
t12_31=l12_0_1+l12_11_1;
t12_41=l12_0_1+l12_12_1+l12_11_1+l12_2121;
e12_0 = u12_0;
e12_1 = u12_1;


!ITEM 13:
NEW (l13_0_0*5 l13_0_1*5 l13_11*2 u13_0 u13_1);
t13_10=l13_0_0;
t13_11=l13_0_1;
t13_20=l13_0_0+l13_11;
t13_21=l13_0_1+l13_11;
e13_0 = u13_0;
e13_1 = u13_1;


!ITEM 14:
NEW (l14_0_0*5 l14_0_1*5 l14_11*2 u14_0 u14_1);
t14_10=l14_0_0;
t14_11=l14_0_1;
t14_20=l14_0_0+l14_11;
t14_21=l14_0_1+l14_11;
e14_0 = u14_0;
e14_1 = u14_1;
```

APPENDIX S

MPLUS CODE FOR STRUCTURAL INVARIANCE TESTING FOR LOG-LINEAR COGNITIVE DIAGNOSTIC MODEL

```
TITLE:          Body Dysmorphic Disorder Items

DATA:           FILE IS itemsandsex.csv;

VARIABLE:

        NAMES = x1-x14 g;

   CLASSES =  c(4) gender(2);

   KNOWNCLASS = gender (g=0 g=1);

ANALYSIS:

        TYPE=MIXTURE;

        STARTS=0;

MODEL:

%OVERALL%

%c#1.gender#1%

[x1] (t1_10);
x1* (e1_0);

[x2] (t2_10);
x2* (e2_0);

[x3] (t3_10);
x3* (e3_0);

[x4] (t4_10);
x4* (e4_0);

[x5] (t5_10);
x5* (e5_0);

[x6] (t6_10);
x6* (e6_0);
```

[x7] (t7_10);
x7* (e7_0);

[x8] (t8_10);
x8* (e8_0);

[x9] (t9_10);
x9* (e9_0);

[x10] (t10_10);
x10* (e10_0);

[x11] (t11_10);
x11* (e11_0);

[x12] (t12_10);
x12* (e12_0)

[x13] (t13_10);
x13* (e13_0);

[x14] (t14_10);
x14* (e14_0);

%c#2.gender#1%

[x1] (t1_10);
x1* (e1_0);

[x2] (t2_10);
x2* (e2_0);

[x3] (t3_20);
x3* (e3_0);

[x4] (t4_20);
x4* (e4_0);

[x5] (t5_10);
x5* (e5_0);

[x6] (t6_20);
x6* (e6_0);

[x7] (t7_20);
x7* (e7_0);

[x8] (t8_10);
x8* (e8_0);

[x9] (t9_20);
x9* (e9_0);

[x10] (t10_20);
x10* (e10_0);

[x11] (t11_20);
x11* (e11_0);

[x12] (t12_20);
x12* (e12_0);

[x13] (t13_10);
x13* (e13_0);

[x14] (t14_10);
x14* (e14_0);

%c#3.gender#1%

[x1] (t1_20);
x1* (e1_0);

[x2] (t2_20);
x2* (e2_0);

[x3] (t3_30);
x3* (e3_0);

[x4] (t4_30);
x4* (e4_0);

[x5] (t5_20);
x5* (e5_0);

[x6] (t6_30);
x6* (e6_0);

[x7] (t7_10);
x7* (e7_0);

[x8] (t8_20);
x8* (e8_0);

[x9] (t9_10);
x9* (e9_0);

[x10] (t10_10);
x10* (e10_0);

[x11] (t11_10);
x11* (e11_0);

[x12] (t12_30);
x12* (e12_0);

[x13] (t13_20);
x13* (e13_0);

[x14] (t14_20);
x14* (e14_0);

%c#4.gender#1%

[x1] (t1_20);
x1* (e1_0);

[x2] (t2_20);
x2* (e2_0);

[x3] (t3_40);
x3* (e3_0);

[x4] (t4_40);
x4* (e4_0);

[x5] (t5_20);
x5* (e5_0);

[x6] (t6_40);
x6* (e6_0);

[x7] (t7_20);
x7* (e7_0);

[x8] (t8_20);
x8* (e8_0);

[x9] (t9_20);
x9* (e9_0);

[x10] (t10_20);
x10* (e10_0);

[x11] (t11_20);
x11* (e11_0);

[x12] (t12_40);
x12* (e12_0);

[x13] (t13_20);
x13* (e13_0);

[x14] (t14_20);
x14* (e14_0);

%c#1.gender#2%

[x1] (t1_11);
x1* (e1_1);

[x2] (t2_11);
x2* (e2_1);

[x3] (t3_11);
x3* (e3_1);

[x4] (t4_11);
x4* (e4_1);

[x5] (t5_11);
x5* (e5_1);

[x6] (t6_11);
x6* (e6_1);

[x7] (t7_11);
x7* (e7_1);

[x8] (t8_11);
x8* (e8_1);

[x9] (t9_11);
x9* (e9_1);

[x10] (t10_11);
x10* (e10_1);

[x11] (t11_11);
x11* (e11_1);

[x12] (t12_11);
x12* (e12_1)

[x13] (t13_11);
x13* (e13_1);

[x14] (t14_11);
x14* (e14_1);

```
%c#2.gender#2%

[x1] (t1_11);
x1* (e1_1);

[x2] (t2_11);
x2* (e2_1);

[x3] (t3_21);
x3* (e3_1);

[x4] (t4_21);
x4* (e4_1);

[x5] (t5_11);
x5* (e5_1);

[x6] (t6_21);
x6* (e6_1);

[x7] (t7_21);
x7* (e7_1);

[x8] (t8_11);
x8* (e8_1);

[x9] (t9_21);
x9* (e9_1);

[x10] (t10_21);
x10* (e10_1);

[x11] (t11_21);
x11* (e11_1);

[x12] (t12_21);
x12* (e12_1);

[x13] (t13_11);
x13* (e13_1);

[x14] (t14_11);
x14* (e14_1);


%c#3.gender#2%
```

[x1] (t1_21);
x1* (e1_1);

[x2] (t2_21);
x2* (e2_1);

[x3] (t3_31);
x3* (e3_1);

[x4] (t4_31);
x4* (e4_1);

[x5] (t5_21);
x5* (e5_1);

[x6] (t6_31);
x6* (e6_1);

[x7] (t7_11);
x7* (e7_1);

[x8] (t8_21);
x8* (e8_1);

[x9] (t9_11);
x9* (e9_1);

[x10] (t10_11);
x10* (e10_1);

[x11] (t11_11);
x11* (e11_1);

[x12] (t12_31);
x12* (e12_1);

[x13] (t13_21);
x13* (e13_1);

[x14] (t14_21);
x14* (e14_1);

%c#4.gender#2%

[x1] (t1_21);
x1* (e1_1);

[x2] (t2_21);
x2* (e2_1);

```
[x3] (t3_41);
x3* (e3_1);

[x4] (t4_41);
x4* (e4_1);

[x5] (t5_21);
x5* (e5_1);

[x6] (t6_41);
x6* (e6_1);

[x7] (t7_21);
x7* (e7_1);

[x8] (t8_21);
x8* (e8_1);

[x9] (t9_21);
x9* (e9_1);

[x10] (t10_21);
x10* (e10_1);

[x11] (t11_21);
x11* (e11_1);

[x12] (t12_41);
x12* (e12_1);

[x13] (t13_21);
x13* (e13_1);

[x14] (t14_21);
x14* (e14_1);
```

MODEL CONSTRAINT:

```
!ITEM 1:
NEW (l1_0*5 l1_11*2 u1);
t1_10=l1_0;
t1_11=l1_0;
t1_20=l1_0+l1_11;
t1_21=l1_0+l1_11;
e1_0 = u1;
e1_1 = u1;


!ITEM 2:
NEW (l2_0*5 l2_11*2 u2);
```

```
t2_10=l2_0;
t2_11=l2_0;
t2_20=l2_0+l2_11;
t2_21=l2_0+l2_11;
e2_0 = u2;
e2_1 = u2;


!ITEM 3:
NEW (l3_0*5 l3_11*2);
NEW (l3_12*2 l3_212*0 u3);
t3_10=l3_0;
t3_20=l3_0+l3_12;
t3_30=l3_0+l3_11;
t3_40=l3_0+l3_12+l3_11+l3_212;
t3_11=l3_0;
t3_21=l3_0+l3_12;
t3_31=l3_0+l3_11;
t3_41=l3_0+l3_12+l3_11+l3_212;
e3_0 = u3;
e3_1 = u3;


!ITEM 4:
NEW (l4_0*5 l4_11*2);
NEW (l4_12*2 l4_212*0 u4);
t4_10=l4_0;
t4_20=l4_0+l4_12;
t4_30=l4_0+l4_11;
t4_40=l4_0+l4_12+l4_11+l4_212;
t4_11=l4_0;
t4_21=l4_0+l4_12;
t4_31=l4_0+l4_11;
t4_41=l4_0+l4_12+l4_11+l4_212;
e4_0 = u4;
e4_1 = u4;


!ITEM 5:
NEW (l5_0*5 l5_11*2 u5);
t5_10=l5_0;
t5_11=l5_0;
t5_20=l5_0+l5_11;
t5_21=l5_0+l5_11;
```

```
e5_0 = u5;
e5_1 = u5;


!ITEM 6:
NEW (l6_0*5 l6_11*2);
NEW (l6_12*2 l6_212*0 u6);
t6_10=l6_0;
t6_20=l6_0+l6_12;
t6_30=l6_0+l6_11;
t6_40=l6_0+l6_12+l6_11+l6_212;
t6_11=l6_0;
t6_21=l6_0+l6_12;
t6_31=l6_0+l6_11;
t6_41=l6_0+l6_12+l6_11+l6_212;
e6_0 = u6;
e6_1 = u6;


!ITEM 7:
NEW (l7_0*5 l7_12*2 u7);
t7_10=l7_0;
t7_11=l7_0;
t7_20=l7_0+l7_12;
t7_21=l7_0+l7_12;
e7_0 = u7;
e7_1 = u7;


!ITEM 8:
NEW (l8_0*5 l8_11*2 u8);
t8_10=l8_0;
t8_11=l8_0;
t8_20=l8_0+l8_11;
t8_21=l8_0+l8_11;
e8_0 = u8;
e8_1 = u8;


!ITEM 9:
NEW (l9_0*5 l9_12*2 u9);
t9_10=l9_0;
t9_11=l9_0;
t9_20=l9_0+l9_12;
t9_21=l9_0+l9_12;
```

```
e9_0 = u9;
e9_1 = u9;

!ITEM 10:
NEW (l10_0*5 l10_12*2 u10);
t10_10=l10_0;
t10_11=l10_0;
t10_20=l10_0+l10_12;
t10_21=l10_0+l10_12;
e10_0 = u10;
e10_1 = u10;


!ITEM 11:
NEW (l11_0*5 l11_12*2 u11);
t11_10=l11_0;
t11_11=l11_0;
t11_20=l11_0+l11_12;
t11_21=l11_0+l11_12;
e11_0 = u11;
e11_1 = u11;


!ITEM 12:
NEW (l12_0*5 l12_11*2);
NEW (l12_12*2 l12_212*0 u12);
t12_10=l12_0;
t12_20=l12_0+l12_12;
t12_30=l12_0+l12_11;
t12_40=l12_0+l12_12+l12_11+l12_212;
t12_11=l12_0;
t12_21=l12_0+l12_12;
t12_31=l12_0+l12_11;
t12_41=l12_0+l12_12+l12_11+l12_212;
e12_0 = u12;
e12_1 = u12;


!ITEM 13:
NEW (l13_0*5 l13_11*2 u13);
t13_10=l13_0;
t13_11=l13_0;
t13_20=l13_0+l13_11;
t13_21=l13_0+l13_11;
```

```
e13_0 = u13;
e13_1 = u13;


!ITEM 14:
NEW (l14_0*5 l14_11*2 u14);
t14_10=l14_0;
t14_11=l14_0;
t14_20=l14_0+l14_11;
t14_21=l14_0+l14_11;
e14_0 = u14;
e14_1 = u14;
```