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Empirical Evaluation of Different Features of Design in Confirmatory Factor Analysis

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EMPIRICAL EVALUATION OF DIFFERENT FEATURES OF DESIGN
IN CONFIRMATORY FACTOR ANALYSIS

by

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Factor analysis (FA) is the study of variance within a group. Within-subject variance (WSV) is affected by multiple features in a study context, such as: the study experimental design (ED) and sampling design (SD), thus anything that influences or changes variance may affect the conclusions related to FA.

The aim of this study was to provide empirical evaluation of the influence of different aspects of ED and SD on WSV in the context of FA in terms of model precision and model estimate stability. Four Monte Carlo population correlation matrices were hypothesized based on different communality magnitudes (high, moderate, low, and mixed). Within each population matrix this study investigated: (a) variable-to-factor ratio (VTF) (4:1, 7:1, and 10:1) that were randomly sampled from a population of 100 indicator variables, and (b) subjects-to-variables ratio (STV) (2:1, 4:1, 8:1, 16:1, and 32:1).

Overall model precision (RQ1) of factor solutions was evaluated by the examination of chi-square value (χ^2) and overall model fit indices (OMF) after aggregating 1000 simulation replications in separate three-way ANOVAs. The procedure for measurement and structural mean invariance were conducted to compare the impact

of ED and SD on WSV among groups (RQ2 & 3) by examination of model stability and precision.

Study results showed that the precisions of the overall model fit indices TLI, CFI, and RMR were varying as a function of VTF, STV, h2, and their interaction. Whereas, the precisions of the overall model fit indices GFI, AGFI, and RMSEA were varying as a function of VTF, STV, and their interactions. Factorial invariance result revealed that stability and precision of the models were varying over increasingly levels of measurement and structural mean invariance as a function of VTF, STV, and their interactions. The researcher must determine the number of indicator variables that represent each latent trait and adequate sample size. This is a necessary consideration to obtain a precise and stable model.

Several restrictions were imposed on the study design: (a) Use of the normal distribution, and (b) complexity of the factor model. Future research should examine manipulating one or more of these design restrictions.

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CHAPTER I

INTRODUCTION

This chapter clarifies the statement of the problem including background information on the concept, and the literature related to what is known regarding communalities magnitudes (h^2), subject-to-variable (STV) ratio, variable-to-factor (VTF) ratio, and their interaction in the context of confirmatory factor analysis (CFA). It also discusses how the empirical conditions can influence h^2, STV, or VTF. The research significance and study justification, research objectives, and research questions are elaborated. The key concepts of the study are defined and, at the end of the chapter, a summary emphasizes the key points discussed in this chapter.

Statement of the Problem

Factor analysis (FA) is a useful and flexible analytic family of methods that plays a critically important role in many empirical applications. FA is the study of variance within a group, as opposed to statistical analysis, which focuses on partitioning variance among groups (Gorsuch, 1983). FA is extensively applied in education and behavioral science research. A recent two-year analysis (from 2003 to 2005) of the use of FA methods as indexed by the PsycINFO database revealed that more than 1,700 studies used some form of FA (Costello & Osborne, 2005). However, factor analysis is a generic term for a family of statistical techniques, including exploratory factor analysis (EFA) and confirmatory factor analysis (CFA).

The fundamental purpose of EFA is to identify unknown latent constructs in a relatively large set of measured indicator variables that can summarize (or reproduce) the observed covariance or correlations pattern among a set of indicator variables. EFA is used when the "investigator does not have a hypotheses, however vague, about the number or nature of the factors measured by the test" (Crocker & Algina, 1986, p. 304). EFA is often used when a researcher may not have specific expectations of the number of constructs or factors underlying the dimensional structure of the observed correlational pattern, or even in cases when the researcher has emergent ideas about the underlying dimensional structure of the observed correlational pattern among a larger set of indicator variables (Brown, 2015; Crocker & Algina, 1986; Gorsuch, 1983; Thompson, 2005). When conducting an EFA study or analysis, the researcher is faced with a multitude of methodological and technical decisions. For example, there are two different EFA statistical models to choose from: (a) the full component model, or (b) the common factor model (Gorsuch, 1983; McDonald, 1999; Widaman, 1993). The implications for choosing one relative to the other needs to be well understood by the researcher.

CFA is a form of factor analysis that tests hypotheses regarding how well the measured indicator variables represent the number of constructs (Gorsuch, 1983). CFA is a confirmatory method researchers can use to examine, evaluate, and/or test the number of hypothesized factors underlying the variance/covariances in a set of measured indicator variables. CFA allows the researcher to test hypothetical and plausible alternative latent variable structures for the observed indicator variance/covariances (Chapman & Feit, 2015). More recently, CFA has also been used in exploratory analyses too.

Both EFA and CFA attempt to understand variance of the observed indicator variables through studying within-subject variance (WSV). It is well understood that WSV is affected by multiple features of the study conduct, such as the study experimental design (ED) and the sampling design (SD). Thus, anything that influences or changes variance may affect the conclusions related to FA. Previous researches have isolated one or two elements within ED and SD (Garson, 2008; Jung & Lee, 2011; Velicer & Fava, 1998), but no single study can be found in the existing literature that provides a comprehensive examination of multiple WSV factors, yet this is precisely what a researcher must do when planning a WSV study.

To understand the impact of ED and SD or other influences on WSV, a systematic structure for evaluating WSV changes is necessary. One possibility to evaluate WSV systematically is to use factorial invariance (FIV) (Wu, Li, & Zumbo, 2007). Methods of FIV offer a structure that allows for disentangling measurement elements from structural elements in the factor model. Via FIV and evaluation of data-model fit, the impact of ED and SD on WSV can be compared among groups by examination of model precision and stability (Guadagnoli & Velicer, 1988; MacCallum, Widaman, Zhang, & Hong, 1999; Preacher & MacCallum, 2002).

Previous research has investigated the precisions of factor solutions by the examination of chi-square value (χ^2) and overall model fit indices (OMF) such as goodness-of- fit index (GFI), adjusted goodness-of-fit index (AGFI), Tucker-Lewis index (TLI), comparative fit index (CFI), root mean square error of approximation (RMSEA), and root mean square residual (RMR) (Brown, 2006; Gorsuch, 1983; MacCallum et al., 1999; Preacher & MacCallum, 2002). Overall model fit indices examined global

measures of data-model fit. Examinations of measurement invariance (MIV)—configural, weak, and strong—were used to evaluate model stability, whereas the examination of structural mean invariance (SIV) was used to evaluate model precision.

There are three key features of design that are of paramount importance and generally overshadow all of the technical decisions facing the researcher. These three features are (a) the selection of and number of indicator variables, (b) the nature and size of the sample, and (c) the communality magnitude. Understanding the impact of variable-to-factor ratio (VTF), sample size or subject-to-variable ratio (STV), and communalities (h^2) magnitude in FA analyses is relevant because these features affect the model precision and model estimate stability and operationalized (measured) latent variable (factor) variance, which determines model invariance of FA findings.

The benefit of FA is based on its ability to produce "stable, accurate, and interpretable estimates of factor loadings" (Preacher & MacCallum, 2002, p. 154). Therefore, understanding how VTF, STV, and h^2 interact in FA and how they possibly influence or change the model precision and model estimate stability and operationalized (measured) latent variable (factor) variance is the basic problem investigated in this dissertation.

The model precision in this dissertation is operationalized along psychometric lines, not statistical. Statistically, precision is inversely related to the standard error of the sampling distribution and is related to the minimizing the standard error of a statistic. Psychometrically, precision can mean this, but additionally, in a reliability context it can also refer to the accuracy of the estimator to be near (or the same) as the theoretical latent variable (e.g., the true score) (Allen & Yen, 1979). Thus as the standard error of

measurement decreases the precision/accuracy of the observed scores converges to the true score. Model estimate stability, is the ability of sample-based analysis to recover the population factor structure. However, no comprehensive study has been found in the existing literature that has systematically examined the incremental or combined impacts of two features of ED and SD and how best to estimate the model. Therefore, evaluating the impact of ED and SD effects on WSV in FA findings is the basis of the proposed Monte Carlo simulation study.

Background

ED: Variable-to-Factor (VTF) Ratio

Previous research indicates that CFA yields more precise results when each common factor is represented by multiple indicator variables in the analysis (e.g., MacCallum, Widaman, Zhang, and Hong, 1999; Velicer & Fava, 1998). While this concern is related to model identification (Fabrigar, Wegener, MacCallum, & Strahan, 1999; Velicer & Fava, 1998), this is not the focus presented here. Specifically, given an identified model, how does the sample and number of indicator variables inform the understanding of the latent factor? In spite of the importance of this question, it has not received great attention in the CFA literature (Velicer & Fava, 1998). Guadagnoli and Velicer (1988) concluded that the VTF ratio was important for factor stability with more indicator variables per factor yielding more stable result. However, the researchers who have investigated VTF ratio have not reached a mutual decision on an optimal VTF. For example, McDonald and Krane (1977, 1979) and Velicer and Fava (1998) concluded that a VTF of 3:1 is sufficient for factorial precision. Moreover, Fabrigar et al. (1999) found that 24.6% of the studies published in *Journal of Personality and Social Psychology*

(JPSP) and 34.4% of the studies published in *Journal of Applied Psychology* (JAP) have VTF ratio of 4:1 or less. However, other researchers who have investigated the effects of indicator variable sampling did not attempt to systematically manipulate conditions that could potentially affect pattern stability of CFA findings. The issue of variable sampling has been used extensively in conceptual development, but existing literature has received almost no empirical evaluation that generally has sampled indicator variables at random from the universe of variables. The assumption of random sampling is useful to minimize sampling issues and for developing generalizability rather than a prescription for applied research procedures.

SD: Subject-to-Variable (STV) Ratio

Previous research (Costello & Osborne, 2005; Fabrigar et al., 1999; Henson & Roberts, 2006) has found a mixed range in FA sample sizes as described by either the absolute size of the sample or the subject-to-variable ratio (STV). Henson and Roberts (2006) reviewed 60 studies utilizing FA and found the average minimum sample size was 42, and the minimum of STV ratio was 3.25:1, with most of the studies using a STV ratio less than 5:1. Similarly, Fabrigar et al. (1999) reviewed FA studies published in JPSP and JAP (from 1991 to 1995) and found that 18.9% of the published articles utilizing FA in JPSP and 13.8% in JAP had an average minimum sample size of 100 or less. Costello and Osborne (2005) examined publications utilizing FA from the PsychINFO database for two years between 2003 and 2005. They found that 15.4% of the studies reported STV from 10-20:1 and only 3% of the studies used a STV of 20-100:1. High absolute sample size or STV ratio is important to predict precise outcomes, increase the generalizability of the findings, and maximize the accuracy of population estimates (Osborne & Costello,

2004; Preacher & MacCallum, 2002). There are a variety of common practice rules of sample size in the literature. Most of these rules were not empirically based (Guadagnoli & Velicer, 1988). Moreover, a limited number of studies have empirically investigated the effect of STV on the model precision and model estimate stability.

SD: Communalities (h^2) Magnitude

The communality of a variable can be interpreted as the proportion of variation estimated by the common factors. Communalities range from 0 to 1, where 0 means that the factors do not explain any of the variance and 1 means that all of the variance is explained by the factors. A large value of communality suggests a strong effect by an underlying construct (Tabachnick & Fidell, 2013).

The magnitude of communality can be classified into four levels, high, moderate, low, and mixed. Hogarty, Hines, Kromrey, Ferron, and Mumford (2005) and MacCallum et al. (1999) considered communality magnitudes to be: (1) high if the h^2 variable is between 0.6 and 0.8, (2) mixed if the h^2 variable take is between 0.2 and 0.8, and (3) low if the h^2 variable is below 0.2. In contrast, Velicer and Fava (1998) consider a variable has a high level of communality if it has magnitude of 0.8 or greater.

Previous FA simulation studies, such as Coughlin (2013), randomly sampled communality values from the normal distribution, typically choosing values described as low, moderate, or high. However, the limited description of these methods reveals the possibility that the simulated communality values were not actually varied within each replication. Specifically, a communality estimate was sampled, but each replication used the same value or a normal distribution was created around the $h^2$from which a $h^2$was sampled.

Research Significance

FA attempts to understand variance of the observed indicator variables through studying WSV. Literature has well established that different aspects of ED and SD have influence on WSV. In the realm of FA, the model precision and model estimate stability and operationalized (measured) latent variable (factor) variance were the primary outcomes of the analysis. The significance of this research came from a systematic description of how ED and SD impact estimation of WSV. Previous researches have isolated one or two elements within ED and SD, but no single study can be found in the examined literature that provides a comprehensive investigation of these features, yet this is precisely what a researcher must do when planning a WSV study.

Study Objective

The aim of this study was to provide empirical evaluation of the influence of ED and SD on WSV in terms of model precision and model estimate stability relative to a known factor structure via Monte Carlo simulation. The experimental conditions under consideration were:

a. Variable-to-factor ratio (VTF).
b. Subject-to-variable ratio (STV).
c. Communality (h^2) magnitude.

Three features of design were manipulated:

a. Variable-to-factor ratio (4:1, 7:1, and 10:1) that were randomly sampled from a population of 100 indicator variables.
b. Subject-to-variable ratio 2:1 to 32:1 in multiple of 2 (2:1, 4:1, 8:1, 16:1, and 32:1).

c. Communality magnitude (high, moderate, low, and mixed).

Specifically, the following questions further refine the three conditions above relative to how each was evaluated.

Research Questions

1. Does the precision of the overall data-model fit vary as a function of the following conditions and their interactions in the simulated models:
   a. VTF ratio?
   b. STV ratio?
   c. h^2 magnitude?
2. Does the stability of the simulated models vary over increasingly levels of measurement invariance as a function of the following conditions and their interactions:
   a. VTF ratio?
   b. STV ratio?
   c. h^2 magnitude?
3. Does the precision of the simulated models vary in structural mean invariance as a function of the following conditions and their interactions:
   a. VTF ratio?
   b. STV ratio?
   c. h^2 magnitude?

Summary

This chapter clarified the statement of the problem and provided initial background information that will be elaborated in Chapter II. It discussed study features

that researchers must make decision regarding ED and SD, which influence or change WSV. Chapter II will elaborate on how these design features affect FA conclusions. Finally, this chapter introduced the research objectives and research questions.

Definitions

ED: Variable-to-Factor (VTF) ratio: The number of indicator variables that represent each latent trait (factor). For example, if there is 5-factor solution, and the VTF ratio is 10:1, then the number of indicator variables should be 10 × 5 = 50 variables.

SD: Subject-to-Variable (STV) ratio: The number of subjects that respond to each indicator variable. For example, if there are10 indicator variables, and the STV ratio is 15:1, then the number of subjects who should respond to all indicator variables 15 ×10 = 150 subjects.

SD: Communality: It is the "sum of squared loading (SSL) for a variable across factors" (Tabachnick & Fidell, 2013, p. 626).

CHAPTER II

LITERATURE REVIEW

This chapter presents the literature review for this study. It discusses the importance of factor analysis (FA) in social science, and how manipulated study design facets affect within-subject variance in FA, including: (a) experimental design (ED), which includes variable-to-factor ratio and underlying factor structure; and (b) sampling design (SD), which includes subject-to-variable ratio, and communality magnitude.

Factor Analysis in Social Science

FA is a technique used to understand within-group variance. FA is especially helpful in variable-rich social science research because it is often used to reduce the number of variables by identifying or testing whether a smaller set of factors can adequately reproduce the pattern of observed relationships among a larger set of independent variables.

Three major concerns have emerged repeatedly in the literature related to the use and interpretation of FA in social science research: (a) determining an adequate number of indicator variables to describe the latent trait; (b) factoring a sufficient sample size to have reasonable confidence in the precision and stability of the model estimate; and (c) establishing minimum communality levels to determine which indicator variables can represent a latent trait, especially in simulation studies (Barendse, Oort, & Timmerman, 2014; Costello & Osborne, 2005; Garson, 2012; Guadagnoli & Velicer, 1988; Hogarty et al., 2005; Jung & Lee, 2011; Jung & Takane, 2008; MacCallum et al., 1999; McDonald

& Krane, 1977, 1979; Micceri, 1989; Mîndrilă, 2010; Mundfrom, Shaw, & Tian, 2005; Nimon, 2012; Preacher & MacCallum, 2002; Rong, 2012; Velicer & Fava, 1998).

Experimental Design (ED)

Variable-to-Factor Ratio

FA assumes that the indicator variables used should be linearly related to one another. Otherwise, the number of extracted factors will be the same as the number of original variables (Gorsuch, 1983). Survey instrument length and number of variables differ based on discipline, purpose, sample frame, and method of data collection. Recently, the online survey has become an important method of data collection for many researchers and scholars for a variety of reasons (e.g., online surveys are easy to design, conduct, and sometimes they are the only option for data collection). According to SurveyMonkey ("How Many Questions Do People Ask?" 2011), the median length of its paid surveys was 10 questions. While industry-specific surveys and market-research surveys tend to have more questions, event surveys and just-for-fun surveys tend to be shorter (see Figure 1). If the length of the survey is about 10 questions or fewer, it can lead to a higher completion rate and increase the likelihood that people will choose to take the researcher's surveys in the future. More recent studies of factor analysis in the literature do not include the VTF ratio 10:1 in their investigations, nor how this number is relative to sample size or communality magnitude when factor analysis is conducted.

In factor analysis, observed indicator variables can be viewed as representing a sample of potential variables, all of which measure the same construct or factor (Velicer & Fava, 1998). Guadagnoli and Velicer (1988) examined the magnitude of the correlation between the observed variables and the factor components by manipulating sample size,

number of variables, number of components, and component saturation. They concluded that the VTF ratio was important for factor stability, with more variables per factor yielding a more stable result. MacCallum et al. (1999), partially confirmed this conclusion with findings that the necessary minimum indicator variables to attain factor solutions that are adequately stable relative to population factors is dependent on several aspects of any given study, including the level of communality and sample size. Similarly, Hogarty et al. (2005) found that when VTF ratio increased the factor analysis solution improved.

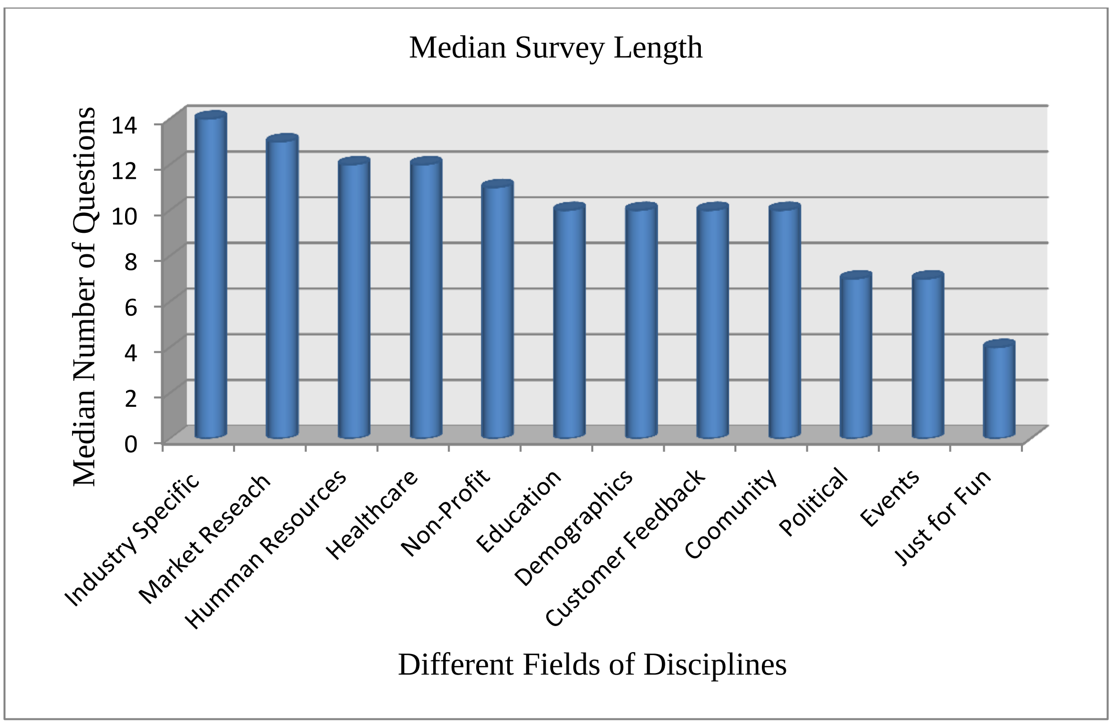


Figure 1. Median survey length in different fields of disciplines.

The issue of variable sampling has been used extensively in conceptual development, but has received almost no empirical evaluation of those that has sampled indicator variables at random from the universe of variables. The assumption of random

sampling is useful to minimize sampling issues and for developing generalizability rather than a prescription for applied research procedures. Fabrigar et al. (1999) examined the quality of factor analytic research published between 1999 and 2009 in five leading developmental disabilities journals. They found 35% of the studies used some form of FA; however, the guidelines for using FA were largely ignored and failed to account for levels of overdetermination and commonalities among measured variables. Furthermore, MacCallum et al. (1999) found that there was a lack of validity in some common practice rules used in FA. Thus, anything that influences or changes variance may affect the conclusions related to FA.

Researchers should determine an adequate number of indicator variables that is required to produce a stable and precise model in order to describe the latent trait. Velicer and Fava (1998) investigated the effects of indicator variables on pattern recovery to determine the sufficient number of indicator variables that is likely to produce patterns that closely approximate the population pattern. They reported that the number of indicator variables can strongly affect the degree to which a sample pattern reproduces the population pattern, and a minimum of three variables per factor is critical. The information about the adequate number of indicator variables that is required to produce a stable and precise model can be used in the design of a study and, retrospectively, in the evaluation of an existing study.

Underlying Factor Structure

In social science studies, researchers usually face a tremendous number of indicator variables, yet FA reduces the number of variables or explains underlying patterns of indictor variables by describing the variance among observed indicator

variables. The factor structural model (simple or complex) describes three types of relationships: the relationships among factors (oblique or orthogonal), the relationships among observed indicator variables, and the relationships between factors and observed indicator variables.

One of the broad domains in social science is the Big Five Personality Traits, which is used to describe human personality and includes extraversion, agreeableness, openness, conscientiousness, and neuroticism. Most commonly used in academic psychology, this model incorporates five different factors into a conceptual model for describing personality traits (Goldberg, 1992; John & Srivastava, 1999). It has been selected as the structural model for this study because of its wide use in social science.

There are many different scales that represent the Big Five Personality Traits. Goldberg (1992) developed a test that uses the Big-Five Factor Markers from the International Personality Item Pool. The test contains 50 items, thus the VTF ratio is 10:1, which is the same median number of indicator variables in online surveys.

The model structure of the Big Five Personality Traits theory has received favorable attention from researchers in the psychological discipline. “The Five Factor Model, of course, posits that there is structural to individual differences in human behavior, such that the traits of personality can be reduce to five orthogonal factors of personality—the so-called Big Five” (Paunonen & Jackson, 2000, p. 821). Saucier (2002) also concluded that the measurement structure of the Big Five Personality Traits is an orthogonal solution and the variation on each one of the Big Five Personality Traits dimensions is commonly proposed to be independent of variation on each of the others.

Sampling Design (SD)

Subject-to-Variable Ratio

Determining sample size requirements for factor analysis is complicated because it is dependent on other aspects of design, such as VTF and h^2. Previous studies in FA revealed several approaches that have been used to propose guidelines for the sample sizes. However, most of these approaches were concerned with identifying either the subject-to-variable ratio or the absolute sample size, regardless of the effect of these rules on WSV. The following examples describe some of what has been studied about sample size in the context of factor analysis.

The researcher must determine the adequate sample size. This is a necessary consideration in order to obtain a stable and precise model. There is no consensus regarding the ideal sample size or subject-to-variable ratio. Previous studies have suggested that the required sample size be determined as a function of the STV ranging from 3:1 to 20:1; these studies used either artificial or empirical data to investigate the sample size (Everitt, 1975; Garson, 2008; Guadagnoli & Velicer, 1988; Hogarty et al., 2005; Kunce, Cook, & Miller, 1975; MacCallum et al., 1999; Marascuilo & Levin, 1983).

There are a variety of common practice rules of sample size in the literature. Most of these rules were not empirically based (Guadagnoli & Velicer, 1988). A limited number of studies have empirically investigated the effect of sample size on the model precision and model estimate stability. Hogarty et al. (2005) investigated the relationship between sample size and the quality of factor solutions obtained from FA. The results showed that with high communalities magnitude, sample size tended to have less influence on the quality of factor solutions than when communalities are low.

Previous studies of the sample size question in factor analysis have taken a mathematical framework to determine the influence of sample size on the model stability. In particular, MacCallum et al. (1999) presented a theoretical and mathematical framework that concludes that an adequate sample size fundamentally depends on facets of design, e.g., level of communality and level of overdetermination. In addition, they found that sample size is relative to determining the level of power. However, Guadagnoli and Velicer (1988) found that “sample size was not an important factor in determining stability” (p. 265).

A larger sample size is better than a smaller sample size because it is minimizes misfit and the probability of errors. In many cases, increasing the sample size may not be possible. In medical research, it is very difficult to collect a large sample of patients suffering from a certain disease (Jung & Lee, 2011). Investigating the minimum STV ratio or small absolute sample size to obtain the precision and stability of the model is necessary. Only a very limited number of studies on the role of sample size in factor analysis have investigated real or simulated small sample size. De Winter, Dodou, and Wieringa (2009) investigated the minimum sample size necessary to obtain reliable factor solutions under various conditions. They concluded that under the conditions of high communality, high number of observed variables, and small number of factors, FA yields a stable estimates model for sample sizes below 50.

Selecting the adequate sample size is an important decision in study design. A researcher must determine how large the sample should be and what is the most appropriate sampling frame. Literature has proposed tremendous guidelines for estimating an adequate sample size for FA. One problem is that these recommendations

vary dramatically. MacCallum et al. (1999) reported, “Clearly the wide range in these recommendations causes them to be of rather limited value to empirical researchers” (p. 85). Yet, there is a need to conduct studies examining systematically the model precision and model estimate stability latent variable variance with different facets of DE and SD.

Communality Magnitude

Communality is the sum of the squared factor loadings for observed variables variances accounted for by all the factors (Tabachnick & Fidell, 2013). The communality measures the percent of variance in observed variables explained by all the factors. The larger the communality for each variable, the more successful the factor analysis solution is. The smaller the communality, the more questionable the solution (Tabachnick & Fidell, 2013). Communality takes a range between 0 and 1; if the communality exceeds 1.0, there is something wrong with data, which may reflect model specification or SD problems. Low values of communalities across the set of observed variables indicate the variables are marginally related to each other and the factors provide little explanation of variances in the observed variables (Garson, 2008; Tabachnick & Fidell, 2013).

The effects of communality magnitude in FA have been mostly vague. Studies have revealed a varied range of communality magnitude and common practice rules (Garson, 2008; Hatcher, 1994; Hogarty et al., 2005; MacCallum et al., 1999; Stevens, 2002; Velicer & Fava, 1998). The communality measures the percent of variance in a given variable explained by the factors. If communalities are high, model stability in the sample data is normally very good (MacCallum, Widaman, Preacher, & Hong, 2001). Hogarty et al. (2005) investigated the quality of factor solutions. They found that “when

communalities were high, sample size tended to have less influence on the quality of factor solutions than when communalities are low" (p. 202). Garson (2008) confirmed that communality magnitudes play an important role in determining adequate sample size. Moreover, Velicer and Fava (1998) found the communality magnitudes became most relevant in determining the sufficient sample size and the number of variables per component.

MacCallum et al. (1999) also conducted a Monte Carlo study on the effects of communality magnitudes and sample size stability of models. They found that when communalities were greater than 0.7, and with the overdetermination of factors, the results provide an excellent recovery of population factor structure. They suggested communalities should all be greater than 0.6, or the mean level of communality should be at least 0.7. Similarly, Marsh, Hau, Balla, and Grayson (1998) investigated levels of communality magnitudes and sample size in factor analysis. They found that the standard deviations of factor loading estimates decreased with increasing both the sample size and the indicator-to-factor ratio. Further, this decrease in variability of factor loadings was more pronounced for items with high communality than those with low communality.

Estimation Methods

Maximum Likelihood (ML)

ML is the most common method of factor extraction that "estimates population values for factor analysis by calculating loading that maximizes the probability of sampling the observed correlation matrix from a population" (Tabachnick & Fidell, 2013, p. 641) and is often used in CFA. The current study used ML as a method of factor extraction. Fabrigar et al. (1999) concluded that if data are normally distributed, ML is

the best estimation option because “it allows for the computation of a mixed range of indexes of the goodness of fit of the model” (p. 277). The ML estimation method assumes that data are independently sampled from a multivariate normal distribution with mean μ and variance-covariance matrix that takes this form: $\Sigma = LL' + \Psi$ where L is the matrix of factor loadings and ψ is the diagonal matrix of specific variances. Research by Mîndrilă (2010) has indicated that the ML estimation method is the most precise method when the data are continuous and normally distributed, but it does not provide accurate results with ordinal data or when data violate the assumption of multivariate normality.

Simulation Data

Simulation data are used in social science to answer a particular research question, solve a statistical problem, or improve analysis procedures techniques. Statistical program developers and research designers usually perform simulation data techniques for several reasons: gathering real data may be difficult, time-consuming, expensive, or real data sometime violate distributional assumptions. Simulation data “often leads to greater understanding of an analysis and the results one can expect from various oddities of real-life data” (Starkweather, 2012, p. 1). Simulation may approximate real-world results, yet requires less time and effort and gives the researcher a chance to experiment with data under various conditions.

Data can be simulated by several methods. The Monte Carlo technique is one popular method that has been used in social science since the 1940s (Tucker, Koopman, & Linn, 1969). A Monte Carlo simulation is a numerical technique that can be used to conduct experiments and repeated random sampling to simulate data for a given mathematical model.

Monte Carlo techniques have received a great deal of investigative study and development. Paxton, Curran, Bollen, Kirby, and Chen (2001) conducted a study to illustrate the design and implementation of a Monte Carlo simulation. They presented nine steps in preparing and performing a Monte Carlo simulation technique:
"(1) developing a theoretically derived research question of interest, (2) creating a valid model, (3) designing specific experimental conditions, (4) choosing values of population parameters, (5) choosing an appropriate software package, (6) executing the simulations, (7) file storage, (8) troubleshooting and verification, and (9) summarizing results" (pp. 288-289).

The Monte Carlo simulation technique is often used for methodological investigations of the performance of statistical estimators under varieties of conditions. It is an empirical and flexible method for evaluating statistics. Thus, parameters of the population model and sampling distribution can be created in relevant statistics (Paxton et al., 2001).

Model Precision and Model Estimate Stability

A limited number of studies have been conducted to understand data-model precision and model estimate stability (Meade & Bauer, 2007). Precision is the measurement of how close the data values are to each other for a number of measurements under the same quantity display. Precision of data-model parameter estimates is a function of models' structure, data characteristics, and other related conditions. Stability is the ability of sample-based analysis to recover the population factor structure. Subject-to-variable ratio (STV) or number of factors (m) retained,

variable-to-factor ratio (VTF), and the communality magnitude (h^2) influence generalizability.

The current study attempted to further understand how the variance of the observed variables affects the FA solution by studying within-subject variance (WSV). It is well understood that WSV is affected by multiple features in the study being conducted, such as the study experiment design (ED) and sampling design (SD); thus anything that affects the model precision and model estimate stability may affect the conclusions related to FA.

The primary comparison employed for the overall model in this study was to evaluate model precision and model estimate stability relative to a known factor structure via Monte Carlo simulation. The examination of overall model fit indices (OMF) and chi-square (χ^2) were used to evaluate model precision. Measurement invariance (MIV) was used to evaluate stability among models, and the examination of structural mean invariance (SIV) was used to evaluate the precision among models. More details about the analysis procedures and how they align with the research questions are presented below.

Most existing empirical investigations provide results that are limited in scope, focusing on the limited types of analysis procedures. In previous research, the model precision or model estimate stability was evaluated by using only the summary of statistics or congruence coefficient. Recently, the study of factorial invariance has become a more popular method of analysis in social science studies. When conducting a multiple-group confirmatory factor analysis, factorial invariance should be in place. If a

researcher establishes factorial invariance, then he or she is measuring the same construct across groups or across time (Millsap & Meredith, 2007).

Procedure for Testing Model Precision

Chi-square value and overall model fit indices were used to answer research question one. Table 1 illustrates the procedure for testing model precision starting with a CFA model relative to a known factor structure for each condition involved in the study separately.

Table 1

Procedure for Testing Model Precision

Test Name	Symbols	Statistics Guidelines	Resources
Chi-square value	χ^2		
Goodness-of-fit index	GFI	GFI ≥ 0.9 good fit	(Schumacker & Lomax, 1996)
Adjusted goodness-of-fit index	AGFI	AGFI ≥ 0.9 good fit	(Schumacker & Lomax, 1996)
Tucker-Lewis index	TLI	TLI ≥ 0.96 good fit	(Brown, 2006; Hu & Bentler, 1999)
Comparative fit index	CFI	CFI > 0.95 good fit	(Hu & Bentler, 1999)
Root mean square error of approximation	RMSEA	RMSEA: 0.00 - 0.05 very good fit RMSEA: 0.05 - 0.08 fair fit RMSEA: 0.08 - 0.10 mediocre fit	(Steiger, 1989)
Root mean square residual	RMR	RMR ≤ 0.05 good fit RMR > 0.05 unacceptable fit	(Byrne, 1998; Diamantopoulos & Siguaw, 2000)

Goodness-of-fit index (GFI). GFI measures the amount of variation in the observed covariance matrix that is predicted by the reproduced covariance matrix. GFI

values range between 0 and 1, where 1 denotes a perfect model fit and 0 denotes no fit. The common practice rules suggest that a GFI greater than or equal to 0.9 is considered a good fit (Schumacker & Lomax, 1996).

Adjusted goodness-of-fit index (AGFI). AGFI adjusts the GFI for degrees of freedom of the model relative to the number of indicator variables. AGFI takes a range between 0 and 1, where 1 denotes a perfect model fit and 0 denotes no fit. The common practice rules suggest that an AGFI greater than or equal to 0.9 is considered a good fit (Schumacher & Lomax, 1996).

Tucker-Lewis index (TLI). TLI referred to as the non-normed fit index (NNFI) (Bentler & Bonnett, 1980). TLI is computed by using ratios of the model chi-square and the null model chi-square and degrees of freedom for the models. It has a value that ranges between approximately 0 and 1.0, and TLI may be larger than 1 or slightly below 0. Values of the TLI close to 1.0 suggest a good fit. Brown (2006) and Hu and Bentler (1999) suggested that TLI $\geq$ 0.96 is a good fit as well.

The comparative fit index (CFI). The common practice rules by Hu and Bentler (1999) suggest guidelines for the interpretation of CFI: a value greater than roughly .95 or higher may indicate reasonably good fit of the model.

Root mean square error of approximation (RMSEA). The RMSEA is currently the most popular measure of model fit and it is based on the non-centrality parameter. RMSEA estimates the amount of error of approximation per model degree of freedom and takes sample size into account. The guidelines by Steiger (1989) suggest for the interpretation of RMSEA that values in the range of 0.00 to 0.05 indicate very good

fit, values between 0.05 and 0.08 indicate fair fit, and values between 0.08 and 0.10 indicate mediocre fit. RMSEA values above 0.10 indicate unacceptable fit.

Root mean square residual (RMR). It represents the closeness of the reproduced covariance matrix to the observed covariance matrix, and common practice rules suggest a value of RMR less than or equal to 0.05 is considered a good fit, whereas values greater than 0.05 indicate an unacceptable fit (Byrne, 1998; Diamantopoulos & Siguaw, 2000).

Procedure for Testing Stability Across Models

The procedure for testing measurement invariance was performed to answer the second research question in order to evaluate the variation over increasingly levels of measurement invariance among models. There were different approaches that could be used to evaluate the measurement invariance among groups. The present study used a *multiple-group confirmatory factor analysis* (MGCFA) model to test invariance among levels of STV ratios. Table 2 illustrates the order for testing measurement invariance starting with configural invariance (model 0). Model testing was evaluated by the chi-square difference test ($\Delta\chi^2$) between two groups (Brown, 2006; Byrne, 1998), and RSMA, CFI, and TLI were used to evaluate the all model fits. As previously referenced, the following criteria values suggested by Hu and Bentler (1999) and Schumacker and Lomax (1996) were used in this study: RMSEA: 0.00 - 0.05 very good fit, CFI > 0.95 good fit, and TLI ≥ 0.96 good fit. Three levels of MIV were tested:

Configural invariance (model 0) indicates that across groups, the pattern of group1 and group2 is equivalent $\lambda^1_{\text{group}} = \lambda^2_{\text{group}} = \cdots = \lambda^{\text{g}}_{\text{group}}$ where, λ represents the number of factor patterns across g^{th} groups. Configural invariance at best indicates that the group factors are similar but gives no indication that they hold measurement

equivalence. $\Delta\chi^2$ was used to judge configural invariance. For instance, if the χ^2 was not significant, the indicator variables loaded to the same factors across the groups. In other words, there were no differences in factor construct between the groups.

Weak measurement invariance (model 1) indicates that across groups, corresponding factor loadings are equivalent, $\lambda_J^{\text{group1}} = \lambda_J^{\text{group2}} = \cdots = \lambda_J^{\text{groupg}}$, where $\lambda_J^{\text{group1}}$represents the factor loading of j^{th} indicator variable in the group. Factor loadings represent the direct effect of the latent construct on each indicator variable, and factor loadings are represented by lambda (λ) (Thompson, 2005). At this level, weak measurement invariance, variables were loaded to the same factors across the group and the factor loadings across groups were equal. $\Delta\chi^2$ was used to judge weak invariance. For instance, if the χ^2 was not significant, the factor loadings across groups were equal. In other words, there were no differences in the factor loading of the indicator variables and their construct between the groups.

Strong measurement invariance (model 2) means that across groups, corresponding indicators' means are equivalent, $\tau_j^{\text{group1}} = \tau_j^{group2} = \cdots = \tau_j^{g\text{roupg}}$, where τ represents the intercept (means) of j^{th} indicator variable in the group. At this level, strong measurement invariance, indicator variables were loaded to the same factors across the groups; factor loading and indicators intercepts across groups were equal. $\Delta\chi^2{}_{M2-M1}$was used to judge strong invariance. For instance, if the χ^2 wass not significant, the variables intercepts across groups were equal.

Table 2

Procedure for Testing Stability and Precision Among Models

Baseline Model		Parameter Constrained to be Equal	Test Name	Null Hypothesis	Symbol	$\Delta\chi^2$ Test	Test Statistics Guidelines
Model 0	Measurement Invariance (MIV)	Equal factor pattern	Configural invariance	$H_0: \lambda^1_{\mathrm{group}} = \lambda^2_{\mathrm{group}} = \cdots = \lambda^{\mathrm{g}}_{\mathrm{group}}$	λ: The number of factor patterns across g^{th} groups		If $\Delta\chi^2$ NS, model shows configural factorial invariance in place
Model 1		Equal factor loading	Weak measurement invariance	$H_0: \lambda_{\mathrm{J}}^{\mathrm{group1}} = \lambda_{\mathrm{J}}^{\mathrm{group2}} = \cdots = \lambda_{\mathrm{J}}^{\mathrm{groupg}}$	$\lambda_{\mathrm{J}}^{\mathrm{group1}}$: The factor loading of j^{th} indicator variable in the group	${\Delta\chi^2}_{M1-M0}$	If $\Delta\chi^2$ NS, model shows weak factorial invariance in place
Model 2		Equal intercept	Strong measurement invariance	$H_0: \tau_{\mathrm{j}}^{\mathrm{group1}} = \tau_{\mathrm{j}}^{group2} = \cdots = \tau_{\mathrm{j}}^{groupg}$	τ: The indicator variables intercept (means) of j^{th} indicator variable in the group	${\Delta\chi^2}_{M2-M1}$	If $\Delta\chi^2$ NS, model shows strong factorial invariance in place
Model 3	Structural Invariance (SIV)	Equal latent mean	Structural means invariance	$H_0: \xi_{\tau j}^{group1} = \xi_{\tau j}^{group2} = \cdots = \xi_{\tau j}^{groupg}$	$\xi_{\tau j}^{th}$: The mean of latent j in across groups	${\Delta\chi^2}_{M3-M2}$	If $\Delta\chi^2$ NS, model shows equal structural means in place

Procedure for Testing Precision Across Models

The procedure for testing structural mean invariance was performed to answer the third research question. The present study used the *multiple-group confirmatory factor analysis* (MGCFA) to test structural invariance among levels of STV ratios. Model testing was evaluated by the chi-square difference test ($\Delta\chi^2$) between two groups (Brown, 2006; Byrne, 2004), and RSMA, CFI, and TLI were used to evaluate the all model fits.

Structural means invariance (model 3) refers to the differences between groups in the latent means, $\xi_{\tau j}^{group1} = \xi_{\tau j}^{group2} = \cdots = \xi_{\tau j}^{groupg}$, where $\xi_{\tau j}^{th}$ is the mean of latent *j* across groups. $\Delta\chi^2{}_{M4-M2}$was used to judge mean structure invariance. For instance, if the $\Delta\chi^2$ was not significant, the latent means across groups were equal.

Summary

This chapter presented the literature review of the present study. It discussed the importance of factor analysis (FA) in social science, and how manipulated and non-manipulated study design facets affect within-subject variance in FA, including (a) experimental design (ED), which includes variables-to-factor ratio and underlying factor structure; and (b) sampling design (SD), which includes subject-to-variable ratio and communality magnitude.

CHAPTER III

METHODOLOGY

This chapter presents the research design and methodology to investigate empirical evaluation of the influence of different aspects of ED and SD on WSV in terms of model precision and model estimate stability relative to a known factor structure via Monte Carlo simulation. Evaluation of model fit, statistical analysis, and pilot study illustrated the validity of the procedures used in this study were examined.

Study Design

The study was designed to investigate empirical evaluation of the influence of different aspects of ED and SD on WSV in terms of model precision and model estimate stability and operationalized (measured) latent variable (factor) variance relative to a known factor structure via Monte Carlo simulation. To directly address the research questions, this study manipulated: (a) variable-to-factor ratio (4:1, 7:1, and 10:1) that were randomly sampled from a population of 100 indicator variables, (b) subject-to-variable ratio of 2:1 to 32:1 in multiple of 2 (2:1, 4:1, 8:1, 16:1, and 32:1), and (c) communality magnitude (high, moderate, low, and mixed). These factors were varied in a known factor structure with: (a) continuous variables (measurement scale), (b) normal distribution, (c) 5-factor solutions (common factor), and (d) orthogonal solution (factor structure). Specifically, the following questions further refine the study conditions above.

1. Does the precision of the overall data-model fit vary as a function of the following conditions and their interactions in the simulated models:

a. VTF ratio?

b. STV ratio?

c. h^2 magnitude?

The precision of factor solution RQ1 was evaluated by examination of CFA for an orthogonal 5-factor (common factor) model. Chi-square value and overall model fit indices criteria were used to evaluate models across all conditions. The Monte Carlo simulation populated 60 cells of the three-way between subjects factorial design matrix: h^2 (high, moderate, low, and mixed) by VTF ratio (4:1, 7:1, and 10:1) by STV ratio (2:1, 4:1, 8:1, 16:1, and 32) with 1000 replicate samples. Chi-square value and six overall model fit indices (GFI, AGFI, RMSEA, TLI, CFI, and RMR) were treated as dependent variables (DVs) in three-way ANOVAs using level of communalities magnitudes, variable-to-factor ratio, and subject-to-variable ratio as independent variables. Figure 2 illustrates the design used to answer RQ1.

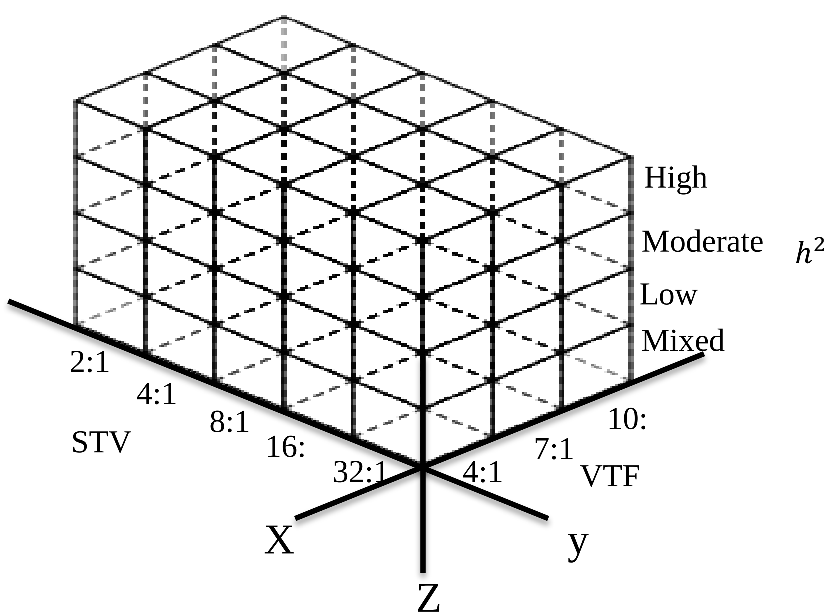


Figure 2. Design of interactions conditions in research question 1.

2. Does the stability of the simulated models vary over increasingly levels of measurement invariance as a function of the following conditions and their interactions:
    a. VTF ratio?
    b. STV ratio?
    c. h^2 magnitude?

Multiple-group confirmatory factor analysis (MGCFA) was used to test measurement invariance among levels of STV ratios in order to evaluate model stability for RQ2. Model testing was evaluated by the chi-square difference test ($\Delta\chi^2$) between two groups (Brown, 2006; Byrne, 1998), and RSMA, CFI, and TLI were used to evaluate all model fits. Figure 3 illustrates the RQ2 design. Measurement invariance of the STV levels, as shown in Table 3, were examined in each cell of the h^2*VTF study.

	High			
	Moderate			
h^2	Low			
	Mixed			
		4:1	7:1	10:1
			VTF	

Figure 3. Design of interactions conditions in research question 2 and 3.

3. Does the precision of the simulated models vary in structural mean invariance as a function of the following conditions and their interactions:

a. VTF ratio?

b. STV ratio?

c. h^2 magnitude?

Multiple-group confirmatory factor analysis (MGCFA) was used to test structural mean invariance among levels of STV ratios in order to evaluate model precision for RQ3. Model testing was evaluated by the chi-square difference test ($\Delta\chi^2$) between two groups (Brown, 2006; Byrne, 1998), and RSMA, CFI, and TLI were used to evaluate all model fits. Figure 3 illustrates the RQ3 design. Structural mean invariance of the STV levels, as shown in Table 3, were examined in each cell of the h^2*VTF study.

Table 3

Order of Invariance Testing Among Levels of STV

Step	Models	Step	Models	Step	Models	Step	Models
(4)	2:1 vs 4:1						
(3)	2:1 vs 8:1	(7)	4:1 vs 8:1				
(2)	2:1 vs 16:1	(6)	4:1 vs 16:1	(9)	8:1 vs 16:1		
(1)	2:1 vs 32:1	(5)	4:1 vs 32:1	(8)	8:1 vs 32:1	(10)	16:1 vs 32:1

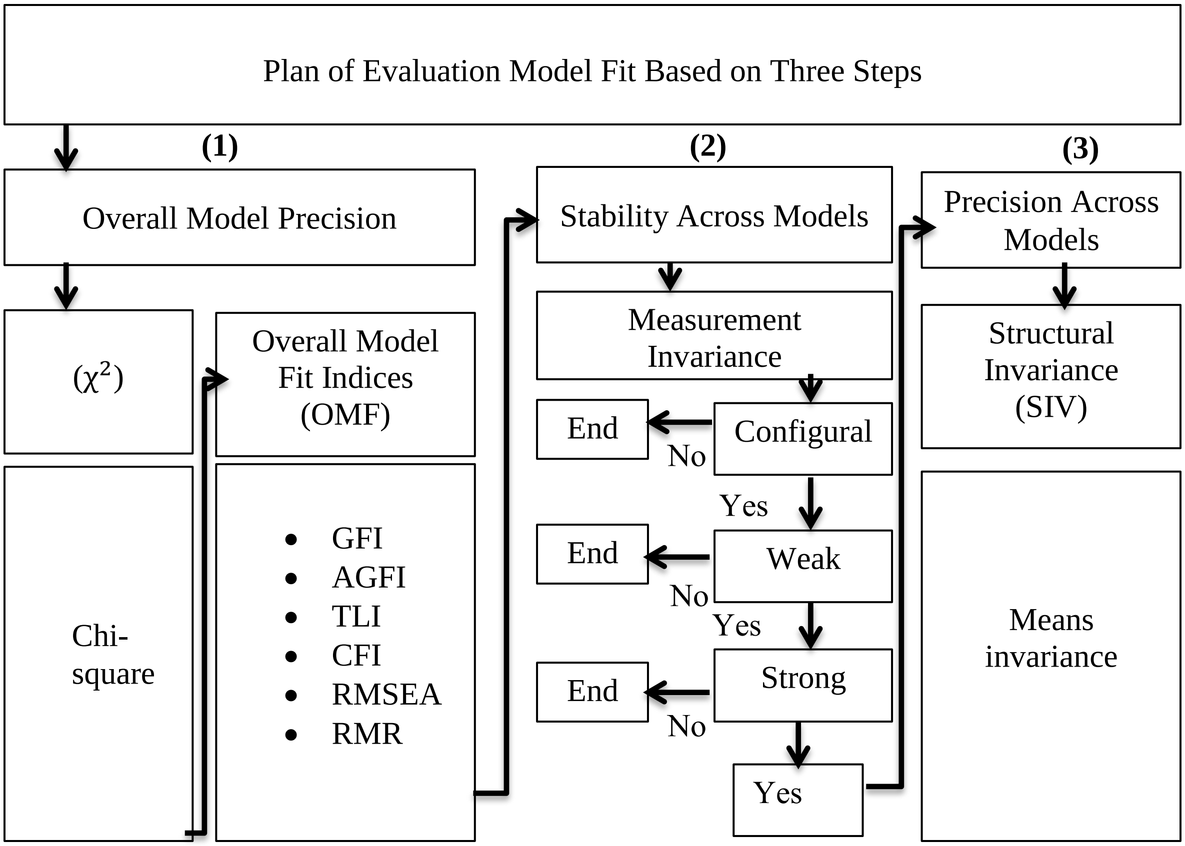
Evaluating Model Fit

Based on the research questions the primary comparison employed for the overall model in this study was to evaluate model precision and model estimate stability. Figure 4 describes the three steps of the evaluation procedure: (1) estimation precision (RQ1) was examined via overall model fit indices (OMF) and chi-square (χ^2) for each condition, (2) measurement invariance (MIV) tests evaluated model stability (RQ2), and

(3) structural mean invariance (SIV) tests evaluated model precision (RQ3). Recently, the study of factorial invariance has become more popular in social science studies. When conducting multiple-group confirmatory factor analysis, factorial invariance should be in place. If a researcher establishes factorial invariance, then he or she is measuring the same construct across groups or across time (Millsap & Meredith, 2007).

Research Question 1

The precision of factor solution was evaluated by examination of CFA for an orthogonal 5-factor (common factor) model. Chi-square value and overall model fit indices criteria were used to evaluate models across all conditions. The following criteria suggested by Hu and Bentler (1999) and Schumacker and Lomax (1996) were used in this study: GFI $\geq$ 0.9 is good fit, AGFI $\geq$ 0.9 is good fit, RMSEA: 0.00 - 0.05 is very good fit, CFI > 0.95 is good fit, TLI $\geq$ 0.96 is good fit, and RMR $\leq$ 0.05 is good fit. Chi-square value and six overall model fit indices (GFI, AGFI, RMSEA, TLI, CFI, and RMR) were treated as dependent variables (DVs) in three-way ANOVAs using level of communalities magnitudes, variable-to-factor ratio, and subject-to-variable ratio as independent variables. Separate parallel univariate ANOVAs were conducted. To control for multiplicity among DVs a type I error rate was adjusted by a Bonferroni correlation: .05/7=0.007.



Symbols are:

- Goodness-of-fit index (GFI)
- Adjusted goodness-of-fit index (AGFI)
- Tucker-Lewis index (TLI)
- The comparative fit index (CFI)
- Root mean square error of approximation (RMSEA)
- Root mean square residual (RMR)

Figure 4. Life-cycle steps of the analysis procedures to evaluate models.

Research Question 2

Multiple-group confirmatory factor analysis (MGCFA) was used to test measurement invariance among levels of STV ratios. Several null hypotheses described below were required:

a. Configural invariance: the pattern across groups was equivalent $\lambda_{\mathrm{group}}^{1} = \lambda_{\mathrm{group}}^{2} = \cdots = \lambda_{\mathrm{group}}^{\mathrm{g}}$

b. Weak measurement invariance: across groups, corresponding factor loadings were equivalent, $\lambda_{\mathrm{J}}^{\mathrm{group1}} = \lambda_{\mathrm{J}}^{\mathrm{group2}} = \cdots = \lambda_{\mathrm{J}}^{\mathrm{groupg}}$

c. Strong measurement invariance: across groups, corresponding indicator means were equivalent, $\tau_{\mathrm{j}}^{\mathrm{group1}} = \tau_{\mathrm{j}}^{group2} = \cdots = \tau_{\mathrm{j}}^{g\mathrm{roupg}}$

Model testing was evaluated by the chi-square difference test ($\Delta\chi^2$) between two groups (Brown, 2006; Byrne, 1998), and RSMA, CFI, and TLI were used to evaluate all model fits. As previously referenced, the following criteria values suggested by Hu and Bentler (1999), and Schumacker and Lomax (1996) were used in this study: RMSEA: 0.00 - 0.05 is very good fit, CFI > 0.95 is good fit, and TLI ≥ 0.96 is good fit.

Research Question 3

Multiple-group confirmatory factor analysis (MGCFA) was used to test structural invariance among levels of STV ratios. The null hypothesis described below was required for testing the structural means invariance:

Differences between groups in the latent means were equal, $\xi_{\tau j}^{group1} = \xi_{\tau j}^{group2} = \cdots = \xi_{\tau j}^{groupg}$

Model testing was evaluated by the chi-square difference test ($\Delta\chi^2$) between two groups (Brown, 2006; Byrne, 1998), and RSMA, CFI, and TLI were used to evaluate all model fits. As previously referenced, the following criteria values suggested by Hu and Bentler (1999) and Schumacker and Lomax (1996) were used in this study: RMSEA: 0.00 - 0.05 is very good fit, CFI > 0.95 is good fit, and TLI $\geq$ 0.96 is good fit. Additionally, RQ3 was examined via frequency analysis by tabulating a count of statistically significant chi-square values observed over the 1000 replications. The null proportion of replication failures was hypothesized to be $\pi = 0.05$. Specifically, no more than 5% of the replications should have resulted in a statistically significant chi-square statistic, e.g., $p <= 0.05$. Model fit indices RMSEA, CFI, and TLI were averaged over the 1000 replications.

Procedures

Data Generation

Based on prior methodological research in the field of factor analysis, the techniques of Tucker et al. (1969) with appropriate adaptations was used to generate four Monte Carlo population correlation matrices based on communality magnitudes (high, moderate, low, and mixed) with 100 indicator variables in each matrix. The population matrices were generated with the following characteristics: (a) continuous variables (measurement scale), (b) normal distribution, (c) 5-factor solutions (common factor), and (d) orthogonal solution (factor structure) as shown in Figure 5. Four correlation matrices for each level of VTF ratio, 4:1, 7:1 and 10:1, were randomly sampled from each set of population correlation matrices. Using five systematically increased STV ratios (2:1, 4:1, 8:1, 16:1, and 32:1), data sets with 1000 replications for each level of VTF ratio were

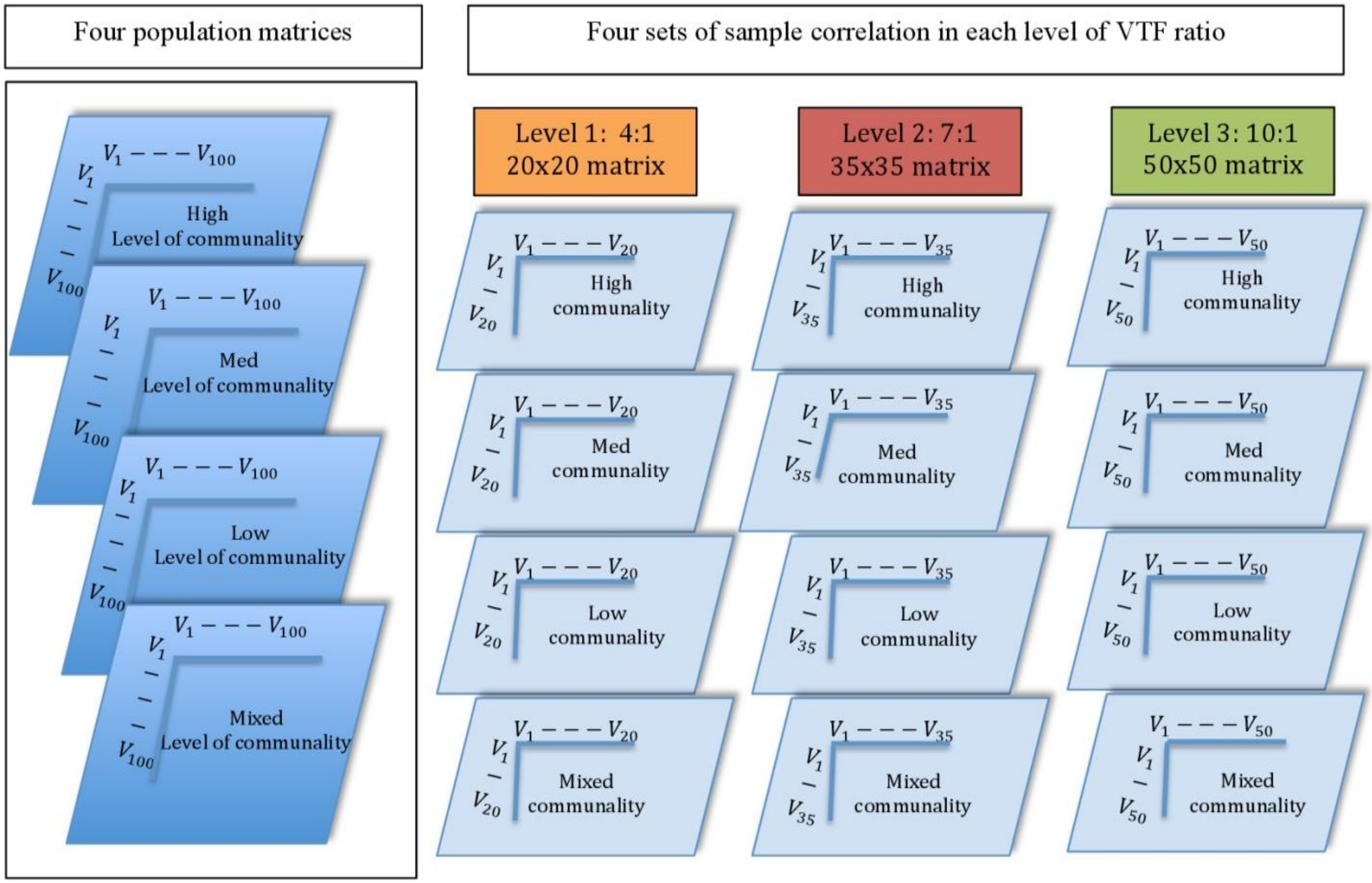


Figure 5. Procedures for data generation.

generated. Table 4 explains how to generate the sample data to answer the three research questions.

Table 4

Summary Description of Generating Sample Data

VTF	STV	Communality Magnitudes and Number of Subject			
		High	Moderate	Low	Mixed
	2:1	40	40	40	40
	4:1	80	80	80	80
4:1	8:1	160	160	160	160
	16:1	320	320	320	320
	32:1	640	640	640	640
	2:1	70	70	70	70
	4:1	140	140	140	140
7:1	8:1	280	280	280	280
	16:1	560	560	560	560
	32:1	1120	1120	1120	1120
	2:1	100	100	100	100
	4:1	200	200	200	200
10:1	8:1	400	400	400	400
	16:1	800	800	800	800
	32:1	1600	1600	1600	1600

Note. VTF = variable-to-factor ratio, STV = subject-to-variable ratio.

Generating Correlation Matrices

The present study used Monte Carlo simulation method to generate four 100×100 population correlation matrices that differed in communality magnitude. Based on prior methodological research in the field of factor analysis, the technique of Tucker et al. (1969), with appropriate adaptations. This method developed the data that generally have sampled indicator variables at random, from the universe of variables. The assumption of random sampling is useful to minimize sampling issues, and for developing generalizability rather than a prescription for applied research procedures

(Coughlin, 2013). The four population correlation matrices included 100 normally distributed random variables based on four levels of communality magnitude (high, moderate, low, and mixed) conforming to a 5-orthogonal-fac-or model.

The section below draws heavily from Tucker et al. (1969) and is paraphrased below, highlighting specific alterations that were made for this simulation. Moreover, the equations presented were taken directly from Tucker et al. (1969) and are included for the readers' benefit. Figure 6 illustrates the simulation technique implemented by Tucker et al. Tucker's simulation method begins by differentiating three types of factors: (1) major factor domain, which has influence on observed scores of individuals, (2) minor factor, and (3) unique factor. Minor and unique factors have influences outside the major factor domain. Tucker et al. (1969) said that:

> For each type of factor, there is a matrix A_s with entries of actual input factor loadings. There is a row in A_s for each variable and a column for each factor in section s of factors; thus, A_s is a matrix of order $J\ X\ M_S$. (p. 425)
>
> A matrix A_S^* is defined for each matrix A_s by adjusting the rows A_s to unit length vectors. A matrix P_s is defined from each A_S^* by:
>
> (1) $$P_s = A_S^* A_S^{*\prime}$$
>
> (2) $$Diag\ (P_s) = I,$$
>
> The simulation correlation matrix R is defined by:
>
> (3) $$R = B_1 P_1 B_1 + B_2 P_2 B_2 + B_3 P_3 B_3$$
>
> Where B_1, B_2, and (in general B_s) are diagonal matrices with entries $b_{1i}, b_{2i}, and\ b_{3i}$ (in general b_{si}). These entries b_{si} are restricted to being real, positive numbers such that:
>
> (4) $$b_{1i}^2 + b_{2i}^2 + b_{3i}^2 = 1$$
>
> A consequence of the restriction on rows of the matrices A_S^* to being unit vectors and, thus, of the diagonal entries in matrices P_s being unities as stated in (2) is that

(5) $$r_{ii} = 1;$$

$$Diag\ (R) = I,$$

> The matrix A_s of actual input factor loadings may be defined in terms of the matrices B_s and A_s^* by:
>
> (6) $$A_s = B_s A_s^*$$
>
> From (1), (3), and (6):
>
> (7) $$R = A_1 A_1' + A_2 A_2' + A_3 A_3'$$
>
> Where $(A_1 A_2 A_3)$ is a supermatrix containing the matrices A_1, A_2, AND A_3as horizontal sections. Note that the constructed matrix R has the formal properties, required for a correlation matrix, of having unit diagonal entries and being symmetric, positive, and semi-definite. (p. 425)
>
> Coefficients in the B_s matrices are important parameters of the simulation model, functioning to regulate the proportions of the variances of the variables derived from the three types of factors. When B_2 is zero, the simulation model is identical with the formal model and B_1^2 contains the communalities while B_3^2contains the uniquenesses of the variables. (p. 426)

The key point of the simulation model is the development of the matrices A_s for a 5-factor domain as an example of the factor types (major, minor, and unique) through a three-step process. To create population matrix with 100 indicator variables some adjustments were made in the Tucker et al. (1969) technique and the SAS code written by Coughlin (2013) to ensure that each factor receives 20 loadings of indicator variables using the follow guidelines:

1. Four is upper limit of sum loadings in each indicator variable; that means if the first loading obtained is 4, the other four loadings are 0.
2. Indicator variables from 1 to 20 restricted to load factor one, indicator variables from 21 to 40 restricted to load factor two, indicator variables 41 to 60 restricted to load factor three, indicator variables from 61 to 80 restricted to

load factor four, and indicator variables from 81 to 100 restricted to load factor five. In addition, Tucker et al. (1969) described that:

A three step procedure was utilized to develop the matrix A_1 of actual input factor loadings for the major factor domain from the matrix A_1' of conceptual input factor loadings. First, relative conceptual input loadings were developed for the variable, which constituted a row vector, then, the vector was adjusted to unit length by a multiplying factor. (P. 428)

(8) $$(y_1)_{jm1} = (\tilde{a}_1)_{jm1} c_{m1} + d_{1i} x_{jm1} (1 - c_{m1}^2)^{1/2}$$

where

1. $(\tilde{a}_1)_{jm1}$ is the entry in row j and column m_1 of the matrix $\widetilde{A}_1$.
2. x_{jm1} is a random normal deviate $(\mu = 0, \sigma = 1)$.
3. c_{m1} is the constant of each factor m_1 and it is limited in the range of 0 to 1
4. d_{1i} is a constant for each indicator variables j, and the constant d_{1i} normalizes row of x_{jm1} to unit length vector and is defined by:

(9) $$d_{1i} = (\textstyle\sum_{m1} x_{im1}^2)^{-1/2}$$

The second step, in development of actual input factor loadings; the translation process includes a skewing function that limits negativity in factor loadings $(\tilde{a}_1)_{jm1}$. This function yields coefficients $(z_1)_{jm1}$ as following:

(10) $$(z_1)_{jm1} = \frac{(1+k)}{(2+k)} \frac{(y_1)_{jm1}[(y_1)_{jm1} + |(y_1)_{jm1}| + k]}{[|(y_1)_{jm1}| + k]}$$

Where k is the parameter, value is chosen within the range of 0 to infinity, and each vector of $(z_1)_{jm1}$ is adjusted to unit length by the following:

(11) $$(a_1^*)_{jm1} = g_{1i} (z_1)_{jm1}$$

Where

(12) $$g_{1i} = [\textstyle\sum_{m1} (z_1)^2{}_{jm1}]^{-1/2}$$ (p. 430)

The third step “ensure[s] desired levels of communality” (Hogarty et al., 2005, p. 207).

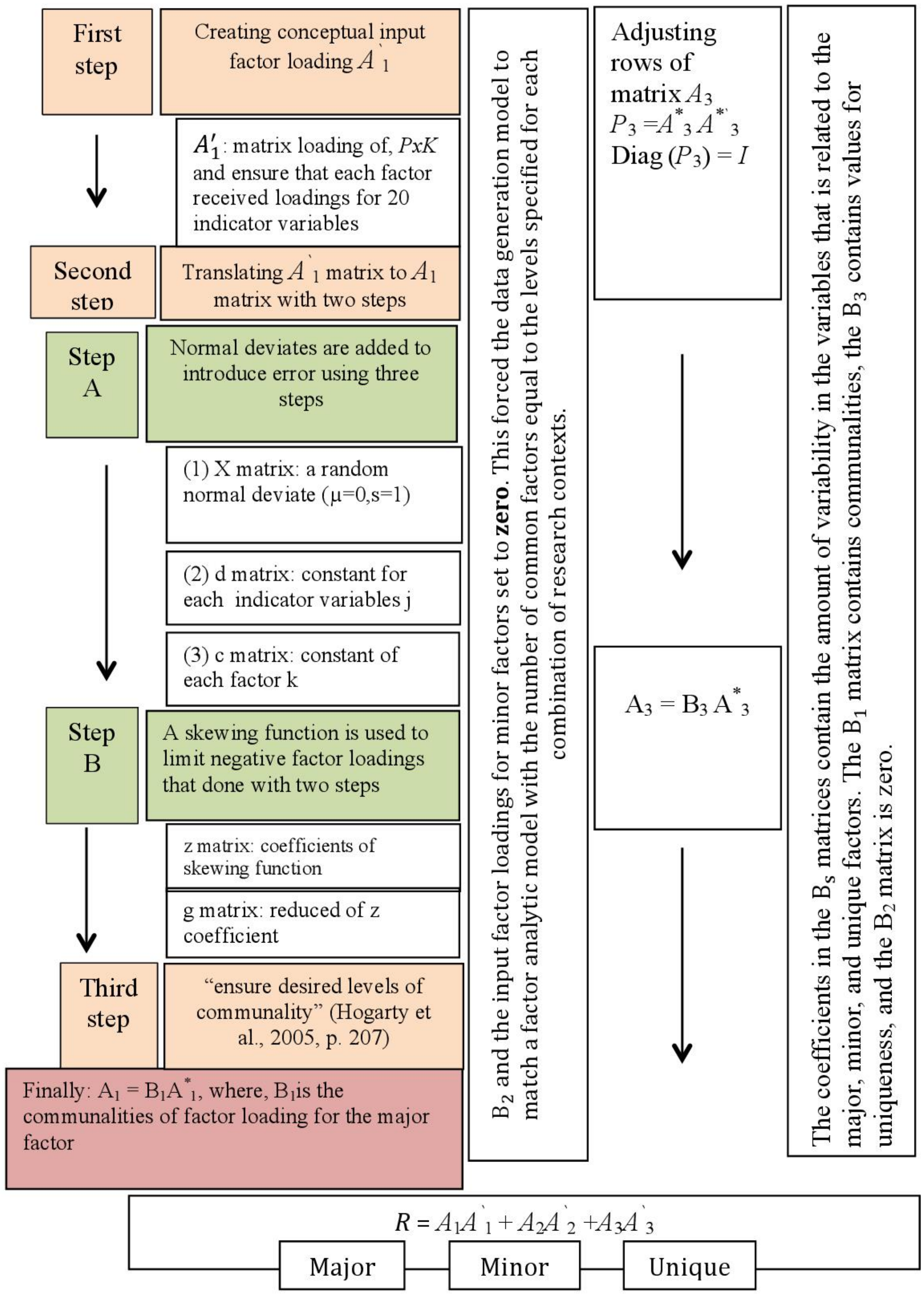


Figure 6. Summary of simulation procedures.

Summary of Data Generation

The aim of this study was to provide empirical evaluation of the influence of ED and SD on WSV in terms of model precision and model estimate stability. The current study used the techniques of Tucker et al. (1969) to generate Monte Carlo population correlation matrices. Figure 7 presents a description for a summary of the generated and evaluated data sets. The simulation was generated in SAS 9.4 and the IML code was adapted from the study conducted by Coughlin (2013) to contain all aspects of ED and SD. The procedure of generating data incorporated the following conditions:

1. Four range of communality magnitudes (high, moderate, low, and mixed).
2. Three sample correlation matrices of variables (20, 35, and 50) were randomly partitioned from each set of population correlation matrices to represent three levels of VTF ratio (4:1, 7:1, and 10:1).
3. For each sample correlation matrix, systematic variation of STV ratios (2:1, 4:1, 8:1, 16:1, and 32:1) generated data sets with 1000 replication.

Presentation of the Simulation

This section illustrates three steps of the procedures for generating population correlation matrices. Each population matrix represents one level of communality (low, high, moderate, and mixed) and 100 indicator variables with characteristics as follows: (a) continuous variables (measurement scale), (b) normal distribution, (c) 5-factor solutions (common factor), and (d) orthogonal solution (factor structure). The following example illustrates the procedure for generating a high communality population correlation matrix, and the raw data drawn from it.

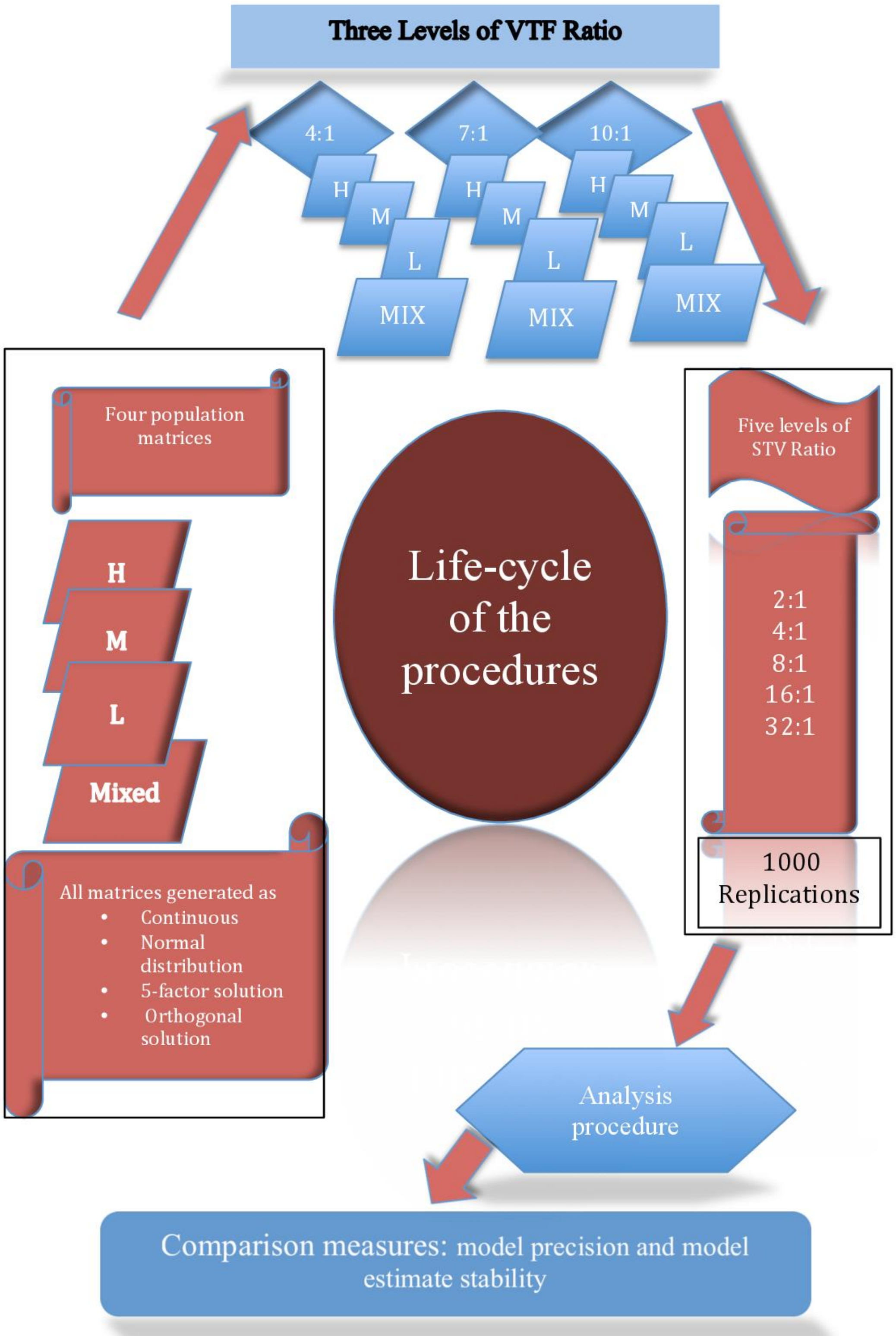


Figure 7. Summary of generation and analysis of all data.

Step 1: Generating Population Matrix

The first phase in the simulation procedure is identifying the communality level. This simulation is based on high communality magnitude. Figures A1 and A2 in Appendix A exhibit four different areas under normal distribution that represent four different types of communalities. The values were randomly selected to represent each type of communality in simulation data (see SAS code in Appendix D).

The central part of simulation model is the development of the matrices of A_s (conceptual input factor loadings $\tilde{A}_s$, and actual input factor loadings A_s) of five common factors. Table 5 presents $\tilde{A}_1$the matrix of conceptual factor input loadings for the first five indicator variables in each factor loading, where four is the upper limit of sum loadings in each indicator variable. That means if the first loading obtained is 4, the other four loadings are 0.

Based on equations from (8) to (12), the translating process of conceptual input factor loadings matrix $\tilde{A}_1$ to actual input factor loadings matrix A_1 requires the incorporation of variation and discrepancies. This process includes random normal deviates, constants for each factor, and a constant for each indicator variable. Table 6 presents the final estimates of these processes for the first five indicator variables in each factor loading. Table 7 shows the communalities of the same first five indicator variables in which the unique factors influence the variability in the 100 indicator variables. Table 8 contains the population correlation matrix for the first 10 observed indicator variables in each factor loading.

Table 5

Conceptual Input Factor Loadings $\tilde{A}_1$

Variables	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
1	4	0	0	0	0
2	4	0	0	0	0
3	4	0	0	0	0
4	4	0	0	0	0
5	4	0	0	0	0
⋮	⋮	⋮	⋮	⋮	⋮
21	0	4	0	0	0
22	0	4	0	0	0
23	0	4	0	0	0
24	0	4	0	0	0
25	0	4	0	0	0
⋮	⋮	⋮	⋮	⋮	⋮
41	0	0	4	0	0
42	0	0	4	0	0
43	0	0	4	0	0
44	0	0	4	0	0
45	0	0	4	0	0
⋮	⋮	⋮	⋮	⋮	⋮
61	0	0	0	4	0
62	0	0	0	4	0
63	0	0	0	4	0
64	0	0	0	4	0
65	0	0	0	4	0
⋮	⋮	⋮	⋮	⋮	⋮
81	0	0	0	0	4
82	0	0	0	0	4
83	0	0	0	0	4
84	0	0	0	0	4
85	0	0	0	0	4

Table 6

Actual Input Factor Loadings A_1

Variables	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
1	0.7746	0	0	0	0
2	0.8944	0	0	0	0
3	0.8366	0	0	0	0
4	0.9486	0	0	0	0
5	0.9487	0	0	0	0
⋮	⋮	⋮	⋮	⋮	⋮
21	0	0.8944	0	0	0
22	0	0.9487	0	0	0
23	0	0.9485	0	0	0
24	0	0.8944	0	0	0
25	0	0.7746	0	0	0
⋮	⋮	⋮	⋮	⋮	⋮
41	0	0	0.9486	0	0
42	0	0	0.7746	0	0
43	0	0	0.8367	0	0
44	0	0	0.8366	0	0
45	0	0	0.7745	0	0
⋮	⋮	⋮	⋮	⋮	⋮
61	0	0	0	0.7745	0
62	0	0	0	0.9486	0
63	0	0	0	0.9487	0
64	0	0	0	0.7746	0
65	0	0	0	0.9487	0
⋮	⋮	⋮	⋮	⋮	⋮
81	0	0	0	0	0.9486
82	0	0	0	0	0.8944
83	0	0	0	0	0.9486
84	0	0	0	0	0.8367
85	0	0	0	0	0.7745

Table 7

Values of Factor Input Loadings (Factors Communalities) A_3 *for the First Five of Indicator Variables in Each Factor Loadings*

Variables	Communalities
1	0.7746
2	0.8944
3	0.8366
4	0.9486
5	0.9487
⋮	⋮
21	0.8944
22	0.9486
23	0.8944
24	0.7745
25	0.8366
⋮	⋮
41	0.9486
42	0.7746
43	0.8366
44	0.7745
45	0.8944
⋮	⋮
61	0.7746
62	0.9487
63	0.9486
64	0.7745
65	0.9486
⋮	⋮
81	0.9487
82	0.8944
83	0.9486
84	0.8366
85	0.7745

Table 8

Population Correlation Matrix for Only the First 10 Observed Indicator Variables

	1	2	3	4	5	6	7	8	9	10
1	1									
2	0.693	1								
3	0.648	0.629	1							
4	0.735	0.645	0.685	1						
5	0.734	0.573	0.634	0.714	1					
6	0.692	0.623	0.788	0.883	0.827	1				
7	0.693	0.660	0.640	0.618	0.877	0.693	1			
8	0.648	0.624	0.788	0.782	0.832	0.799	0.628	1		
9	0.708	0.729	0.671	0.671	0.759	0.669	0.724	0.670	1	
10	0.649	0.660	0.604	0.893	0.604	0.877	0.619	0.887	0.698	1

Step 2: Generating Sample Correlation Matrix

After correlation population matrix was generated to represent high range of communality magnitude, three sample correlation matrices of variables (20, 35, and 50) were randomly partitioned from each set of population correlation matrices to represent three levels of VTF ratio (4:1, 7:1, and 10:1).

Step 3: Generating Raw Data Set

For each sample correlation matrix, systematic variation of STV ratios (2:1, 4:1, 8:1, 16:1, and 32:1) to generate raw data sets with 1000 replications yielded 60,000 raw data sets.

Summary

This chapter has presented the research design and methodology to investigate empirical evaluation of influence of different aspects of ED and SD on WSV in terms of model precision and model estimate stability. It then has described research methods and Monte Carlo technique to generate correlation matrices, and evaluation model fit procedures. An example of the simulation population correlation matrix was presented to illustrate the validity of data generation procedures that were used in this study.

CHAPTER IV

RESULTS

This chapter presents the results of the data analysis for this study. The aim of this study was to provide empirical evaluation of the influence of ED and SD on WSV in terms of model precision and model estimate stability relative to a known factor structure. The experimental conditions under consideration were:

a. Variable-to-factor ratio (VTF).

b. Subject-to-variable ratio (STV).

c. Communality (h^2) magnitude.

Specifically, the following questions further refine the three conditions above relative to how each was evaluated.

1. Does the precision of the overall data-model fit vary as a function of the following conditions and their interactions in the simulated models:

    a. VTF ratio?

    b. STV ratio?

    c. h^2 magnitude?

The precision of factor solution was evaluated by examination of CFA for an orthogonal 5-factor (common factor) models. Chi-square value and overall model fit indices criteria were used to evaluate models across all conditions with the following criteria: Goodness-of-fit index (GFI) values range between zero and one, where one denotes a perfect model fit and zero denotes no fit. The common practice suggests that if

GFI greater than or equal to 0.9 is considered a good fit (Schumacker & Lomax, 1996). Adjusted goodness-of-fit index (AGFI) adjusts the GFI for degrees of freedom of the model relative to the number of indicator variables. AGFI takes a range between zero and one, where one denotes a perfect model fit and zero denotes no fit. The common practice suggests that if AGFI greater than or equal to 0.9 is considered a good fit (Schumacher & Lomax, 1996). Tucker-Lewis index (TLI) is usually referred to as the non-normed fit index (NNFI) (Bentler & Bonnett, 1980). It has a value that ranges between approximately 0 and 1.0, and TLI may be larger than 1 or slightly below 0. Values of the TLI close to 1.0 suggest a good fit. Comparative fit index (CFI) is one in a class of fit statistics, which are among the least commonly used statistics in SEM. The common practice by Hu and Bentler (1999) suggested guidelines for the interpretation of CFI: a value roughly .95 or higher may indicate reasonably good fit of the model. Root mean square error of approximation (RMSEA) is currently the most popular measure of model fit and it is based on the non-centrality parameter. The guidelines by Steiger (1989) suggest for the interpretation of RMSEA: values in the range of 0.00 to 0.05 indicate very good fit, values between 0.05 and 0.08 indicate fair fit, and values between 0.08 and 0.10 indicate mediocre fit. RMSEA values above 0.10 indicate unacceptable fit. Root mean square residual (RMR) represents the closeness of the reproduced covariance matrix to the observed covariance matrix, and as indicated in common practice, a value of RMR less than or equal to 0.05 is conceded a good fit, whereas values greater than 0.05 indicate unacceptable fit.

2. Does the stability of the simulated models vary over increasingly levels of measurement invariance as a function of the following conditions and their interactions:
    a. VTF ratio?
    b. STV ratio?
    c. h^2 magnitude?

The stability of the simulated models was evaluated by examination of measurement invariance (MIV). Three levels of MIV were tested:

Configural invariance (model 0) indicates that across groups, the pattern of group1 and group2 is equivalent $\lambda^1_{\mathrm{group}} = \lambda^2_{\mathrm{group}} = \cdots = \lambda^{\mathrm{g}}_{\mathrm{group}}$ where, λ represents the number of factor patterns across g^{th} groups. Configural invariance at best indicates that the group factors are similar but gives no indication that they hold measurement equivalence. $\Delta\chi^2$ was used to judge configural invariance. For instance, if the χ^2 was not significant, the indicator variables loaded to the same factors across the groups. In other words, there were no differences in factor construct between the groups.

Weak measurement invariance (model 1) indicates that across groups, corresponding factor loadings are equivalent, $\lambda^{\mathrm{group1}}_{\mathrm{J}} = \lambda^{\mathrm{group2}}_{\mathrm{J}} = \cdots = \lambda^{\mathrm{groupg}}_{\mathrm{J}}$, where $\lambda^{\mathrm{group1}}_{\mathrm{J}}$represents the factor loading of j^{th}indicator variable in the group. Factor loadings represent the direct effect of the latent construct on each indicator variable, and factor loadings are represented by lambda (λ) (Thompson, 2005). At this level, weak measurement invariance, variables were loaded to the same factors across the groups and the factor loadings across groups were equal. $\Delta\chi^2$ was used to judge weak invariance. For instance, if the χ^2 was not significant, the factor loadings across groups were equal. In

other words, there were no differences in the factor loading of the indicator variables and their construct between the groups.

Strong measurement invariance (model 2) indicates that across groups, corresponding indicators' means are equivalent, $\tau_j^{\text{group1}} = \tau_j^{group2} = \cdots = \tau_j^{groupg}$, where τ represents the intercept (means) of j^{th} indicator variable in the group. At this level, strong measurement invariance, indicator variables were loaded to the same factors across the groups; factor loading and indicator intercepts across groups were equal. $\Delta\chi^2{}_{M2-M1}$ was used to judge strong invariance. For instance, if the χ^2 was not significant, the variables' intercepts across groups were equal.

3. Does the precision of the simulated models vary in structural mean invariance as a function of the following conditions and their interactions:
   a. VTF ratio?
   b. STV ratio?
   c. h^2 magnitude?

The precision of the simulated models was evaluated by examination of structural mean invariance (SIV). Structural means invariance (model 3) refers to the differences between groups in the latent means, $\xi_{\tau j}^{group1} = \xi_{\tau j}^{group2} = \cdots = \xi_{\tau j}^{groupg}$, where, $\xi_{\tau j}^{th}$ is the mean of latent *j* across groups. $\Delta\chi^2{}_{M4-M2}$ was used to judge mean structure invariance. For instance, if the χ^2 was not significant, the latent means across groups were equal.

Results: Research Question 1

The Monte Carlo simulation populated 60 cells of three-way between subjects factorial design matrix: h^2 (high, moderate, low, and mixed) by VTF ratio (4:1, 7:1, and 10:1) by STV ratio (2:1, 4:1, 8:1, 16:1, and 32) with 1000 replicate samples (see Figure

2). Chi-square values and overall model fit indices (GFI, AGFI, RMSEA, TLI, CFI, and RMR) were treated as dependent variables (DVs) in parallel three-way ANOVAs. To control for multiplicity among DVs a type I error rate was adjusted by a Bonferroni correlation: .05/7=0.007.

Chi-square Test (χ^2)

Descriptive statistics for the chi-square values among all design cells are presented in Table 9.

Table 9

Descriptive Statistics for Chi-square Averaged Over 1000 Replications

		h^2							
VTF	STV	High		Moderate		Low		Mixed	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD
	2:1	220.06	23.89	219.86	24.60	219.37	23.41	220.42	23.53
	4:1	190.87	20.99	190.00	20.53	189.98	20.92	189.54	20.48
4:1	8:1	179.30	19.28	179.20	19.64	180.09	19.59	178.70	19.13
	16:1	174.21	19.25	174.41	18.70	174.69	19.18	174.07	18.33
	32:1	171.77	18.61	171.53	19.68	172.81	18.08	171.63	17.72
	2:1	709.50	43.65	709.71	42.05	705.16	43.12	709.22	42.58
	4:1	620.06	38.25	621.19	36.03	618.77	37.49	622.59	37.60
7:1	8:1	588.44	34.59	589.28	36.56	587.06	34.58	589.76	36.09
	16:1	573.35	34.51	574.42	34.97	573.77	34.94	574.10	34.05
	32:1	566.23	33.91	566.33	33.26	568.73	33.68	568.56	33.57
	2:1	1471.88	61.47	1469.46	59.60	1473.04	60.34	1472.52	60.92
	4:1	1298.02	55.87	1297.31	52.89	1296.04	53.45	1296.67	52.45
10:1	8:1	1231.67	49.54	1230.17	49.97	1228.86	51.12	1228.82	50.92
	16:1	1203.03	48.41	1203.64	50.24	1201.30	50.37	1201.90	48.66
	32:1	1186.37	47.61	1187.40	49.00	1188.81	50.89	1187.65	49.20

Note. h^2= communality magnitude; VTF = variable-to-factor ratio; STV = subject-to-variable ratio.

Overall ANOVA finding for the χ^2 revealed statistically significant model, $F(59, 59940) =137546$, $p <. 0001$. As can be seen in Table 10, there were statistically

significant results for main effects VTF and STV, and a statistically significant interaction between VTF*STV. Surprisingly, no statistically significant main effect or interaction involving communality was found. A complete ANOVA summary table is presented in Table B1 of Appendix B.

Table 10

Three-Way Analysis of Variance for χ^2 by Conditions

Conditions	*df*	*F*	*p-value*
h^2	3	0.49	0.6876
VTF	2	3967031	<. 0001
h^2*VTF	6	1.39	0.2143
STV	4	32825.9	<. 0001
h^2* STV	12	0.94	0.5024
VTF *STV	8	6224.92	<. 0001
h^2* VTF *STV	24	0.70	0.8589

Note. h^2 = communality magnitude; VTF = variable-to-factor ratio; STV = subject-to-variable ratio.

Post hoc analysis of VTF*STV interaction focused on splitting out the levels of STV and examined five one-way ANOVAs for the levels of VTF. Visual examination of the mean chi-square values suggests a small, but significant decreases in mean chi-square values as STV increases among all levels of VTF that decreased in magnitude as VTF increased (see Figure 8).

Table 11 presents the simple effect ANOVAs on VTF for each STV level. Pairwise comparisons among levels of VTF at each level of STV, e.g., VTF 4:1 vs. 7:1 @ STV=2:1, were statistically significant with all p-values <. 0001, and the directional pattern in means confirmed the decreasing trends seen in Figure 1.

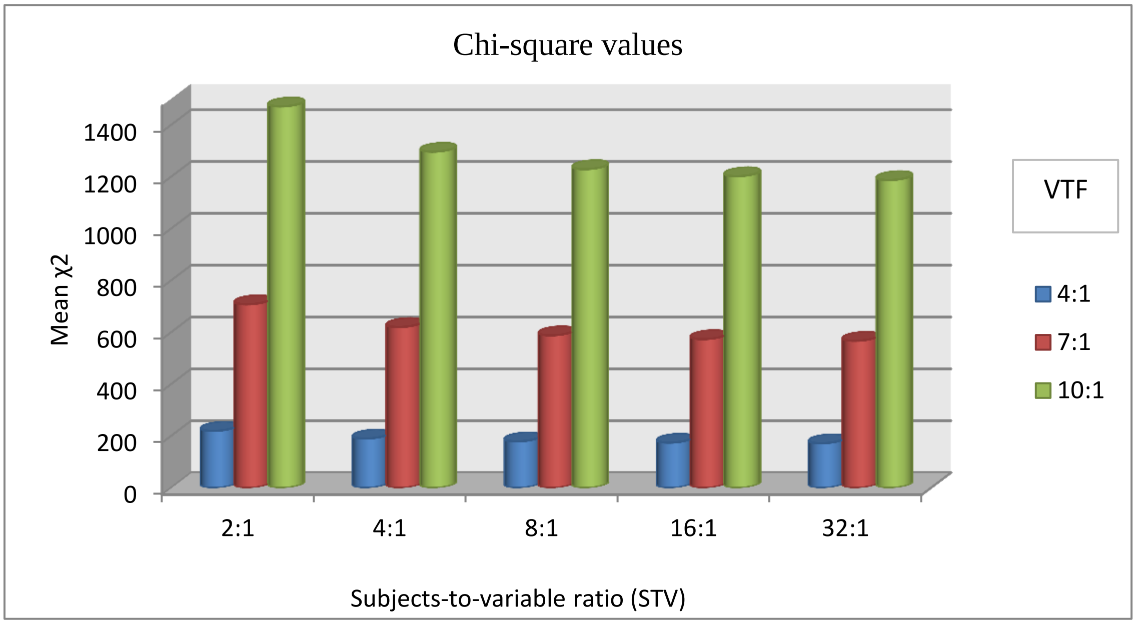


Figure 8. Chi-square mean values of interaction between STV and VTF ratios.

Table 11

One-Way Analysis of Variance Simple Effect of STV by Levels of VTF

STV	*df*	*SS*	*MS*	*F*	*p-value*
2:1	2	3184352017	1592176009	1045038	<. 0001
4:1	2	2490770164	1245385082	817419	<. 0001
8:1	2	2243166665	1121583332	736161	<. 0001
16:1	2	2149012490	1074506245	705261	<. 0001
32:1	2	2096571177	1048285588	688051	<. 0001

Goodness-of-Fit Index (GFI)

Goodness-of-fit index statistics were averaged over 1000 replication for the 60 cells in the three-way design are presented in Table 12. Additionally, the percentage of GFI statistics meeting the standard threshold of acceptable fit, e.g., >=. 90, was tabulated.

Table 12

Descriptive Statistics for Goodness-of- Fit Index Averaged Over 1000 Replications

		h^2							
VTF	STV	High		Moderate		Low		Mixed	
		Mean	P %	Mean	P %	Mean	P %	Mean	P %
	2:1	0.69	0.00	0.69	0.00	0.69	0.00	0.69	0.00
	4:1	0.82	0.00	0.82	0.00	0.82	0.00	0.82	0.00
4:1	8:1	0.90	65.60	0.90	65.70	0.90	61.60	0.90	68.00
	16:1	0.94	100.00	0.94	100.00	0.94	100.00	0.94	100.00
	32:1	0.97	100.00	0.97	100.00	0.97	100.00	0.97	100.00
	2:1	0.68	0.00	0.68	0.00	0.68	0.00	0.68	0.00
	4:1	0.81	0.00	0.81	0.00	0.81	0.00	0.81	0.00
7:1	8:1	0.90	28.80	0. 90	30.90	0. 90	31.70	0.90	28.60
	16:1	0.94	100.00	0.94	100.00	0.94	100.00	0.94	100.00
	32:1	0.97	100.00	0.97	100.00	0.97	100.00	0.97	100.00
	2:1	0.67	0.00	0.67	0.00	0.67	0.00	0.67	0.00
	4:1	0.80	0.00	0.80	0.00	0.80	0.00	0.80	0.00
10:1	8:1	0.90	7.60	0. 90	7.80	0. 90	9.10	0.90	8.80
	16:1	0.94	100.00	0.94	100.00	0.94	100.00	0.94	100.00
	32:1	0.97	100.00	0.97	100.00	0.97	100.00	0.97	100.00

Note. GFI = goodness-of-fit Index; h^2 = communality magnitude; VTF = variable-to-factor ratio; STV = subject-to-variable ratio; P = percentage of replications that met the criteria-of-fit index.

Overall ANOVA findings for GFI revealed an overall statistically significant model, $F(59, 59940) = 138368$, $p <. 0001$. As can be seen in Table 13, there were statistically significant main effects VTF and STV, and a statistically significant interaction between VTF*STV. Once again, the communality factor was not significant. The complete ANOVA summary table is presented in Table B2 of Appendix B.

Post hoc analysis of VTF*STV interaction focused on splitting out the levels of STV and examined five one-way ANOVAs for the levels of VTF. Visual examination of the mean GFI values suggests a significant increase in mean GFI values as STV increases mixed with decreasing mean GFI as VTF ratios increased (see Figure 9).

Table 13

Three-Way Analysis of Variance for GFI by Conditions

Conditions	*df*	*F*	*p-value*
h^2	3	1.27	0.2820
VTF	2	6671.43	<. 0001
h^2*VTF	6	1.52	0.1683
STV	4	2036352	<. 0001
h^2* STV	12	1.41	0.1534
VTF *STV	8	610.99	<. 0001
h^2* VTF *STV	24	0.85	0.6733

Note. h^2 = communality magnitude; VTF = variable-to-factor ratio; STV = subject-to-variable ratio.

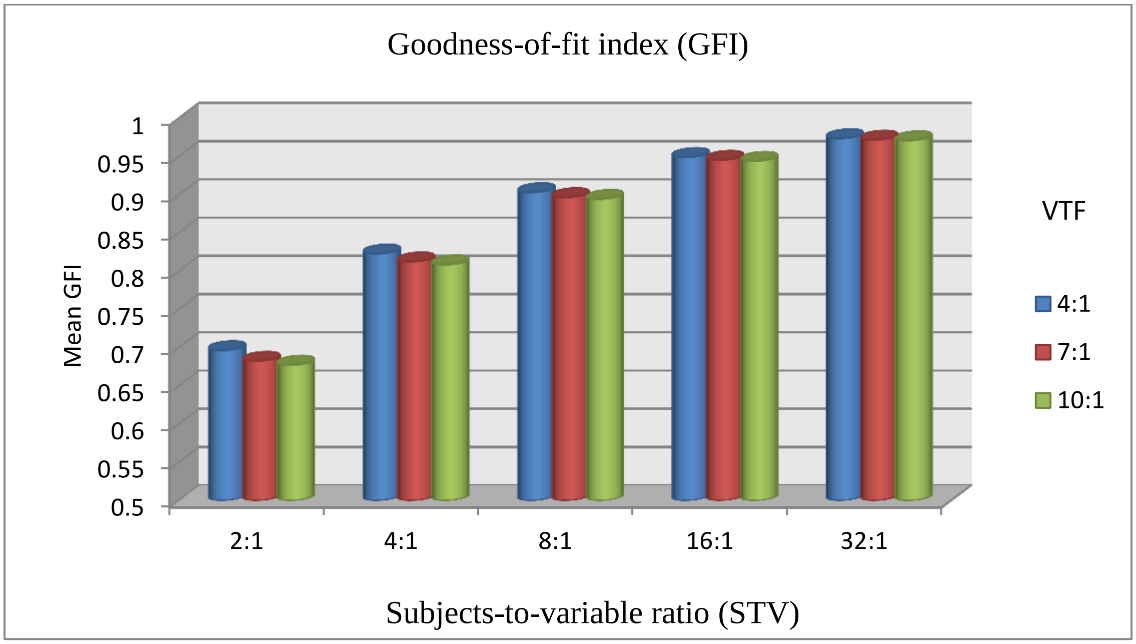


Figure 9. Goodness-of-fit index of interaction between STV and VTF ratios.

Table 14 presents the simple effect ANOVAs on VTF for each STV level. Pairwise comparisons among levels of VTF at each level of STV, e.g., VTF 4:1 vs. 7:1 @ STV=2:1, were statistically significant with all p-values <. 0001, and the directional pattern in means confirmed the patterns seen in Figure 2.

Table 14

One-Way Analysis of Variance Simple Effect of STV by Levels of VTF

STV	*df*	*SS*	*MS*	*F*	*p-value*
2:1	2	0.7851	0.3925	4941.23	<. 0001
4:1	2	0.4301	0.2150	2707.26	<. 0001
8:1	2	0.1641	0.0820	1032.93	<. 0001
16:1	2	0.0537	0.0268	338.14	<. 0001
32:1	2	0.0152	0.0076	95.83	<. 0001

Adjusted Goodness-of-Fit Index (AGFI)

Adjusted Goodness-of-fit index statistics were averaged over 1000 replication for the 60 cells in the three-way design are presented in Table 15. Additionally, the percentage of AGFI statistics meeting the standard threshold of acceptable fit, e.g., >=. 90, was tabulated.

Overall ANOVA findings for AGFI revealed an overall statistically significant model, $F(59, 59940) = 127526$, $p <. 0001$. As can be seen in Table 16, there were statistically significant main effects VTF and STV, and a statistically significant interaction between VTF*STV. Once again, the communality factor was not significant. The complete ANOVA summary table is presented in Table B3 of Appendix B.

Post hoc analysis of VTF*STV interaction focused on splitting out the levels of STV and examined five one-way ANOVAs for the levels of VTF. Visual examination of the mean AGFI values suggests a significant increase in mean AGFI values as STV increases mixed with decreasing mean AGFI as VTF ratios increased (see Figure 10).

Table 15

Descriptive Statistics for Adjusted Goodness-of-Fit Index Averaged Over 1000 Replications

		h^2							
VTF	STV	High		Moderate		Low		Mixed	
		Mean	P %	Mean	P %	Mean	P %	Mean	P %
	2:1	0.62	0.00	0.62	0.00	0.62	0.00	0.62	0.00
	4:1	0.78	0.00	0.78	0.00	0.78	0.00	0.78	0.00
4:1	8:1	0.88	4.30	0.88	4.70	0.88	4.10	0.88	4.80
	16:1	0.93	100.00	0.93	100.00	0.93	100.00	0.93	100.00
	32:1	0.96	100.00	0.96	100.00	0.96	100.00	0.99	100.00
	2:1	0.64	0.00	0.64	0.00	0.64	0.00	0.64	0.00
	4:1	0.78	0.00	0.78	0.00	0.79	0.00	0.78	0.00
7:1	8:1	0.88	0.40	0.88	0.40	0.88	0.20	0.88	0.30
	16:1	0.93	100.00	0.93	100.00	0.93	100.00	0.93	100.00
	32:1	0.96	100.00	0.96	100.00	0.96	100.00	0.96	100.00
	2:1	0.65	0.00	0.65	0.00	0.65	0.00	0.64	0.00
	4:1	0.79	0.00	0.79	0.00	0.79	0.00	0.79	0.00
10:1	8:1	0.88	0.00	0.88	0.00	0.88	0.10	0.88	0.00
	16:1	0.93	100.00	0.93	100.00	0.93	100.00	0.93	100.00
	32:1	0.96	100.00	0.96	100.00	0.96	100.00	0.96	100.00

Note. AGFI = adjusted goodness-of- fit index; h^2 = communality magnitude; VTF = variable-to-factor ratio; STV = subject-to-variable ratio; P = percentage of replications that met the criteria-of-fit index.

Table 16

Three-Way Analysis of Variance for AGFI by Conditions

Conditions	*df*	*F*	*p-value*
h^2	3	1.14	0.3316
VTF	2	3619.03	<. 0001
h^2*VTF	6	1.42	0.2012
STV	4	1877402	<. 0001
h^2* STV	12	1.39	0.1606
VTF *STV	8	889.92	<. 0001
h^2* VTF *STV	24	0.87	0.6514

Note. h^2 = communality magnitude; VTF = variable-to-factor ratio; STV = subject-to-variable ratio.

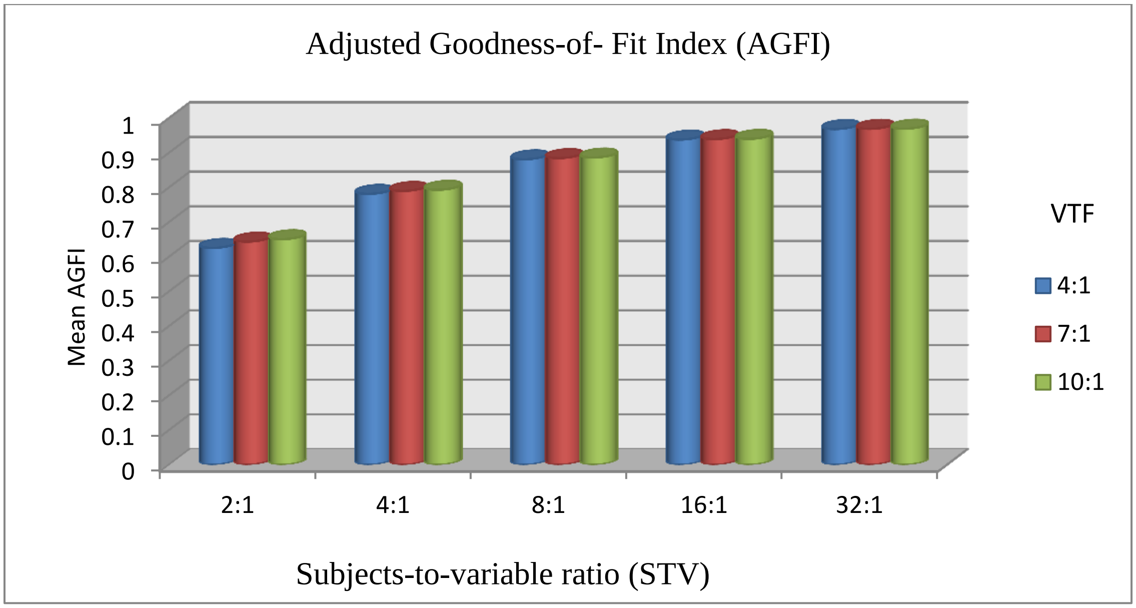


Figure 10. Adjusted goodness-of-fit index of interaction between STV and VTF ratios.

Table 17 presents the simple effect ANOVAs on VTF for each STV level. Pairwise comparisons among levels of VTF at each level of STV, e.g., VTF 4:1 vs. 7:1 @ STV=2:1, were statistically significant with all p-values <. 0001, and the directional pattern in means confirmed the patterns seen in Figure 2.

Table 17

One-Way Analysis of Variance Simple Effect of STV by Levels of VTF

STV	*df*	*SS*	*MS*	*F*	*p-value*
2:1	2	1.3002	0.650	5735.08	<. 0001
4:1	2	0.2632	0.131	1161.01	<. 0001
8:1	2	0.0523	0.026	230.95	<. 0001
16:1	2	0.0096	0.004	42.59	<. 0001
32:1	2	0.0020	0.001	9.06	<. 0001

Root Mean Square Error of Approximation (RMSEA)

RMSEA statistics were averaged over 1000 replication for the 60 cells in the three-way design are presented in Table 18. Additionally, the percentage of RMSEA statistics meeting the standard threshold of acceptable fit, e.g., =<. 05, was tabulated.

Overall ANOVA findings for RMSEA revealed an overall statistically significant model, $F(59, 59940) = 4901.85$, $p < .0001$. As can be seen in Table 19, there were statistically significant main effects VTF and STV, and a statistically significant interaction between VTF*STV. Once again, the communality factor was not significant. The complete ANOVA summary table is presented in Table B4 of Appendix B.

Table 18

Descriptive Statistics for Root Mean Square Error of Approximation Averaged Over 1000 Replications

		h^2							
VTF	STV	High		Moderate		Low		Mixed	
		Mean	P %	Mean	P %	Mean	P %	Mean	P %
4:1	2:1	0.08	7.50	0.08	8.80	0.08	7.10	0.08	6.70
	4:1	0.03	73.80	0.03	75.50	0.03	75.70	0.03	76.00
	8:1	0.01	99.90	0.01	99.70	0.01	99.60	0.01	99.90
	16:1	0.00	100.00	0.00	100.00	0.00	100.00	0.00	100.00
	32:1	0.00	100.00	0.00	100.00	0.00	100.00	0.00	100.00
7:1	2:1	0.06	11.50	0.06	8.80	0.06	13.20	0.06	10.60
	4:1	0.02	100.00	0.02	100.00	0.02	100.00	0.02	100.00
	8:1	0.01	100.00	0.01	100.00	0.01	100.00	0.01	100.00
	16:1	0.00	100.00	0.00	100.00	0.00	100.00	0.00	100.00
	32:1	0.00	100.00	0.00	100.00	0.00	100.00	0.00	100.00
10:1	2:1	0.05	47.20	0.05	45.20	0.05	47.20	0.05	46.70
	4:1	0.02	100.00	0.02	100.00	0.02	100.00	0.02	100.00
	8:1	0.00	100.00	0.00	100.00	0.00	100.00	0.00	100.00
	16:1	0.00	100.00	0.00	100.00	0.00	100.00	0.00	100.00
	32:1	0.00	100.00	0.00	100.00	0.00	100.00	0.00	100.00

Note. RMSEA = root mean square error of approximation; h^2 = communality magnitude; VTF = variable-to-factor ratio; STV = subject-to-variable ratio; P = percentage of replications that met the criteria-of-fit index.

Table 19

Three-Way Analysis of Variance for RMSEA by Conditions

Conditions	*df*	*F*	*p-value*
h^2	3	0.41	0.7467
VTF	2	6698.38	<. 0001
h^2*VTF	6	1.45	0.1919
STV	4	66127.9	<. 0001
h^2* STV	12	0.75	0.7077
VTF *STV	8	1408.03	<. 0001
h^2* VTF *STV	24	0.72	0.8337

Note. h^2 = communality magnitude; VTF = variable-to-factor ratio; STV = subject-to-variable ratio.

Post hoc analysis of VTF*STV interaction focused on splitting out the levels of STV and examined five one-way ANOVAs for the levels of VTF. Visual examination of the mean RMSEA values suggests a significant decrease in mean RMSEA values as STV increases mixed with increasing mean RMSEA as VTF ratios decreased (see Figure 11).

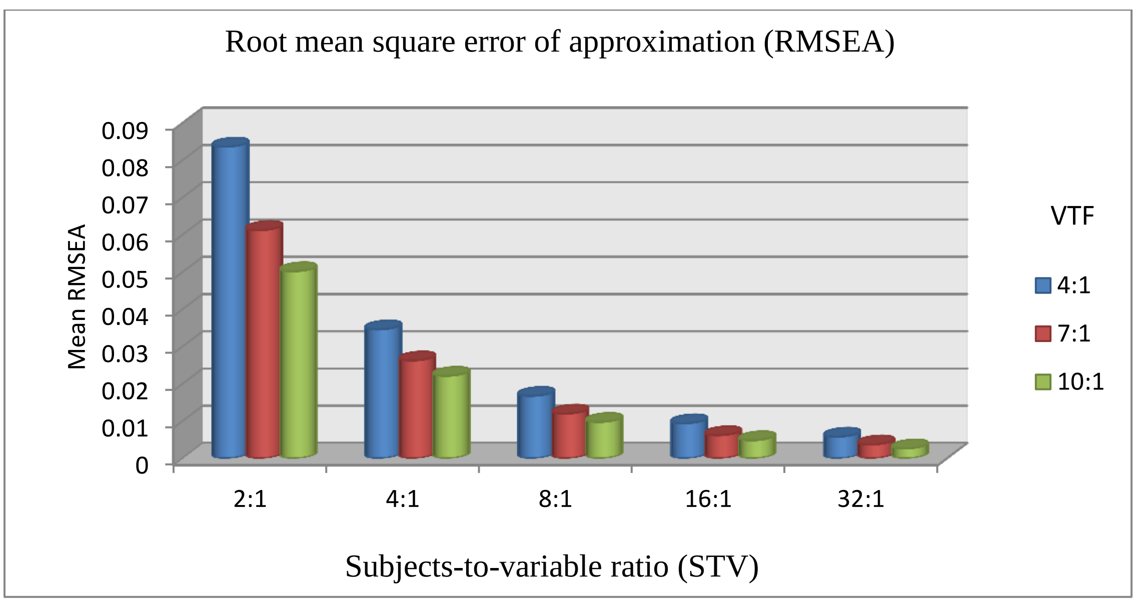


Figure 11. Root mean square error of approximation of interaction between STV and VTF ratios.

Table 20 presents the simple effect ANOVAs on VTF for each STV level. Pairwise comparisons among levels of VTF at each level of STV, e.g., VTF 4:1 vs. 7:1 @ STV=2:1, were statistically significant with all p-values <. 0001, and the directional pattern in means confirmed the patterns seen in Figure 2.

Table 20

One-Way Analysis of Variance Simple Effect of STV by Levels of VTF

STV	*df*	*SS*	*MS*	*F*	*p-value*
2:1	2	2.3236	1.1618	10188.3	<. 0001
4:1	2	0.3222	0.1611	1413.01	<. 0001
8:1	2	0.1021	0.0510	447.68	<. 0001
16:1	2	0.0436	0.0218	191.23	<. 0001
32:1	2	0.0206	0.0103	90.34	<. 0001

Non-Normed-Fit Index (TLI)

TLI statistics were averaged over 1000 replication for the 60 cells in the three-way design are presented in Table 21. Additionally, the percentage of TLI statistics meeting the standard threshold of acceptable fit, e.g., >=. 96, was tabulated.

Overall ANOVA findings for TLI revealed an overall statistically significant model, $F(59, 59940)$ =4556.25, p <. 0001. As can be seen in Table 22, there were statistically significant main effects and interactions, including statistically significant triple interaction between h^2*VTF*STV. The complete ANOVA table is presented in Table B5 of Appendix B.

Visual examination of the mean TLI values reveals a differential increase in mean TLI within levels of STV as a function of h^2 magnitude. In the h^2 = high condition, mean TLI values evidences minimal gains even between 2:1 and 4:1 STV levels. Within the mixed and moderate h^2 conditions mean TLI values show asymptotic gains after STV >

4:1. However, in the low h^2 condition mean TLI values were markedly lower in the 2:1 and 4:1 STV levels, only showing asymptotic values when STV > 8:1 (see Figure 12).

Table 21

Descriptive Statistics for Non-Normed-Fit Index Averaged Over 1000 Replications

		h^2							
VTF	STV	High		Moderate		Low		Mixed	
		Mean	P %	Mean	P %	Mean	P %	Mean	P %
	2:1	0.92	15.90	0.81	4.60	0.53	1.90	0.82	3.90
	4:1	0.98	93.10	0.95	48.50	0.86	22.90	0.96	50.90
4:1	8:1	0.99	100.00	0.98	91.30	0.96	48.20	0.99	94.40
	16:1	0.99	100.00	0.99	99.90	0.99	77.20	0.99	100.00
	32:1	0.99	100.00	0.99	100.00	0.99	95.90	0.99	100.00
	2:1	0.93	10.50	0.86	0.20	0.60	0.00	0.90	1.60
	4:1	0.98	99.90	0.97	71.80	0.88	14.70	0.97	94.50
7:1	8:1	0.99	100.00	0.99	100.00	0.97	63.20	0.99	100.00
	16:1	0.99	100.00	0.99	100.00	0.99	95.60	0.99	100.00
	32:1	0.99	100.00	0.99	100.00	0.99	100.00	0.99	100.00
	2:1	0.94	7.30	0.88	0.00	0.68	0.00	0.91	0.20
	4:1	0.98	100.00	0.97	87.60	0.91	10.80	0.98	99.90
10:1	8:1	0.99	100.00	0.99	100.00	0.98	86.50	0.99	100.00
	16:1	0.99	100.00	0.99	100.00	0.99	100.00	0.99	100.00
	32:1	0.99	100.00	0.99	100.00	0.99	100.00	0.99	100.00

Note. TLI = non-normed-fit index (Tucker-Lewis index); h^2 = communality magnitude; VTF = variable-to-factor ratio; STV = subject-to-variable ratio; P = percentage of replications that met the criteria-of-fit index.

Table 22

Three-Way Analysis of Variance for TLI by Conditions

Conditions	*df*	*F*	*p-value*
h^2	3	13451.2	<. 0001
VTF	2	1437.33	<. 0001
h^2*VTF	6	211.73	<. 0001
STV	4	36383.3	<. 0001
h^2* STV	12	5964.08	<. 0001
VTF *STV	8	659.74	<. 0001
h^2* VTF *STV	24	80.84	<. 0001

Note. h^2 = communality magnitude; VTF = variable-to-factor ratio; STV = subject-to-variable ratio.

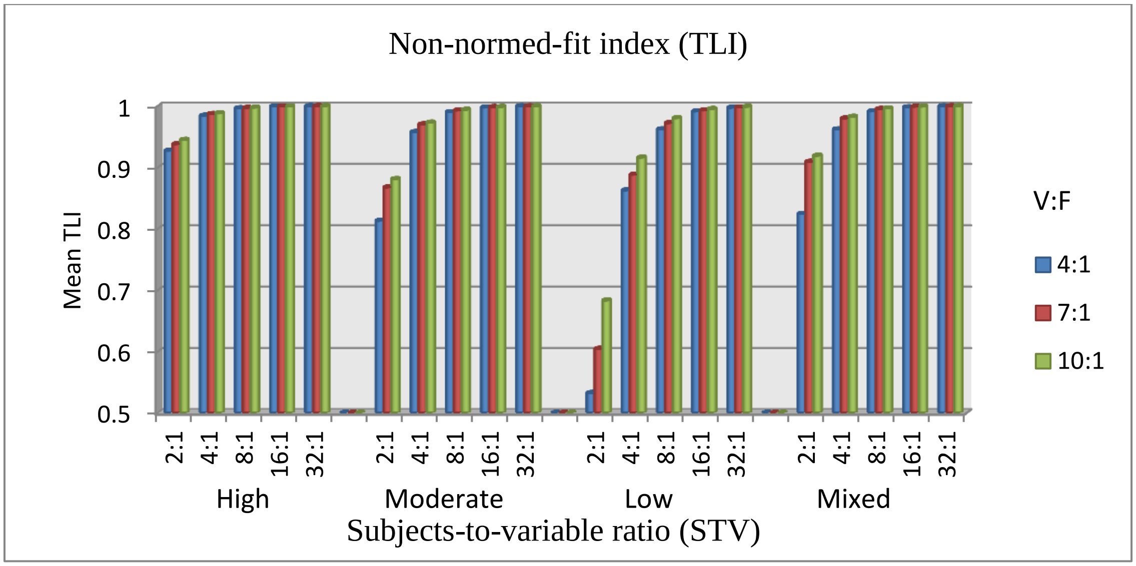


Figure 12. Non-normal-fit index mean values for the interaction between STV and VTF ratios at different levels of communalities.

Post hoc analysis of 3-way interaction h^2*VTF*STV first focused on the simple effect interaction of h^2*VTF after blocking on STV, specifically the test of 2-way interaction h^2*VTF at each level of STV. Results revealed statistically significant 2-way interactions at all STV levels: STV=(2:1), $F(6, 11988) = 160.34$, $p < .0001$; STV=(4:1), $F(6, 11988) = 40.07$, $p < .0001$; STV=(8:1), $F(6, 11988) = 18.51$, $p < .0001$; STV=(16:1), $F(6, 11988) = 3.48$, $p = 0.0019$; and STV=(32:1), $F(6, 11988) = 0.43$, $p = 0.0115$. Further analysis of the four by three 2-way interactions focused on the simple-simple effects of STV blocking on the STV* h^2 interaction. Specifically the analysis examined differences in mean TLI values among VTF levels for each STV* h^2 interaction. Table 23 presents these findings, statistically significant results are presented in bold.

Table 23

*Simple-Simple Effect of STV*VTF * h^2sliced by STV * h^2*

h^2	STV	*df*	*F*	*p-value*	VTF		
					(4:1)vs(7:1)	(4:1)vs(10:1)	(7:1)vs(10:1)
Low	2	2	344.22	**<. 0001**	**<. 0001**	**<. 0001**	**<. 0001**
	4	2	69.76	**<. 0001**	**<. 0001**	**<. 0001**	**<. 0001**
	8	2	28.98	**<. 0001**	**<. 0001**	**<. 0001**	**0.0023**
	16	2	5.14	**0.0059**	0.3846	**0.0041**	0.1474
	32	2	3.46	0.0314	0.6692	0.0266	0.1945
Moderate	2	2	446.74	**<. 0001**	**<. 0001**	**<. 0001**	**<. 0001**
	4	2	85.32	**<. 0001**	**<. 0001**	**<. 0001**	0.0563
	8	2	19.74	**<. 0001**	**<. 0001**	**<. 0001**	0.2112
	16	2	3.75	0.0237	0.1040	0.0251	0.8368
	32	2	0.06	0.9392	--	--	--
High	2	2	156.43	**<. 0001**	**<. 0001**	**<. 0001**	0.2111
	4	2	35.22	**<. 0001**	**<. 0001**	**<. 0001**	0.0470
	8	2	6.32	0.0018	0.1169	**0.0011**	0.2606
	16	2	0.65	0.5222	--	--	--
	32	2	0.23	0.7978	--	--	--
Mixed	2	2	1304.21	**<. 0001**	**<. 0001**	**<. 0001**	**0.0008**
	4	2	204.56	**<. 0001**	**<. 0001**	**<. 0001**	0.0322
	8	2	43.24	**<. 0001**	**<. 0001**	**<. 0001**	0.1836
	16	2	9.26	**<. 0001**	**0.0025**	**0.0002**	0.7672
	32	2	1.02	0.3604	--	--	--

Note. h^2 = communality magnitude; VTF = variable-to-factor ratio; STV = subject-to-variable ratio.

Comparative-Fit Index (CFI)

CFI statistics were averaged over 1000 replication for the 60 cells in the three-way design are presented in Table 24. Additionally, the percentage of CFI statistics meeting the standard threshold of acceptable fit, e.g., >=. 95, was tabulated.

Table 24

Descriptive Statistics for Comparative-Fit Index Averaged Over 1000 Replications

VTF	STV	h^2							
		High		Moderate		Low		Mixed	
		Mean	P %	Mean	P %	Mean	P %	Mean	P %
4:1	2:1	0.93	28.90	0.83	6.10	0.57	2.30	0.84	5.60
	4:1	0.98	99.20	0.95	61.90	0.85	25.70	0.96	67.00
	8:1	0.99	100.00	0.98	97.90	0.95	55.40	0.98	98.90
	16:1	0.99	100.00	0.99	100.00	0.98	85.80	0.99	100.00
	32:1	0.99	100.00	0.99	100.00	0.99	99.60	0.99	100.00
7:1	2:1	0.94	30.90	0.87	0.70	0.62	0.00	0.91	6.60
	4:1	0.98	100.00	0.97	91.20	0.89	18.50	0.98	99.40
	8:1	0.99	100.00	0.99	100.00	0.96	67.40	0.99	100.00
	16:1	0.99	100.00	0.99	100.00	0.98	99.20	0.99	100.00
	32:1	0.99	100.00	0.99	100.00	0.99	100.00	0.99	100.00
10:1	2:1	0.94	41.00	0.88	0.00	0.69	0.00	0.92	3.00
	4:1	0.98	100.00	0.97	98.70	0.91	18.90	0.98	100.00
	8:1	0.99	100.00	0.99	100.00	0.97	96.20	0.99	100.00
	16:1	0.99	100.00	0.99	100.00	0.99	100.00	0.99	100.00
	32:1	0.99	100.00	0.99	100.00	0.99	100.00	0.99	100.00

Note. CFI = comparative-fit index; h^2 = communality magnitude; VTF = variable-to-factor ratio; STV = subject-to-variable ratio; P = percentage of replications that met the criteria-of-fit index.

Overall ANOVA findings for CFI revealed an overall statistically significant model, F (59, 59940) =6535.47, p <. 0001. As can be seen in Table 25, there were statistically significant main effects and interactions, including statistically significant triple interaction between h^2*VTF*STV. The complete ANOVA table is presented in Table B6 of Appendix B.

Table 25

Three-Way Analysis of Variance for CFI by Conditions

Conditions	*df*	*F*	*p-value*
h^2	3	21591.5	<. 0001
VTF	2	2208.58	<. 0001
h^2*VTF	6	359.17	<. 0001
STV	4	51446.3	<. 0001
h^2* STV	12	8444.73	<. 0001
VTF *STV	8	626.81	<. 0001
h^2* VTF *STV	24	87.90	<. 0001

Note. h^2 = communality magnitude; VTF = variable-to-factor ratio; STV = subject-to-variable ratio.

Visual examination of the mean CFI values reveals a differential increase in mean CFI within levels of STV as a function of h^2 magnitude. In the h^2 = high condition, mean CFI values evidences minimal gains even between 2:1 and 4:1 STV levels. Within the mixed and moderate h^2 conditions mean CFI values show asymptotic gains after STV > 4:1. However, in the low h^2 condition mean CFI values were markedly lower in the 2:1 and 4:1 STV levels, only showing asymptotic values when STV > 8:1 (see Figure 13).

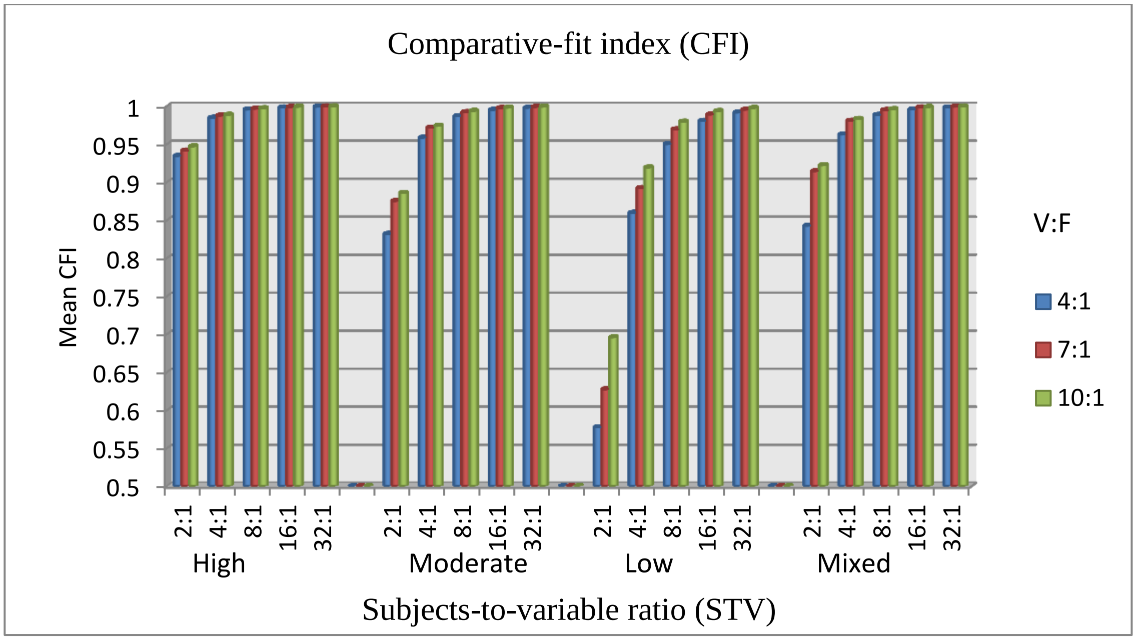


Figure 13. Comparative-fit index mean values for the interaction between STV and VTF ratios at different levels of communalities.

Post hoc analysis of 3-way interaction h^2*VTF*STV first focused on the simple effect interaction of h^2*VTF after blocking on STV, specifically the test of 2-way interaction h^2*VTF at each level of STV. Results revealed statistically significant 2-way interactions at all STV levels: STV=(2:1), $F(6, 11988) = 168.36$, $p < .0001$; STV=(4:1), $F(6, 11988) = 93.29$, $p < .0001$; STV=(8:1), $F(6, 11988) = 109.95$, $p < .0001$; STV=(16:1), $F(6, 11988) = 96.87$, $p < .0001$; and STV=(32:1), $F(6, 11988) = 92.47$, $p < .0001$. Further analysis of the four by three 2-way interactions focused on the simple-simple effects of STV blocking on the STV* h^2 interaction. Specifically the analysis examined differences in mean TLI values among VTF levels for each STV* h^2 interaction. Table 26 presents these findings, statistically significant results are presented in bold.

Table 26

*Simple-Simple Effect of STV*VTF * h^2sliced by STV * h^2*

h^2	STV	*df*	*F*	*p-value*	VTF		
					(4:1)vs(7:1)	(4:1)vs(10:1)	(7:1)vs(10:1)
	2	2	354.69	**<. 0001**	**<. 0001**	**<. 0001**	**<. 0001**
	4	2	163.44	**<. 0001**	**<. 0001**	**<. 0001**	**<. 0001**
Low	8	2	179.25	**<. 0001**	**<. 0001**	**<. 0001**	**<. 0001**
	16	2	156.49	**<. 0001**	**<. 0001**	**<. 0001**	**<. 0001**
	32	2	150.44	**<. 0001**	**<. 0001**	**<. 0001**	**<. 0001**
	2	2	355.85	**<. 0001**	**<. 0001**	**<. 0001**	**<. 0001**
	4	2	142.19	**<. 0001**	**<. 0001**	**<. 0001**	0.0345
Moderate	8	2	131.28	**<. 0001**	**<. 0001**	**<. 0001**	**0.0012**
	16	2	134.42	**<. 0001**	**<. 0001**	**<. 0001**	0.0105
	32	2	138.10	**<. 0001**	**<. 0001**	**<. 0001**	0.0127
	2	2	95.38	**<. 0001**	**<. 0001**	**<. 0001**	**<. 0001**
	4	2	50.45	**<. 0001**	**<. 0001**	**<. 0001**	0.0327
High	8	2	59.65	**<. 0001**	**<. 0001**	**<. 0001**	**0.0015**
	16	2	81.82	**<. 0001**	**<. 0001**	**<. 0001**	**0.0004**
	32	2	87.18	**<. 0001**	**<. 0001**	**<. 0001**	**<. 0001**
	2	2	1151.76	**<. 0001**	**<. 0001**	**<. 0001**	**<. 0001**
	4	2	334.92	**<. 0001**	**<. 0001**	**<. 0001**	0.0120
Mixed	8	2	251.77	**<. 0001**	**<. 0001**	**<. 0001**	**0.0024**
	16	2	216.54	**<. 0001**	**<. 0001**	**<. 0001**	0.0164
	32	2	206.02	**<. 0001**	**<. 0001**	**<. 0001**	**0.0037**

Note. h^2 = communality magnitude; VTF = variable-to-factor ratio; STV = subject-to-variable ratio.

Root Mean Square Residual (RMR)

RMR statistics were averaged over 1000 replication for the 60 cells in the three-way design are presented in Table 27. Additionally, the percentage of RMR statistics meeting the standard threshold of acceptable fit, e.g., =<. 05, was tabulated.

Table 27

Descriptive Statistics for Root Mean Square Residual Averaged Over 1000 Replications

		h^2							
VTF	STV	High		Moderate		Low		Mixed	
		Mean	P %	Mean	P %	Mean	P %	Mean	P %
4:1	2:1	0.13	0.00	0.14	0.00	0.14	0.00	0.14	0.00
	4:1	0.09	0.00	0.09	0.00	0.10	0.00	0.09	0.00
	8:1	0.06	3.90	0.06	0.00	0.07	0.00	0.06	0.10
	16:1	0.04	63.00	0.04	62.10	0.04	52.70	0.04	59.90
	32:1	0.03	99.70	0.03	100.00	0.03	100.00	0.03	100.00
7:1	2:1	0.10	0.00	0.10	0.00	0.11	0.00	0.10	0.00
	4:1	0.07	0.00	0.07	0.00	0.07	0.00	0.07	0.00
	8:1	0.05	39.10	0.05	22.00	0.05	1.00	0.05	23.10
	16:1	0.03	98.60	0.03	99.90	0.03	100.00	0.03	100.00
	32:1	0.02	100.00	0.02	100.00	0.02	100.00	0.02	100.00
10:1	2:1	0.08	0.00	0.09	0.00	0.09	0.00	0.09	0.00
	4:1	0.06	3.90	0.06	0.00	0.06	0.00	0.06	0.10
	8:1	0.04	98.80	0.04	92.50	0.04	82.20	0.04	92.10
	16:1	0.03	100.00	0.03	100.00	0.03	100.00	0.03	100.00
	32:1	0.02	100.00	0.02	100.00	0.02	100.00	0.02	100.00

Note. RMR = root mean square residual; h^2 = communality magnitude; VTF = variable-to-factor ratio; STV = subject-to-variable ratio.

Overall ANOVA findings for CFI revealed an overall statistically significant model, $F(59, 59940) = 18430.00$, $p <. 0001$. As can be seen in Table 28, there were statistically significant main effects and interactions, including statistically significant triple interaction between h^2*VTF*STV. The complete ANOVA table is presented in Table B7 of Appendix B.

Table 28

Three-Way Analysis of Variance for RMR by Conditions

Conditions	*df*	*F*	*p-value*
h^2	3	284.47	<. 0001
VTF	2	65494.8	<. 0001
h^2 *VTF	6	3.84	0.0008
STV	4	230816	<. 0001
h^2 * STV	12	16.03	<. 0001
VTF *STV	8	3999.89	<. 0001
h^2 * VTF *STV	24	1.98	0.0029

Note. h^2 = communality magnitude; VTF = variable-to-factor ratio; STV = subject-to-variable ratio.

Visual examination of Figure 14 reveals several systematic changes in mean RMR as a function of the three independent variables. First, regardless of h^2 and VTF, it appears that there are only minimal decreases in mean RMR the high STV levels (STV >= 16:1). Moreover increases in VTF coincide with systematic decreases in mean RMR in all STV and h^2 combinations. What is driving the triple interaction is that the influence of VTF on mean RMR gets exaggerated differentially when STV levels rise, resulting in differentially lower mean RMR values at higher VTF levels and this does not seem heavily influenced by h^2 level.

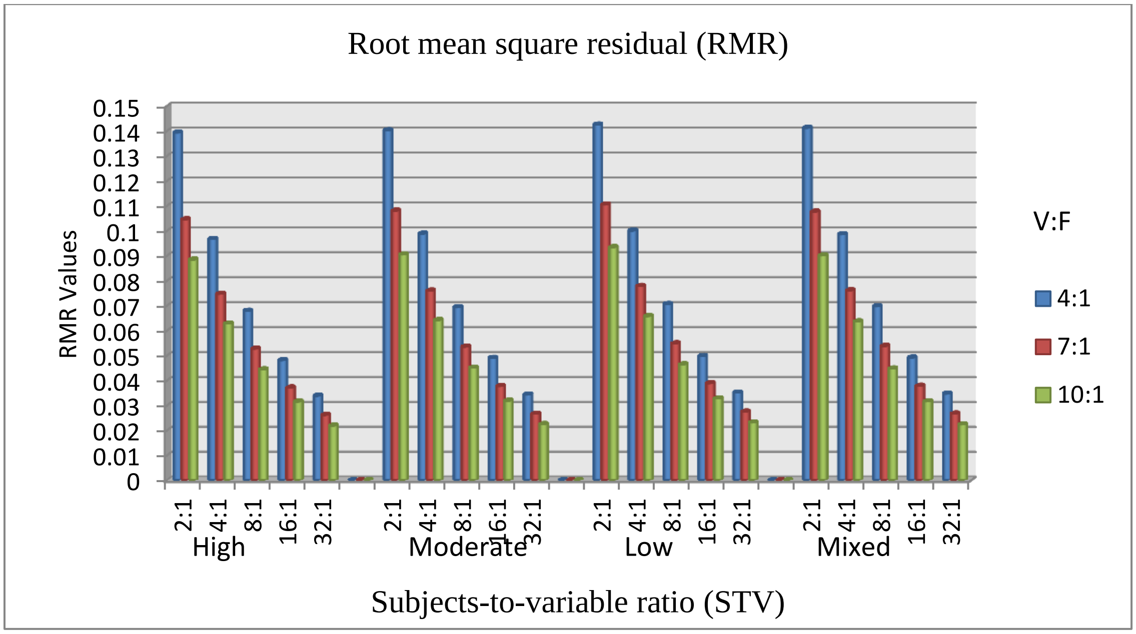


Figure 14. Root mean square residual mean values for the interaction between STV and VTF ratios at different levels of communalities.

Post hoc analysis of 3-way interaction h^2*VTF*STV first focused on the simple effect interaction of h^2*VTF after blocking on STV, specifically the test of 2-way interaction h^2*VTF at each level of STV. Results of 2-way interactions revealed that at: STV=(2:1), $F(6, 11988) = 2.89$, $p = 0.0081$; STV=(4:1), $F(6, 11988) = 0.89$, $p < .0001$; STV=(8:1), $F(6, 11988) = 2.83$, $p = 0.0094$; STV=(16:1), $F(6, 11988) = 2.63$, $p = 0.0151$; and STV=(32:1), $F(6, 11988) = 1.63$, $p = 0.1349$. Further analysis of the four by three 2-way interactions focused on the simple-simple effects of STV blocking on the STV* h^2 interaction. Specifically the analysis examined differences in mean TLI values among VTF levels for each STV* h^2 interaction. Table 29 presents these findings, statistically significant results are presented in bold.

Table 29

*Simple-Simple Effect of STV*VTF * h^2 sliced by STV * h^2*

h^2	STV	*df*	*F*	*p-value*	VTF		
					(4:1)vs(7:1)	(4:1)vs(10:1)	(7:1)vs(10:1)
Low	2	2	9733.55	**<. 0001**	**<. 0001**	**<. 0001**	**<. 0001**
	4	2	11688.5	**<. 0001**	**<. 0001**	**<. 0001**	**<. 0001**
	8	2	14242.8	**<. 0001**	**<. 0001**	**<. 0001**	**<. 0001**
	16	2	15397.9	**<. 0001**	**<. 0001**	**<. 0001**	**<. 0001**
	32	2	15866.2	**<. 0001**	**<. 0001**	**<. 0001**	**<. 0001**
Moderate	2	2	4608.28	**<. 0001**	**<. 0001**	**<. 0001**	**<. 0001**
	4	2	5244.23	**<. 0001**	**<. 0001**	**<. 0001**	**<. 0001**
	8	2	5591.21	**<. 0001**	**<. 0001**	**<. 0001**	**<. 0001**
	16	2	6063.84	**<. 0001**	**<. 0001**	**<. 0001**	**<. 0001**
	32	2	5783.31	**<. 0001**	**<. 0001**	**<. 0001**	**<. 0001**
High	2	2	2096.68	**<. 0001**	**<. 0001**	**<. 0001**	**<. 0001**
	4	2	1994.86	**<. 0001**	**<. 0001**	**<. 0001**	**<. 0001**
	8	2	2001.08	**<. 0001**	**<. 0001**	**<. 0001**	**<. 0001**
	16	2	2176.69	**<. 0001**	**<. 0001**	**<. 0001**	**<. 0001**
	32	2	2307.28	**<. 0001**	**<. 0001**	**<. 0001**	**<. 0001**
Mixed	2	2	4535.20	**<. 0001**	**<. 0001**	**<. 0001**	**<. 0001**
	4	2	5301.64	**<. 0001**	**<. 0001**	**<. 0001**	**<. 0001**
	8	2	5500.99	**<. 0001**	**<. 0001**	**<. 0001**	**<. 0001**
	16	2	5825.37	**<. 0001**	**<. 0001**	**<. 0001**	**<. 0001**
	32	2	5991.33	**<. 0001**	**<. 0001**	**<. 0001**	**<. 0001**

Note. h^2 = communality magnitude; VTF = variable-to-factor ratio; STV = subject-to-variable ratio

Results: Research Questions 2 and 3

Multiple-group confirmatory factor analysis (MGCFA) was used to test invariance among levels of STV ratio. Measurement invariance was used to address RQ2 and a structural invariance test of the latent mean models was used to address RQ3. Model testing was evaluated by the chi-square difference test ($\Delta\chi^2$) between two groups (Brown, 2006; Byrne, 1998), significant at the 0.05 probability level, and RSMA, CFI, and TLI were used to evaluate all model fits. As previously referenced, the following

criteria values suggested by Hu and Bentler (1999) and Schumacker and Lomax (1996) were used in this study: RMSEA: 0.00 - 0.05 is very good fit, CFI > 0.95 is good fit, and TLI $\geq$ 0.96 is good fit. Additionally, RQ3 was examined via frequency analysis by tabulating a count of statistically significant chi-square values observed over the 1000 replications. The null proportion of replication failures was hypothesized to be $\pi = 0.05$. Specifically, no more than 5% of the replications should have resulted in a statistically significant chi-square statistic, e.g., $p <= 0.05$. Model fit indices RMSEA, CFI, and TLI were averaged over the 1000 replications and presented in Figures C1-C12 in Appendix C.

For the benefit of the reader, Figure 3 and Table 3, as presented in Chapter III, illustrate the full study design for RQ2 and 3. Measurement and structural mean invariance of the STV levels were examined in each cell of the h^2*VTF study design as shown in Figure 3 (see page 31).

Table 3 (page 32) presents the order of invariance testing among levels of STV. Invariance testing was conducted as follows: M0 represents configural invariance, M1 represents weak measurement invariance, M2 represents strong measurement invariance, and M3 represents structural mean invariance, e.g., RQ3.

High Communality

Table 30 presents complete findings of measurement and structural mean invariance for high communality among levels of STV over 1000 replications. Due to the nature of the invariance testing, both RQ2 and 3 are presented together in this section, but noted for the readers' benefit.

Table 30

Test of Factorial Invariance for High Communality Across VTF Ratios and STV Ratios Averaged Over 1000 Replications

VTF	Between Groups	Models	χ^2	df	Model Comparison	$\Delta\chi^2$	Δdf	*p*-value	RMSA	CFI	TLI
4:1	(STV=2:1) & (STV=32:1)	M0	370.923	320	M0	---	---	0.0261*	0.0205	0.9958	0.9951
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
	(STV=2:1) & (STV=16:1)	M0	373.242	320	M0	---	---	0.0214*	0.0288	0.9918	0.9904
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
	(STV=2:1) & (STV=8:1)	M0	378.341	320	M0	---	---	0.0137*	0.0411	0.9841	0.9811
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
	(STV=2:1) & (STV=4:1)	M0	389.548	320	M0	---	---	0.0057*	0.0586	0.9687	0.9629
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
	(STV=4:1) & (STV=32:1)	M0	342.458	320	M0	---	---	0.1856	0.0122	0.9980	0.9979
		M1	357.782	335	M1-M0	15.324	15	0.4283	0.0121	0.9980	0.9980
		M2	372.929	350	M2-M1	15.147	15	0.4408	0.0119	0.9980	0.9981
		M3	377.818	355	M3-M2	4.889	5	0.4295	0.0118	0.9980	0.9981

Table 30—Continued

VTF	Between Groups	Models	χ^2	df	Model Comparison	$\Delta\chi^2$	Δdf	*p*-value	RMSA	CFI	TLI
		M0	344.777	320	M0	---	---	0.1631	0.0175	0.9962	0.9958
	(STV=4:1) &	M1	359.956	335	M1-M0	15.179	15	0.4386	0.0171	0.9962	0.9961
	(STV=16:1)	M2	375.153	350	M2-M1	15.197	15	0.4373	0.0168	0.9961	0.9962
		M3	380.060	355	M3-M2	4.907	5	0.4273	0.0166	0.9961	0.9963
		M0	349.877	320	M0	---	---	0.1205	0.0252	0.9928	0.9919
	(STV=4:1) & (STV=8:1)	M1	365.028	335	M1-M0	15.151	15	0.4405	0.0247	0.9927	0.9922
		M2	380.142	350	M2-M1	15.114	15	0.4432	0.0241	0.9927	0.9925
		M3	385.144	355	M3-M2	5.002	5	0.4156	0.0239	0.9926	0.9926
		M0	331.245	320	M0	---	---	0.3207	0.0086	0.9988	0.9990
	(STV=8:1) &	M1	346.407	335	M1-M0	15.162	15	0.4398	0.0085	0.9988	0.9991
	(STV=32:1)	M2	361.117	350	M2-M1	14.77	15	0.4681	0.0082	0.9988	0.9991
		M3	366.051	355	M3-M2	4.934	5	0.4239	0.0082	0.9988	0.9991
		M0	333.562	320	M0	---	---	0.2894	0.0119	0.9979	0.9981
	(STV=8:1) &	M1	348.683	335	M1-M0	15.121	15	0.4427	0.0117	0.9978	0.9982
	(STV=16:1)	M2	363.685	350	M2-M1	15.002	15	0.4512	0.0115	0.9978	0.9983
		M3	368.696	355	M3-M2	5.011	5	0.4145	0.0115	0.9978	0.9983
		M0	326.152	320	M0	---	---	0.3943	0.0067	0.9992	0.9995
	(STV=16:1) &	M1	341.001	335	M1-M0	14.849	15	0.4623	0.0066	0.9991	0.9996
	(STV=32:1)	M2	356.396	350	M2-M1	15.395	15	0.4233	0.0066	0.9991	0.9996
		M3	361.193	355	M3-M2	4.797	5	0.4411	0.0065	0.9991	0.9996
7:1		M0	1255.61	1100	M0	---	---	0.0007*	0.0151	0.9962	0.9959
	(STV=2:1) &	M1	---	---	M1-M0	---	---	---	---	---	---
	(STV=32:1)	M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---

Table 30—Continued

VTF	Between Groups	Models	χ^2	df	Model Comparison	$\Delta\chi^2$	Δdf	*p*-value	RMSA	CFI	TLI
	(STV=2:1) & (STV=16:1)	M0	1262.70	1100	M0	---	---	0.0004*	0.0213	0.9926	0.9920
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
	(STV=2:1) & (STV=8:1)	M0	1277.65	1100	M0	---	---	0.0002*	0.0300	0.9855	0.9843
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
	(STV=2:1) & (STV=4:1)	M0	1309.11	1100	M0	---	---	<.0001*	0.0422	0.9719	0.9696
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
	(STV=4:1) & (STV=32:1)	M0	1165.96	1100	M0	---	---	0.0819	0.0089	0.9984	0.9983
		M1	1196.34	1130	M1-M0	30.38	30	0.4463	0.0088	0.9984	0.9984
		M2	1225.91	1160	M2-M1	29.57	30	0.4878	0.0087	0.9984	0.9984
		M3	1230.96	1165	M3-M2	5.05	5	0.4098	0.0086	0.9984	0.9984
	(STV=4:1) & (STV=16:1)	M0	1173.04	1100	M0	---	---	0.0621	0.0128	0.9969	0.9967
		M1	1203.32	1130	M1-M0	30.28	30	0.4513	0.0126	0.9969	0.9968
		M2	1233.03	1160	M2-M1	29.71	30	0.4805	0.0124	0.9969	0.9969
		M3	1238.05	1165	M3-M2	5.02	5	0.4134	0.0124	0.9969	0.9969
	(STV=4:1) & (STV=8:1)	M0	1187.99	1100	M0	---	---	0.0328*	0.0185	0.9939	0.9934
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---

Table 30—Continued

VTF	Between Groups	Models	χ^2	df	Model Comparison	$\Delta\chi^2$	Δdf	*p*-value	RMSA	CFI	TLI
		M0	1134.50	1100	M0	---	---	0.2289	0.0059	0.9991	0.9992
	(STV=8:1) &	M1	1164.11	1130	M1-M0	29.61	30	0.4857	0.0058	0.9991	0.9992
	(STV=32:1)	M2	1193.65	1160	M2-M1	29.54	30	0.4893	0.0057	0.9991	0.9992
		M3	1198.66	1165	M3-M2	5.01	5	0.4146	0.0057	0.9991	0.9992
		M0	1141.58	1100	M0	---	---	0.1872	0.0084	0.9983	0.9984
	(STV=8:1) &	M1	1171.36	1130	M1-M0	29.78	30	0.4769	0.0082	0.9983	0.9985
	(STV=16:1)	M2	1201.43	1160	M2-M1	30.07	30	0.4620	0.0082	0.9983	0.9985
		M3	1206.53	1165	M3-M2	5.1	5	0.4037	0.0081	0.9983	0.9985
		M0	1119.55	1100	M0	---	---	0.3345	0.0042	0.9994	0.9996
	(STV=16:1) &	M1	1149.23	1130	M1-M0	29.68	30	0.4821	0.0042	0.9994	0.9996
	(STV=32:1)	M2	1179.70	1160	M2-M1	30.47	30	0.4417	0.0042	0.9994	0.9996
		M3	1184.67	1165	M3-M2	4.97	5	0.4195	0.0042	0.9994	0.9996
10:1		M0	2638.35	2330	M0	---	---	<.0001*	0.0123	0.9966	0.9964
	(STV=2:1) &	M1	---	---	M1-M0	---	---	---	---	---	---
	(STV=32:1)	M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
		M0	2654.47	2230	M0	---	---	<.0001*	0.0174	0.9933	0.9929
	(STV=2:1) &	M1	---	---	M1-M0	---	---	---	---	---	---
	(STV=16:1)	M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
		M0	2683.10	2330	M0	---	---	<.0001*	0.0245	0.9869	0.9862
	(STV=2:1) & (STV=8:1)	M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---

Table 30—Continued

VTF	Between Groups	Models	χ^2	df	Model Comparison	$\Delta\chi^2$	Δdf	*p*-value	RMSA	CFI	TLI
	(STV=2:1) & (STV=4:1)	M0	2749.42	2330	M0	---	---	<.0001*	0.0345	0.9744	0.9731
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
	(STV=4:1) & (STV=32:1)	M0	2464.30	2330	M0	---	---	0.0261*	0.0076	0.998	0.9985
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
	(STV=4:1) & (STV=16:1)	M0	2480.42	2330	M0	---	---	0.0151*	0.0109	0.9971	0.9970
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
	(STV=4:1) & (STV=8:1)	M0	2509.05	2330	M0	---	---	0.0051*	0.0155	0.9944	0.9941
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
	(STV=8:1) & (STV=32:1)	M0	2397.98	2330	M0	---	---	0.1598	0.0048	0.9993	0.9993
		M1	2442.93	2375	M1-M0	44.95	45	0.4740	0.0048	0.9993	0.9993
		M2	2487.93	2420	M2-M1	45	45	0.4719	0.0047	0.9993	0.9993
		M3	2493.07	2425	M3-M2	5.14	5	0.3990	0.0047	0.9993	0.9993
	(STV=8:1) & (STV=16:1)	M0	2414.10	2330	M0	---	---	0.1098	0.0070	0.9986	0.9986
		M1	2459.45	2375	M1-M0	45.35	45	0.4573	0.0070	0.9986	0.9986
		M2	2504.09	2420	M2-M1	44.64	45	0.4870	0.0069	0.9986	0.9986
		M3	2509.21	2425	M3-M2	5.12	5	0.4014	0.0069	0.9986	0.9986

Table 30—Continued

VTF	Between Groups	Models	χ^2	df	Model Comparison	$\Delta\chi^2$	Δdf	*p*-value	RMSA	CFI	TLI
		M0	2369.35	2330	M0	---	---	0.2801	0.0033	0.9996	0.9996
	(STV=16:1) &	M1	2415.27	2375	M1-M0	45.92	45	0.4338	0.0033	0.9995	0.999
	(STV=32:1)	M2	2460.28	2420	M2-M1	45.01	45	0.4715	0.0033	0.9995	0.9996
		M3	2465.25	2425	M3-M2	4.97	5	0.4195	0.0033	0.9995	0.9996

* Significant at the 0.05 probability level.

Variable to factor ratio (4:1). RQ2 focuses on examination of the measurement invariance, beginning with configural (M0) to weak (M1) to strong (M2). The findings revealed that for VTF ratios (4:1), $\chi^2{}_{M_0}$ showed statistically significant results when testing configural invariance: (2:1 with 32:1); (2:1 with 16:1); (2:1 with 8:1); and (2:1 with 4:1). Thus, non-invariance was established precluding further invariance testing, e.g., weak, strong, and structural. However, at higher STV ratios, e.g., groups (4:1 with 32:1); (4:1 with 16:1); (4:1 with 8:1); (8:1 with 32:1), (8:1 with 16:1); (8:1 with 32:1) and (16:1 with 32:1), $\chi^2{}_{M_0}$ was not statistically significant indicating configural invariance was established. Given the presence of configural invariance, testing for weak invariance was conducted. Again, chi-square difference between $\Delta\chi^2{}_{M1-M0}$ was not statistically significant supporting the hypothesis of weak factorial invariance between the two groups. After weak invariance was supported, examination of the indicator intercepts was tested. Results again supported the finding of strong invariance, e.g., the $\Delta\chi^2{}_{M2-M1}$was not statistically significant. In conclusion, there were invariant factor loadings and invariant intercepts among the groups indicating that measurement invariance was achieved as described above.

RQ3 focused on the structural invariance, e.g., Model 3. In cases where strong factorial invariance was observed, a final test of structural invariance was conducted. As can be seen from Table 30, for VTF=4:1 structural invariance was noted in all cases where there was strong invariance.

Variable to factor ratio (7:1). RQ2 focuses on examination of the measurement invariance, beginning with configural (M0) to weak (M1) to strong (M2). The findings revealed that for VTF ratios (4:1), $\chi^2{}_{M_0}$ showed statistically significant results when

testing configural invariance: (2:1 with 32:1); (2:1 with 16:1); (2:1 with 8:1); (2:1 with 4:1); and (4:1 with 8:1). Thus, non-invariance was established precluding further invariance testing, e.g., weak, strong, and structural. However, at higher STV ratios, e.g., groups (4:1 with 32:1); (4:1 with 16:1); (8:1 with 32:1), (8:1 with 16:1); (8:1 with 32:1) and (16:1 with 32:1), $\chi^2{}_{M_0}$ was not statistically significant indicating configural invariance was established. Given the presence of configural invariance, testing for weak invariance was conducted. Again, chi-square difference between $\Delta\chi^2{}_{M1-M0}$ was not statistically significant supporting the hypothesis of weak factorial invariance between the two groups. After weak invariance was supported, examination of the indicator intercepts was tested. Results again supported the finding of strong invariance, e.g., the $\Delta\chi^2{}_{M2-M1}$was not statistically significant. In conclusion, there were invariant factor loadings and invariant intercepts among the groups indicating that measurement invariance was achieved as described above.

RQ3 focused on the structural invariance, e.g., Model 3. In cases where strong factorial invariance was observed, a final test of structural invariance was conducted. As can be seen from Table 30, for VTF=7:1 structural invariance was noted in all cases where there was strong invariance.

Variable to factor ratio (10:1). RQ2 focuses on examination of the measurement invariance, beginning with configural (M0) to weak (M1) to strong (M2). The findings revealed that for VTF ratios (4:1), $\chi^2{}_{M_0}$ showed statistically significant results when testing configural invariance: (2:1 with 32:1); (2:1 with 16:1); (2:1 with 8:1); (2:1 with 4:1); (4:1 with 8:1); (4:1 with 16:1); and (4:1 with 32:1). Thus, non-invariance was established precluding further invariance testing, e.g., weak, strong, and structural.

However, at higher STV ratios, e.g., groups (8:1 with 16:1); (8:1 with 32:1) and (16:1 with 32:1), ${\chi^2}_{M_0}$ was not statistically significant indicating configural invariance was established. Given the presence of configural invariance, testing for weak invariance was conducted. Again, chi-square difference between $\Delta{\chi^2}_{M1-M0}$ was not statistically significant supporting the hypothesis of weak factorial invariance between the two groups. After weak invariance was supported, examination of the indicator intercepts was tested. Results again supported the finding of strong invariance, e.g., the $\Delta{\chi^2}_{M2-M1}$was not statistically significant. In conclusion, there were invariant factor loadings and invariant intercepts among the groups indicating that measurement invariance was achieved as described above.

RQ3 focused on the structural invariance, e.g., Model 3. In cases where strong factorial invariance was observed, a final test of structural invariance was conducted. As can be seen from Table 30, for VTF=10:1 structural invariance was noted in all cases where there was strong invariance.

Table 31 presents a frequency analysis of a chi-square *p*-values > 0.05 was tested against the null proportion $\pi = 0.05$ to determine if there was a statistically significant number of invariance failures.

Table 31

Chi-square Frequency Against the Null Proportion of Structural Mean Invariance in High Communality

VTF	Nested Models	Invariance Status	Frequency	Percent	*p*-value
4:1	(STV=4:1)&(STV=32:1)	Successful	769	76.90	<.0001*
		Failures	231	23.10	
	(STV=4:1)&(STV=16:1)	Successful	751	75.10	<.0001*
		Failures	249	24.90	
	(STV=4:1)&(STV=8:1)	Successful	691	69.10	<.0001*
		Failures	309	30.90	
	(STV=8:1)&(STV=32:1)	Successful	884	88.40	<.0001*
		Failures	116	11.60	
	(STV=8:1)&(STV=16:1)	Successful	874	87.40	<.0001*
		Failures	126	12.60	
	(STV=16:1)&(STV=32:1)	Successful	910	91.00	<.0001*
		Failures	90	9.00	
7:1	(STV=4:1)&(STV=32:1)	Successful	599	59.90	<.0001*
		Failures	401	40.10	
	(STV=4:1)&(STV=16:1)	Successful	545	54.50	<.0001*
		Failures	455	45.50	
	(STV=8:1)&(STV=32:1)	Successful	818	81.80	<.0001*
		Failures	182	18.20	
	(STV=8:1)&(STV=16:1)	Successful	767	76.70	<.0001*
		Failures	233	23.30	
	(STV=16:1)&(STV=32:1)	Successful	879	87.90	<.0001*
		Failures	121	12.10	
10:1	(STV=8:1)&(STV=32:1)	Successful	740	74.00	<.0001*
		Failures	260	26.00	
	(STV=8:1)&(STV=16:1)	Successful	657	65.70	<.0001*
		Failures	343	34.30	
	(STV=16:1)&(STV=32:1)	Successful	851	85.10	<.0001*
		Failures	149	14.90	

* Significant at the 0.05 probability level.

Moderate Communality

Table 32 presents complete findings of measurement and structural mean invariance for high communality among levels of STV over 1000 replications. Due to the

nature of the invariance testing, both RQ2 and 3 are presented together in this section, but noted for the readers' benefit.

Variable to factor ratio (4:1). RQ2 focuses on examination of the measurement invariance, beginning with configural (M0) to weak (M1) to strong (M2). The findings revealed that for VTF ratios (4:1), ${\chi^2}_{M_0}$ showed statistically significant results when testing configural invariance: (2:1 with 32:1); (2:1 with 16:1); (2:1 with 8:1); and (2:1 with 4:1). Thus, non-invariance was established precluding further invariance testing, e.g., weak, strong, and structural. However, at higher STV ratios, e.g., groups (4:1 with 32:1); (4:1 with 16:1); (4:1 with 8:1); (8:1 with 32:1), (8:1 with 16:1); (8:1 with 32:1) and (16:1 with 32:1), ${\chi^2}_{M_0}$ was not statistically significant indicating configural invariance was established. Given the presence of configural invariance, testing for weak invariance was conducted. Again, chi-square difference between $\Delta{\chi^2}_{M1-M0}$ was not statistically significant supporting the hypothesis of weak factorial invariance between the two groups. After weak invariance was supported, examination of the indicator intercepts was tested. Results again supported the finding of strong invariance, e.g., the $\Delta{\chi^2}_{M2-M1}$was not statistically significant. In conclusion, there were invariant factor loadings and invariant intercepts among the groups indicating that measurement invariance was achieved as described above.

RQ3 focused on the structural invariance, e.g., Model 3. In cases where strong factorial invariance was observed, a final test of structural invariance was conducted. As can be seen from Table 32, for VTF=4:1 structural invariance was noted in all cases where there was strong invariance.

Table 32

Test of Factorial Invariance for Moderate Communality Across VTF Ratios and STV Ratios Averaged Over 1000 Replications

VTF	Between Groups	Models	χ^2	df	Model Comparison	$\Delta\chi^2$	Δdf	*p*-value	RMSA	CFI	TLI
4:1	(STV=2:1) & (STV=32:1)	M0	369.66	320	M0	---	---	0.0289*	0.0201	0.9881	0.9860
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
	(STV=2:1) & (STV=16:1)	M0	372.08	320	M0	---	---	0.0237*	0.0285	0.9768	0.9726
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
	(STV=2:1) & (STV=8:1)	M0	376.62	320	M0	---	---	0.0160*	0.0403	0.9556	0.9477
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
	(STV=2:1) & (STV=4:1)	M0	387.01	320	M0	---	---	0.0060*	0.0574	0.9170	0.9017
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
	(STV=4:1) & (STV=32:1)	M0	340.99	320	M0	---	---	0.2008	0.0120	0.9945	0.9944
		M1	356.57	335	M1-M0	15.58	15	0.4105	0.0119	0.9944	0.9945
		M2	371.54	350	M2-M1	14.97	15	0.4358	0.0116	0.9944	0.9947
		M3	376.65	355	M3-M2	5.11	5	0.4026	0.0115	0.9944	0.9948

Table 32—Continued

VTF	Between Groups	Models	χ^2	df	Model Comparison	$\Delta\chi^2$	Δdf	*p*-value	RMSA	CFI	TLI
	(STV=4:1) & (STV=16:1)	M0	343.41	320	M0	---	---	0.2008	0.0170	0.9895	0.9888
		M1	359.23	335	M1-M0	18.24	15	0.2502	0.0170	0.9892	0.9890
		M2	374.06	350	M2-M1	14.83	15	0.4637	0.0165	0.9892	0.9895
		M3	379.21	355	M3-M2	5.15	5	0.3978	0.0164	0.9892	0.9896
	(STV=4:1) & (STV=8:1)	M0	347.89	320	M0	---	---	0.1360	0.0242	0.9801	0.9781
		M1	363.46	335	M1-M0	15.57	15	0.4111	0.0239	0.9797	0.9787
		M2	378.38	350	M2-M1	14.92	15	0.4571	0.0233	0.9798	0.9797
		M3	383.46	355	M3-M2	5.08	5	0.4061	0.0232	0.9797	0.9799
	(STV=8:1) & (STV=32:1)	M0	330.55	320	M0	---	---	0.3303	0.0085	0.9966	0.9974
		M1	345.87	335	M1-M0	15.32	15	0.4286	0.0083	0.9965	0.9975
		M2	360.93	350	M2-M1	15.06	15	0.4471	0.0082	0.9964	0.9976
		M3	366.12	355	M3-M2	5.19	5	0.4378	0.0082	0.9964	0.9976
	(STV=8:1) & (STV=16:1)	M0	332.97	320	M0	---	---	0.2972	0.0117	0.9939	0.9948
		M1	348.45	335	M1-M0	15.48	15	0.4174	0.0116	0.9938	0.9949
		M2	363.62	350	M2-M1	15.17	15	0.4392	0.0115	0.9936	0.9950
		M3	368.62	355	M3-M2	5	5	0.4158	0.0115	0.9936	0.9951
	(STV=16:1) & (STV=32:1)	M0	326.07	320	M0	---	---	0.3956	0.0065	0.9976	0.9988
		M1	341.10	335	M1-M0	15.03	15	0.4492	0.0064	0.9976	0.9988
		M2	356.08	350	M2-M1	14.98	15	0.4528	0.0063	0.9976	0.9989
		M3	361.07	355	M3-M2	4.99	5	0.4171	0.0063	0.9975	0.9989
7:1	(STV=2:1) & (STV=32:1)	M0	1255.41	1100	M0	---	---	0.0007*	0.0151	0.9914	0.9907
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---

Table 32—Continued

VTF	Between Groups	Models	χ^2	df	Model Comparison	$\Delta\chi^2$	Δdf	*p*-value	RMSA	CFI	TLI
	(STV=2:1) & (STV=16:1)	M0	1263.41	1100	M0	---	---	0.0004*	0.0214	0.9831	0.9817
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
	(STV=2:1) & (STV=8:1)	M0	1278.05	1100	M0	---	---	0.0001*	0.0301	0.9673	0.9647
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
	(STV=2:1) & (STV=4:1)	M0	1309.86	1100	M0	---	---	<.0001*	0.0424	0.9377	0.9326
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
	(STV=4:1) & (STV=32:1)	M0	1167.25	1100	M0	---	---	0.0779	0.0090	0.9964	0.9962
		M1	1197.64	1130	M1-M0	30.39	30	0.4458	0.0089	0.9963	0.9962
		M2	1227.73	1160	M2-M1	30.09	30	0.4610	0.0088	0.9963	0.9963
		M3	1232.85	1165	M3-M2	5.12	5	0.4014	0.0087	0.9963	0.9963
	(STV=4:1) & (STV=16:1)	M0	1175.25	1100	M0	---	---	0.0567	0.0130	0.9928	0.9923
		M1	1205.70	1130	M1-M0	30.45	30	0.4427	0.0129	0.9927	0.9925
		M2	1235.67	1160	M2-M1	29.97	30	0.4671	0.0127	0.9927	0.9927
		M3	1240.73	1165	M3-M2	5.06	5	0.4086	0.0126	0.9927	0.9927
	(STV=4:1) & (STV=8:1)	M0	1189.89	1100	M0	---	---	0.0301*	0.0186	0.9859	0.9848
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---

Table 32—Continued

VTF	Between Groups	Models	χ^2	df	Model Comparison	$\Delta\chi^2$	Δdf	*p*-value	RMSA	CFI	TLI
	(STV=8:1) & (STV=32:1)	M0	1135.44	1100	M0	---	---	0.2233	0.0060	0.9980	0.9981
		M1	1165.72	1130	M1-M0	30.28	30	0.4513	0.0060	0.9979	0.9982
		M2	1196.12	1160	M2-M1	30.4	30	0.4453	0.0059	0.9979	0.9982
		M3	1201.25	1165	M3-M2	5.13	5	0.4002	0.0059	0.9979	0.9982
	(STV=8:1) & (STV=16:1)	M0	1143.44	1100	M0	---	---	0.1768	0.0086	0.9961	0.9963
		M1	1173.52	1130	M1-M0	30.08	30	0.4615	0.0084	0.9961	0.9964
		M2	1203.48	1160	M2-M1	29.96	30	0.4677	0.0083	0.9961	0.9965
		M3	1208.60	1165	M3-M2	5.12	5	0.4014	0.0083	0.9961	0.9965
	(STV=16:1) & (STV=32:1)	M0	1120.80	1100	M0	---	---	0.3245	0.0043	0.9988	0.9991
		M1	1150.47	1130	M1-M0	29.67	30	0.4826	0.0043	0.9987	0.9991
		M2	1180.18	1160	M2-M1	29.71	30	0.4805	0.0042	0.9987	0.9991
		M3	1185.19	1165	M3-M2	5.01	5	0.4146	0.0042	0.9987	0.9991
10:1	(STV=2:1) & (STV=32:1)	M0	2636.66	2330	M0	---	---	<.0001*	0.0123	0.9922	0.9918
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
	(STV=2:1) & (STV=16:1)	M0	2652.96	2330	M0	---	---	<.0001*	0.0174	0.9846	0.9838
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
	(STV=2:1) & (STV=8:1)	M0	2679.40	2330	M0	---	---	<.0001*	0.0243	0.9705	0.9689
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---

Table 32—Continued

VTF	Between Groups	Models	χ^2	df	Model Comparison	$\Delta\chi^2$	Δdf	*p*-value	RMSA	CFI	TLI
	(STV=2:1) & (STV=4:1)	M0	2746.22	2330	M0	---	---	<.0001*	0.0344	0.9429	0.9400
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
	(STV=4:1) & (STV=32:1)	M0	2464.42	2330	M0	---	---	0.0260*	0.0076	0.9967	0.9966
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
	(STV=4:1) & (STV=16:1)	M0	2480.72	2330	M0	---	---	0.0149*	0.0109	0.9934	0.9931
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
	(STV=4:1) & (STV=8:1)	M0	2507.16	2330	M0	---	---	0.0055*	0.0155	0.9873	0.9866
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
	(STV=8:1) & (STV=32:1)	M0	2397.60	2330	M0	---	---	0.1609	0.0048	0.9984	0.9984
		M1	2443.21	2375	M1-M0	45.61	45	0.4465	0.0048	0.9983	0.9984
		M2	2488.23	2420	M2-M1	45.02	45	0.4711	0.0047	0.9983	0.9985
		M3	2493.06	2425	M3-M2	4.83	5	0.4369	0.0047	0.9983	0.9985
	(STV=8:1) & (STV=16:1)	M0	2413.89	2330	M0	---	---	0.1106	0.0070	0.9968	0.9968
		M1	2459.43	2375	M1-M0	45.54	45	0.4494	0.0070	0.9968	0.9968
		M2	2504.49	2420	M2-M1	45.06	45	0.4694	0.0069	0.9968	0.9969
		M3	2509.29	2425	M3-M2	4.8	5	0.4407	0.0069	0.9968	0.9969

Table 32—Continued

VTF	Between Groups	Models	χ^2	df	Model Comparison	$\Delta\chi^2$	Δdf	*p*-value	RMSA	CFI	TLI
	(STV=16:1) & (STV=32:1)	M0	2371.15	2330	M0	---	---	0.2714	0.0034	0.9990	0.9992
		M1	2416.38	2375	M1-M0	45.23	45	0.4623	0.0034	0.9990	0.9992
		M2	2461.59	2420	M2-M1	45.21	45	0.4631	0.0034	0.9990	0.9992
		M3	2466.36	2425	M3-M2	4.77	5	0.4445	0.0033	0.9990	0.9992

* Significant at the 0.05 probability level.

Variable to factor ratio (7:1). RQ2 focuses on examination of the measurement invariance, beginning with configural (M0) to weak (M1) to strong (M2). The findings revealed that for VTF ratios (4:1), $\chi^2{}_{M_0}$ showed statistically significant results when testing configural invariance: (2:1 with 32:1); (2:1 with 16:1); (2:1 with 8:1); (2:1 with 4:1); and (4:1 with 8:1). Thus, non-invariance was established precluding further invariance testing, e.g., weak, strong, and structural. However, at higher STV ratios, e.g., groups (4:1 with 32:1); (4:1 with 16:1); (8:1 with 32:1), (8:1 with 16:1); (8:1 with 32:1) and (16:1 with 32:1), $\chi^2{}_{M_0}$ was not statistically significant indicating configural invariance was established. Given the presence of configural invariance, testing for weak invariance was conducted. Again, chi-square difference between $\Delta\chi^2{}_{M1-M0}$ was not statistically significant supporting the hypothesis of weak factorial invariance between the two groups. After weak invariance was supported, examination of the indicator intercepts was tested. Results again supported the finding of strong invariance, e.g., the $\Delta\chi^2{}_{M2-M1}$was not statistically significant. In conclusion, there were invariant factor loadings and invariant intercepts among the groups indicating that measurement invariance was achieved as described above.

RQ3 focused on the structural invariance, e.g., Model 3. In cases where strong factorial invariance was observed, a final test of structural invariance was conducted. As can be seen from Table 32, for VTF=7:1 structural invariance was noted in all cases where there was strong invariance.

Variable to factor ratio (10:1). RQ2 focuses on examination of the measurement invariance, beginning with configural (M0) to weak (M1) to strong (M2). The findings revealed that for VTF ratios (4:1), $\chi^2{}_{M_0}$ showed statistically significant results when

testing configural invariance: (2:1 with 32:1); (2:1 with 16:1); (2:1 with 8:1); (2:1 with 4:1); (4:1 with 8:1); (4:1 with 16:1); and (4:1 with 32:1). Thus, non-invariance was established precluding further invariance testing, e.g., weak, strong, and structural. However, at higher STV ratios, e.g., groups (8:1 with 16:1); (8:1 with 32:1) and (16:1 with 32:1), ${\chi^2}_{M_0}$ was not statistically significant indicating configural invariance was established. Given the presence of configural invariance, testing for weak invariance was conducted. Again, chi-square difference between $\Delta{\chi^2}_{M1-M0}$ was not statistically significant supporting the hypothesis of weak factorial invariance between the two groups. After weak invariance was supported, examination of the indicator intercepts was tested. Results again supported the finding of strong invariance, e.g., the $\Delta{\chi^2}_{M2-M1}$was not statistically significant. In conclusion, there were invariant factor loadings and invariant intercepts among the groups indicating that measurement invariance was achieved as described above.

RQ3 focused on the structural invariance, e.g., Model 3. In cases where strong factorial invariance was observed, a final test of structural invariance was conducted. As can be seen from Table 32, for VTF=10:1 structural invariance was noted in all cases where there was strong invariance.

Table 33 presents a frequency analysis of a chi-square *p*-values > 0.05 was tested against the null proportion $\pi = 0.05$ to determine if there was a statistically significant number of invariance failures.

Table 33

Chi-square Frequency Against the Null Proportion of Structural Mean Invariance in Moderate Communality

VTF	Nested Models	Invariance Status	Frequency	Percent	*p*-value
4:1	(STV=4:1)&(STV=32:1)	Successful	789	78.90	<.0001*
		Failures	211	21.10	
	(STV=4:1)&(STV=16:1)	Successful	757	75.70	<.0001*
		Failures	243	24.30	
	(STV=4:1)&(STV=8:1)	Successful	719	71.90	<.0001*
		Failures	281	28.10	
	(STV=8:1)&(STV=32:1)	Successful	875	87.50	<.0001*
		Failures	125	12.50	
	(STV=8:1)&(STV=16:1)	Successful	870	87.00	<.0001*
		Failures	130	13.00	
	(STV=16:1)&(STV=32:1)	Successful	904	90.40	<.0001*
		Failures	96	9.60	
7:1	(STV=4:1)&(STV=32:1)	Successful	575	57.50	<.0001*
		Failures	425	42.50	
	(STV=4:1)&(STV=16:1)	Successful	529	52.90	<.0001*
		Failures	471	47.10	
	(STV=8:1)&(STV=32:1)	Successful	792	79.20	<.0001*
		Failures	208	20.80	
	(STV=8:1)&(STV=16:1)	Successful	757	75.70	<.0001*
		Failures	243	24.30	
	(STV=16:1)&(STV=32:1)	Successful	885	88.50	<.0001*
		Failures	115	11.50	
10:1	(STV=8:1)&(STV=32:1)	Successful	717	71.70	<.0001*
		Failures	283	28.30	
	(STV=8:1)&(STV=16:1)	Successful	662	66.20	<.0001*
		Failures	338	33.80	
	(STV=16:1)&(STV=32:1)	Successful	843	84.30	<.0001*
		Failures	157	15.70	

* Significant at the 0.05 probability level.

Low Communality

Table 34 presents complete findings of measurement and structural mean invariance for high communality among levels of STV over 1000 replications. Due to the

nature of the invariance testing, both RQ2 and 3 are presented together in this section, but noted for the readers' benefit.

Variable to factor ratio (4:1). RQ2 focuses on examination of the measurement invariance, beginning with configural (M0) to weak (M1) to strong (M2). The findings revealed that for VTF ratios (4:1), $\chi^2{}_{M_0}$ showed statistically significant results when testing configural invariance: (2:1 with 32:1); (2:1 with 16:1); (2:1 with 8:1); and (2:1 with 4:1). Thus, non-invariance was established precluding further invariance testing, e.g., weak, strong, and structural. However, at higher STV ratios, e.g., groups (4:1 with 32:1); (4:1 with 16:1); (4:1 with 8:1); (8:1 with 32:1), (8:1 with 16:1); (8:1 with 32:1) and (16:1 with 32:1), $\chi^2{}_{M_0}$ was not statistically significant indicating configural invariance was established. Given the presence of configural invariance, testing for weak invariance was conducted. Again, chi-square difference between $\Delta\chi^2{}_{M1-M0}$ was not statistically significant supporting the hypothesis of weak factorial invariance between the two groups. After weak invariance was supported, examination of the indicator intercepts was tested. Results again supported the finding of strong invariance, e.g., the $\Delta\chi^2{}_{M2-M1}$was not statistically significant. In conclusion, there were invariant factor loadings and invariant intercepts among the groups indicating that measurement invariance was achieved as described above.

RQ3 focused on the structural invariance, e.g., Model 3. In cases where strong factorial invariance was observed, a final test of structural invariance was conducted. As can be seen from Table 34, for VTF=4:1 structural invariance was noted in all cases where there was strong invariance.

Table 34

Test of Factorial Invariance for Low Communality Across VTF Ratios and STV Ratios Averaged Over 1000 Replications

VTF	Between Groups	Models	χ^2	df	Model Comparison	$\Delta\chi^2$	Δdf	*p*-value	RMSA	CFI	TLI
4:1		M0	363.00	320	M0	---	---	0.0489*	0.0185	0.9614	0.9549
	(STV=2:1) &	M1	---	---	M1-M0	---	---	---	---	---	---
	(STV=32:1)	M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
		M0	364.32	320	M0	---	---	0.0442*	0.0260	0.9286	0.9168
	(STV=2:1) &	M1	---	---	M1-M0	---	---	---	---	---	---
	(STV=16:1)	M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
		M0	369.33	320	M0	---	---	0.0297*	0.0372	0.8709	0.8485
	(STV=2:1) & (STV=8:1)	M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
		M0	376.85	320	M0	---	---	0.0156*	0.0524	0.7862	0.7473
	(STV=2:1) & (STV=4:1)	M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
		M0	338.84	320	M0	---	---	0.2245	0.0112	0.9810	0.9811
	(STV=4:1) &	M1	356.95	335	M1-M0	18.11	15	0.2569	0.0119	0.9786	0.9789
	(STV=32:1)	M2	372.19	350	M2-M1	15.24	15	0.4342	0.0118	0.9782	0.9795
		M3	377.47	355	M3-M2	5.28	5	0.3826	0.0118	0.9779	0.9796

Table 34—Continued

VTF	Between Groups	Models	χ^2	df	Model Comparison	$\Delta\chi^2$	Δdf	*p*-value	RMSA	CFI	TLI
		M0	340.24	320	M0	---	---	0.2094	0.0159	0.9640	0.9649
	(STV=4:1) &	M1	358.30	335	M1-M0	18.06	15	0.2595	0.0166	0.9602	0.9611
	(STV=16:1)	M2	373.47	350	M2-M1	15.17	15	0.4392	0.0163	0.9596	0.9625
		M3	378.69	355	M3-M2	5.22	5	0.3896	0.0163	0.9592	0.9626
		M0	345.09	320	M0	---	---	0.1603	0.0228	0.9346	0.9312
	(STV=4:1) & (STV=8:1)	M1	363.19	335	M1-M0	18.1	15	0.2574	0.0237	0.9281	0.9257
		M2	378.19	350	M2-M1	15	15	0.4514	0.0231	0.9280	0.9288
		M3	383.52	355	M3-M2	7.33	5	0.1972	0.0231	0.9271	0.9289
		M0	331.11	320	M0	---	---	0.3225	0.0087	0.9870	0.9900
	(STV=8:1) &	M1	347.34	335	M1-M0	16.23	15	0.3669	0.0088	0.9863	0.9894
	(STV=32:1)	M2	362.27	350	M2-M1	14.94	15	0.4557	0.0086	0.9862	0.9899
		M3	367.30	355	M3-M2	5.03	5	0.4122	0.0086	0.9862	0.9900
		M0	332.49	320	M0	---	---	0.3037	0.0117	0.9770	0.9820
	(STV=8:1) &	M1	348.42	335	M1-M0	15.93	15	0.3867	0.0117	0.9759	0.9815
	(STV=16:1)	M2	363.42	350	M2-M1	15	15	0.4514	0.0114	0.9756	0.9823
		M3	368.37	355	M3-M2	4.95	5	0.4220	0.0114	0.9755	0.9826
		M0	326.17	320	M0	---	---	0.3940	0.0065	0.9911	0.9954
	(STV=16:1) &	M1	341.85	335	M1-M0	15.68	15	0.4036	0.0066	0.9906	0.9951
	(STV=32:1)	M2	356.81	350	M2-M1	14.96	15	0.4543	0.0065	0.9905	0.9954
		M3	361.82	355	M3-M2	5.01	5	0.41466	0.0065	0.9905	0.9954
7:1		M0	1251.43	1100	M0	---	---	0.0009*	0.0149	0.9646	0.9617
	(STV=2:1) &	M1	---	---	M1-M0	---	---	---	---	---	---
	(STV=32:1)	M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---

Table 34—Continued

VTF	Between Groups	Models	χ^2	df	Model Comparison	$\Delta\chi^2$	Δdf	*p*-value	RMSA	CFI	TLI
	(STV=2:1) & (STV=16:1)	M0	1246.03	1100	M0	---	---	0.0013*	0.0208	0.9335	0.9281
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
	(STV=2:1) & (STV=8:1)	M0	1269.57	1100	M0	---	---	0.0002*	0.0293	0.8779	0.8679
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
	(STV=2:1) & (STV=4:1)	M0	1300.43	1100	M0	---	---	<.0001*	0.0414	0.7851	0.7675
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
	(STV=4:1) & (STV=32:1)	M0	1166.44	1100	M0	---	---	0.0804	0.0090	0.9845	0.9838
		M1	1197.87	1130	M1-M0	31.43	30	0.3944	0.0090	0.9842	0.9839
		M2	1227.89	1160	M2-M1	30.02	30	0.4646	0.0089	0.9842	0.9843
		M3	1233.03	1165	M3-M2	5.14	5	0.3990	0.0089	0.9841	0.9844
	(STV=4:1) & (STV=16:1)	M0	1171.44	1100	M0	---	---	0.0662	0.0125	0.9709	0.9693
		M1	1202.78	1130	M1-M0	31.34	30	0.3988	0.0125	0.9703	0.9695
		M2	1232.65	1160	M2-M1	29.87	30	0.4723	0.0123	0.9704	0.9704
		M3	1237.74	1165	M3-M2	5.09	5	0.4049	0.0123	0.9703	0.9705
	(STV=4:1) & (STV=8:1)	M0	1184.88	1100	M0	---	---	0.0377*	0.0181	0.9447	0.9409
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---

Table 34—Continued

VTF	Between Groups	Models	χ^2	df	Model Comparison	$\Delta\chi^2$	Δdf	*p*-value	RMSA	CFI	TLI
	(STV=8:1) & (STV=32:1)	M0	1135.57	1100	M0	---	---	0.2227	0.0060	0.9913	0.9922
		M1	1166.10	1130	M1-M0	30.53	30	0.4387	0.0060	0.9912	0.9923
		M2	1195.80	1160	M2-M1	29.7	30	0.4810	0.0059	0.9912	0.9925
		M3	1200.80	1165	M3-M2	5	5	0.4158	0.0059	0.9912	0.9925
	(STV=8:1) & (STV=16:1)	M0	1140.57	1100	M0	---	---	0.1929	0.0082	0.9846	0.9853
		M1	1171.33	1130	M1-M0	30.76	30	0.4272	0.0082	0.9843	0.9854
		M2	1201.18	1160	M2-M1	29.85	30	0.4733	0.0081	0.9843	0.9859
		M3	1206.19	1165	M3-M2	5.01	5	0.4146	0.0081	0.9843	0.9859
	(STV=16:1) & (STV=32:1)	M0	1122.10	1100	M0	---	---	0.3148	0.0044	0.9945	0.9959
		M1	1152.22	1130	M1-M0	30.12	30	0.4595	0.0044	0.9944	0.9960
		M2	1182.17	1160	M2-M1	29.95	30	0.4682	0.0044	0.9944	0.9961
		M3	1187.19	1165	M3-M2	5.02	5	0.4134	0.0043	0.9944	0.9961
10:1	(STV=2:1) & (STV=32:1)	M0	2641.18	2330	M0	---	---	<.0001*	0.0124	0.9740	0.9726
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
	(STV=2:1) & (STV=16:1)	M0	2653.45	2330	M0	---	---	<.0001*	0.0174	0.9501	0.9476
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
	(STV=2:1) & (STV=8:1)	M0	2681.07	2330	M0	---	---	<.0001*	0.0244	0.9070	0.9022
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---

Table 34—Continued

VTF	Between Groups	Models	χ^2	df	Model Comparison	$\Delta\chi^2$	Δdf	*p*-value	RMSA	CFI	TLI
	(STV=2:1) & (STV=4:1)	M0	2748.14	2330	M0	---	---	<.0001*	0.0345	0.8305	0.8218
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
	(STV=4:1) & (STV=32:1)	M0	2464.73	2330	M0	---	---	0.0258*	0.0076	0.9891	0.9886
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
	(STV=4:1) & (STV=16:1)	M0	2477.00	2330	M0	---	---	0.0170*	0.0107	0.9789	0.9779
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
	(STV=4:1) & (STV=8:1)	M0	2504.62	2330	M0	---	---	0.0061*	0.0153	0.9593	0.9572
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
	(STV=8:1) & (STV=32:1)	M0	2397.84	2330	M0	---	---	0.1602	0.0048	0.9946	0.9948
		M1	2443.33	2375	M1-M0	45.49	45	0.4515	0.0048	0.9945	0.9949
		M2	2487.91	2420	M2-M1	44.58	45	0.4896	0.0047	0.9946	0.9950
		M3	2493.00	2425	M3-M2	5.09	5	0.4049	0.0047	0.9945	0.9950
	(STV=8:1) & (STV=16:1)	M0	2410.11	2330	M0	---	---	0.1210	0.0068	0.9898	0.9899
		M1	2455.83	2375	M1-M0	45.72	45	0.4420	0.0068	0.9897	0.9900
		M2	2500.99	2420	M2-M1	45.16	45	0.4652	0.0067	0.9897	0.9901
		M3	2506.15	2425	M3-M2	5.16	5	0.3966	0.0067	0.9897	0.9901

Table 34—Continued

VTF	Between Groups	Models	χ^2	df	Model Comparison	$\Delta\chi^2$	Δdf	*p*-value	RMSA	CFI	TLI
	(STV=16:1) & (STV=32:1)	M0	2370.22	2330	M0	---	---	0.2758	0.0034	0.9968	0.9974
		M1	2416.00	2375	M1-M0	45.78	45	0.4395	0.0034	0.9967	0.9974
		M2	2460.52	2420	M2-M1	44.52	45	0.4921	0.0033	0.9967	0.9975
		M3	2465.54	2425	M3-M2	5.02	5	0.4134	0.0033	0.9967	0.9975

* Significant at the 0.05 probability level.

Variable to factor ratio (7:1). RQ2 focuses on examination of the measurement invariance, beginning with configural (M0) to weak (M1) to strong (M2). The findings revealed that for VTF ratios (4:1), $\chi^2_{M_0}$ showed statistically significant results when testing configural invariance: (2:1 with 32:1); (2:1 with 16:1); (2:1 with 8:1); (2:1 with 4:1); and (4:1 with 8:1). Thus, non-invariance was established precluding further invariance testing, e.g., weak, strong, and structural. However, at higher STV ratios, e.g., groups (4:1 with 32:1); (4:1 with 16:1); (8:1 with 32:1), (8:1 with 16:1); (8:1 with 32:1) and (16:1 with 32:1), $\chi^2_{M_0}$ was not statistically significant indicating configural invariance was established. Given the presence of configural invariance, testing for weak invariance was conducted. Again, chi-square difference between $\Delta\chi^2_{M1-M0}$ was not statistically significant supporting the hypothesis of weak factorial invariance between the two groups. After weak invariance was supported, examination of the indicator intercepts was tested. Results again supported the finding of strong invariance, e.g., the $\Delta\chi^2_{M2-M1}$was not statistically significant. In conclusion, there were invariant factor loadings and invariant intercepts among the groups indicating that measurement invariance was achieved as described above.

RQ3 focused on the structural invariance, e.g., Model 3. In cases where strong factorial invariance was observed, a final test of structural invariance was conducted. As can be seen from Table 34, for VTF=7:1 structural invariance was noted in all cases where there was strong invariance.

Variable to factor ratio (10:1). RQ2 focuses on examination of the measurement invariance, beginning with configural (M0) to weak (M1) to strong (M2). The findings revealed that for VTF ratios (4:1), $\chi^2_{M_0}$ showed statistically significant results when

testing configural invariance: (2:1 with 32:1); (2:1 with 16:1); (2:1 with 8:1); (2:1 with 4:1); (4:1 with 8:1); (4:1 with 16:1); and (4:1 with 32:1). Thus, non-invariance was established precluding further invariance testing, e.g., weak, strong, and structural. However, at higher STV ratios, e.g., groups (8:1 with 16:1); (8:1 with 32:1) and (16:1 with 32:1), ${\chi^2}_{M_0}$ was not statistically significant indicating configural invariance was established. Given the presence of configural invariance, testing for weak invariance was conducted. Again, chi-square difference between $\Delta{\chi^2}_{M1-M0}$ was not statistically significant supporting the hypothesis of weak factorial invariance between the two groups. After weak invariance was supported, examination of the indicator intercepts was tested. Results again supported the finding of strong invariance, e.g., the $\Delta{\chi^2}_{M2-M1}$was not statistically significant. In conclusion, there were invariant factor loadings and invariant intercepts among the groups indicating that measurement invariance was achieved as described above.

RQ3 focused on the structural invariance, e.g., Model 3. In cases where strong factorial invariance was observed, a final test of structural invariance was conducted. As can be seen from Table 34, for VTF=10:1 structural invariance was noted in all cases where there was strong invariance.

Table 35 presents a frequency analysis of a chi-square *p*-values > 0.05 was tested against the null proportion $\pi = 0.05$ to determine if there was a statistically significant number of invariance failures.

Table 35

Chi-square Frequency Against the Null Proportion of Structural Mean Invariance in Low Communality

VTF	Nested Models	Invariance Status	Frequency	Percent	*p*-value
4:1	(STV=4:1)&(STV=32:1)	Successful	775	77.50	<.0001*
		Failures	225	22.50	
	(STV=4:1)&(STV=16:1)	Successful	763	76.30	<.0001*
		Failures	237	23.70	
	(STV=4:1)&(STV=8:1)	Successful	700	70.00	<.0001*
		Failures	300	30.00	
	(STV=8:1)&(STV=32:1)	Successful	886	88.60	<.0001*
		Failures	114	11.40	
	(STV=8:1)&(STV=16:1)	Successful	847	84.70	<.0001*
		Failures	153	15.30	
	(STV=16:1)&(STV=32:1)	Successful	903	90.30	<.0001*
		Failures	97	9.70	
7:1	(STV=4:1)&(STV=32:1)	Successful	562	56.20	<.0001*
		Failures	438	43.80	
	(STV=4:1)&(STV=16:1)	Successful	541	54.10	<.0001*
		Failures	459	45.90	
	(STV=8:1)&(STV=32:1)	Successful	802	80.20	<.0001*
		Failures	198	19.80	
	(STV=8:1)&(STV=16:1)	Successful	764	76.40	<.0001*
		Failures	236	23.60	
	(STV=16:1)&(STV=32:1)	Successful	876	87.60	<.0001*
		Failures	124	12.40	
10:1	(STV=8:1)&(STV=32:1)	Successful	733	73.30	<.0001*
		Failures	267	26.70	
	(STV=8:1)&(STV=16:1)	Successful	676	67.60	<.0001*
		Failures	324	32.40	
	(STV=16:1)&(STV=32:1)	Successful	845	84.50	<.0001*
		Failures	155	15.50	

* Significant at the 0.05 probability level.

Mixed Communality

Table 36 presents complete findings of measurement and structural mean invariance for high communality among levels of STV over 1000 replications. Due to the

nature of the invariance testing, both RQ2 and 3 are presented together in this section, but noted for the readers' benefit.

Variable to factor ratio (4:1). RQ2 focuses on examination of the measurement invariance, beginning with configural (M0) to weak (M1) to strong (M2). The findings revealed that for VTF ratios (4:1), ${\chi^2}_{M_0}$ showed statistically significant results when testing configural invariance: (2:1 with 32:1); (2:1 with 16:1); (2:1 with 8:1); and (2:1 with 4:1). Thus, non-invariance was established precluding further invariance testing, e.g., weak, strong, and structural. However, at higher STV ratios, e.g., groups (4:1 with 32:1); (4:1 with 16:1); (4:1 with 8:1); (8:1 with 32:1), (8:1 with 16:1); (8:1 with 32:1) and (16:1 with 32:1), ${\chi^2}_{M_0}$ was not statistically significant indicating configural invariance was established. Given the presence of configural invariance, testing for weak invariance was conducted. Again, chi-square difference between $\Delta{\chi^2}_{M1-M0}$ was not statistically significant supporting the hypothesis of weak factorial invariance between the two groups. After weak invariance was supported, examination of the indicator intercepts was tested. Results again supported the finding of strong invariance, e.g., the $\Delta{\chi^2}_{M2-M1}$was not statistically significant. In conclusion, there were invariant factor loadings and invariant intercepts among the groups indicating that measurement invariance was achieved as described above.

RQ3 focused on the structural invariance, e.g., Model 3. In cases where strong factorial invariance was observed, a final test of structural invariance was conducted. As can be seen from Table 36, for VTF=4:1 structural invariance was noted in all cases where there was strong invariance.

Table 36

Test of Factorial Invariance for Mixed Communality Across VTF Ratios and STV Ratios Averaged Over 1000 Replications

VTF	Between Groups	Models	χ^2	df	Model Comparison	$\Delta\chi^2$	Δdf	*p*-value	RMSA	CFI	TLI
4:1											
	(STV=2:1) & (STV=32:1)	M0	369.18	320	M0	---	---	0.0301*	0.0201	0.9893	0.9874
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
	(STV=2:1) & (STV=16:1)	M0	371.33	320	M0	---	---	0.0252*	0.0285	0.9791	0.9754
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
	(STV=2:1) & (STV=8:1)	M0	375.77	320	M0	---	---	0.0172*	0.0399	0.9602	0.9530
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
	(STV=2:1) & (STV=4:1)	M0	386.26	320	M0	---	---	0.0065*	0.0573	0.9245	0.9104
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
	(STV=4:1) & (STV=32:1)	M0	340.29	320	M0	---	---	0.2084	0.0117	0.9952	0.9950
		M1	356.07	335	M1-M0	15.78	15	0.3968	0.0117	0.9950	0.9951
		M2	370.63	350	M2-M1	14.56	15	0.4835	0.0114	0.9950	0.9954
		M3	375.75	355	M3-M2	5.12	5	0.4014	0.0114	0.9949	0.9954

Table 36—Continued

VTF	Between Groups	Models	χ^2	df	Model Comparison	$\Delta\chi^2$	Δdf	*p*-value	RMSA	CFI	TLI
	(STV=4:1) & (STV=16:1)	M0	342.43	320	M0	---	---	0.1859	0.0164	0.9907	0.9902
		M1	358.02	335	M1-M0	15.59	15	0.4098	0.0163	0.9904	0.9904
		M2	372.60	350	M2-M1	14.58	15	0.4820	0.0159	0.9905	0.9910
		M3	377.67	355	M3-M2	5.07	5	0.4073	0.0157	0.9905	0.9911
	(STV=4:1) & (STV=8:1)	M0	346.89	320	M0	---	---	0.1444	0.0237	0.9825	0.9808
		M1	362.81	335	M1-M0	15.92	15	0.3873	0.0236	0.9819	0.9810
		M2	377.46	350	M2-M1	14.65	15	0.4769	0.0229	0.9820	0.9820
		M3	382.56	355	M3-M2	5.1	5	0.4037	0.0228	0.9819	0.9822
	(STV=8:1) & (STV=32:1)	M0	329.85	320	M0	---	---	0.3402	0.0082	0.9971	0.9978
		M1	345.07	335	M1-M0	15.22	15	0.4356	0.0081	0.9970	0.9979
		M2	360.13	350	M2-M1	15.06	15	0.4471	0.0080	0.9969	0.9979
		M3	365.24	355	M3-M2	5.11	5	0.4026	0.0079	0.9969	0.9979
	(STV=8:1) & (STV=16:1)	M0	331.88	320	M0	---	---	0.3120	0.0115	0.9946	0.9957
		M1	346.96	335	M1-M0	15.08	15	0.4456	0.0113	0.9945	0.9958
		M2	362.06	350	M2-M1	15.1	15	0.4442	0.0111	0.9945	0.9960
		M3	366.93	355	M3-M2	4.87	5	0.4319	0.0110	0.9945	0.9961
	(STV=16:1) & (STV=32:1)	M0	325.34	320	M0	---	---	0.4066	0.0063	0.9980	0.9990
		M1	340.40	335	M1-M0	15.06	15	0.4471	0.0062	0.9980	0.9990
		M2	355.28	350	M2-M1	14.88	15	0.4600	0.0061	0.9980	0.9991
		M3	360.45	355	M3-M2	5.17	5	0.3954	0.0062	0.9978	0.9991
7:1	(STV=2:1) & (STV=32:1)	M0	1257.15	1100	M0	---	---	0.0006*	0.0152	0.9942	0.9938
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---

Table 36—Continued

VTF	Between Groups	Models	χ^2	df	Model Comparison	$\Delta\chi^2$	Δdf	*p*-value	RMSA	CFI	TLI
	(STV=2:1) & (STV=16:1)	M0	1262.68	1100	M0	---	---	0.0004*	0.0213	0.9888	0.9879
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
	(STV=2:1) & (STV=8:1)	M0	1262.65	1100	M0	---	---	0.0004*	0.0213	0.9888	0.9879
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
	(STV=2:1) & (STV=4:1)	M0	1310.82	1100	M0	---	---	<0.0001*	0.0425	0.9579	0.9544
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
	(STV=4:1) & (STV=32:1)	M0	1170.54	1100	M0	---	---	0.0686	0.0093	0.9975	0.9973
		M1	1200.54	1130	M1-M0	30	30	0.4656	0.0092	0.9975	0.9974
		M2	1230.60	1160	M2-M1	30.06	30	0.4625	0.0090	0.9975	0.9975
		M3	1235.74	1165	M3-M2	5.14	5	0.3990	0.0090	0.9975	0.9975
	(STV=4:1) & (STV=16:1)	M0	1176.06	1100	M0	---	---	0.0549	0.0130	0.9952	0.9949
		M1	1206.12	1130	M1-M0	30.06	30	0.4625	0.0128	0.9951	0.9950
		M2	1236.47	1160	M2-M1	30.35	30	0.4478	0.0127	0.9951	0.9951
		M3	1241.56	1165	M3-M2	5.09	5	0.4049	0.0127	0.9951	0.9951
	(STV=4:1) & (STV=8:1)	M0	1191.49	1100	M0	---	---	0.0279*	0.018	0.9905	0.9898
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---

Table 36—Continued

VTF	Between Groups	Models	χ^2	df	Model Comparison	$\Delta\chi^2$	Δdf	*p*-value	RMSA	CFI	TLI
	(STV=8:1) & (STV=32:1)	M0	1137.82	1100	M0	---	---	0.2086	0.0062	0.9986	0.9987
		M1	1167.98	1130	M1-M0	30.16	30	0.4574	0.0061	0.9986	0.9987
		M2	1197.93	1160	M2-M1	29.95	30	0.4682	0.0061	0.9986	0.9987
		M3	1202.91	1165	M3-M2	4.98	5	0.4183	0.0060	0.9986	0.9988
	(STV=8:1) & (STV=16:1)	M0	1143.33	1100	M0	---	---	0.1773	0.0086	0.9975	0.9975
		M1	1173.42	1130	M1-M0	30.09	30	0.4610	0.0085	0.9975	0.9976
		M2	1203.61	1160	M2-M1	30.19	30	0.4559	0.0084	0.9974	0.9976
		M3	1208.55	1165	M3-M2	4.94	5	0.4232	0.0084	0.9974	0.9977
	(STV=16:1) & (STV=32:1)	M0	1122.39	1100	M0	---	---	0.3133	0.0044	0.9991	0.9993
		M1	1152.28	1130	M1-M0	29.89	30	0.4712	0.0044	0.9991	0.9993
		M2	1182.31	1160	M2-M1	30.03	30	0.4641	0.0044	0.9991	0.9994
		M3	1187.14	1165	M3-M2	4.83	5	0.4469	0.0044	0.9991	0.9994
10:1	(STV=2:1) & (STV=32:1)	M0	2640.05	2330	M0	---	---	<0.0001*	0.01241	0.9948	0.9946
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
	(STV=2:1) & (STV=16:1)	M0	2654.33	2330	M0	---	---	<0.0001*	0.0174	0.9899	0.9894
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
	(STV=2:1) & (STV=8:1)	M0	2681.11	2330	M0	---	---	<0.0001*	0.0244	0.9806	0.9796
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---

Table 36—Continued

VTF	Between Groups	Models	χ^2	df	Model Comparison	$\Delta\chi^2$	Δdf	*p*-value	RMSA	CFI	TLI
	(STV=2:1) & (STV=4:1)	M0	2748.81	2330	M0	---	---	<0.0001*	0.0345	0.9621	0.9601
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
	(STV=4:1) & (STV=32:1)	M0	2464.25	2330	M0	---	---	<0.0001*	0.0076	0.9978	0.9978
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
	(STV=4:1) & (STV=16:1)	M0	2478.53	2330	M0	---	---	<0.0001*	0.0108	0.9958	0.9956
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
	(STV=4:1) & (STV=8:1)	M0	2505.31	2330	M0	---	---	0.0059*	0.0154	0.9918	0.9914
		M1	---	---	M1-M0	---	---	---	---	---	---
		M2	---	---	M2-M1	---	---	---	---	---	---
		M3	---	---	M3-M2	---	---	---	---	---	---
	(STV=8:1) & (STV=32:1)	M0	2396.55	2330	M0	---	---	0.1648	0.0047	0.9989	0.9990
		M1	2441.69	2375	M1-M0	45.14	45	0.4661	0.0047	0.9989	0.9990
		M2	2486.29	2420	M2-M1	44.6	45	0.4470	0.0046	0.9989	0.9990
		M3	2491.42	2425	M3-M2	5.13	5	0.4002	0.0046	0.9989	0.9990
	(STV=8:1) & (STV=16:1)	M0	2410.83	2330	M0	---	---	0.1190	0.0069	0.9980	0.9980
		M1	2455.99	2375	M1-M0	45.16	45	0.4652	0.0068	0.9980	0.9980
		M2	2500.68	2420	M2-M1	44.69	45	0.4432	0.0067	0.9980	0.9980
		M3	2505.72	2425	M3-M2	5.04	5	0.4110	0.0067	0.9980	0.9980

Table 36—Continued

VTF	Between Groups	Models	χ^2	df	Model Comparison	$\Delta\chi^2$	Δdf	*p*-value	RMSA	CFI	TLI
		M0	2369.77	2330	M0	---	---	0.2782	0.0034	0.9993	0.9995
	(STV=16:1) &	M1	2413.98	2375	M1-M0	44.21	45	0.5053	0.0033	0.9993	0.9995
	(STV=32:1)	M2	2458.99	2420	M2-M1	45.01	45	0.4715	0.0033	0.9993	0.9995
		M3	2463.93	2425	M3-M2	4.94	5	0.4232	0.0033	0.9993	0.9995

* Significant at the 0.05 probability level.

Variable to factor ratio (7:1). RQ2 focuses on examination of the measurement invariance, beginning with configural (M0) to weak (M1) to strong (M2). The findings revealed that for VTF ratios (4:1), $\chi^2_{M_0}$ showed statistically significant results when testing configural invariance: (2:1 with 32:1); (2:1 with 16:1); (2:1 with 8:1); (2:1 with 4:1); and (4:1 with 8:1). Thus, non-invariance was established precluding further invariance testing, e.g., weak, strong, and structural. However, at higher STV ratios, e.g., groups (4:1 with 32:1); (4:1 with 16:1); (8:1 with 32:1), (8:1 with 16:1); (8:1 with 32:1) and (16:1 with 32:1), $\chi^2_{M_0}$ was not statistically significant indicating configural invariance was established. Given the presence of configural invariance, testing for weak invariance was conducted. Again, chi-square difference between $\Delta\chi^2_{M1-M0}$ was not statistically significant supporting the hypothesis of weak factorial invariance between the two groups. After weak invariance was supported, examination of the indicator intercepts was tested. Results again supported the finding of strong invariance, e.g., the $\Delta\chi^2_{M2-M1}$was not statistically significant. In conclusion, there were invariant factor loadings and invariant intercepts among the groups indicating that measurement invariance was achieved as described above.

RQ3 focused on the structural invariance, e.g., Model 3. In cases where strong factorial invariance was observed, a final test of structural invariance was conducted. As can be seen from Table 36, for VTF=7:1 structural invariance was noted in all cases where there was strong invariance.

Variable to factor ratio (10:1). RQ2 focuses on examination of the measurement invariance, beginning with configural (M0) to weak (M1) to strong (M2). The findings revealed that for VTF ratios (4:1), $\chi^2_{M_0}$ showed statistically significant results when

testing configural invariance: (2:1 with 32:1); (2:1 with 16:1); (2:1 with 8:1); (2:1 with 4:1); (4:1 with 8:1); (4:1 with 16:1); and (4:1 with 32:1). Thus, non-invariance was established precluding further invariance testing, e.g., weak, strong, and structural. However, at higher STV ratios, e.g., groups (8:1 with 16:1); (8:1 with 32:1) and (16:1 with 32:1), ${\chi^2}_{M_0}$ was not statistically significant indicating configural invariance was established. Given the presence of configural invariance, testing for weak invariance was conducted. Again, chi-square difference between $\Delta{\chi^2}_{M1-M0}$ was not statistically significant supporting the hypothesis of weak factorial invariance between the two groups. After weak invariance was supported, examination of the indicator intercepts was tested. Results again supported the finding of strong invariance, e.g., the $\Delta{\chi^2}_{M2-M1}$was not statistically significant. In conclusion, there were invariant factor loadings and invariant intercepts among the groups indicating that measurement invariance was achieved as described above.

RQ3 focused on the structural invariance, e.g., Model 3. In cases where strong factorial invariance was observed, a final test of structural invariance was conducted. As can be seen from Table 36, for VTF=10:1 structural invariance was noted in all cases where there was strong invariance.

Table 37 presents a frequency analysis of a chi-square *p*-values > 0.05 was tested against the null proportion $\pi = 0.05$ to determine if there was a statistically significant number of invariance failures.

Table 37

Chi-square Frequency Against the Null Proportion of Structural Mean Invariance in Mixed Communality

VTF	Nested Models	Invariance Status	Frequency	Percent	*p*-value
4:1	(STV=4:1)&(STV=32:1)	Successful	799	79.90	<.0001*
		Failures	201	20.10	
	(STV=4:1)&(STV=16:1)	Successful	765	76.50	<.0001*
		Failures	235	23.50	
	(STV=4:1)&(STV=8:1)	Successful	712	71.20	<.0001*
		Failures	288	28.80	
	(STV=8:1)&(STV=32:1)	Successful	899	89.90	<.0001*
		Failures	101	10.01	
	(STV=8:1)&(STV=16:1)	Successful	878	87.80	<.0001*
		Failures	122	12.20	
	(STV=16:1)&(STV=32:1)	Successful	933	93.90	<.0001*
		Failures	67	6.70	
7:1	(STV=4:1)&(STV=32:1)	Successful	569	56.90	<.0001*
		Failures	431	43.10	
	(STV=4:1)&(STV=16:1)	Successful	513	51.30	<.0001*
		Failures	487	48.70	
	(STV=8:1)&(STV=32:1)	Successful	790	79.00	<.0001*
		Failures	210	21.00	
	(STV=8:1)&(STV=16:1)	Successful	752	75.20	<.0001*
		Failures	248	24.80	
	(STV=16:1)&(STV=32:1)	Successful	868	86.80	<.0001*
		Failures	132	13.20	
10:1	(STV=8:1)&(STV=32:1)	Successful	734	73.40	<.0001*
		Failures	266	26.60	
	(STV=8:1)&(STV=16:1)	Successful	670	67.00	<.0001*
		Failures	330	33.00	
	(STV=16:1)&(STV=32:1)	Successful	840	84.00	<.0001*
		Failures	160	16.00	

* Significant at the 0.05 probability level

Summary

This chapter has presented the data analysis results focused on the three research questions as examined across the various design conditions.

Study results RQ1 showed that the precisions of the overall model fit indices TLI, CFI, and RMR were varying as a function of VTF, STV, h^2, and their interaction,

whereas the precisions of the overall model fit indices GFI, AGFI, and RMSEA were varying as a function of VTF, STV, and their interactions. Factorial invariance result RQ2 and 3 revealed that stability and precision of the models were varying over increasingly levels of measurement and structural mean invariance as a function of VTF, STV, and their interactions.

CHAPTER V

DISCUSSION

This chapter presents summary, conclusion of the study, discussion, the limitations, and recommendations for future research.

Summary

The aim of this study was to provide empirical evaluation of the influence of ED and SD on WSV in terms of model precision and model estimate stability relative to a known factor structure via Monte Carlo simulation. The experimental conditions under consideration were: (a) variable-to-factor ratio (4:1, 7:1, and 10:1) that were randomly sampled from a population of 100 indicator variables, (b) subject-to-variable ratio 2:1 to 32:1 in multiple of 2 (2:1, 4:1, 8:1, 16:1, and 32:1), and (c) communality magnitude (high, moderate, low, and mixed). Specifically, three research questions were proposed.

The study used the techniques of Tucker et al. (1969) to generate Monte Carlo population correlation matrices. The simulation was generated in SAS 9.4 and the IML code was adapted from the study conducted by Coughlin (2013) to contain all aspects of ED and SD. The procedure of generating data incorporated the following conditions: (1) four communality magnitudes (high, moderate, low, and mixed); (2) three sample correlation matrices of variables (20, 35, and 50) were randomly partitioned from each set of population correlation matrices to represent three levels of VTF ratio (4:1, 7:1, and 10:1); and (3) for each sample correlation matrix, systematic variation of STV ratios (2:1, 4:1, 8:1, 16:1, and 32:1) generated data sets with 1000 replication.

General Findings and Conclusion

RQ 1: *Does the precision of the overall data-model fit vary as a function of the following conditions and their interactions in the simulated models?*

a. VTF ratio?

b. STV ratio?

c. h^2 magnitude?

Overall model fit indices TLI, CFI, and RMR all varied as a function of VTF, STV, h^2, and their interaction. Chi-square value and overall model fit indices GFI, AGFI, and RMSEA only varied as a function of VTF, STV, and their interactions.

Post hoc analysis of 2-way interaction VTF*STV focused on splitting out the levels of STV and examined five one-way ANOVAs for the levels of VTF. Specifically the analysis examined differences in mean χ^2, GFI, AGFI, and RMSEA values among VTF levels for each STV level. Post hoc analysis of 3-way interaction h^2*VTF*STV first focused on the simple effect interaction of h^2*VTF after blocking on STV. Further analysis of the four by three 2-way interactions focused on the simple-simple effects of STV blocking on the STV* h^2 interaction. Specifically the analysis examined differences in mean TLI, CFI, and RMR values among VTF levels for each STV* h^2 interaction.

In general, the results revealed that examination of the means of χ^2 and RMSEA values suggest significant decreases values as STV increases, and increasing means of χ^2 and RMSEA as VTF ratios decreased. However, the examination of the means GFI and AGFI values suggest significant increases in means GFI and AGFI values as STV increases, as well as decreasing means GFI and AGFI as VTF ratios increased.

Examination of the means of TLI and CFI values reveal a differential increase in means of TLI and CFI within levels of STV as a function of h^2 magnitude. In the h^2 = high condition, means of TLI and CFI values evidences minimal gains even between STV levels 2:1 and 4:1. Within the mixed and moderate h^2 conditions means of TLI and CFI values show asymptotic gains after STV > 4:1. However, in the low h^2 condition means of TLI and CFI values were markedly lower in the STV levels 2:1 and 4:1, only showing asymptotic values when STV > 8:1. Table 38 presents the summary of minimum STV ratio that was required in each model fit index to gain acceptable fit criteria.

Examination of the mean RMR reveals several systematic changes in mean RMR as a function of the three independent variables. First, regardless of h^2 and VTF, it appears that there are only minimal decreases in mean RMR the high STV levels (STV >= 16:1). Moreover increases in VTF coincide with systematic decreases in mean RMR in all STV and h^2 combinations. What is driving the triple interaction is that the influence of VTF on mean RMR gets exaggerated differentially when STV levels rise, resulting in differentially lower mean RMR values at higher VTF levels and this does not seem heavily influenced by h^2 level.

Table 38

Summary of STV Ratio Required to Yield Precision in Factor Solution Based on Communality Magnitudes and Levels of VTF Ratio

	Communalities											
Criteria	High			Moderate			Low			Mixed		
	$\begin{pmatrix}\text{VTF}\\4:1\end{pmatrix}$	$\begin{pmatrix}\text{VTF}\\7:1\end{pmatrix}$	$\begin{pmatrix}\text{VTF}\\10:1\end{pmatrix}$	$\begin{pmatrix}\text{VTF}\\4:1\end{pmatrix}$	$\begin{pmatrix}\text{VTF}\\7:1\end{pmatrix}$	$\begin{pmatrix}\text{VTF}\\10:1\end{pmatrix}$	$\begin{pmatrix}\text{VTF}\\4:1\end{pmatrix}$	$\begin{pmatrix}\text{VTF}\\7:1\end{pmatrix}$	$\begin{pmatrix}\text{VTF}\\10:1\end{pmatrix}$	$\begin{pmatrix}\text{VTF}\\4:1\end{pmatrix}$	$\begin{pmatrix}\text{VTF}\\7:1\end{pmatrix}$	$\begin{pmatrix}\text{VTF}\\10:1\end{pmatrix}$
TLI	8:1	4:1	4:1	16:1	8:1	8:1	32:1	16:1	16:1	8:1	4:1	4:1
CFI	4:1	4:1	4:1	8:1	8:1	4:1	32:1	16:1	8:1	8:1	4:1	4:1
RMR	32:1	16:1	8:1	32:1	16:1	16:1	32:1	16:1	16:1	32:1	16:1	16:1
GFI	16:1	16:1	16:1	16:1	16:1	16:1	16:1	16:1	16:1	16:1	16:1	16:1
AGFI	16:1	16:1	16:1	16:1	16:1	16:1	16:1	16:1	16:1	16:1	16:1	16:1
RMSEA	8:1	4:1	4:1	8:1	4:1	4:1	8:1	4:1	4:1	8:1	4:1	4:1

Due to the nature of the invariance testing, both RQ2 and 3 are presented together in this part, but noted for the readers' benefit.

RQ 2: *Does the stability of the simulated models vary over increasingly levels of measurement invariance as a function of the following conditions and their interactions:*

a. VTF ratio?

b. STV ratio?

c. h^2 magnitude?

RQ3: *Does the precision of the simulated models vary in structural mean invariance as a function of the following conditions and their interactions:*

a. VTF ratio?

b. STV ratio?

c. h^2 magnitude?

Surprisingly, results of RQ2 and 3 revealed that the communality magnitudes manipulation (high, moderate, low, and mixed) did not show any effects related to invariance testing. Thus, to simplify the presentation of the results, findings focus on the VTF and STV.

RQ2 focused on the stability of models through examination of measurement invariance levels. RQ3 focused on the precision of models by examination of structural mean invariance. In cases where stability of model was observed, a precision of model was in place.

Overall measurement and structural mean invariance findings revealed that for VTF ratio (4:1), the models started to showed stability and precision over levels of measurement and structural mean invariance when STV ratio was 4:1. Yet, the frequency

of stability and precision models over 1000 replications increased (from 77% to 91%) as STV ratio increased. The models showed more stability and precision at or above 32:1 STV.

For VTF ratio (7:1), the models started to showed stability and precision over levels of measurement and structural mean invariance when STV ratio was 8:1. Yet, the frequency of stability and precision models over 1000 replications again increased (from 60% to 88%) as STV ratio increased. The models showed more stability and precision at or above 32:1 STV.

For VTF ratio (10:1), the models started to showed stability and precision over levels of measurement and structural mean invariance when STV ratio was 8:1. Yet, the frequency of stability and precision models over 1000 replications increased (from 74% to 85%) as STV ratio increased. The models showed more stability and precision at or above 32:1 STV.

Discussion

This study provided empirical evaluation of the influence of ED and SD on WSV in terms of model precision and model estimate stability relative to a known factor structure via Monte Carlo simulation. The experimental conditions under consideration were: (a) variables-to-factor ratio (VTF), (b) subject-to-variable ratio (STV), and (c) communality magnitude (h^2).

The study findings refuted some of the guidelines found in the literature, e.g., Guadagnoli, and Velicer (1988) reported a sample size was not an important factor in determining model stability, and Bryant and Yarnold (1995) reported that the subject-to-variable ratio should be no lower than five. Current study results revealed that sample

size did have a strong effect on both stability and precision of the simulated models. For instance, when VTF ratio = 4:1 mean values related to data-model fit indices were adequate at STV ratio >= 4:1. However, looking at the frequency of rejections based on conventional thresholds over the 1000 replications depicted a different conclusion. The percentage of stable (invariant) models ranged from 77% at 4:1 STV to 91% at 32:1 STV clearly indicating that larger STV ratios are related to higher stability levels with a model. These findings validated Meade and Bauer (2007), who reported that the percentage of invariance tests were varied based on the sample size per group. Current study findings do agree with other research (Cobham, 1998) where in some models a STV of 30:1 was needed to produce stable model and minimize the amount of misfit.

The concern over suitable sample sizes has been raised by previous researchers, for example, Costello and Osborne (2005) examined publications utilizing FA from the PsychINFO database for two years between 2003 and 2005 and found that only 3% of the studies used STV ratios of 20-100:1. This suggests that an overwhelming percentage of researchers employing FA may be estimating models that may not be accurate-precise and thus increasing the rate of non-replication (Bullón, 2015).

Study findings also contradicted some previous research that investigated the effect of VTF ratio on precision and stability of factor solutions. Guadagnoli and Velicer (1988) concluded that the VTF ratio was important for factor stability with more indicator variables per factor yielding more stable result. In current study, there was a trend in the findings over all RQ1 analyses that suggests that data-model fit diminished as VTF increases. Most probably this is a result of the increasing complexity of the measurement models, i.e., number of paths. For example, in the 10:1 VTF there are 100

paths estimated, where as in the 4:1 condition there are 40 paths estimated. The accumulation of many small deviations from the population correlation matrix negatively impacted the global fit statistics more so in the high VTF conditions relative to the low VTF conditions.

Surprisingly, the communality magnitudes manipulation (high, moderate, low, and mixed) did not show consistent effects related to the precision of factor solution based on χ^2, GFI, AGFI, and RMSEA criteria. Again, this is likely due to the choice of model fit indices, which focused on whole model fit. These indices may not be sensitive to detecting the influence of communality manipulation. However, some of the model fit indices e.g., TLI, CFI, and RMR, did react to the manipulation of communality estimates. Thus, the effects of communality magnitude may depend on the criteria a researcher applies when evaluating data-model fit. For example, using CFI as a criterion of data-model fit, a low subject-to-variable ratio of 4:1 was needed for high communality; however, a minimum subject-to-variable ratio of 8:1 or above was required when communality magnitude low. These findings validated some of the rules appearing in the literature, such as the Hogarty et al. (2005) who reported that when communalities were high sample size effects tended to be less influential on the quality of factor solutions than when communalities are low.

Limitations

A limitation of this study was that the factor model used was somewhat restrictive: First, the raw data were simulated only in orthogonal factor structure. Since this study examined orthogonal factor structure, the oblique solution could have revealed different findings of precision and stability of factor solution. Second, data were

simulated using form of normal distribution, while many data in social science do not meet the assumption of normality (Micceri, 1989). Third, specified factor structure of this study was fixed to a 5-factor model. This study did not investigate other types of model structure such as bifactor or second order model structures. Fourth, the factor model used contained only 4:1, 7:1, and 10:1 variable-to-factor ratio with no more 32:1 subject-to-variable ratio.

Recommendations for Researchers

Based on the findings and conclusions of this study, the following recommendations for researchers are made for factor models with following characteristics: (a) continuous (measurement scale), (b) normal distribution, (c) 5-factor solutions (common factor), and (d) orthogonal solution (factor structure).

It is recommended that:

1. The minimum subject-to-variable ratio of 16:1is required to show precision in factor solution based on GFI acceptable fit criteria.
2. The minimum subject-to-variable ratio of 16:1is required to show precision in factor solution based on AGFI acceptable fit criteria.
3. The minimum subject-to-variable ratio of 8:1 is required to show precision in factor solution when variable-to-factor ratio of 4:1 based on RMSEA acceptable fit criteria. However, the minimum subject-to-variable ratio of 4:1 is required when variable-to-factor ratio of 7:1 or 10:1.
4. The minimum subject-to-variable ratio of 8:1 with communality levels (high, moderate, and mixed) is required to show precision in factor solution based on TLI and CFI acceptable fit criteria. However, when communality level is low

the minimum subject-to-variable ratio of 32:1 is required.

5. The minimum subject-to-variable ratio of 32:1 is required to show precision in factor solution when variable-to-factor ratio of 4:1 based on RMR acceptable fit criteria. However, when variable-to-factor ratio of 7:1 or 10:1 the minimum subject-to-variable ratio of 16:1 is required.

Overall, it is recommended that:

1. When variable-to-factor ratio is 4:1 the subject-to-variable ratio of 16:1 or above is required to show precision in factor solution and stability of model as indicated by four or more fit indices.
2. When variable-to-factor ratio is 7:1 or 10:1 the subject-to-variable ratio of 32:1 or above is required to show precision in factor solution and stability of model as indicated by four or more fit indices.
3. If the researcher is interested in minimizing misfit or meeting more than four overall model fit indices criteria, more than 32:1 subject-to-variable ratio and 10:1 variable-to-factor ratio would be necessary to gain precise and stable model.

Recommendations for Future Research

Based on the conclusions and limitations of this study, recommendations for future research are offered.

This study provides fundamental knowledge required for simulation process of orthogonal model based on Tucker et al. (1969) simulation technique. A recommendation for other researchers who have interest in simulation study will be to use this study as

guidance to simulate different types of model structures such as oblique, bifactor, and second order models.

Much of the data originating from social science research shows a lack of symmetry. In other words, the data in social science research often violate the assumption of multivariate normality (Micceri, 1989). A recommendation for other researchers in social science is to examine data from skewed or kurtotic symmetrical distributions. This can easily be accomplished by investigating symmetric and nonsymmetrical ordered response scales.

The findings of this study contribute to the growing body of literature focused on improving the simulation procedure, e.g., orthogonal factor structure, and the evolution of model precision and model estimate stability. It is important to keep in mind that any working recommendations provided herein are based on the current simulated models. However, different effects of ED and SD on WSV in terms of model precision and model estimate stability are possible in the examination of different underlying model structure such as bifactor or oblique structural models. Future empirical investigation of the effect of sample size on the model precision and model estimate stability should examine data from skewed or kurtotic symmetrical distributions in different types of model structures, and would likely render informative suggestions and more fine-grained recommendations.

REFERENCES

Allen, M. J., & Yen, W. M. (1979). *Introduction to measurement theory.* Monterey, CA: Brooks/Cole.

Barendse, M. T., Oort, F. J., & Timmerman, M. E. (2014). Using exploratory factor analysis to determine the dimensionality of discrete responses. *Structural Equation Modeling: A Multidisciplinary Journal, 22*(1), 87-101. doi:10.1080/10705511.2014.934850

Bentler, P. M., & Bonnett, D. G. (1980). Significance tests and goodness of fit in the analysis of covariance structures. *Psychological Bulletin, 88,* 588-606.

Brown, T. A. (2006). *Confirmatory factor analysis for applied research*. New York: Guilford Press.

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

Bryant, F. B., & Yarnold, P. R. (1995). Principal components analysis and exploratory and confirmatory factor analysis. In L. G. Grimm & R. R. Yarnold (Eds.), *Reading and understanding multivariate statistics* (pp. 99-136). Washington, DC: American Psychological Association.

Bullón, P. (2015). *Failing to replicate: Hypothesis testing as a crucial key to make direct replications more credible and predictable* (Doctoral dissertation).Avaiable from ProQuest Dissertations and Theses database. (UMI No. 3708865)

Byrne, B. M. (1998). *Structural equation modeling with LISREL, PRELIS and SIMPLIS: Basic concepts, applications and programming.* Mahwah, NJ: Lawrence Erlbaum Associates.

Chapman, C. N., & Feit, E. M. (2015). Confirmatory factor analysis and structural equation modeling. In C. N. Chapman & E. M. Feit (Eds.), *R for marketing research and analytics* (pp. 267-298). Switzerland: Springer International.

Cobham, I. (1998). *The effects of subject-to-variable ratio, measurement scale, and number of factor on the stability of the factor model.* Retrieved from the University of Miami website: http://scholarlyrepository.miami.edu/dissertations/3635/

Costello, A. B., & Osborne, J. W. (2005). Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis. *Practical Assessment, Research & Evaluation*, 1531-7714.

Coughlin, K. B. (2013). *An analysis of factor extraction strategies: A comparison of the relative strengths of principal axis, ordinary least squares, and maximum likelihood in research contexts that include both categorical and continuous variables*. Retrieved from the University of South Florida website: http://scholarcommons.usf.edu/etd/4459

Crocker, L., & Algina, J. (1986). *Introduction to classical and modern test theory*. New York: CBS College.

De Winter, J. C. F, Dodou, D., & Wieringa, P. A. (2009). Exploratory factor analysis with small sample sizes. *Multivariate Behavioral Research, 44*, 147-181.

Diamantopoulos, A., & Siguaw, J. A. (2000). *Introducing LISREL.* London: Sage.

Everitt, S. (1975). Multivariate analysis: The need for data, and other problems. *British Journal of Psychiatry*, *126*, 237-240.

Fabrigar, L., Wegener, D., MacCallum, R., & Strahan, E. (1999). Evaluating the use of exploratory factor analysis in psychological research. *Psychological Methods, 4*(3), 272-299.

Garson, G. D. (2008). *Factor analysis: Statnotes: Topics in multivariate analysis.* Retrieved from http://www2.chass.ncsu.edu/garson/pa765/factor.htm

Garson, G. D. (2012). *Testing statistical assumption*. Asheboro, NC: Statistical Associates. Retrieved from www.statisticalassociates.com/assumptions.pdf.

Goldberg, L. R. (1992). The development of markers for the Big-Five factor structure. *Psychological Assessment, 4*(1),26-42.

Gorsuch, R. L. (1983). *Factor analysis.* Hillsdale, NJ: Lawrence Erlbaum Associates.

Guadagnoli, E., & Velicer, W. F. (1988). Relation of sample-size to the stability of component patterns. *Psychological Bulletin, 103*(2), 265-275.

Hatcher, L. (1994*). A step-by-step approach to using the SAS® system for factor analysis and structural equation modeling.* Cary, NC: SAS Institute.

Henson, R. K., & Roberts, J. K. (2006). Use of exploratory factor analysis in published research: Common errors and some comment on improved practice. *Educational and Psychological Measurement, 66*, 393-416.

Hogarty, K. Y., Hines, C. V., Kromrey, J. D., Ferron, J. M. & Mumford, K. R. (2005). The quality of factor solutions in exploratory factor analysis: The influence of sample size, communality, and overdetermination. *Educational and Psychological Measurement, 65*, 202-226.

How many questions do people ask? (2015, January). *SurveyMonkey*. Retrieved from

https://www.surveymonkey.com/blog/en/blog/2011/12/13/how-many-questions-do-people-ask/

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

John, O., & Srivastava, S. (1999). *The Big-Five Trait taxonomy: History, measurement, and theoretical perspectives*. New York: Guilford.

Jung, S., & Lee, S. (2011). Exploratory factor analysis for small samples. *Psychonomic Society, 43*, 701-709.

Jung, S., & Takane, Y. (2008). Regularized common factor analysis. In K. Shigemasu, A. Okada, T. Imaizumi, & T. Hoshino (Eds.), *New trends in psychometrics* (pp. 141-149). Tokyo: Universal Academy Press.

Kunce, J. T., Cook, W. D., & Miller, D. E. (1975). Random variables and correlational overkill. *Educational and Psychological Measurement, 35*, 529-534.

MacCallum, R., Widaman, K., Preacher, K., & Hong, S. (2001). Sample size in factor analysis: The role of model error. *Multivariate Behavioral Research*, *36*(4), 611-637.

MacCallum, R., Widaman, K., Zhang, S., & Hong, S. (1999). Sample size in factor analysis. *American Psychological Association*, *4*, 84-99.

Marascuilo, L. A., & Levin, J. R. (1983). *Multivariate statistics in the social sciences*. Monterey, CA: Brooks/Cole.

Marsh, H. W., Hau, K. T., Balla, J. R., & Grayson, D. (1998). Is more ever too much? The number of indicators per factor in confirmatory factor analysis. *Multivariate Behavioral Research, 33*, 181-220.

McDonald, R. P., & Krane, W. R. (1977). A note on local identifiability and degrees of freedom in the Asymptotic Likelihood Ratio Test. *British Journal Mathematical and Statistical Psychology, 30*, 198-203.

McDonald, R. P., & Krane, W. R. (1979). A Monte-Carlo study of local identifiability and degrees of freedom in the Asymptotic Likelihood Ratio Test. *British Journal of Mathematical and Statistical Psychology, 32*, 121-132.

Meade, A. W., & Bauer, D. J. (2007) Power and precision in confirmatory factor analytic tests of measurement invariance. *Structural Equation Modeling*, *14*(4), 611-635.

Micceri, T. (1989). The unicorn, the normal curve, than other improbable creatures. *Psychological Bulletin, 105*, 156-166.

Millsap, R. E., & Meredith, W. (2007). Factorial invariance: Historical perspectives and new problems. In R. Cudeck & R. C. MacCallum (Eds.), *Factor analysis at 100* (pp. 131-152). Mahwah, NJ: Lawrence Erlbaum Associates.

Mîndrilă, D. (2010). Maximum likelihood (ml) and diagonally weighted least squares (DWLS) estimation procedures: A comparison of estimation bias with ordinal and multivariate non-normal data. *International Journal of Digital Society, 1*(1), 60-66.

Mundfrom, D., Shaw, D., & Tian, L. (2005). Minimum sample size recommendations for conducting factor analyses. *International Journal of Testing, 5*, 159-168.

Nimon, K. F. (2012). Statistical assumptions of substantive analyses across the general linear model: A mini-review. *Frontiers in Psychology, 3*, 322.

Osborne, J. W., & Costello, A. B. (2004). Sample size and subject to item ratio in principal components analysis. *Practical Assessment, Research & Evaluation, 72,* 971.

Paunonen, S. V., & Jackson, D. N. (2000). What is beyond the Big Five? Plenty! *Journal of Personality, 68*, 821-835.

Paxton, P., Curran, P. J., Bollen, K. A., Kirby, J., & Chen, F. (2001). Monte Carlo experiments: Design and implementation. *Structural Equation Molding*, 8(2), 287-312.

Preacher, K. J., & MacCallum, R. C. (2002). Exploratory factor analysis in behavior genetics research: Factor recovery with small sample sizes. *Behavior Genetics, 32*, 153-161.

Rong, J. (2012). Sample size in exploratory factor analysis with ordinal data. UMI Dissertations Publishing, 3647906.

Saucier, G. (2002). Orthogonal markers for orthogonal factor: The case of the Big Five. *Journal of Research in Personality, 36*, 1-31.

Schumacker, R. E., & Lomax, R. G. (1996). *A beginner's guide to structural equation model*. Mahwah, NJ: Lawrence Erlbaum Associates.

Starkweather, J. (2012). Simulation as an important method for learning and a necessary step of good research practice. *Benchmarks Online*. Retrieved from http://it.unt.edu/benchmarks/issues/2012/04/rss-matters

Steiger, J. H. (1989). *Causal modeling: A supplementary module for SYSTAT and SYGRAPH*. Evanston, IL: SYSTAT.

Stevens, J. (2002). *Applied multivariate statistics for the social sciences* (4th ed.). Mahwah, NJ: Lawrence Erlbaum Associates.

Tabachnick, B. G., & Fidell, L. S. (2013). *Using multivariate statistics* (6th ed.). Boston, MA: Pearson.

Thompson, B. (2005). *Exploratory and confirmatory factor analysis: Understanding concepts and applications*. Washington, DC: American Psychological Association.

Tucker, L., Koopman, R., & Linn, R. (1969). Evalualuation of factor analytic research procedures by means of simulated correlation matrices. *Psychometrika, 34*, 421-459.

Velicer, W. F., & Fava, J. L. (1998). Effects of variable and subject sampling on factor pattern recovery. *American Psychological Association, 3*, 231-251.

Widaman, K. (1993). Common factor analysis versus principle component analysis: Differential bias in representing model parameters. *Multivariate Behavioral Research*, *28*(3), 263-311.

Wu. A. D., Li, Z., & Zumbo, B. D. (2007). Decoding the meaning of factorial invariance and updating the practice of multigroup confirmatory factor analysis: A demonstration with TIMSS data. *Practical Assessment, Research and Evaluation, 12*(3), 1-26.

Appendix A

Test Different Types of Communalities Construction

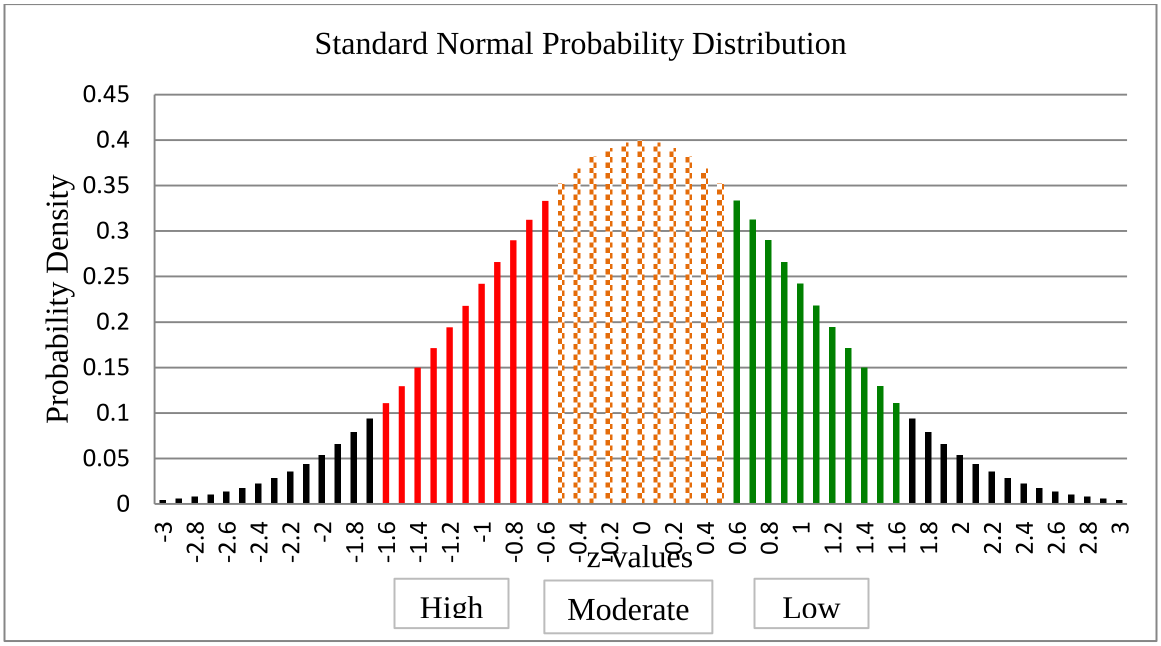


Figure A1. Different area under normal distribution to represent different types of communalities.

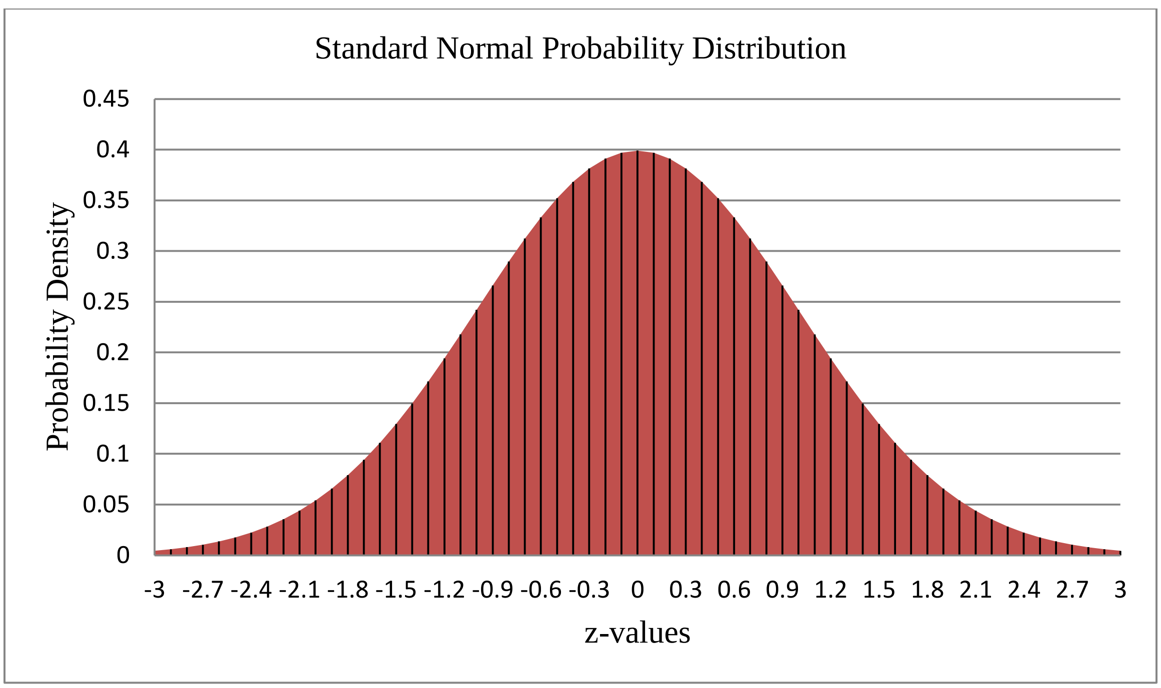


Figure A2. Area under normal distribution to represent mixed communality.

Appendix B

Completed ANOVA Tables of Three-Way Analysis of Variance of Overall Model Fit Indices

Table B1

Three-Way Analysis of Variance of χ^2 by Conditions

Conditions	*df*	*SS*	*MS*	*F*	*p-value*
h^2	3	2250	750	0.49	0.6876
VTF	2	12088000357	6044000178	3967031	<. 0001
h^2*VTF	6	12705	2117	1.39	0.2143
STV	4	200048542	50012135	32825.9	<. 0001
h^2* STV	12	17234	1436	0.94	0.5024
VTF *STV	8	75872156	9484020	6224.92	<. 0001
h^2* VTF *STV	24	25525	1064	0.70	0.8589

Note. h^2= Communality, VTF = variable-to-factor, STV = subject-to-variable ratio

Table B2

Three-Way Analysis of Variance of GFI by Conditions

Conditions	*df*	*SS*	*MS*	*F*	*p-value*
h^2	3	0.0003032	0.0001011	1.27	0.2820
VTF	2	1.0600911	0.5300455	6671.43	<. 0001
h^2*VTF	6	0.0007226	0.0001204	1.52	0.1683
STV	4	647.1536395	161.7884099	2036352	<. 0001
h^2* STV	12	0.0013428	0.0001119	1.41	0.1534
VTF *STV	8	0.3883465	0.0485433	610.99	<. 0001
h^2* VTF *STV	24	0.0016215	0.0000676	0.85	0.6733

Note. h^2= Communality, VTF = variable-to-factor, STV = subject-to-variable ratio

Table B3

Three -Way Analysis of Variance of AGFI by Conditions

Conditions	*df*	*SS*	*MS*	*F*	*p-value*
h^2	3	0.0003874	0.0001	1.14	0.3316
VTF	2	0.8205171	0.4102	3619.03	<. 0001
h^2*VTF	6	0.00009681	0.00016	1.42	0.2012
STV	4	851.2997233	212.8249	1877402	<. 0001
h^2* STV	12	0.0018949	0.00015	1.39	0.1606
VTF *STV	8	0.8070564	0.10088	889.92	<. 0001
h^2* VTF *STV	24	0.0023562	0.00009	0.87	0.6514

Note. h^2= Communality, VTF = variable-to-factor, STV = subject-to-variable ratio

Table B4

Three -Way Analysis of Variance of RMSEA by Conditions

Conditions	*df*	*SS*	*MS*	*F*	*p-value*
h^2	3	0.00013986	0.00004662	0.41	0.7467
VTF	2	1.52772202	0.76386101	6698.38	<. 0001
h^2*VTF	6	0.00099079	0.00016513	1.45	0.1919
STV	4	30.1640169	7.54100423	66127.9	<. 0001
h^2* STV	12	0.00101199	0.00008499	0.75	0.7077
VTF *STV	8	1.284538	0.16056730	1408.03	<. 0001
h^2* VTF *STV	24	0.00197751	0.00008240	0.72	0.8337

Note. h^2= Communality, VTF = variable-to-factor, STV = subject-to-variable ratio

Table B5

Three -Way Analysis of Variance of TLI by Conditions

Conditions	*df*	*SS*	*MS*	*F*	*p-value*
h^2	3	76.4756	25.49186	13451.2	<. 0001
VTF	2	5.4478	2.7239	1437.33	<. 0001
h^2*VTF	6	2.40759	0.40126	211.73	<. 0001
STV	4	275.80525	68.95131	36383.3	<. 0001
h^2* STV	12	135.6328	11.3027	5964.08	<. 0001
VTF *STV	8	10.0023	1.2502	659.74	<. 0001
h^2* VTF *STV	24	3.67666	0.15319	80.84	<. 0001

Note. h^2= Communality, VTF = variable-to-factor, STV = subject-to-variable ratio

Table B6

Three -Way Analysis of Variance of CFI by Conditions

Conditions	*df*	*SS*	*MS*	*F*	*p-value*
h^2	3	73.037618	24.3458	21591.5	<. 0001
VTF	2	4.98064	2.49032	2208.58	<. 0001
h^2*VTF	6	2.429929	0.40498	359.17	<. 0001
STV	4	232.0364156	58.009232	51446.3	<. 0001
h^2* STV	12	114.2642	9.522013	8444.73	<. 0001
VTF *STV	8	5.6542	0.7067753	626.81	<. 0001
h^2* VTF *STV	24	2.3788	0.099118	87.90	<. 0001

Note. h^2= Communality, VTF = variable-to-factor, STV = subject-to-variable ratio

Table B7

Three -Way Analysis of Variance of RMR by Conditions

Conditions	*df*	*SS*	*MS*	*F*	*p-value*
h^2	3	0.05106	0.01702	284.47	<. 0001
VTF	2	7.83682	3.91891	65494.8	<. 0001
h^2*VTF	6	0.001379	0.00022913.81097	3.84	0.0008
STV	4	55.24390	13.8109	230816	<. 0001
h^2* STV	12	0.01151	0.00095	16.03	<. 0001
VTF *STV	8	1.91468	0.23933	3999.89	<. 0001
h^2* VTF *STV	24	0.002840	0.000118	1.98	0.0029

Note. h^2= Communality, VTF = variable-to-factor, STV = subject-to-variable ratio

Appendix C

Model Fit Indices for Structural Mean Invariance Over 1000 Replications

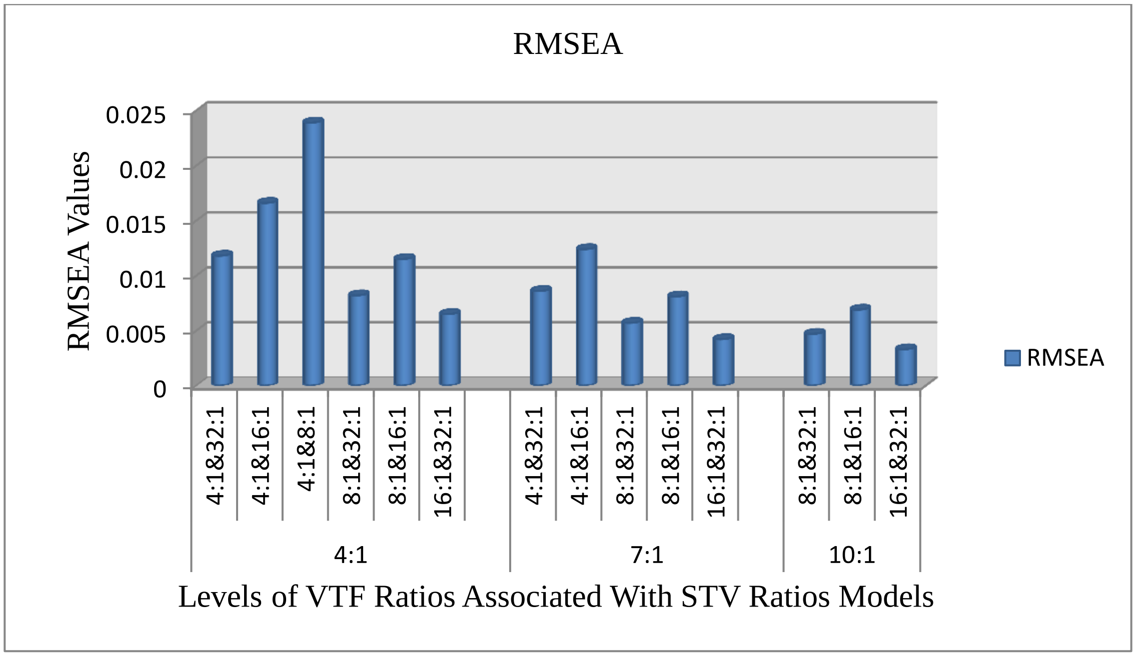


Figure C1. Root mean square error of approximation (RMSEA) mean values at structural mean invariance level for the interaction between STV and VTF ratios at high communality

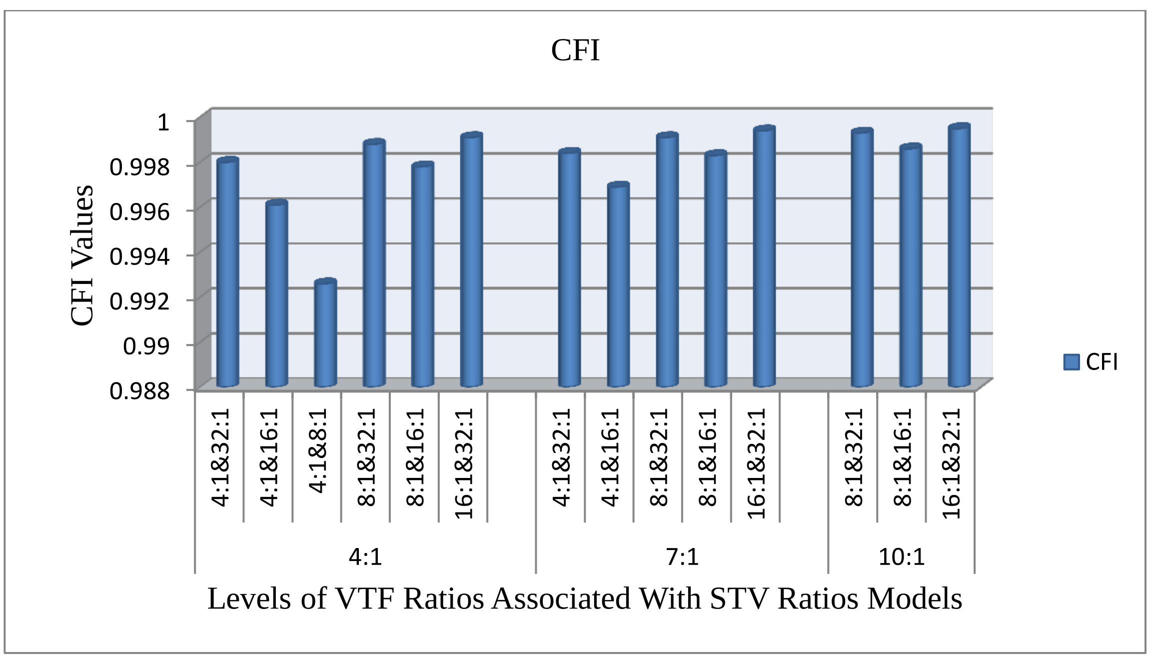


Figure C2. Comparative-fit Index (CFI) mean values at structural mean invariance level for the interaction between STV and VTF ratios at high communality

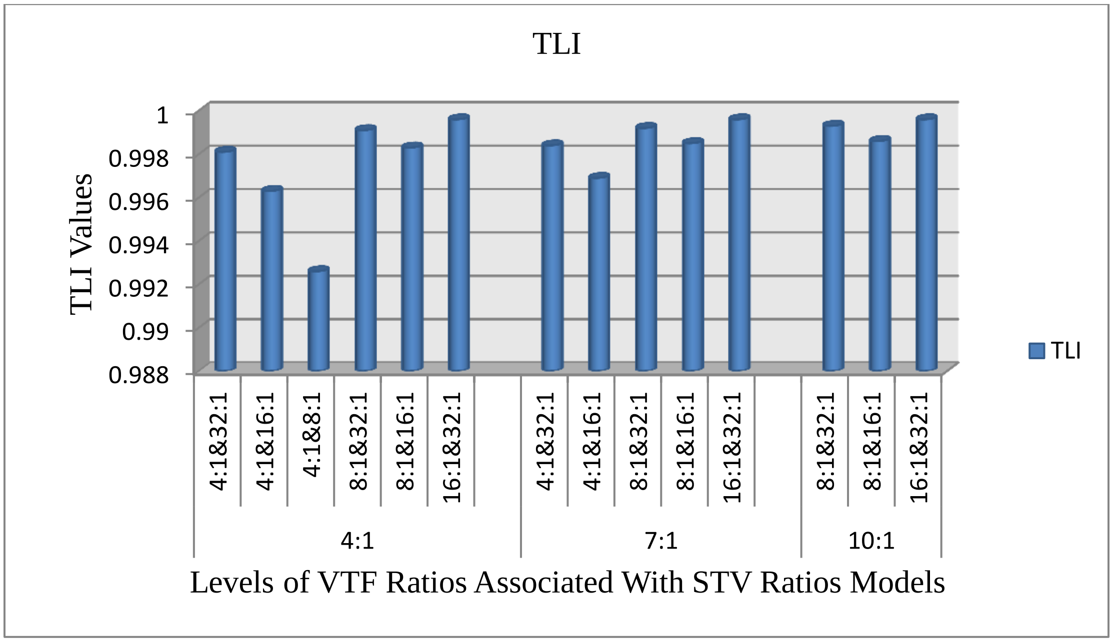


Figure C3. Tuker Lewis index (TLI) mean values at structural mean invariance level for the interaction between STV and VTF ratios at high communality

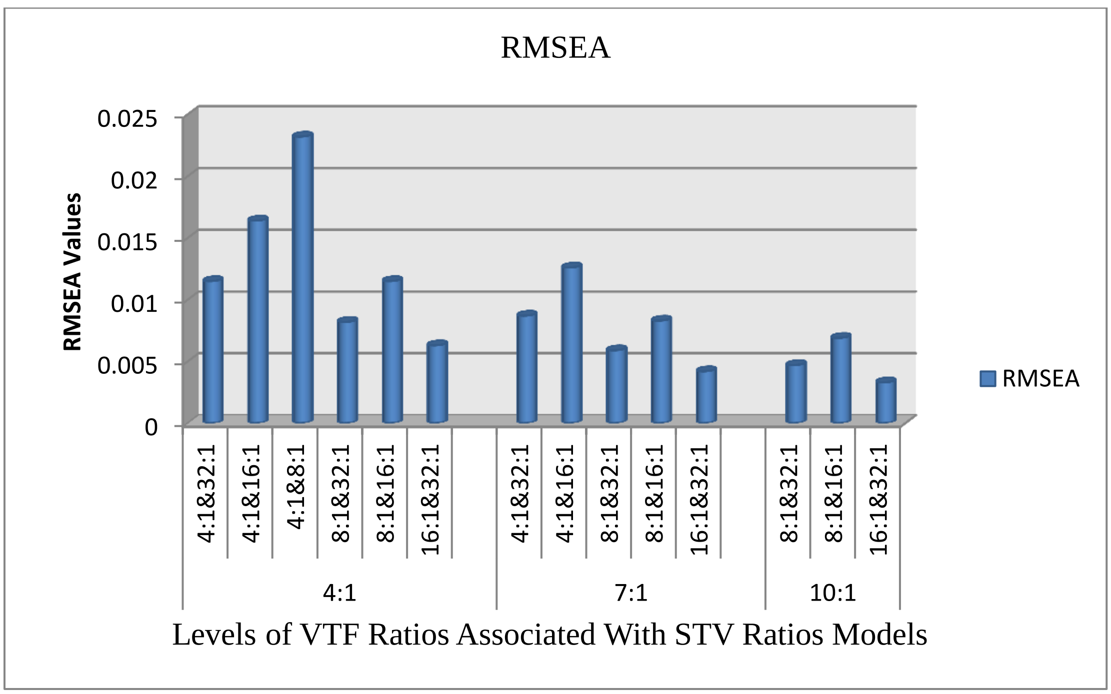


Figure C4. Root mean square error of approximation (RMSEA) mean values at structural mean invariance level for the interaction between STV and VTF ratios at moderate communality

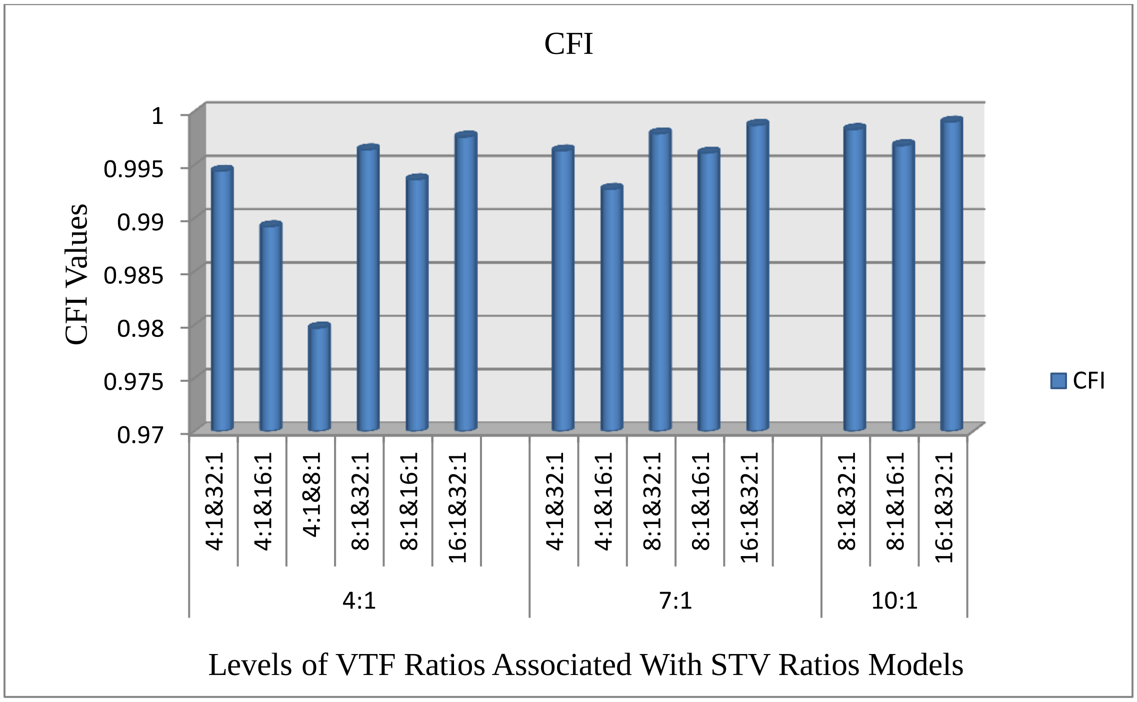


Figure C5. Comparative-fit Index (CFI) mean values at structural mean invariance level for the interaction between STV and VTF ratios at moderate communality

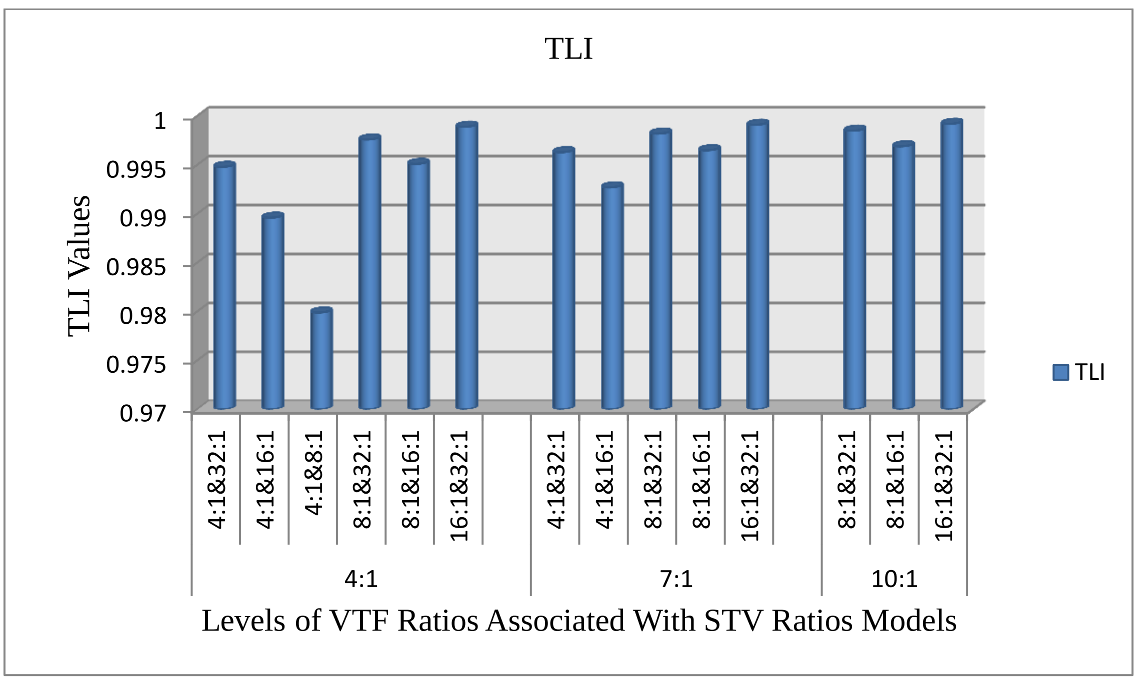


Figure C6. Tuker Lewis index (TLI) mean values at structural mean invariance level for the interaction between STV and VTF ratios at moderate communality

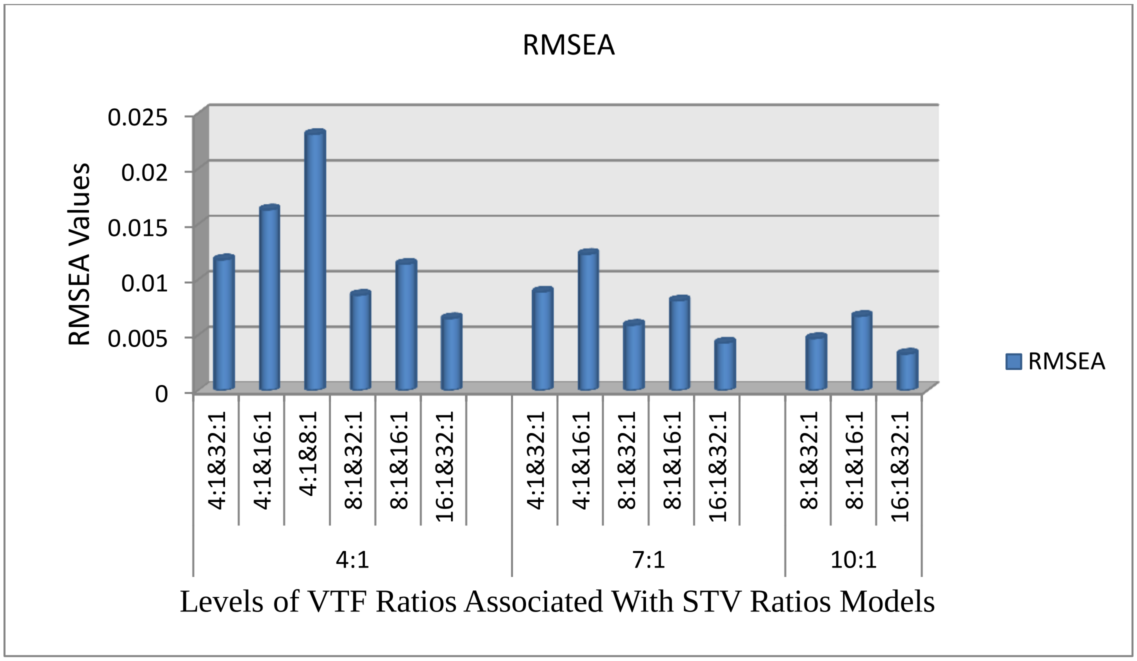


Figure C7. Root mean square error of approximation (RMSEA) mean values at structural mean invariance level for the interaction between STV and VTF ratios at low communality

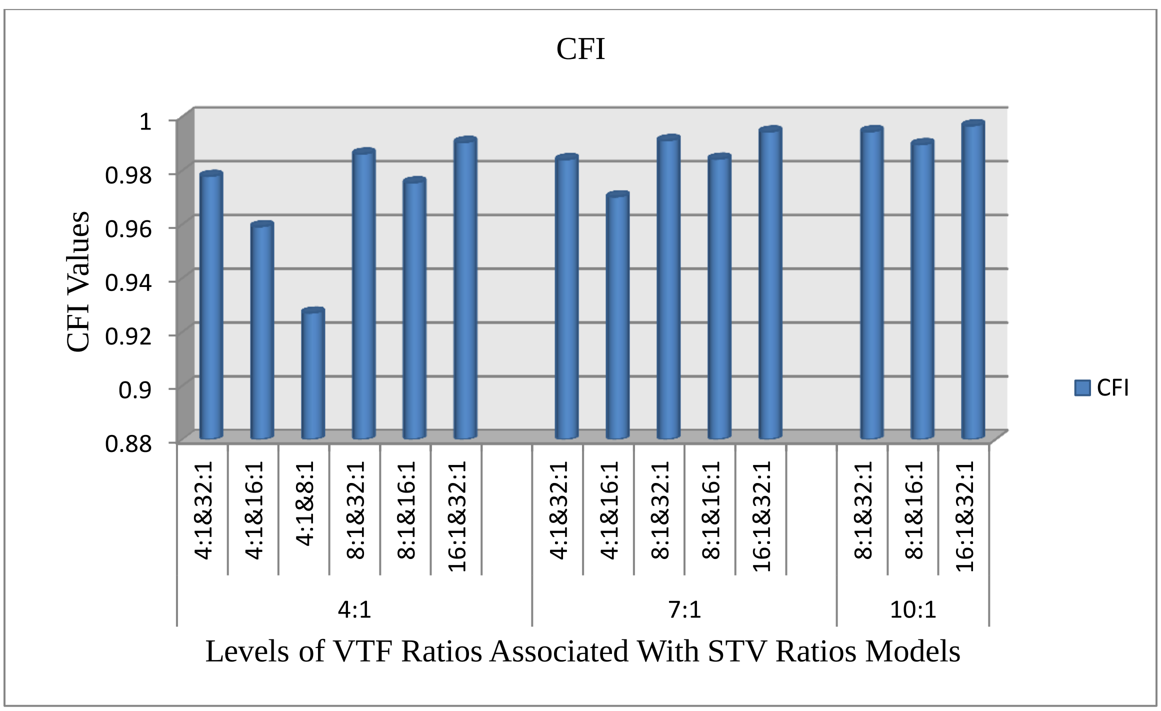


Figure C8. Comparative-fit Index (CFI) mean values at structural mean invariance level for the interaction between STV and VTF ratios at low communality

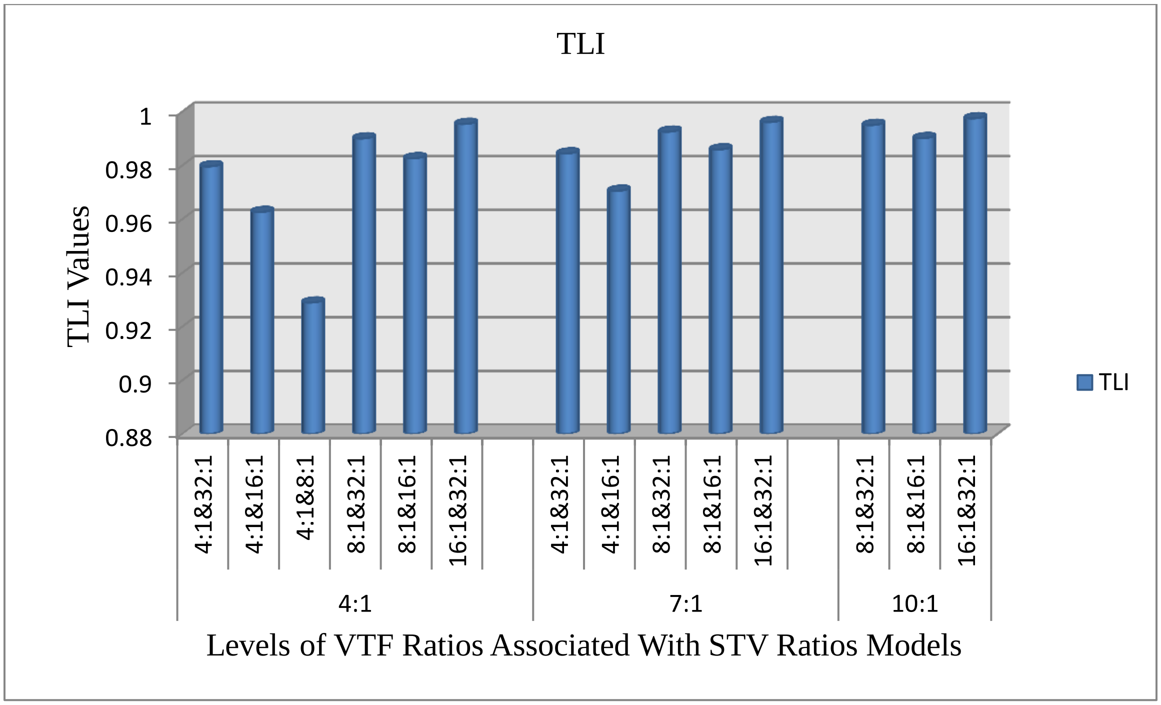


Figure C9. Tuker Lewis index (TLI) mean values at structural mean invariance level for the interaction between STV and VTF ratios at low communality

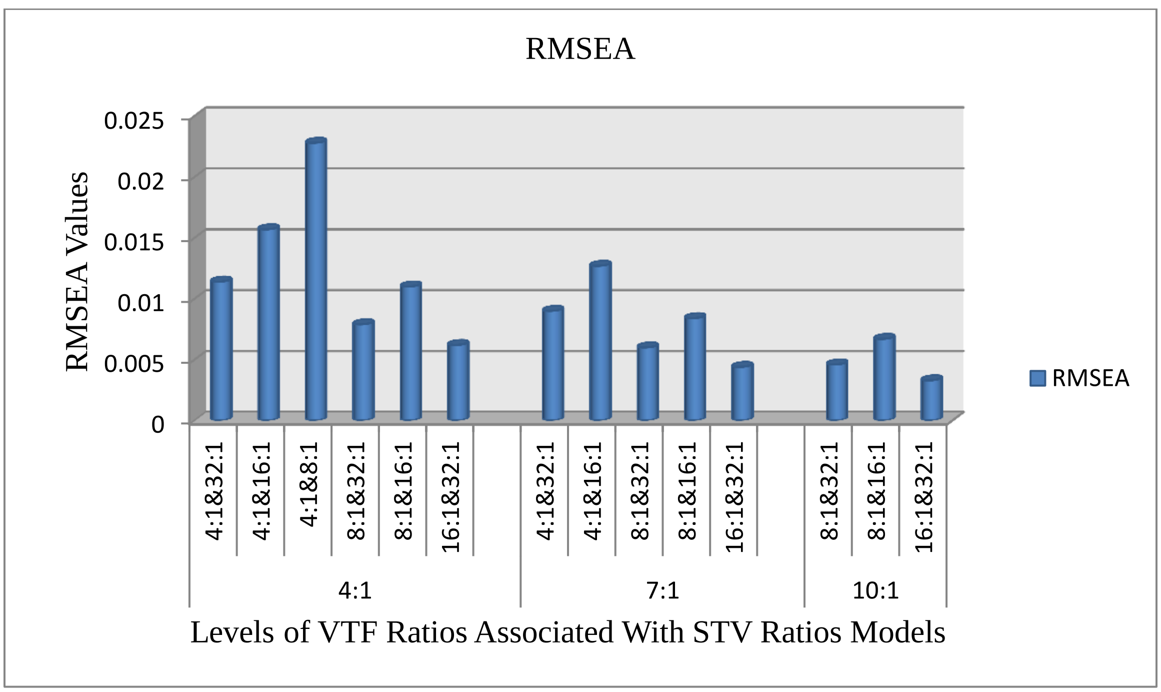


Figure C10. Root mean square error of approximation (RMSEA) mean values at structural mean invariance level for the interaction between STV and VTF ratios at mixed communality

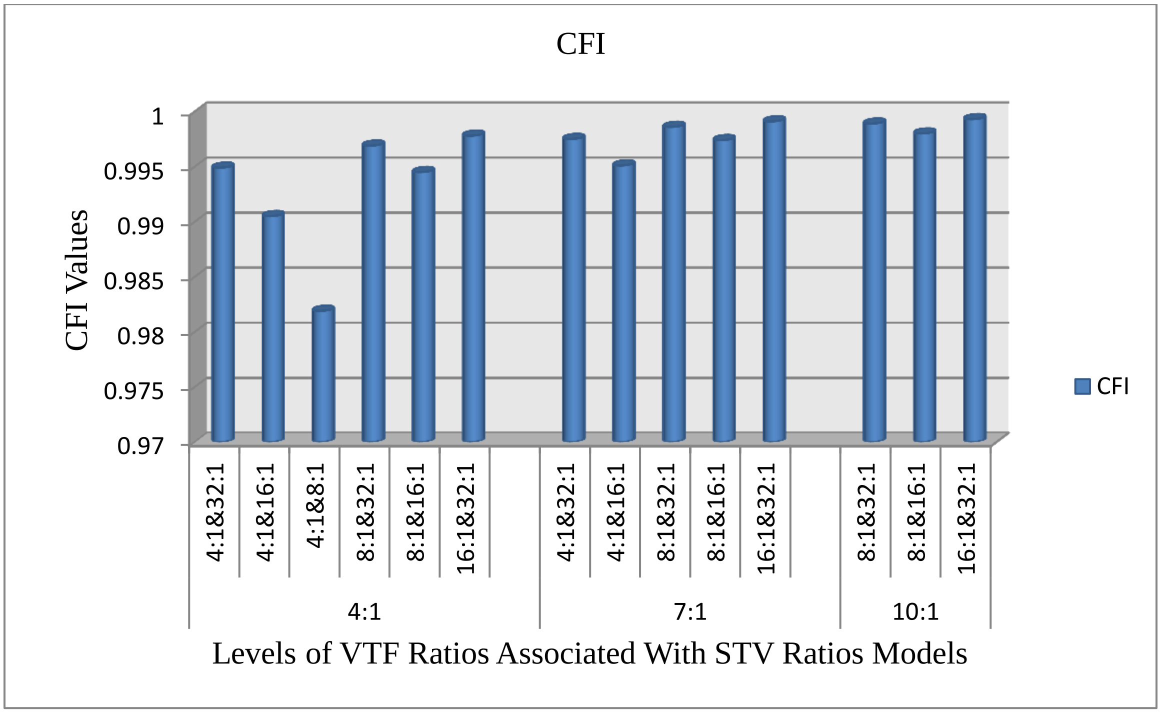


Figure C11. Comparative-fit Index (CFI) mean values at structural mean invariance level for the interaction between STV and VTF ratios at mixed communality

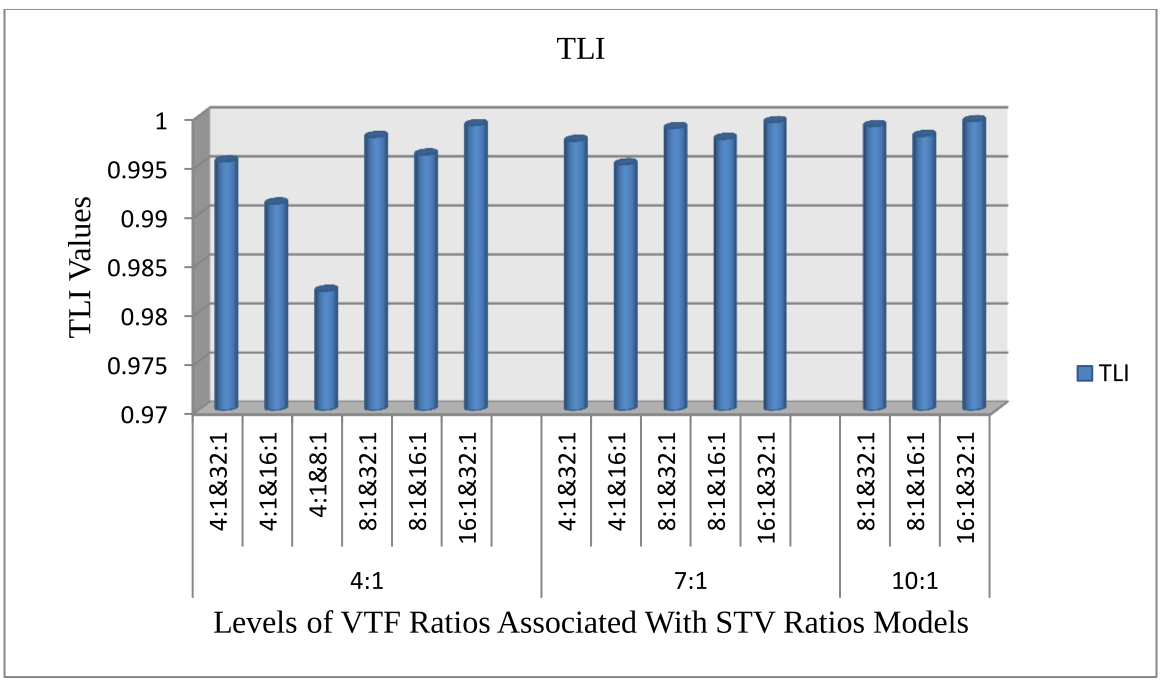


Figure C12. Tuker Lewis index (TLI) mean values at structural mean invariance level for the interaction between STV and VTF ratios at mixed communality

Appendix D

SAS Code

Appendix D1

```
**********************************************************************;
*************** Dissertation Simulation Primary program              *;
*************** Written by Deyab Almaleki                            *;
*************** Supervised by Dr. Applegate                          *;
*************** Code developed 2015                                  *;
*************** Communality construction                            *;
**********************************************************************;
*communality construction (high, moderate, low);
options nocenter;

data &ddname1..H2ALL
        &ddname0..H2high
        &ddname0..H2med
        &ddname0..h2low;
do i=1 to 1000000;
     x=rannor(0);
               H2=probnorm(x);
               grp=0;
               I_H=.; I_M=.; I_L=.;
     if  0.126<x<= 1.645 then do;
                      grp=1;
                      I_H=1;
                      output &ddname0..H2high;
                      end;
     if -0.524<x<= 0.524 then do;
                      grp=2;
                      I_M=1;
                      output &ddname0..H2med;
                      end;
     if -1.645<x<=-0.126 then do;
                      grp=3;
                      I_L=1;
                      output &ddname0..H2low;
                      end;
               if I_H=1 and I_M=1 then grp=4;
               if I_M=1 and I_L=1 then grp=5;
               output &ddname1..H2ALL;
end;
run;
proc surveyselect data=&ddname0..H2high method=srs n=100
out=&ddname1..H2_high(keep=h2) seed=0;
        run;
proc surveyselect data=&ddname0..H2med method=srs n=100
out=&ddname1..H2_med(keep=h2) seed=0;
        run;
```

Appendix D1 (Continued)

```
proc surveyselect data=&ddname0..H2low method=srs n=100
out=&ddname1..H2_low(keep=h2) seed=0;
        run;
*communality construction (mixed);
options nocenter;

data &ddname1..H2ALL_W
         &ddname0..H2wid;
do i=1 to 1000000;
                x=rannor(0);
                H2=probnorm(x);
                grp=0;
                I_W=.;
     if -1.645<x<=1.645 then do;
                        grp=1;
                        I_W=1;
                        output &ddname0..H2wid;
                        end;
                if I_W=1  then grp=2;
                output &ddname1..H2ALL_W;

end;
run;

proc surveyselect data=&ddname0..H2wid method=srs n=100
out=&ddname1..H2_wid(keep=h2) seed=0;
        run;
```

Appendix D2

```
*******************************************************************;
*************** Dissertation Simulation Primary program           *;
*************** Written by Deyab Almaleki                          *;
*************** Supervised by Dr. Applegate                        *;
*************** Code developed 2015                                *;
*************** Test communality construction                      *;
*******************************************************************;
options nocenter;
proc univariate data=&ddname1..H2ALL;
        var x h2;
        histogram x/normal;
        histogram h2;
        run;
proc freq data=&ddname1..H2ALL;
        tables I_H I_M I_L I_H*I_M I_M*I_L;
        run;
pattern1 c=black v=solid;
pattern2 c=red v=solid;
pattern3 c=yellow v=solid;
pattern4 c=green v=solid;
pattern5 c=red v=X;
pattern6 c=yellow v=x;
proc gchart data=&ddname1..H2ALL;
      vbar x/midpoints=(-4 to 4 by .1) subgroup=grp patternid=subgroup;
      run;
quit;
proc means data=&ddname1..H2_high mean std var;
        var h2;
        run;
proc means data=&ddname1..H2_med mean std var;
        var h2;
        run;
proc means data=&ddname1..H2_low mean std var;
        var h2;
        run;
****** Mixed communality construction test *****;
proc univariate data=&ddname1..H2ALL_W;
        var x h2;
        histogram x/normal;
        histogram h2;
        run;
proc freq data=&ddname1..H2ALL_W;
        tables I_w ;
        run;
pattern1 c=black v=solid;
```

Appendix D2 (Continued)

```
pattern2 c=red v=x;
proc gchart data=&ddname1..H2ALL_W;
      vbar x/midpoints=(-4 to 4 by .1) subgroup=grp patternid=subgroup;
      run;
quit;
proc means data=&ddname1..H2_wid mean std var;
         var h2;
         run;
```

Appendix D3

```
***********************************************************************;
*************** Dissertation Simulation Primary program                        *;
*************** Written by Deyab Almaleki                                      *;
*************** Supervised by Dr. Applegate                                    *;
*************** Code developed 2015                                            *;
*************** IML code was adapted from the study                            *;
*************** Conducted by Coughlin (2013)                                   *;
***********************************************************************;

proc iml;
***** program constants;
p = 100;                            * # of variables;
k = 5;                              * # of factors;
nvars=p; nfactors=k;          * # percentge of binary data; *0%;
d_frac = 0;                       * # no Dichotomous binary proportion;
N_pops = 1;                       * # populations to generate;
replicat=1;                       * # of samples from each population;
                                          * # Primary Study H2:(4 levels-
3=High,
                                              2=Med, 1=Low, 4=Wide);
Commun_type = 1;
*************** End Specification of Data Conditions ************;
*************** Begin Subroutines for the Program ***************;
*****************************************************************;
nn1 = 100000;
means=j(1,p,0);       * creting a transpose vector of p-elements = 0 *row,column, value;
variance = j(1,p,1);

start Make_PopR(nvars,nfactors,commun_type,A1tilde,B1,x,x2,d,A1,R);
bp1=j(nvars,nvars,0);                    * b1 is the communality in each p variables,
which means the sum squared of factor loadings in each variable;

        if commun_type=3 then do;
                use &ddname1..h2_high;
                read all  into _h2_;
        close &ddname1..h2_High;
                temp=diag(bp1+_h2_);
        end;

        if commun_type=2 then do;
                use &ddname1..h2_med;
                read all  into _h2_;
        close &ddname1..h2_med;
                temp=diag(bp1+_h2_);
        end;
```

Appendix D3 (Continued)

```
if commun_type=1 then do;
		use &ddname1..h2_low;
		read all  into _h2_;
	close &ddname1..h2_low;
```

Appendix D3 (Continued)

```
		temp=diag(bp1+_h2_);
	end;

	if commun_type=4 then do;
		use &ddname1..h2_wid;
		read all  into _h2_;
	close &ddname1..h2_wid;
		temp=diag(bp1+_h2_);
	end;
b1square=round(diag(temp),.1);                * b1square: processing to create lambda for
each p variables;
B1=b1square##.5;
b3square=I(nvars)-b1square;          * b3square: processing to create unique variance;

B3=b3square##.5;
*******************************************************************;
** construct A1tilde the matrix of conceptual input factor loadings*;
** so that each element is a whole number between 0 and nfactor and*;
** the sum of each row equals nfactor-1  ***************************;
*******************************************************************;
A1tilde=j(nvars,nfactors,0);
***new trial code;
do i=1 to 20;
	A1tilde[i,1]=4;
end;
do i=21 to 40;
	A1tilde[i,2]=4;
end;
do i=41 to 60;
	A1tilde[i,3]=4;
end;
do i=61 to 80;
	A1tilde[i,4]=4;
end;
do i=81 to 100;
	A1tilde[i,5]=4;
end;
```

Appendix D3 (Continued)

```
*************************************************************************
*********************;
**** Translating conceptual input factor loading A1 matrices into matrices of actual
********;
**** input factor loadings is accomplished through a three-step process
*********************;
*************************************************************************
*********************;

*************************************************************************
*********************;
* FIRST STEP, the conceptual input factor loadings are combined with random normal
deviates *;
*************************************************************************
*********************;
x=j(nvars,nfactors,0);
***new trial code;
        do i=1 to 20;
                x[i,1]=normal(A1tilde)[i,1];
        end;
        do i=21 to 40;
                x[i,2]=normal(A1tilde)[i,2];
        end;
        do i=41 to 60;
                x[i,3]=normal(A1tilde)[i,3];
        end;
        do i=61 to 80;
                x[i,4]=normal(A1tilde)[i,4];
        end;
        do i=81 to 100;
                x[i,5]=normal(A1tilde)[i,5];
        end;
x2=x##2;
d=j(nvars,nfactors,0);
***new trial code;
        do i=1 to 20;
                d[i,1]=sum(x2[i,1:nfactors])##-.5;
        end;
        do i=21 to 40;
                d[i,2]=sum(x2[i,1:nfactors])##-.5;
        end;
        do i=41 to 60;
                d[i,3]=sum(x2[i,1:nfactors])##-.5;
        end;
        do i=61 to 80;
```

Appendix D3 (Continued)

```
			d[i,4]=sum(x2[i,1:nfactors])##-.5;
		end;
		do i=81 to 100;
			d[i,5]=sum(x2[i,1:nfactors])##-.5;
		end;
	c=j(nvars,nfactors,0);
	***new trial code;
		do i=1 to 20;
			c[i,1]=round((uniform(0)*.2999999)+.65,.1);
		end;
		do i=21 to 40;
			c[i,2]=round((uniform(0)*.2999999)+.65,.1);
		end;
		do i=41 to 60;
			c[i,3]=round((uniform(0)*.2999999)+.65,.1);
		end;
		do i=61 to 80;
			c[i,4]=round((uniform(0)*.2999999)+.65,.1);
		end;
		do i=81 to 100;
			c[i,5]=round((uniform(0)*.2999999)+.65,.1);
		end;
	c2=c##2;
	ones=j(nvars,nfactors,0);
		***new trial code;
		do i=1 to 20;
			ones[i,1]=1;
		end;
		do i=21 to 40;
			ones[i,2]=1;
		end;
		do i=41 to 60;
			ones[i,3]=1;
		end;
		do i=61 to 80;
			ones[i,4]=1;
		end;
		do i=81 to 100;
			ones[i,5]=1;
		end;
	y=A1tilde#c + d#x#((ones-c2)##.5);
```

Appendix D3 (Continued)

```
*************************************************************************
*********************;
****** SECOND STEP,translation process includes a skewing function that reduces
*************;
****** negativity in factor loadings
*******************************************************;
k=.2;                              * is a parameter that can range from zero to infinity.
Each vector of Z;
z=j(nvars,nfactors,0);
***new trial code;
    do i=1 to 20;
        z[i,1]=((1+k)*y[i,1]*(y[i,1]+abs(y[i,1])+k))/((2+k)*(abs(y[i,1])+k));
    end;
    do i=21 to 40;
        z[i,2]=((1+k)*y[i,2]*(y[i,2]+abs(y[i,2])+k))/((2+k)*(abs(y[i,2])+k));
    end;
    do i=41 to 60;
        z[i,3]=((1+k)*y[i,3]*(y[i,3]+abs(y[i,3])+k))/((2+k)*(abs(y[i,3])+k));
    end;
    do i=61 to 80;
        z[i,4]=((1+k)*y[i,4]*(y[i,4]+abs(y[i,4])+k))/((2+k)*(abs(y[i,4])+k));
    end;
    do i=81 to 100;
        z[i,5]=((1+k)*y[i,5]*(y[i,5]+abs(y[i,5])+k))/((2+k)*(abs(y[i,5])+k));
    end;
z2=z##2;
g=j(nvars,nfactors,0);
***new trial code;
    do i=1 to 20;
        g[i,1]=sum(z2[i,1:nfactors])##-.5;
    end;
    do i=21 to 40;
        g[i,2]=sum(z2[i,2:nfactors])##-.5;
    end;
    do i=41 to 60;
        g[i,3]=sum(z2[i,3:nfactors])##-.5;
    end;
    do i=61 to 80;
        g[i,4]=sum(z2[i,4:nfactors])##-.5;
    end;
    do i=81 to 100;
        g[i,5]=sum(z2[i,5:nfactors])##-.5;
    end;
A1star=g#z;
```

Appendix D3 (Continued)

```
A1=B1*A1star;                                          * factor loading values;
A3star=I(nvars);                                  * I is the diagonal values of the
matrix ;
A3=B3*A3star;                                          * Input Loadings for the
Unique Factors, A3;
R=A1*A1`+A3*A3`;
/*
PRINT A3;
PRINT B3;
print B1;
print bp1;
print A3star;
print A1star;
print A1tilde;
print x;
print x2;
print d;
print ones;
print c;
print c2;
print y;
print z;
print z2;
print g;
print b3square;
print b1square;
print R;
*/
Finish;
************************************************************************
********************;
****** THIRD STEP,"ensure desired levels of communality" (Hogarty et al., 2005, p.
207) *****;
************************************************************************
********************;
start gendata2a(NN1,seed1,variance,bb,cc,dd,mu,r_matrix,YY,p,d_frac);
     L = eigval(r_matrix);
     neg_eigval = 0;
     do r = 1 to nrow(L);
          if L[r,1] < 0 then neg_eigval = 1;
     end;
     if neg_eigval = 0 then do; * matrix is positive definite, so use the Cholesky root
                                                       approach;
          COLS = NCOL(r_matrix);
```

Appendix D3 (Continued)

```
			G = ROOT(r_matrix);
			YY=rannor(repeat(seed1,nn1,COLS));
			YY = YY*G;
			do r = 1 to NN1;
			do c = 1 to COLS;
				YY[r,c] = (-1*cc) + (bb*YY[r,c]) + (cc*YY[r,c]##2) +
(dd*YY[r,c]##3);
				YY[r,c] = (YY[r,c] * SQRT(variance[1,c])) + mu[1,c];
			end;
			end;
		end;
		if neg_eigval = 1 then do; * matrix is not positive definite, so use the PCA
approach;
			COLS = NCOL(r_matrix);
			V = eigvec(r_matrix);
			do i = 1 to nrow(L);
			do j = 1 to ncol(V);
						if L[i,1] > 0 then V[j,i] = V[j,i] # sqrt(L[i,1]);
						if L[i,1] <= 0 then V[j,i] = V[j,i] #
sqrt(.000000001);
				end;
			end;
			YY=rannor(repeat(seed1,nn1,COLS));
			YY = V*YY`;
			YY = YY`;
			do r = 1 to NN1;
			do c = 1 to COLS;
				YY[r,c] = (-1*cc) + (bb*YY[r,c]) + (cc*YY[r,c]##2) +
(dd*YY[r,c]##3);
				YY[r,c] = (YY[r,c] * SQRT(variance[1,c])) + mu[1,c];
			end;
			end;
		end;
			if d_frac > 0 then do;
					do r = 1 to nn1;
							do c = 1 to (p*d_frac);
							if yy[r,c] < 0 then yy[r,c] = 0;
							else if yy[r,c] = 0 then yy[r,c] = 1;
							else if yy[r,c] > 0 then yy[r,c] = 1;
							end;
					end;
			end;
finish;
```

Appendix D3 (Continued)

```
start gendata2b(NN2,seed1,variance,bb,cc,dd,mu,r_matrix,YY,p,d_frac);
        L = eigval(r_matrix);
        neg_eigval = 0;
        do r = 1 to nrow(L);
                if L[r,1] < 0 then neg_eigval = 1;
        end;
        if neg_eigval = 0 then do; * matrix is positive definite, so use the Cholesky root
approach;
                COLS = NCOL(r_matrix);
                G = ROOT(r_matrix);
                YY=rannor(repeat(seed1,nn2,COLS));
                YY = YY*G;
                do r = 1 to NN2;
                do c = 1 to COLS;
                                YY[r,c] = (-1*cc) + (bb*YY[r,c]) + (cc*YY[r,c]##2) +
(dd*YY[r,c]##3);
                                YY[r,c] = (YY[r,c] * SQRT(variance[1,c])) + mu[1,c];
                end;
                end;
        end;
        if neg_eigval = 1 then do; * matrix is not positive definite, so use the PCA
approach;
                COLS = NCOL(r_matrix);
                V = eigvec(r_matrix);
                do i = 1 to nrow(L);
                do j = 1 to ncol(V);
                                        if L[i,1] > 0 then V[j,i] = V[j,i] # sqrt(L[i,1]);
                                        if L[i,1] <= 0 then V[j,i] = V[j,i] #
sqrt(.000000001);
                                end;
                end;
                YY=rannor(repeat(seed1,nn2,COLS));
                YY = V*YY`;
                YY = YY`;
                do r = 1 to NN2;
                do c = 1 to COLS;
                                YY[r,c] = (-1*cc) + (bb*YY[r,c]) + (cc*YY[r,c]##2) +
(dd*YY[r,c]##3);
                                YY[r,c] = (YY[r,c] * SQRT(variance[1,c])) + mu[1,c];
                end;
                end;
        end;
                if d_frac > 0 then do;
                                do r = 1 to nn2;
```

```
                    do c = 1 to (p*d_frac);
                    if yy[r,c] < 0 then yy[r,c] = 0;
                    else if yy[r,c] = 0 then yy[r,c] = 1;
                    else if yy[r,c] > 0 then yy[r,c] = 1;
                    end;
            end;
        end;
finish;
*************;
Do pop_num = 1 to N_pops; * Loop for 10 populations;
run Make_PopR(p,k,commun_type,A1tilde,B1,x,x2,d,A1,R_pop);
Lambda = A1;
numr = r_pop[+,+] - p;
deno = r_pop[+,+];
ratio = numr/deno;
f2_pop = (p/(p-1))*ratio;
r2_pop = f2_pop/(1+f2_pop);
corr = r_pop;
seed1=round(1000000*rannor(0));
chg = 1;
cycle = 0;
corr_tmp = corr;
do until (chg = 0);
            run
gendata2a(NN1,seed1,variance,1,0,0,means,corr_tmp,sim_data,p,d_frac);
            sim_corr = corr(sim_data);
            resid_m = sim_corr - corr;
            tot_res = sum(abs(resid_m));
            if cycle = 0 then do;
            best_corr = corr_tmp;
            best_res = tot_res;
        end;
        if cycle > 0 then do;
            if tot_res < best_res then do;
                best_corr = corr_tmp;
                best_res = tot_res;
            end;
        end;
        if tot_res < (.005#(((p-1)#p)/2)) then CHG = 0; * Convergence!;
        if cycle > 30 then do;
        if tot_res < (.01#(((p-1)#p)/2)) then CHG = 0; * Convergence!;
    end;
        if cycle > 200 then CHG = 0;
```

Appendix D3 (Continued)

```
        if CHG = 1 then corr_tmp = corr_tmp - resid_m; * adjust template and simulate
another large sample;
                cycle = cycle + 1;
                if CHG = 0 then do;
                end;
        end;
end; *End replications loop;
/*
print A1tilde;
print B1;
print x;
print x2;
print d;
print A1;
print R_pop;
print corr_tmp;
*/
create &ddname1..Loading_L from A1;                                    * Create
Factor Loading matrix from A1;
append from A1;                                                         * Set Loading
name based on commnalities level;
close &ddname1..Loading_L;
create &ddname1..Communalities_L from b1;                              * Create
communalities matrix from b1;
append from b1;                                                         * Set the name
based on commnalities level;
close &ddname1..Communalities_L;
create &ddname2..R_L from R_pop;                  * Create Population corrrelation
matrix from R_pop;
append from R_pop;                                            * Set R name based
on commnalities level;
close &ddname2..R_L;
quit;
```

Appendix D4

```
*******************************************************************;
*************** Dissertation Simulation Primary program           *;
*************** Written by Deyab Almaleki                         *;
*************** Supervised by Dr. Applegate                       *;
*************** Code developed 2015                               *;
*************** Test population correlation matrices             *;
*******************************************************************;

*** Test population coreelation matrix *****;
data _r_;
	set primary.R_H;
_type_="CORR";
_name_=trim("COL")||strip(_n_);
run;
proc factor data=_r_(type=corr) nobs=10000 m=p  r=p reorder;
	var COL1-COL100;
run;
```

Appendix D5

```
*********************************************************************;
*************** Dissertation Simulation Primary program              *;
*************** Written by Deyab Almaleki                             *;
*************** Supervised by Dr. Applegate                          *;
*************** Code developed 2015                                  *;
*************** Code developed 2015                                  *;
*************** Random variables from population matrices            *;
*********************************************************************;
***F1***;
DATA Z1(keep=col1 IDnew rndID);
        set &ddname1..Loading_H;   *  Set the name based on commnalities level;
IDNew=_n_;
rndID=ranuni(0);
run;
data Z1_1;
        set Z1 (obs=20);
run;
proc sort data=Z1_1 out=Z1_2;
      by DESCENDING rndID ;
      run;
data COL1;
      set Z1_2(obs=4); ** select upper 4 variables loaings(*7 *10);
run;
proc sort data=COL1;
        by IDnew;
        run;
***F2***;
DATA Z2(keep=col2 IDnew rndID);
        set &ddname1..Loading_H;   *  Set the name based on commnalities level;
IDNew=_n_;
rndID=ranuni(0);
run;
data Z2_1;
        set Z2 (firstobs=21 obs=40);
run;
proc sort data=Z2_1 out=Z2_2;
      by DESCENDING rndID ;
      run;
data COL2;
      set Z2_2(obs=4); ** select upper 4 variables loaings(*7 *10);
run;
proc sort data=COL2;
        by IDnew;
        run;
```

Appendix D5 (Continued)

```
***F3***;
DATA Z3(keep=col3 IDnew rndID);
         set &ddname1..Loading_H;   *  Set the name based on commnalities level;
IDNew=_n_;
rndID=ranuni(0);
run;
data Z3_1;
         set Z3 (firstobs=41 obs=60);
run;
proc sort data=Z3_1 out=Z3_2;
      by DESCENDING rndID ;
      run;
data COL3;
      set Z3_2(obs=4); ** select upper 4 variables loaings(*7 *10);
run;
proc sort data=COL3;
         by IDnew;
         run;
***F4***;
DATA Z4(keep=col4 IDnew rndID);
         set &ddname1..Loading_H;*Set the name based on commnality level;
IDNew=_n_;
rndID=ranuni(0);
run;
data Z4_1;
         set Z4 (firstobs=61 obs=80);
run;
proc sort data=Z4_1 out=Z4_2;
      by DESCENDING rndID ;
      run;
data COL4;
      set Z4_2(obs=4); ** select upper 4 variables loaings(*7 *10);
run;
proc sort data=COL4;
         by IDnew;
         run;
***F5***;
DATA Z5(keep=col5 IDnew rndID);
         set &ddname1..Loading_H;   *  Set the name based on commnalities level;
IDNew=_n_;
rndID=ranuni(0);
run;
data Z5_1;
         set Z5 (firstobs=81 obs=100);
```

Appendix D5 (Continued)

```
run;
proc sort data=Z5_1 out=Z5_2;
      by DESCENDING rndID ;
      run;
data COL5;
      set Z5_2(obs=4); ** select upper 4 variables loaings(*7 *10);
run;
proc sort data=COL5;
         by IDnew;
         run;
data &ddname1..COLUMNs(keep=IDnew2 );
length IDnew2 $7. base $5.;
         set col1 col2 col3 col4 col5;
base="COL0";
if IDnew<10 then base="COL00";
IDnew2=strip(base)||strip(put(IDnew,2.));
run;
```

Appendix D6

```
*********************************************************************;
*************** Dissertation Simulation Primary program            *;
*************** Written by Deyab Almaleki                          *;
*************** Supervised by Dr. Applegate                        *;
*************** Code developed 2015                                *;
*************** Partitioned Sample correlation matrix  (20x20); *(35x35); *(50x50)*;
*********************************************************************;
data r1;
	set &ddname2..R_L;                         *  Set R name based on
commnalities level;
	ROW=trim("COL")||strip(_n_);
run;
****** Rename all variables
************************************************;
data r2 (rename=(COL1-COL9=COL001-COL009 COL10-COL99=COL010-
COL099));
	set r1;
run;
************************************************;
data r3;
	set r2;
if ROW='COL1' then ROW='COL001';
if ROW='COL2' then ROW='COL002';
if ROW='COL3' then ROW='COL003';
if ROW='COL4' then ROW='COL004';
if ROW='COL5' then ROW='COL005';
if ROW='COL6' then ROW='COL006';
if ROW='COL7' then ROW='COL007';
if ROW='COL8' then ROW='COL008';
if ROW='COL9' then ROW='COL009';
if ROW='COL10' then ROW='COL010';
if ROW='COL11' then ROW='COL011';
if ROW='COL12' then ROW='COL012';
if ROW='COL13' then ROW='COL013';
if ROW='COL14' then ROW='COL014';
if ROW='COL15' then ROW='COL015';
if ROW='COL16' then ROW='COL016';
if ROW='COL17' then ROW='COL017';
if ROW='COL18' then ROW='COL018';
if ROW='COL19' then ROW='COL019';
if ROW='COL20' then ROW='COL020';
if ROW='COL21' then ROW='COL021';
if ROW='COL22' then ROW='COL022';
if ROW='COL23' then ROW='COL023';
```

Appendix D6 (Continued)

```
if ROW='COL24' then ROW='COL024';
if ROW='COL25' then ROW='COL025';
if ROW='COL26' then ROW='COL026';
if ROW='COL27' then ROW='COL027';
if ROW='COL28' then ROW='COL028';
if ROW='COL29' then ROW='COL029';
if ROW='COL30' then ROW='COL030';

if ROW='COL31' then ROW='COL031';
if ROW='COL32' then ROW='COL032';
if ROW='COL33' then ROW='COL033';
if ROW='COL34' then ROW='COL034';
if ROW='COL35' then ROW='COL035';
if ROW='COL36' then ROW='COL036';
if ROW='COL37' then ROW='COL037';
if ROW='COL38' then ROW='COL038';
if ROW='COL39' then ROW='COL039';
if ROW='COL40' then ROW='COL040';
if ROW='COL41' then ROW='COL041';
if ROW='COL42' then ROW='COL042';
if ROW='COL43' then ROW='COL043';
if ROW='COL44' then ROW='COL044';
if ROW='COL45' then ROW='COL045';
if ROW='COL46' then ROW='COL046';
if ROW='COL47' then ROW='COL047';
if ROW='COL48' then ROW='COL048';
if ROW='COL49' then ROW='COL049';
if ROW='COL50' then ROW='COL050';
if ROW='COL51' then ROW='COL051';
if ROW='COL52' then ROW='COL052';
if ROW='COL53' then ROW='COL053';
if ROW='COL54' then ROW='COL054';
if ROW='COL55' then ROW='COL055';
if ROW='COL56' then ROW='COL056';
if ROW='COL57' then ROW='COL057';
if ROW='COL58' then ROW='COL058';
if ROW='COL59' then ROW='COL059';
if ROW='COL60' then ROW='COL060';
if ROW='COL61' then ROW='COL061';
if ROW='COL62' then ROW='COL062';
if ROW='COL63' then ROW='COL063';
if ROW='COL64' then ROW='COL064';
if ROW='COL65' then ROW='COL065';
if ROW='COL66' then ROW='COL066';
```

Appendix D6 (Continued)

```
if ROW='COL67' then ROW='COL067';
if ROW='COL68' then ROW='COL068';
if ROW='COL69' then ROW='COL069';
if ROW='COL70' then ROW='COL070';
if ROW='COL71' then ROW='COL071';
if ROW='COL72' then ROW='COL072';
if ROW='COL73' then ROW='COL073';
if ROW='COL74' then ROW='COL074';
if ROW='COL75' then ROW='COL075';
if ROW='COL76' then ROW='COL076';
if ROW='COL77' then ROW='COL077';
if ROW='COL78' then ROW='COL078';
if ROW='COL79' then ROW='COL079';
if ROW='COL80' then ROW='COL080';
if ROW='COL81' then ROW='COL081';
if ROW='COL82' then ROW='COL082';
if ROW='COL83' then ROW='COL083';
if ROW='COL84' then ROW='COL084';
if ROW='COL85' then ROW='COL085';
if ROW='COL86' then ROW='COL086';
if ROW='COL87' then ROW='COL087';
if ROW='COL88' then ROW='COL088';
if ROW='COL89' then ROW='COL089';
if ROW='COL90' then ROW='COL090';
if ROW='COL91' then ROW='COL091';
if ROW='COL92' then ROW='COL092';
if ROW='COL93' then ROW='COL093';
if ROW='COL94' then ROW='COL094';
if ROW='COL95' then ROW='COL095';
if ROW='COL96' then ROW='COL096';
if ROW='COL97' then ROW='COL097';
if ROW='COL98' then ROW='COL098';
if ROW='COL99' then ROW='COL099';

run;
proc sort data=r3;
  by ROW ;
  run;
proc transpose name=COL  data=r3 out=r4 prefix=m;
  by ROW;
  run;
data r5;
  set r4;
```

Appendix D6 (Continued)

```
        if ROW in
        ('COL001','COL002','COL003','COL005','COL006','COL007','COL008','COL010'
,'COL011','COL012','COL014','COL015','COL016','COL018','COL019','COL020',

        'COL021','COL022','COL024','COL025','COL026','COL028','COL029','COL030',
'COL031','COL032','COL033','COL035','COL036','COL037','COL038','COL040',

        'COL042','COL043','COL044','COL045','COL046','COL047','COL049','COL050',
'COL051','COL052','COL053','COL055','COL056','COL057','COL058','COL060',

        'COL061','COL062','COL064','COL065','COL066','COL067','COL068','COL070',
'COL071','COL073','COL074','COL075','COL076','COL077','COL078','COL079',

        'COL081','COL083','COL084','COL085','COL086','COL088','COL089','COL090',
'COL091','COL092','COL095','COL096','COL097','COL098','COL099','COL100') then
delete;

        if COL in
        ('COL001','COL002','COL003','COL005','COL006','COL007','COL008','COL010'
,'COL011','COL012','COL014','COL015','COL016','COL018','COL019','COL020',

        'COL021','COL022','COL024','COL025','COL026','COL028','COL029','COL030',
'COL031','COL032','COL033','COL035','COL036','COL037','COL038','COL040',


        'COL042','COL043','COL044','COL045','COL046','COL047','COL049','COL050',
'COL051','COL052','COL053','COL055','COL056','COL057','COL058','COL060',

        'COL061','COL062','COL064','COL065','COL066','COL067','COL068','COL070',
'COL071','COL073','COL074','COL075','COL076','COL077','COL078','COL079',

        'COL081','COL083','COL084','COL085','COL086','COL088','COL089','COL090',
'COL091','COL092','COL095','COL096','COL097','COL098','COL099','COL100')then
delete;
  run;
proc sort data=r5;
 by  ROW COL ;
  run;
proc transpose data=r5 out=r6 (drop= _NAME_);
  by ROW;
  id COL;
  run;
data r7 (type=corr);
set r6 ;
```

Appendix D6 (Continued)

```
run;
*********************************************************************;
***** End Partitoined Sample correlation matrix *(20x20); *(35x35); *(50x50)**;
*********************************************************************;
****** start generate data from partitioned matrix *****************;
proc factor data=r7 n=20 outstat=sample1 noprint;
run;
data sample2;
        set sample1;
if _type_="PATTERN";
run;
proc transpose data=sample2 out=sample3;
        id _name_;
        run;
********************************************************************;
libname T32 "C:\Users\user\Desktop\Generation\Data\Primary\L\V-4\S-32";
*********************************************************************;
***** generate N observations with specified correlation structure;
proc iml;
names = "L_4_32_1":"L_4_32_1000";                    * # Loop of generation
multiple data;
do i = 1 to nCOL(names);
        use sample3;
        read all var _NUM_ INTO F;                * # read in factor pattern as matrix
'F';
SEED=0;
H=rannor(J(640,20,SEED));                 * # generates a 1000 row by 5 (1000,5) col
by "H" matrix;
* set the sample size based on S:V ratios, 2:1, 4:1, 8:1, 16:1, and 32:1;


H=H`;                                                * # transpose to 5,1000
matrix;
z=f*H;                                               * # premultiple by F
(5,5)*(5,1000) = 5,1000 matrix;
z=z`;
COL004=z[,1];                                        * # create col-- as a linear
tansform of z,Col-- to mean=0, sd=1;
COL009=z[,2];
COL013=z[,3];
COL017=z[,4];
COL023=z[,5];
COL027=z[,6];
COL034=z[,7];
```

Appendix D6 (Continued)

```
COL039=z[,8];
COL041=z[,9];
COL048=z[,10];
COL054=z[,11];
COL059=z[,12];
COL063=z[,13];
COL069=z[,14];
COL072=z[,15];
COL080=z[,16];
COL082=z[,17];
COL087=z[,18];
COL093=z[,19];
COL094=z[,20];
* # reload a new matrix Z1 with columns={col--};
* # *creates a temp SAS data ;
z1 = i;
dsname= names[i];                                   * # construct each name of data;
z1=COL004||COL009||COL013||COL017||COL023||COL027||COL034||COL039||COL04
1||COL048||COL054||COL059||COL063||COL069||COL072||COL080||COL082||COL087|
|COL093||COL094;
CREATE (dsname) FROM z1[COLNAME={COL004 COL009 COL013 COL017
COL023 COL027 COL034 COL039 COL041 COL048 COL054 COL059 COL063
COL069 COL072 COL080 COL082 COL087 COL093 COL094}];
APPEND FROM z1;
close (dsname);
end;                                                          * # end the loop;

RUN;
QUIT;
******** Move the data to external folder *********;
proc datasets library=T32;
        copy in=work out=T32; * st the extrnal file based on data conditions ;
                select L_4_32_1-L_4_32_1000;
        run;
        quit;
proc datasets library=work nolist;
        delete L_4_32_1-L_4_32_1000;
        run;
```

Appendix D7

SAS syntax of analysis RQ1

```
*********************************************************************;
*************** Dissertation Simulation Primary program              *;
*************** Written by Deyab Almaleki                             *;
*************** Supervised by Dr. Applegate                          *;
*************** Code developed 2015                                   *;
*************** Roll-up-all data                                     *;
*********************************************************************;
********** High Communalities;
libname S_H_4_2 "C:\Users\user\Desktop\Generation\Data\Primary\H\V-4\S-2";
libname S_H_4_4 "C:\Users\user\Desktop\Generation\Data\Primary\H\V-4\S-4";
libname S_H_4_8 "C:\Users\user\Desktop\Generation\Data\Primary\H\V-4\S-8";
libname S_H_4_16 "C:\Users\user\Desktop\Generation\Data\Primary\H\V-4\S-16";
libname S_H_4_32 "C:\Users\user\Desktop\Generation\Data\Primary\H\V-4\S-32";

libname S_H_7_2 "C:\Users\user\Desktop\Generation\Data\Primary\H\V-7\S-2";
libname S_H_7_4 "C:\Users\user\Desktop\Generation\Data\Primary\H\V-7\S-4";
libname S_H_7_8 "C:\Users\user\Desktop\Generation\Data\Primary\H\V-7\S-8";
libname S_H_7_16 "C:\Users\user\Desktop\Generation\Data\Primary\H\V-7\S-16";
libname S_H_7_32 "C:\Users\user\Desktop\Generation\Data\Primary\H\V-7\S-32";

libname S_H_10_2 "C:\Users\user\Desktop\Generation\Data\Primary\H\V-10\S-2";
libname S_H_10_4 "C:\Users\user\Desktop\Generation\Data\Primary\H\V-10\S-4";
libname S_H_10_8 "C:\Users\user\Desktop\Generation\Data\Primary\H\V-10\S-8";
libname S_H_1016 "C:\Users\user\Desktop\Generation\Data\Primary\H\V-10\S-16";
libname S_H_1032 "C:\Users\user\Desktop\Generation\Data\Primary\H\V-10\S-32";
********** Moderate Communalities;
libname S_M_4_2 "C:\Users\user\Desktop\Generation\Data\Primary\M\V-4\S-2";
libname S_M_4_4 "C:\Users\user\Desktop\Generation\Data\Primary\M\V-4\S-4";
libname S_M_4_8 "C:\Users\user\Desktop\Generation\Data\Primary\M\V-4\S-8";
libname S_M_4_16 "C:\Users\user\Desktop\Generation\Data\Primary\M\V-4\S-16";
libname S_M_4_32 "C:\Users\user\Desktop\Generation\Data\Primary\M\V-4\S-32";


libname S_M_7_2 "C:\Users\user\Desktop\Generation\Data\Primary\M\V-7\S-2";
libname S_M_7_4 "C:\Users\user\Desktop\Generation\Data\Primary\M\V-7\S-4";
libname S_M_7_8 "C:\Users\user\Desktop\Generation\Data\Primary\M\V-7\S-8";
libname S_M_7_16 "C:\Users\user\Desktop\Generation\Data\Primary\M\V-7\S-16";
libname S_M_7_32 "C:\Users\user\Desktop\Generation\Data\Primary\M\V-7\S-32";

libname S_M_10_2 "C:\Users\user\Desktop\Generation\Data\Primary\M\V-10\S-2";
libname S_M_10_4 "C:\Users\user\Desktop\Generation\Data\Primary\M\V-10\S-4";
libname S_M_10_8 "C:\Users\user\Desktop\Generation\Data\Primary\M\V-10\S-8";
libname S_M_1016 "C:\Users\user\Desktop\Generation\Data\Primary\M\V-10\S-16";
```

Appendix D7 (Continued)

```
libname S_M_1032 "C:\Users\user\Desktop\Generation\Data\Primary\M\V-10\S-32";
********** Low Communalities;
libname S_L_4_2 "C:\Users\user\Desktop\Generation\Data\Primary\L\V-4\S-2";
libname S_L_4_4 "C:\Users\user\Desktop\Generation\Data\Primary\L\V-4\S-4";
libname S_L_4_8 "C:\Users\user\Desktop\Generation\Data\Primary\L\V-4\S-8";
libname S_L_4_16 "C:\Users\user\Desktop\Generation\Data\Primary\L\V-4\S-16";
libname S_L_4_32 "C:\Users\user\Desktop\Generation\Data\Primary\L\V-4\S-32";

libname S_L_7_2 "C:\Users\user\Desktop\Generation\Data\Primary\L\V-7\S-2";
libname S_L_7_4 "C:\Users\user\Desktop\Generation\Data\Primary\L\V-7\S-4";
libname S_L_7_8 "C:\Users\user\Desktop\Generation\Data\Primary\L\V-7\S-8";
libname S_L_7_16 "C:\Users\user\Desktop\Generation\Data\Primary\L\V-7\S-16";
libname S_L_7_32 "C:\Users\user\Desktop\Generation\Data\Primary\L\V-7\S-32";

libname S_L_10_2 "C:\Users\user\Desktop\Generation\Data\Primary\L\V-10\S-2";
libname S_L_10_4 "C:\Users\user\Desktop\Generation\Data\Primary\L\V-10\S-4";
libname S_L_10_8 "C:\Users\user\Desktop\Generation\Data\Primary\L\V-10\S-8";
libname S_L_1016 "C:\Users\user\Desktop\Generation\Data\Primary\L\V-10\S-16";
libname S_L_1032 "C:\Users\user\Desktop\Generation\Data\Primary\L\V-10\S-32";

********** Mixed Communalities;
libname S_W_4_2 "C:\Users\user\Desktop\Generation\Data\Primary\W\V-4\S-2";
libname S_W_4_4 "C:\Users\user\Desktop\Generation\Data\Primary\W\V-4\S-4";
libname S_W_4_8 "C:\Users\user\Desktop\Generation\Data\Primary\W\V-4\S-8";
libname S_W_4_16 "C:\Users\user\Desktop\Generation\Data\Primary\W\V-4\S-16";
libname S_W_4_32 "C:\Users\user\Desktop\Generation\Data\Primary\W\V-4\S-32";

libname S_W_7_2 "C:\Users\user\Desktop\Generation\Data\Primary\W\V-7\S-2";
libname S_W_7_4 "C:\Users\user\Desktop\Generation\Data\Primary\W\V-7\S-4";
libname S_W_7_8 "C:\Users\user\Desktop\Generation\Data\Primary\W\V-7\S-8";
libname S_W_7_16 "C:\Users\user\Desktop\Generation\Data\Primary\W\V-7\S-16";
libname S_W_7_32 "C:\Users\user\Desktop\Generation\Data\Primary\W\V-7\S-32";

libname S_W_10_2 "C:\Users\user\Desktop\Generation\Data\Primary\W\V-10\S-2";
libname S_W_10_4 "C:\Users\user\Desktop\Generation\Data\Primary\W\V-10\S-4";
libname S_W_10_8 "C:\Users\user\Desktop\Generation\Data\Primary\W\V-10\S-8";
libname S_W_1016 "C:\Users\user\Desktop\Generation\Data\Primary\W\V-10\S-16";
libname S_W_1032 "C:\Users\user\Desktop\Generation\Data\Primary\W\V-10\S-32";
*********************************************************************;
***** S:roll-up
*********************************************************************;
data primary.All_data;
	set
S_H_4_2.fit_H_4_2
```

Appendix D7 (Continued)

S_H_4_4.fit_H_4_4
S_H_4_8.fit_H_4_8
S_H_4_16.fit_H_4_16
S_H_4_32.fit_H_4_32
S_H_7_2.fit_H_7_2
S_H_7_4.fit_H_7_4
S_H_7_8.fit_H_7_8
S_H_7_16.fit_H_7_16
S_H_7_32.fit_H_7_32
S_H_10_2.fit_H_10_2
S_H_10_4.fit_H_10_4
S_H_10_8.fit_H_10_8
S_H_1016.fit_H_10_16
S_H_1032.fit_H_10_32

S_M_4_2.fit_M_4_2
S_M_4_4.fit_M_4_4
S_M_4_8.fit_M_4_8
S_M_4_16.fit_M_4_16
S_M_4_32.fit_M_4_32

S_M_7_2.fit_M_7_2
S_M_7_4.fit_M_7_4
S_M_7_8.fit_M_7_8
S_M_7_16.fit_M_7_16
S_M_7_32.fit_M_7_32

S_M_10_2.fit_M_10_2
S_M_10_4.fit_M_10_4
S_M_10_8.fit_M_10_8
S_M_1016.fit_M_10_16
S_M_1032.fit_M_10_32

S_L_4_2.fit_L_4_2
S_L_4_4.fit_L_4_4
S_L_4_8.fit_L_4_8
S_L_4_16.fit_L_4_16
S_L_4_32.fit_L_4_32

S_L_7_2.fit_L_7_2
S_L_7_4.fit_L_7_4
S_L_7_8.fit_L_7_8
S_L_7_16.fit_L_7_16
S_L_7_32.fit_L_7_32

Appendix D7 (Continued)

```
S_L_10_2.fit_L_10_2
S_L_10_4.fit_L_10_4
S_L_10_8.fit_L_10_8
S_L_1016.fit_L_10_16
S_L_1032.fit_L_10_32

S_W_4_2.fit_W_4_2
S_W_4_4.fit_W_4_4
S_W_4_8.fit_W_4_8
S_W_4_16.fit_W_4_16
S_W_4_32.fit_W_4_32

S_W_7_2.fit_W_7_2
S_W_7_4.fit_W_7_4
S_W_7_8.fit_W_7_8
S_W_7_16.fit_W_7_16
S_W_7_32.fit_W_7_32

S_W_10_2.fit_W_10_2
S_W_10_4.fit_W_10_4
S_W_10_8.fit_W_10_8
S_W_1016.fit_W_10_16
S_W_1032.fit_W_10_32;
run;
```

Appendix D8

```
*******************************************************************;
*************** Dissertation Simulation Primary program           *;
*************** Written by Deyab Almaleki                         *;
*************** Supervised by Dr. Applegate                       *;
*************** Code developed 2015                               *;
*************** CFA V=4 roll-up 1000 dataset                      *;
*******************************************************************;
libname S_H_4_2 "C:\Users\user\Desktop\Generation\Data\Primary\H\V-4\S-2";
libname S_H_4_4 "C:\Users\user\Desktop\Generation\Data\Primary\H\V-4\S-4";
libname S_H_4_8 "C:\Users\user\Desktop\Generation\Data\Primary\H\V-4\S-8";
libname S_H_4_16 "C:\Users\user\Desktop\Generation\Data\Primary\H\V-4\S-16";
libname S_H_4_32 "C:\Users\user\Desktop\Generation\Data\Primary\H\V-4\S-32";

proc datasets library=scratch nolist;
	delete fit fit1-fit1000;
	run;
***** Test Confirmation by CFA ********;
%macro CFA;
%do rep=1 %to 1000;
	proc calis data=S32.L_4_32_&rep modification outfit=scratch.Fit&rep noprint; *
addapted line to call the data;
	factor
		factor1--->COL004 COL009 COL013 COL017,
		factor2--->COL023 COL027 COL034 COL039,
		factor3--->COL041 COL048 COL054 COL059,
		factor4--->COL063 COL069 COL072 COL080,
		factor5--->COL082 COL087 COL093 COL094;
	pvar
		COL004 = e004,		COL023 = e023,		COL041 = e041,
	COL063 = e063,		COL082 = e082,
		COL009 = e009,		COL027 = e027,		COL048 = e048,
	COL069 = e069,		COL087 = e087,
		COL013 = e013,		COL034 = e034,		COL054 = e054,
	COL072 = e072,		COL093 = e093,
		COL017 = e017,		COL039 = e039,		COL059 = e059,
	COL080 = e080,		COL094 = e094,
	Factor1 Factor2 Factor3 Factor4 Factor5  = 5 * 1.;
   cov
		Factor1 Factor2 = 0,Factor1 Factor3 = 0,Factor1 Factor4 = 0,Factor1
Factor5 = 0,
		Factor2 Factor3 = 0,Factor2 Factor4 = 0,Factor2 Factor5 = 0,
		Factor3 Factor4 = 0,Factor3 Factor5 = 0,
		Factor4 Factor5 = 0;
	run;
```

Appendix D8 (Continued)

```
		data scratch.Fit&rep;
			set scratch.Fit&rep;
			replication=&rep;
			if IndexCode in
(203,204,213,214,215,301,302,303,304,305,307,308,309,310,312,401,403);
		run;
%end;
%mend;
***** execute CFA macro;
%CFA;
***** Test for rolled-up FIT statistics dataset;
***** Creates it is not present;
%macro opends(name);
%let flg=%sysfunc(exist(scratch.&name,data));
%if &flg=1 %then %do;
			%put "Data set present";
		%end;
		%else %do;
			%put "Data set &name does not exist.";
			data S32.fit; *this will create the initial dataset;
				set scratch.Fit1;
			run;
		%end;
%mend opends;
%opends(fit);

%macro rollup;
%do rep=2 %to 1000;
		proc datasets library=scratch nolist;
			append base=S32.fit data=scratch.fit&rep;
		run;
		quit;
%end;
%mend;

%rollup;

* adjust data name ;
**************************************************;
***** Level of communalities is L=1, M=2, H=3, W=4;
***** Level of V:F  4,7, 10;
***** level of S:V  2, 4, 8, 16, 32;
**************************************************;
```

Appendix D8 (Continued)

```
proc transpose data=S_H_10_8.fit(drop=IndexCode)
out=trnsFIT_H_10_8(drop=_name_ _label_);
        id FitIndex;
        by replication;
run;
data S_H_10_8.FIT_H_10_8;
        set trnsFIT_H_10_8;

VTF=10; H2=3; STV=8;

***** GFI ***;
if Goodness_of_Fit_Index__GFI_ >= 0.9 then GFI_fit=1;
        else GFI_fit=0;

***** AGFI ***;
if Adjusted_GFI__AGFI_ >= 0.9 then AGFI_fit=1;
        else AGFI_fit=0;
***** TLI ***;
if Bentler_Bonett_Non_normed_Index >= 0.96 then TLI_fit=1;
        else TLI_fit=0;
***** RMSEA ***;
if RMSEA_Estimate =< 0.05 then RMSEA_fit=1;
        else RMSEA_fit=0;
***** RMR ***;
if Root_Mean_Square_Residual__RMR_ <= 0.05 then RMR_fit=1;
        else RMR_fit=0;
***** CFI ***;
if Bentler_Comparative_Fit_Index > 0.95 then CFI_fit=1;
        else CFI_fit=0;
run;
```

Appendix D9

```
*******************************************************************;
*************** Dissertation Simulation Primary program          *;
*************** Written by Deyab Almaleki                        *;
*************** Supervised by Dr. Applegate                      *;
*************** Code developed 2015                              *;
*************** Seven separate three-way ANOVAs analysis         *;
*******************************************************************;
libname primary "C:\Users\dnp2969\Desktop\Generation\Data\Primary";
data primary.all_dataREV1;
  set primary.all_data /*(rename=(h2=h))*/;

if h=1 and vtf=4 and stv=2 then ALLgroup=  'H1V4S2  ';
if h=1 and vtf=4 and stv=4 then ALLgroup=  'H1V4S4  ';
if h=1 and vtf=4 and stv=8 then ALLgroup=  'H1V4S8  ';
if h=1 and vtf=4 and stv=16 then ALLgroup= 'H1V4S16 ';
if h=1 and vtf=4 and stv=32 then ALLgroup= 'H1V4S32 ';

if h=1 and vtf=7 and stv=2 then ALLgroup=  'H1V7S2  ';
if h=1 and vtf=7 and stv=4 then ALLgroup=  'H1V7S4  ';
if h=1 and vtf=7 and stv=8 then ALLgroup=  'H1V7S8  ';
if h=1 and vtf=7 and stv=16 then ALLgroup= 'H1V7S16 ';
if h=1 and vtf=7 and stv=32 then ALLgroup= 'H1V7S32 ';

if h=1 and vtf=10 and stv=2 then ALLgroup= 'H1V10S2 ';
if h=1 and vtf=10 and stv=4 then ALLgroup= 'H1V10S4 ';
if h=1 and vtf=10 and stv=8 then ALLgroup= 'H1V10S8 ';
if h=1 and vtf=10 and stv=16 then ALLgroup='H1V10S16';
if h=1 and vtf=10 and stv=32 then ALLgroup='H1V10S32';

if h=2 and vtf=4 and stv=2 then ALLgroup=  'H2V4S2  ';
if h=2 and vtf=4 and stv=4 then ALLgroup=  'H2V4S4  ';
if h=2 and vtf=4 and stv=8 then ALLgroup=  'H2V4S8  ';
if h=2 and vtf=4 and stv=16 then ALLgroup= 'H2V4S16 ';
if h=2 and vtf=4 and stv=32 then ALLgroup= 'H2V4S32 ';

if h=2 and vtf=7 and stv=2 then ALLgroup=  'H2V7S2  ';
if h=2 and vtf=7 and stv=4 then ALLgroup=  'H2V7S4  ';
if h=2 and vtf=7 and stv=8 then ALLgroup=  'H2V7S8  ';
if h=2 and vtf=7 and stv=16 then ALLgroup= 'H2V7S16 ';
if h=2 and vtf=7 and stv=32 then ALLgroup= 'H2V7S32 ';

if h=2 and vtf=10 and stv=2 then ALLgroup= 'H2V10S2 ';
if h=2 and vtf=10 and stv=4 then ALLgroup= 'H2V10S4 ';
if h=2 and vtf=10 and stv=8 then ALLgroup= 'H2V10S8 ';
```

Appendix D9 (Continued)

```
if h=2 and vtf=10 and stv=16 then ALLgroup='H2V10S16';
if h=2 and vtf=10 and stv=32 then ALLgroup='H2V10S32';

if h=3 and vtf=4 and stv=2 then ALLgroup=  'H3V4S2  ';
if h=3 and vtf=4 and stv=4 then ALLgroup=  'H3V4S4  ';
if h=3 and vtf=4 and stv=8 then ALLgroup=  'H3V4S8  ';
if h=3 and vtf=4 and stv=16 then ALLgroup= 'H3V4S16 ';
if h=3 and vtf=4 and stv=32 then ALLgroup= 'H3V4S32 ';

if h=3 and vtf=7 and stv=2 then ALLgroup=  'H3V7S2  ';
if h=3 and vtf=7 and stv=4 then ALLgroup=  'H3V7S4  ';
if h=3 and vtf=7 and stv=8 then ALLgroup=  'H3V7S8  ';
if h=3 and vtf=7 and stv=16 then ALLgroup= 'H3V7S16 ';
if h=3 and vtf=7 and stv=32 then ALLgroup= 'H3V7S32 ';

if h=3 and vtf=10 and stv=2 then ALLgroup= 'H3V10S2 ';
if h=3 and vtf=10 and stv=4 then ALLgroup= 'H3V10S4 ';
if h=3 and vtf=10 and stv=8 then ALLgroup= 'H3V10S8 ';
if h=3 and vtf=10 and stv=16 then ALLgroup='H3V10S16';
if h=3 and vtf=10 and stv=32 then ALLgroup='H3V10S32';

if h=4 and vtf=4 and stv=2 then ALLgroup=  'H4V4S2  ';
if h=4 and vtf=4 and stv=4 then ALLgroup=  'H4V4S4  ';
if h=4 and vtf=4 and stv=8 then ALLgroup=  'H4V4S8  ';
if h=4 and vtf=4 and stv=16 then ALLgroup= 'H4V4S16 ';
if h=4 and vtf=4 and stv=32 then ALLgroup= 'H4V4S32 ';

if h=4 and vtf=7 and stv=2 then ALLgroup=  'H4V7S2  ';
if h=4 and vtf=7 and stv=4 then ALLgroup=  'H4V7S4  ';
if h=4 and vtf=7 and stv=8 then ALLgroup=  'H4V7S8  ';
if h=4 and vtf=7 and stv=16 then ALLgroup= 'H4V7S16 ';
if h=4 and vtf=7 and stv=32 then ALLgroup= 'H4V7S32 ';

if h=4 and vtf=10 and stv=2 then ALLgroup= 'H4V10S2 ';
if h=4 and vtf=10 and stv=4 then ALLgroup= 'H4V10S4 ';
if h=4 and vtf=10 and stv=8 then ALLgroup= 'H4V10S8 ';
if h=4 and vtf=10 and stv=16 then ALLgroup='H4V10S16';
if h=4 and vtf=10 and stv=32 then ALLgroup='H4V10S32';
run;
proc format;
        value Hfmt  1='Low communality'
                    2='Moderate communality'
                    3='High communality'
                    4='Mixed communality';
```

Appendix D9 (Continued)

```
        value vfmt      4='4:1 variable to factor ratio'
                            7='7:1 variable to factor ratio'
                            10='10:1 variable to factor ratio';
        value sfmt      2='2:1 subjects to variable ratio'
                            4='4:1 subjects to variable ratio'
                            8='8:1 subjects to variable ratio'
                            16='16:1 subjects to variable ratio'
                            32='32:1 subjects to variable ratio';
        value $agfmt 'H1V4S2  '='H=Low, VTF=4:1, STF=2:1';

        run;

****Sort data;
proc sort data=primary.all_data;
  by H;
  run;

*** frq of fit indices ***;
proc freq data=primary.all_dataREV1;

        tables ALLgroup*(GFI_fit AGFI_fit TLI_fit RMR_fit RMSEA_fit CFI_fit);
        title1 "Frequency based on the criteria of fit indices";
        run;

****************************************************;
*******  Means of fit indices **************************;
****************************************************;
ods rtf file="C:\Users\user\Desktop\Generation\Data\Primary\RQ1 means.rtf";
ods graphics on;
proc means data=primary.all_dataREV1 mean std;
        var Chi_Square
                Goodness_of_Fit_Index__GFI_
                Adjusted_GFI__AGFI_
                Bentler_Bonett_Non_normed_Index
                RMSEA_Estimate
                Bentler_Comparative_Fit_Index
                Root_Mean_Square_Residual__RMR_
                Akaike_Information_Criterion
                Schwarz_Bayesian_Criterion;
        output out=RQ1mean mean=Mean_Chi Mean_GFI Mean_AGFI Mean_TLI
                                                        Mean_RMSEA mean_CFI
mean_RMR
                                                        mean_AIC mean_BIC;
        class ALLgroup;
```

Appendix D9 (Continued)

```
        id h stv vtf;
        format ALLgroup $agfmt.;
title1 "Mean calculations in GFI_fit index";
run;
ods _all_ close;
ods listing;
******************************************************************;
******* RQ1 Overall ANOVA *****;
******************************************************************;
proc glm data=primary.all_dataREV1;
        class H vtf stv;
        model  Chi_Square
                        Goodness_of_Fit_Index__GFI_
                        Adjusted_GFI__AGFI_
                        Bentler_Bonett_Non_normed_Index
                        RMSEA_Estimate
                        Bentler_Comparative_Fit_Index
                        Root_Mean_Square_Residual__RMR_
                        Akaike_Information_Criterion
                        Schwarz_Bayesian_Criterion = h|vtf|stv;
        title1 "RQ1 Overall ANOVA";
        run;
quit;
****************************************;
***** Post Hoc setup (2-way);
***** DV=Chi_Square;
****************************************;
options nocenter;
proc glm data=primary.all_dataREV1;
```



```
        class H vtf stv;
        model Chi_Square = h|vtf|stv;
        *lsmeans vtf*stv/slice=vtf pdiff adjust=tukey;
        lsmeans vtf*stv/slice=stv adjust=tukey alpha=.007 out=Chi_RQ1;
        run;
quit;
pattern1 c=black value=x2;
pattern2 c=red   value=x2;
pattern3 c=blue  value=x2;
axis1 label=(a=90 h=1.25 f=swiss "Mean Chi_Square")
         order=(0 to 1200 by 50)
         minor=none;
axis2 label=(h=1.25 f=swiss "STV*VTF")
```

Appendix D9 (Continued)

```
          minor=none;
proc gchart data=Chi_RQ1;
        vbar vtf/group=stv sumvar=LSMEAN discrete patterid=midpoint
                        raxis=axis1 gaxis=axis2 noframe;
        run;
        quit;
*******************************************;
***** Post Hoc setup (2-way);
***** DV=GFI;
*******************************************;
proc glm data=primary.all_dataREV1;
        class H vtf stv;
        model Goodness_of_Fit_Index__GFI_ = h|vtf|stv;
*       lsmeans vtf*stv/slice=vtf pdiff adjust=tukey;
        lsmeans vtf*stv/slice=stv adjust=tukey alpha=.007 out=GFI_RQ1;
run;
quit;
pattern1 c=black value=x2;
pattern2 c=red   value=x2;
pattern3 c=blue  value=x2;
axis1 label=(a=90 h=1.25 f=swiss "Mean GFI")
          order=(0.6 to 1.0 by .05)
          minor=none;
axis2 label=(h=1.25 f=swiss "STV*VTF")
          minor=none;
proc gchart data=GFI_RQ1;
        vbar vtf/group=stv sumvar=LSMEAN discrete patterid=midpoint
                        raxis=axis1 gaxis=axis2 noframe;
        run;
        quit;

*******************************;
***** Post Hoc setup (2-way);
***** DV=AGFI;
*******************************;
proc glm data=primary.all_dataREV1;
        class H vtf stv;
        model Adjusted_GFI__AGFI_ = h|vtf|stv;
        *lsmeans vtf*stv/slice=vtf pdiff adjust=tukey;
        lsmeans vtf*stv/slice=stv adjust=tukey alpha=.007 out=AGFI_RQ1;
        run;

quit;
pattern1 c=black value=x2;
```

Appendix D9 (Continued)

```
pattern2 c=red   value=x2;
pattern3 c=blue  value=x2;
axis1 label=(a=90 h=1.25 f=swiss "Mean AGFI")
          order=(0.6 to 1.0 by .05)
          minor=none;
axis2 label=(h=1.25 f=swiss "STV*VTF")
          minor=none;
proc gchart data=AGFI_RQ1;
        vbar vtf/group=stv sumvar=LSMEAN discrete patterid=midpoint
                        raxis=axis1 gaxis=axis2 noframe;
        run;
        quit;
*********************************;
***** Post Hoc setup (2-way);
***** DV=RMSEA;
*********************************;
proc glm data=primary.all_dataREV1;
        class H vtf stv;
        model RMSEA_Estimate = h|vtf|stv;
        *lsmeans vtf*stv/slice=vtf pdiff adjust=tukey;
        lsmeans vtf*stv/slice=stv  adjust=tukey alpha=.007 out=RMSEA_RQ1;
        run;
quit;
pattern1 c=black value=x2;
pattern2 c=red   value=x2;
pattern3 c=blue  value=x2;
axis1 label=(a=90 h=1.25 f=swiss "Mean RMSEA")
          order=(0.001 to 0.09 by .01)
          minor=none;
axis2 label=(h=1.25 f=swiss "STV*VTF")
          minor=none;
proc gchart data=RMSEA_RQ1;
        vbar vtf/group=stv sumvar=LSMEAN discrete patterid=midpoint
                        raxis=axis1 gaxis=axis2 noframe;
        run;
        quit;
******************************************************************;
***** Post Hoc setup (3-way);
***** DV=Bentler_Bonett_Non_normed_Index (TLI);
******************************************************************;
options nocenter;
proc glm data=primary.all_dataREV1;
        class H vtf stv;
        model Bentler_Bonett_Non_normed_Index = h|vtf|stv;
```

Appendix D9 (Continued)

```
        *lsmeans vtf*stv*h/out=RQ1TLI;
        *lsmeans vtf*stv*h/slice=h;
        *lsmeans vtf*stv*h/slice=vtf;
        lsmeans vtf*stv*h/slice=stv;
        run;
**** slice by vtf and h;
        lsmeans vtf*stv*h/slice=h*stv pdiff adjust=tukey alpha=.007 out=CFI_RQ1;
        *lsmeans vtf*h/slice=h pdiff adjust=tukey;
        *lsmeans vtf*h/slice=vtf pdiff adjust=tukey;
        run;
**** slice by stv and vtf;
        *lsmeans vtf*stv*h/slice=vtf*stv pdiff adjust=tukey;
        *lsmeans stv*vtf/slice=vtf pdiff adjust=tukey;
        *lsmeans stv*vtf/slice=stv pdiff adjust=tukey;
        *run;
**** slice by stv and h;
        *lsmeans vtf*stv*h/slice=h*stv  adjust=tukey alpha=.007 out=TLI_RQ1;
        *lsmeans stv*h/slice=h  adjust=tukey alpha=.007;
        *lsmeans stv*h/slice=stv  adjust=tukey alpha=.007;
run;
quit;
pattern1 c=black value=x2;
pattern2 c=red   value=x2;
pattern3 c=blue  value=x2;
axis1 label=(a=90 h=1.25 f=swiss "Mean TLI")
         order=(0.4 to 1.00 by .1)
         minor=none;
axis2 label=(h=1.25 f=swiss "STV*h")
        minor=none;
proc gchart data=TLI_RQ1;
        vbar stv/group=h sumvar=LSMEAN discrete patterid=midpoint
                        raxis=axis1 gaxis=axis2 noframe;
        run;
        quit;
**********************************************************************;
***** Post Hoc setup (3-way);
***** DV=Bentler_Comparative_Fit_Index (CFI);
**********************************************************************;
proc glm data=primary.all_dataREV1;
        class H vtf stv;
        model Bentler_Comparative_Fit_Index = h|vtf|stv;
        *lsmeans vtf*stv*h/slice=h;
        lsmeans vtf*stv*h/slice=vtf;
        *lsmeans vtf*stv*h/slice=stv;
```

Appendix D9 (Continued)

```
        run;
**** slice by vtf and h;
        *lsmeans vtf*stv*h/slice=h*vtf pdiff adjust=tukey;
        *lsmeans vtf*h/slice=h pdiff adjust=tukey;
        *lsmeans vtf*h/slice=vtf pdiff adjust=tukey;
**** slice by stv and vtf;
        *lsmeans vtf*stv*h/slice=vtf*stv pdiff adjust=tukey;
        *lsmeans stv*vtf/slice=vtf pdiff adjust=tukey;
        *lsmeans stv*vtf/slice=stv pdiff adjust=tukey;
**** slice by stv and h;
        lsmeans vtf*stv*h/slice=h*stv  adjust=tukey alpha=.007 out=CFI_RQ1;
        *lsmeans stv*h/slice=h adjust=tukey alpha=.007 out=CFI_RQ1;
        *lsmeans stv*h/slice=stv  adjust=tukey alpha=.007 out=CFI_RQ1;
run;
quit;
pattern1 c=black value=x2;
pattern2 c=red   value=x2;
pattern3 c=blue  value=x2;
axis1 label=(a=90 h=1.25 f=swiss "Mean CFI")
         order=(0.05 to 1.00 by .01)
         minor=none;
axis2 label=(h=1.25 f=swiss "STV*VTF")
         minor=none;
proc gchart data=CFI_RQ1;
        vbar vtf/group=stv sumvar=LSMEAN discrete patterid=midpoint
                        raxis=axis1 gaxis=axis2 noframe;
        run;
        quit;
*****************************************************************;
***** Post Hoc setup (3-way);
***** DV=Root_Mean_Square_Residual (RMR);
*****************************************************************;
proc glm data=primary.all_dataREV1;
        class H vtf stv;
        model Root_Mean_Square_Residual__RMR_ = h|vtf|stv;
        *lsmeans vtf*stv*h/slice=h;
        lsmeans vtf*stv*h/slice=vtf;
        *lsmeans vtf*stv*h/slice=stv;
**** slice by vtf and h;
        *lsmeans vtf*stv*h/slice=h*vtf pdiff adjust=tukey;
        *lsmeans vtf*h/slice=h pdiff adjust=tukey;
        *lsmeans vtf*h/slice=vtf pdiff adjust=tukey;
**** slice by stv and vtf;
        *lsmeans vtf*stv*h/slice=vtf*stv pdiff adjust=tukey;
```

Appendix D9 (Continued)

```
        *lsmeans stv*vtf/slice=vtf pdiff adjust=tukey;
        *lsmeans stv*vtf/slice=stv pdiff adjust=tukey;
**** slice by stv and h;
        lsmeans vtf*stv*h/slice=h*stv adjust=tukey alpha=.007 out=CFI_RQ1;
        *lsmeans stv*h/slice=h pdiff adjust=tukey;
        *lsmeans stv*h/slice=stv  adjust=tukey alpha=.007 out=RMR_RQ1;
run;
quit;
pattern1 c=black value=x2;
pattern2 c=red   value=x2;
pattern3 c=blue  value=x2;
axis1 label=(a=90 h=1.25 f=swiss "Mean RMR")
         order=(0.001 to 0.09 by .01)
         minor=none;
axis2 label=(h=1.25 f=swiss "STV*VTF")
         minor=none;
proc gchart data=RMR_RQ1;
        vbar vtf/group=stv sumvar=LSMEAN discrete patterid=midpoint
                        raxis=axis1 gaxis=axis2 noframe;
        run;
        quit;
```

Appendix D10

SAS syntax of analysis RQ2 and 3

```
*************************************************************************;
*************** Dissertation Simulation Primary program                  *;
*************** Written by Deyab Almaleki                                *;
*************** Supervised by Dr. Applegate                              *;
*************** Code developed 2015                                      *;
*************** Merge the data to one folder                             *;
*************************************************************************;
**** Data Q2 file name;
libname H4_2_32 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\H\V-4\Merge S=2-32";
libname H4_2_16 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\H\V-4\Merge S=2-16";
libname H4_2_8  "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\H\V-4\Merge S=2-8";
libname H4_2_4  "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\H\V-4\Merge S=2-4";
libname H4_4_32 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\H\V-4\Merge S=4-32";
libname H4_4_16 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\H\V-4\Merge S=4-16";
libname H4_4_8  "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\H\V-4\Merge S=4-8";
libname H4_8_32 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\H\V-4\Merge S=8-32";
libname H4_8_16 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\H\V-4\Merge S=8-16";
libname H4_16_32"C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\H\V-4\Merge S=16-32";
libname H7_2_32 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\H\V-7\Merge S=2-32";
libname H7_2_16 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\H\V-7\Merge S=2-16";
libname H7_2_8  "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\H\V-7\Merge S=2-8";
libname H7_2_4  "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\H\V-7\Merge S=2-4";
libname H7_4_32 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\H\V-7\Merge S=4-32";
libname H7_4_16 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\H\V-7\Merge S=4-16";
libname H7_4_8  "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\H\V-7\Merge S=4-8";
```

Appendix D10 (Continued)

```
libname H7_8_32 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\H\V-7\Merge S=8-32";
libname H7_8_16 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\H\V-7\Merge S=8-16";
libname H7_16_32"C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\H\V-7\Merge S=16-32";
libname H0_2_32 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\H\V-10\Merge S=2-32";
libname H0_2_16 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\H\V-10\Merge S=2-16";

libname H0_2_8  "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\H\V-10\Merge S=2-8";
libname H0_2_4  "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\H\V-10\Merge S=2-4";
libname H0_4_32 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\H\V-10\Merge S=4-32";
libname H0_4_16 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\H\V-10\Merge S=4-16";
libname H0_4_8  "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\H\V-10\Merge S=4-8";
libname H0_8_32 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\H\V-10\Merge S=8-32";
libname H0_8_16 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\H\V-10\Merge S=8-16";
libname H0_16_32"C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\H\V-10\Merge S=16-32";
******;
libname M4_2_32 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\M\V-4\Merge S=2-32";
libname M4_2_16 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\M\V-4\Merge S=2-16";
libname M4_2_8  "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\M\V-4\Merge S=2-8";
libname M4_2_4  "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\M\V-4\Merge S=2-4";
libname M4_4_32 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\M\V-4\Merge S=4-32";
libname M4_4_16 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\M\V-4\Merge S=4-16";
libname M4_4_8  "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\M\V-4\Merge S=4-8";
libname M4_8_32 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\M\V-4\Merge S=8-32";
```

Appendix D10 (Continued)

```
libname M4_8_16 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis Q2\M\V-4\Merge S=8-16";
libname M4_16_32"C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis Q2\M\V-4\Merge S=16-32";
libname M7_2_32 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis Q2\M\V-7\Merge S=2-32";
libname M7_2_16 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis Q2\M\V-7\Merge S=2-16";
libname M7_2_8  "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis Q2\M\V-7\Merge S=2-8";
libname M7_2_4  "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis Q2\M\V-7\Merge S=2-4";
libname M7_4_32 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis Q2\M\V-7\Merge S=4-32";
libname M7_4_16 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis Q2\M\V-7\Merge S=4-16";
libname M7_4_8  "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis Q2\M\V-7\Merge S=4-8";
libname M7_8_32 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis Q2\M\V-7\Merge S=8-32";

libname M7_8_16 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis Q2\M\V-7\Merge S=8-16";
libname M7_16_32"C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis Q2\M\V-7\Merge S=16-32";
libname M0_2_32 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis Q2\M\V-10\Merge S=2-32";
libname M0_2_16 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis Q2\M\V-10\Merge S=2-16";
libname M0_2_8  "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis Q2\M\V-10\Merge S=2-8";
libname M0_2_4  "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis Q2\M\V-10\Merge S=2-4";
libname M0_4_32 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis Q2\M\V-10\Merge S=4-32";
libname M0_4_16 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis Q2\M\V-10\Merge S=4-16";
libname M0_4_8  "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis Q2\M\V-10\Merge S=4-8";
libname M0_8_32 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis Q2\M\V-10\Merge S=8-32";
libname M0_8_16 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis Q2\M\V-10\Merge S=8-16";
```

Appendix D10 (Continued)

```
libname M0_16_32"C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis Q2\M\V-10\Merge S=16-32";
********;
libname L4_2_32 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis Q2\L\V-4\Merge S=2-32";
libname L4_2_16 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis Q2\L\V-4\Merge S=2-16";
libname L4_2_8  "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis Q2\L\V-4\Merge S=2-8";
libname L4_2_4  "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis Q2\L\V-4\Merge S=2-4";
libname L4_4_32 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis Q2\L\V-4\Merge S=4-32";
libname L4_4_16 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis Q2\L\V-4\Merge S=4-16";
libname L4_4_8  "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis Q2\L\V-4\Merge S=4-8";
libname L4_8_32 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis Q2\L\V-4\Merge S=8-32";
libname L4_8_16 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis Q2\L\V-4\Merge S=8-16";
libname L4_16_32"C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis Q2\L\V-4\Merge S=16-32";
libname L7_2_32 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis Q2\L\V-7\Merge S=2-32";
libname L7_2_16 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis Q2\L\V-7\Merge S=2-16";
libname L7_2_8  "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis Q2\L\V-7\Merge S=2-8";
libname L7_2_4  "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis Q2\L\V-7\Merge S=2-4";

libname L7_4_32 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis Q2\L\V-7\Merge S=4-32";
libname L7_4_16 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis Q2\L\V-7\Merge S=4-16";
libname L7_4_8  "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis Q2\L\V-7\Merge S=4-8";
libname L7_8_32 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis Q2\L\V-7\Merge S=8-32";
libname L7_8_16 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis Q2\L\V-7\Merge S=8-16";
libname L7_16_32"C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis Q2\L\V-7\Merge S=16-32";
```

Appendix D10 (Continued)

```
libname L0_2_32 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\L\V-10\Merge S=2-32";
libname L0_2_16 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\L\V-10\Merge S=2-16";
libname L0_2_8  "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\L\V-10\Merge S=2-8";
libname L0_2_4  "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\L\V-10\Merge S=2-4";
libname L0_4_32 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\L\V-10\Merge S=4-32";
libname L0_4_16 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\L\V-10\Merge S=4-16";
libname L0_4_8  "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\L\V-10\Merge S=4-8";
libname L0_8_32 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\L\V-10\Merge S=8-32";
libname L0_8_16 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\L\V-10\Merge S=8-16";
libname L0_16_32"C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\L\V-10\Merge S=16-32";

libname W4_2_32 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\W\V-4\Merge S=2-32";
libname W4_2_16 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\W\V-4\Merge S=2-16";
libname W4_2_8  "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\W\V-4\Merge S=2-8";
libname W4_2_4  "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\W\V-4\Merge S=2-4";
libname W4_4_32 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\W\V-4\Merge S=4-32";
libname W4_4_16 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\W\V-4\Merge S=4-16";
libname W4_4_8  "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\W\V-4\Merge S=4-8";
libname W4_8_32 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\W\V-4\Merge S=8-32";
libname W4_8_16 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\W\V-4\Merge S=8-16";
libname W4_16_32"C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\W\V-4\Merge S=16-32";
```

Appendix D10 (Continued)

```
libname W7_2_32 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\W\V-7\Merge S=2-32";
libname W7_2_16 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\W\V-7\Merge S=2-16";
libname W7_2_8  "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\W\V-7\Merge S=2-8";
libname W7_2_4  "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\W\V-7\Merge S=2-4";
libname W7_4_32 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\W\V-7\Merge S=4-32";
libname W7_4_16 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\W\V-7\Merge S=4-16";
libname W7_4_8  "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\W\V-7\Merge S=4-8";
libname W7_8_32 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\W\V-7\Merge S=8-32";
libname W7_8_16 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\W\V-7\Merge S=8-16";
libname W7_16_32"C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\W\V-7\Merge S=16-32";
libname W0_2_32 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\W\V-10\Merge S=2-32";
libname W0_2_16 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\W\V-10\Merge S=2-16";
libname W0_2_8  "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\W\V-10\Merge S=2-8";
libname W0_2_4  "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\W\V-10\Merge S=2-4";
libname W0_4_32 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\W\V-10\Merge S=4-32";
libname W0_4_16 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\W\V-10\Merge S=4-16";
libname W0_4_8  "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\W\V-10\Merge S=4-8";
libname W0_8_32 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\W\V-10\Merge S=8-32";
libname W0_8_16 "C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\W\V-10\Merge S=8-16";
libname W0_16_32"C:\Users\user\Desktop\Generation\Data\Primary\Data and Analysis
Q2\W\V-10\Merge S=16-32";

*** Prepare the data;
libname S_H_4_2  "C:\Users\user\Desktop\Generation\Data\Primary\H\V-4\S-2";
libname S_H_4_4  "C:\Users\user\Desktop\Generation\Data\Primary\H\V-4\S-4";
```

```
libname S_H_4_8  "C:\Users\user\Desktop\Generation\Data\Primary\H\V-4\S-8";
libname S_H_4_16 "C:\Users\user\Desktop\Generation\Data\Primary\H\V-4\S-16";
libname S_H_4_32 "C:\Users\user\Desktop\Generation\Data\Primary\H\V-4\S-32";
libname S_H_7_2  "C:\Users\user\Desktop\Generation\Data\Primary\H\V-7\S-2";
libname S_H_7_4  "C:\Users\user\Desktop\Generation\Data\Primary\H\V-7\S-4";
libname S_H_7_8  "C:\Users\user\Desktop\Generation\Data\Primary\H\V-7\S-8";
libname S_H_7_16 "C:\Users\user\Desktop\Generation\Data\Primary\H\V-7\S-16";
libname S_H_7_32 "C:\Users\user\Desktop\Generation\Data\Primary\H\V-7\S-32";
libname S_H_0_2  "C:\Users\user\Desktop\Generation\Data\Primary\H\V-10\S-2";
libname S_H_0_4  "C:\Users\user\Desktop\Generation\Data\Primary\H\V-10\S-4";
libname S_H_0_8  "C:\Users\user\Desktop\Generation\Data\Primary\H\V-10\S-8";
libname S_H_0_16 "C:\Users\user\Desktop\Generation\Data\Primary\H\V-10\S-16";
libname S_H_0_32 "C:\Users\user\Desktop\Generation\Data\Primary\H\V-10\S-32";
******;
libname S_M_4_2  "C:\Users\user\Desktop\Generation\Data\Primary\M\V-4\S-2";
libname S_M_4_4  "C:\Users\user\Desktop\Generation\Data\Primary\M\V-4\S-4";
libname S_M_4_8  "C:\Users\user\Desktop\Generation\Data\Primary\M\V-4\S-8";
libname S_M_4_16 "C:\Users\user\Desktop\Generation\Data\Primary\M\V-4\S-16";
libname S_M_4_32 "C:\Users\user\Desktop\Generation\Data\Primary\M\V-4\S-32";
libname S_M_7_2  "C:\Users\user\Desktop\Generation\Data\Primary\M\V-7\S-2";
libname S_M_7_4  "C:\Users\user\Desktop\Generation\Data\Primary\M\V-7\S-4";
libname S_M_7_8  "C:\Users\user\Desktop\Generation\Data\Primary\M\V-7\S-8";
libname S_M_7_16 "C:\Users\user\Desktop\Generation\Data\Primary\M\V-7\S-16";
libname S_M_7_32 "C:\Users\user\Desktop\Generation\Data\Primary\M\V-7\S-32";
libname S_M_0_2  "C:\Users\user\Desktop\Generation\Data\Primary\M\V-10\S-2";
libname S_M_0_4  "C:\Users\user\Desktop\Generation\Data\Primary\M\V-10\S-4";
libname S_M_0_8  "C:\Users\user\Desktop\Generation\Data\Primary\M\V-10\S-8";
libname S_M_0_16 "C:\Users\user\Desktop\Generation\Data\Primary\M\V-10\S-16";
libname S_M_0_32 "C:\Users\user\Desktop\Generation\Data\Primary\M\V-10\S-32";

libname S_L_4_2  "C:\Users\user\Desktop\Generation\Data\Primary\L\V-4\S-2";
libname S_L_4_4  "C:\Users\user\Desktop\Generation\Data\Primary\L\V-4\S-4";
libname S_L_4_8  "C:\Users\user\Desktop\Generation\Data\Primary\L\V-4\S-8";
libname S_L_4_16 "C:\Users\user\Desktop\Generation\Data\Primary\L\V-4\S-16";
libname S_L_4_32 "C:\Users\user\Desktop\Generation\Data\Primary\L\V-4\S-32";
libname S_L_7_2  "C:\Users\user\Desktop\Generation\Data\Primary\L\V-7\S-2";
libname S_L_7_4  "C:\Users\user\Desktop\Generation\Data\Primary\L\V-7\S-4";
libname S_L_7_8  "C:\Users\user\Desktop\Generation\Data\Primary\L\V-7\S-8";
libname S_L_7_16 "C:\Users\user\Desktop\Generation\Data\Primary\L\V-7\S-16";
libname S_L_7_32 "C:\Users\user\Desktop\Generation\Data\Primary\L\V-7\S-32";
libname S_L_0_2  "C:\Users\user\Desktop\Generation\Data\Primary\L\V-10\S-2";
libname S_L_0_4  "C:\Users\user\Desktop\Generation\Data\Primary\L\V-10\S-4";
libname S_L_0_8  "C:\Users\user\Desktop\Generation\Data\Primary\L\V-10\S-8";
libname S_L_0_16 "C:\Users\user\Desktop\Generation\Data\Primary\L\V-10\S-16";
```

Appendix D10 (Continued)

```
libname S_L_0_32 "C:\Users\user\Desktop\Generation\Data\Primary\L\V-10\S-32";

libname S_W_4_2  "C:\Users\user\Desktop\Generation\Data\Primary\W\V-4\S-2";
libname S_W_4_4  "C:\Users\user\Desktop\Generation\Data\Primary\W\V-4\S-4";
libname S_W_4_8  "C:\Users\user\Desktop\Generation\Data\Primary\W\V-4\S-8";
libname S_W_4_16 "C:\Users\user\Desktop\Generation\Data\Primary\W\V-4\S-16";
libname S_W_4_32 "C:\Users\user\Desktop\Generation\Data\Primary\W\V-4\S-32";
libname S_W_7_2  "C:\Users\user\Desktop\Generation\Data\Primary\W\V-7\S-2";
libname S_W_7_4  "C:\Users\user\Desktop\Generation\Data\Primary\W\V-7\S-4";
libname S_W_7_8  "C:\Users\user\Desktop\Generation\Data\Primary\W\V-7\S-8";
libname S_W_7_16 "C:\Users\user\Desktop\Generation\Data\Primary\W\V-7\S-16";
libname S_W_7_32 "C:\Users\user\Desktop\Generation\Data\Primary\W\V-7\S-32";
libname S_W_0_2  "C:\Users\user\Desktop\Generation\Data\Primary\W\V-10\S-2";
libname S_W_0_4  "C:\Users\user\Desktop\Generation\Data\Primary\W\V-10\S-4";
libname S_W_0_8  "C:\Users\user\Desktop\Generation\Data\Primary\W\V-10\S-8";


libname S_W_0_16 "C:\Users\user\Desktop\Generation\Data\Primary\W\V-10\S-16";
libname S_W_0_32 "C:\Users\user\Desktop\Generation\Data\Primary\W\V-10\S-32";

******** Merge the data to one folder *********;
proc datasets library=H4_2_32;
	copy in=S_H_4_2 out=H4_2_32;
		select H_4_2_1-H_4_2_1000;
	copy in=S_H_4_32 out=H4_2_32;
		select H_4_32_1-H_4_32_1000;
	run;
	quit;
proc datasets library=H4_2_16;
	copy in=S_H_4_2 out=H4_2_16;
		select H_4_2_1-H_4_2_1000;
	copy in=S_H_4_16 out=H4_2_16;
		select H_4_16_1-H_4_16_1000;
	run;
	quit;
proc datasets library=H4_2_8;
	copy in=S_H_4_2 out=H4_2_8;
		select H_4_2_1-H_4_2_1000;
	copy in=S_H_4_8 out=H4_2_8;
		select H_4_8_1-H_4_8_1000;
	run;
	quit;
proc datasets library=H4_2_4;
	copy in=S_H_4_2 out=H4_2_4;
```

Appendix D10 (Continued)

```
            select H_4_2_1-H_4_2_1000;
        copy in=S_H_4_4 out=H4_2_4;
            select H_4_4_1-H_4_4_1000;
        run;
        quit;
proc datasets library=H4_4_32;
        copy in=S_H_4_4 out=H4_4_32;
            select H_4_4_1-H_4_4_1000;
        copy in=S_H_4_32 out=H4_4_32;
            select H_4_32_1-H_4_32_1000;
        run;
        quit;
proc datasets library=H4_4_16;
        copy in=S_H_4_4 out=H4_4_16;
            select H_4_4_1-H_4_4_1000;
        copy in=S_H_4_16 out=H4_4_16;
            select H_4_16_1-H_4_16_1000;
        run;
        quit;
proc datasets library=H4_4_8;
        copy in=S_H_4_4 out=H4_4_8;
            select H_4_4_1-H_4_4_1000;
        copy in=S_H_4_8 out=H4_4_8;
            select H_4_8_1-H_4_8_1000;
        run;
        quit;
proc datasets library=H4_8_32;
        copy in=S_H_4_8 out=H4_8_32;
            select H_4_8_1-H_4_8_1000;
        copy in=S_H_4_32 out=H4_8_32;
            select H_4_32_1-H_4_32_1000;
        run;
        quit;
proc datasets library=H4_8_16;
        copy in=S_H_4_8 out=H4_8_16;
            select H_4_8_1-H_4_8_1000;
        copy in=S_H_4_16 out=H4_8_16;
            select H_4_16_1-H_4_16_1000;
        run;
        quit;
proc datasets library=H4_16_32;
        copy in=S_H_4_16 out=H4_16_32;
            select H_4_16_1-H_4_16_1000;
        copy in=S_H_4_32 out=H4_16_32;
```

Appendix D10 (Continued)

```
        select H_4_32_1-H_4_32_1000;
    run;
    quit;
*****************************************************************;
proc datasets library=H7_2_32;
    copy in=S_H_7_2 out=H7_2_32;
        select H_7_2_1-H_7_2_1000;
    copy in=S_H_7_32 out=H7_2_32;
        select H_7_32_1-H_7_32_1000;
    run;
    quit;
proc datasets library=H7_2_16;
    copy in=S_H_7_2 out=H7_2_16;
        select H_7_2_1-H_7_2_1000;
    copy in=S_H_7_16 out=H7_2_16;
        select H_7_16_1-H_7_16_1000;
    run;
    quit;
proc datasets library=H7_2_8;
    copy in=S_H_7_2 out=H7_2_8;
        select H_7_2_1-H_7_2_1000;
    copy in=S_H_7_8 out=H7_2_8;
        select H_7_8_1-H_7_8_1000;
    run;
    quit;
proc datasets library=H7_2_4;
    copy in=S_H_7_2 out=H7_2_4;
        select H_7_2_1-H_7_2_1000;
    copy in=S_H_7_4 out=H7_2_4;
        select H_7_4_1-H_7_4_1000;
    run;
    quit;
proc datasets library=H7_4_32;
    copy in=S_H_7_4 out=H7_4_32;
        select H_7_4_1-H_7_4_1000;
    copy in=S_H_7_32 out=H7_4_32;
        select H_7_32_1-H_7_32_1000;
    run;
    quit;
proc datasets library=H7_4_16;
    copy in=S_H_7_4 out=H7_4_16;
        select H_7_4_1-H_7_4_1000;
    copy in=S_H_7_16 out=H7_4_16;
        select H_7_16_1-H_7_16_1000;
```

Appendix D10 (Continued)

```
        run;
        quit;
proc datasets library=H7_4_8;
        copy in=S_H_7_4 out=H7_4_8;
                select H_7_4_1-H_7_4_1000;
        copy in=S_H_7_8 out=H7_4_8;
                select H_7_8_1-H_7_8_1000;
        run;
        quit;
proc datasets library=H7_8_32;
        copy in=S_H_7_8 out=H7_8_32;
                select H_7_8_1-H_7_8_1000;
        copy in=S_H_7_32 out=H7_8_32;
                select H_7_32_1-H_7_32_1000;
        run;
        quit;
proc datasets library=H7_8_16;
        copy in=S_H_7_8 out=H7_8_16;
                select H_7_8_1-H_7_8_1000;
        copy in=S_H_7_16 out=H7_8_16;
                select H_7_16_1-H_7_16_1000;
        run;
        quit;
proc datasets library=H7_16_32;
        copy in=S_H_7_16 out=H7_16_32;
                select H_7_16_1-H_7_16_1000;
        copy in=S_H_7_32 out=H7_16_32;
                select H_7_32_1-H_7_32_1000;
        run;
        quit;
*******************************************************************;
proc datasets library=H0_2_32;
        copy in=S_H_0_2 out=H0_2_32;
                select H_10_2_1-H_10_2_1000;
        copy in=S_H_0_32 out=H0_2_32;
                select H_10_32_1-H_10_32_1000;
        run;
        quit;
proc datasets library=H0_2_16;
        copy in=S_H_0_2 out=H0_2_16;
                select H_10_2_1-H_10_2_1000;
        copy in=S_H_0_16 out=H0_2_16;
                select H_10_16_1-H_10_16_1000;
        run;
```

Appendix D10 (Continued)

```
        quit;

proc datasets library=H0_2_8;
        copy in=S_H_0_2 out=H0_2_8;
                select H_10_2_1-H_10_2_1000;
        copy in=S_H_0_8 out=H0_2_8;
                select H_10_8_1-H_10_8_1000;
        run;
        quit;
proc datasets library=H0_2_4;
        copy in=S_H_0_2 out=H0_2_4;
                select H_10_2_1-H_10_2_1000;
        copy in=S_H_0_4 out=H0_2_4;
                select H_10_4_1-H_10_4_1000;
        run;
        quit;
proc datasets library=H0_4_32;
        copy in=S_H_0_4 out=H0_4_32;
                select H_10_4_1-H_10_4_1000;
        copy in=S_H_0_32 out=H0_4_32;
                select H_10_32_1-H_10_32_1000;
        run;
        quit;
proc datasets library=H0_4_16;
        copy in=S_H_0_4 out=H0_4_16;
                select H_10_4_1-H_10_4_1000;
        copy in=S_H_0_16 out=H0_4_16;
                select H_10_16_1-H_10_16_1000;
        run;
        quit;
proc datasets library=H0_4_8;
        copy in=S_H_0_4 out=H0_4_8;
                select H_10_4_1-H_10_4_1000;
        copy in=S_H_0_8 out=H0_4_8;
                select H_10_8_1-H_10_8_1000;
        run;
        quit;
proc datasets library=H0_8_32;
        copy in=S_H_0_8 out=H0_8_32;
                select H_10_8_1-H_10_8_1000;
        copy in=S_H_0_32 out=H0_8_32;
                select H_10_32_1-H_10_32_1000;
        run;
        quit;
```

Appendix D10 (Continued)

```
proc datasets library=H0_8_16;
        copy in=S_H_0_8 out=H0_8_16;
                select H_10_8_1-H_10_8_1000;
        copy in=S_H_0_16 out=H0_8_16;
                select H_10_16_1-H_10_16_1000;
        run;
        quit;
proc datasets library=H0_16_32;
        copy in=S_H_0_16 out=H0_16_32;
                select H_10_16_1-H_10_16_1000;
        copy in=S_H_0_32 out=H0_16_32;
                select H_10_32_1-H_10_32_1000;
        run;
        quit;
*************************************************************;
proc datasets library=M4_2_32;
        copy in=S_M_4_2 out=M4_2_32;
                select M_4_2_1-M_4_2_1000;
        copy in=S_M_4_32 out=M4_2_32;
                select M_4_32_1-M_4_32_1000;
        run;
        quit;
proc datasets library=M4_2_16;
        copy in=S_M_4_2 out=M4_2_16;
                select M_4_2_1-M_4_2_1000;
        copy in=S_M_4_16 out=M4_2_16;
                select M_4_16_1-M_4_16_1000;
        run;
        quit;
proc datasets library=M4_2_8;
        copy in=S_M_4_2 out=M4_2_8;
                select M_4_2_1-M_4_2_1000;
        copy in=S_M_4_8 out=M4_2_8;
                select M_4_8_1-M_4_8_1000;
        run;
        quit;
proc datasets library=M4_2_4;
        copy in=S_M_4_2 out=M4_2_4;
                select M_4_2_1-M_4_2_1000;
        copy in=S_M_4_4 out=M4_2_4;
                select M_4_4_1-M_4_4_1000;
        run;
        quit;
proc datasets library=M4_4_32;
```

```
        copy in=S_M_4_4 out=M4_4_32;
                select M_4_4_1-M_4_4_1000;
        copy in=S_M_4_32 out=M4_4_32;
                select M_4_32_1-M_4_32_1000;
        run;
        quit;
proc datasets library=M4_4_16;
        copy in=S_M_4_4 out=M4_4_16;
                select M_4_4_1-M_4_4_1000;
        copy in=S_M_4_16 out=M4_4_16;
                select M_4_16_1-M_4_16_1000;
        run;
        quit;
proc datasets library=M4_4_8;
        copy in=S_M_4_4 out=M4_4_8;
                select M_4_4_1-M_4_4_1000;
        copy in=S_M_4_8 out=M4_4_8;
                select M_4_8_1-M_4_8_1000;
        run;
        quit;
proc datasets library=M4_8_32;
        copy in=S_M_4_8 out=M4_8_32;
                select M_4_8_1-M_4_8_1000;
        copy in=S_M_4_32 out=M4_8_32;
                select M_4_32_1-M_4_32_1000;
        run;
        quit;
proc datasets library=M4_8_16;
        copy in=S_M_4_8 out=M4_8_16;
                select M_4_8_1-M_4_8_1000;
        copy in=S_M_4_16 out=M4_8_16;
                select M_4_16_1-M_4_16_1000;
        run;
        quit;
proc datasets library=M4_16_32;
        copy in=S_M_4_16 out=M4_16_32;
                select M_4_16_1-M_4_16_1000;
        copy in=S_M_4_32 out=M4_16_32;
                select M_4_32_1-M_4_32_1000;
        run;
        quit;
*****************************************************************;
proc datasets library=M7_2_32;
        copy in=S_M_7_2 out=M7_2_32;
```

Appendix D10 (Continued)

```
            select M_7_2_1-M_7_2_1000;
        copy in=S_M_7_32 out=M7_2_32;
            select M_7_32_1-M_7_32_1000;
        run;
        quit;
proc datasets library=M7_2_16;
        copy in=S_M_7_2 out=M7_2_16;
            select M_7_2_1-M_7_2_1000;
        copy in=S_M_7_16 out=M7_2_16;
            select M_7_16_1-M_7_16_1000;
        run;
        quit;
proc datasets library=M7_2_8;
        copy in=S_M_7_2 out=M7_2_8;
            select M_7_2_1-M_7_2_1000;
        copy in=S_M_7_8 out=M7_2_8;
            select M_7_8_1-M_7_8_1000;
        run;
        quit;
proc datasets library=M7_2_4;
        copy in=S_M_7_2 out=M7_2_4;
            select M_7_2_1-M_7_2_1000;
        copy in=S_M_7_4 out=M7_2_4;
            select M_7_4_1-M_7_4_1000;
        run;
        quit;
proc datasets library=M7_4_32;
        copy in=S_M_7_4 out=M7_4_32;
            select M_7_4_1-M_7_4_1000;
        copy in=S_M_7_32 out=M7_4_32;
            select M_7_32_1-M_7_32_1000;
        run;
        quit;
proc datasets library=M7_4_16;
        copy in=S_M_7_4 out=M7_4_16;
            select M_7_4_1-M_7_4_1000;
        copy in=S_M_7_16 out=M7_4_16;
            select M_7_16_1-M_7_16_1000;
        run;
        quit;
proc datasets library=M7_4_8;
        copy in=S_M_7_4 out=M7_4_8;
            select M_7_4_1-M_7_4_1000;
        copy in=S_M_7_8 out=M7_4_8;
```

Appendix D10 (Continued)

```
        select M_7_8_1-M_7_8_1000;
    run;
    quit;
proc datasets library=M7_8_32;
    copy in=S_M_7_8 out=M7_8_32;
        select M_7_8_1-M_7_8_1000;
    copy in=S_M_7_32 out=M7_8_32;
        select M_7_32_1-M_7_32_1000;
    run;
    quit;
proc datasets library=M7_8_16;
    copy in=S_M_7_8 out=M7_8_16;
        select M_7_8_1-M_7_8_1000;
    copy in=S_M_7_16 out=M7_8_16;
        select M_7_16_1-M_7_16_1000;
    run;
    quit;
proc datasets library=M7_16_32;
    copy in=S_M_7_16 out=M7_16_32;
        select M_7_16_1-M_7_16_1000;
    copy in=S_M_7_32 out=M7_16_32;
        select M_7_32_1-M_7_32_1000;
    run;
    quit;
****************************************************************;
proc datasets library=M0_2_32;
    copy in=S_M_0_2 out=M0_2_32;
        select M_10_2_1-M_10_2_1000;
    copy in=S_M_0_32 out=M0_2_32;
        select M_10_32_1-M_10_32_1000;
    run;
    quit;
proc datasets library=M0_2_16;
    copy in=S_M_0_2 out=M0_2_16;
        select M_10_2_1-M_10_2_1000;
    copy in=S_M_0_16 out=M0_2_16;
        select M_10_16_1-M_10_16_1000;
    run;
    quit;
proc datasets library=M0_2_8;
    copy in=S_M_0_2 out=M0_2_8;
        select M_10_2_1-M_10_2_1000;
    copy in=S_M_0_8 out=M0_2_8;
        select M_10_8_1-M_10_8_1000;
```

Appendix D10 (Continued)

```
        run;
        quit;
proc datasets library=M0_2_4;
        copy in=S_M_0_2 out=M0_2_4;
                select M_10_2_1-M_10_2_1000;
        copy in=S_M_0_4 out=M0_2_4;
                select M_10_4_1-M_10_4_1000;
        run;
        quit;
proc datasets library=M0_4_32;
        copy in=S_M_0_4 out=M0_4_32;
                select M_10_4_1-M_10_4_1000;
        copy in=S_M_0_32 out=M0_4_32;
                select M_10_32_1-M_10_32_1000;
        run;
        quit;
proc datasets library=M0_4_16;
        copy in=S_M_0_4 out=M0_4_16;
                select M_10_4_1-M_10_4_1000;
        copy in=S_M_0_16 out=M0_4_16;
                select M_10_16_1-M_10_16_1000;
        run;
        quit;
proc datasets library=M0_4_8;
        copy in=S_M_0_4 out=M0_4_8;
                select M_10_4_1-M_10_4_1000;
        copy in=S_M_0_8 out=M0_4_8;
                select M_10_8_1-M_10_8_1000;
        run;
        quit;
proc datasets library=M0_8_32;
        copy in=S_M_0_8 out=M0_8_32;
                select M_10_8_1-M_10_8_1000;
        copy in=S_M_0_32 out=M0_8_32;
                select M_10_32_1-M_10_32_1000;
        run;
        quit;
proc datasets library=M0_8_16;
        copy in=S_M_0_8 out=M0_8_16;
                select M_10_8_1-M_10_8_1000;
        copy in=S_M_0_16 out=M0_8_16;
                select M_10_16_1-M_10_16_1000;
        run;
        quit;
proc datasets library=M0_16_32;
```

Appendix D10 (Continued)

```
        copy in=S_M_0_16 out=M0_16_32;
                select M_10_16_1-M_10_16_1000;
        copy in=S_M_0_32 out=M0_16_32;
                select M_10_32_1-M_10_32_1000;
        run;
        quit;
*****************************************************************;
proc datasets library=L4_2_32;
        copy in=S_L_4_2 out=L4_2_32;
                select L_4_2_1-L_4_2_1000;
        copy in=S_L_4_32 out=L4_2_32;
                select L_4_32_1-L_4_32_1000;
        run;
        quit;
proc datasets library=L4_2_16;
        copy in=S_L_4_2 out=L4_2_16;
                select L_4_2_1-L_4_2_1000;
        copy in=S_L_4_16 out=L4_2_16;
                select L_4_16_1-L_4_16_1000;
        run;
        quit;
proc datasets library=L4_2_8;
        copy in=S_L_4_2 out=L4_2_8;
                select L_4_2_1-L_4_2_1000;
        copy in=S_L_4_8 out=L4_2_8;
                select L_4_8_1-L_4_8_1000;
        run;
        quit;
proc datasets library=L4_2_4;
        copy in=S_L_4_2 out=L4_2_4;
                select L_4_2_1-L_4_2_1000;
        copy in=S_L_4_4 out=L4_2_4;
                select L_4_4_1-L_4_4_1000;
        run;
        quit;
proc datasets library=L4_4_32;
        copy in=S_L_4_4 out=L4_4_32;
                select L_4_4_1-L_4_4_1000;
        copy in=S_L_4_32 out=L4_4_32;
                select L_4_32_1-L_4_32_1000;
        run;
        quit;
proc datasets library=L4_4_16;
        copy in=S_L_4_4 out=L4_4_16;
```

Appendix D10 (Continued)

```
            select L_4_4_1-L_4_4_1000;
        copy in=S_L_4_16 out=L4_4_16;
            select L_4_16_1-L_4_16_1000;
        run;
        quit;
proc datasets library=L4_4_8;
        copy in=S_L_4_4 out=L4_4_8;
            select L_4_4_1-L_4_4_1000;
        copy in=S_L_4_8 out=L4_4_8;
            select L_4_8_1-L_4_8_1000;
        run;
        quit;
proc datasets library=L4_8_32;
        copy in=S_L_4_8 out=L4_8_32;
            select L_4_8_1-L_4_8_1000;
        copy in=S_L_4_32 out=L4_8_32;
            select L_4_32_1-L_4_32_1000;
        run;
        quit;
proc datasets library=L4_8_16;
        copy in=S_L_4_8 out=L4_8_16;
            select L_4_8_1-L_4_8_1000;
        copy in=S_L_4_16 out=L4_8_16;
            select L_4_16_1-L_4_16_1000;
        run;
        quit;
proc datasets library=L4_16_32;
        copy in=S_L_4_16 out=L4_16_32;
            select L_4_16_1-L_4_16_1000;
        copy in=S_L_4_32 out=L4_16_32;
            select L_4_32_1-L_4_32_1000;
        run;
        quit;
*****************************************************************;
proc datasets library=L7_2_32;
        copy in=S_L_7_2 out=L7_2_32;
            select L_7_2_1-L_7_2_1000;
        copy in=S_L_7_32 out=L7_2_32;
            select L_7_32_1-L_7_32_1000;
        run;
        quit;
proc datasets library=L7_2_16;
        copy in=S_L_7_2 out=L7_2_16;
            select L_7_2_1-L_7_2_1000;
```

```
        copy in=S_L_7_16 out=L7_2_16;
                select L_7_16_1-L_7_16_1000;
        run;
        quit;
proc datasets library=L7_2_8;
        copy in=S_L_7_2 out=L7_2_8;
                select L_7_2_1-L_7_2_1000;
        copy in=S_L_7_8 out=L7_2_8;
                select L_7_8_1-L_7_8_1000;
        run;
        quit;
proc datasets library=L7_2_4;
        copy in=S_L_7_2 out=L7_2_4;
                select L_7_2_1-L_7_2_1000;
        copy in=S_L_7_4 out=L7_2_4;
                select L_7_4_1-L_7_4_1000;
        run;
        quit;
proc datasets library=L7_4_32;
        copy in=S_L_7_4 out=L7_4_32;
                select L_7_4_1-L_7_4_1000;
        copy in=S_L_7_32 out=L7_4_32;
                select L_7_32_1-L_7_32_1000;
        run;
        quit;
proc datasets library=L7_4_16;
        copy in=S_L_7_4 out=L7_4_16;

                select L_7_4_1-L_7_4_1000;
        copy in=S_L_7_16 out=L7_4_16;
                select L_7_16_1-L_7_16_1000;
        run;
        quit;
proc datasets library=L7_4_8;
        copy in=S_L_7_4 out=L7_4_8;
                select L_7_4_1-L_7_4_1000;
        copy in=S_L_7_8 out=L7_4_8;
                select L_7_8_1-L_7_8_1000;
        run;
        quit;
proc datasets library=L7_8_32;
        copy in=S_L_7_8 out=L7_8_32;
                select L_7_8_1-L_7_8_1000;
        copy in=S_L_7_32 out=L7_8_32;
```

Appendix D10 (Continued)

```
            select L_7_32_1-L_7_32_1000;
      run;
      quit;
proc datasets library=L7_8_16;
      copy in=S_L_7_8 out=L7_8_16;
            select L_7_8_1-L_7_8_1000;
      copy in=S_L_7_16 out=L7_8_16;
            select L_7_16_1-L_7_16_1000;
      run;
      quit;
proc datasets library=L7_16_32;
      copy in=S_L_7_16 out=L7_16_32;
            select L_7_16_1-L_7_16_1000;
      copy in=S_L_7_32 out=L7_16_32;
            select L_7_32_1-L_7_32_1000;
      run;
      quit;
*****************************************************************;
proc datasets library=L0_2_32;
      copy in=S_L_0_2 out=L0_2_32;
            select L_10_2_1-L_10_2_1000;
      copy in=S_L_0_32 out=L0_2_32;
            select L_10_32_1-L_10_32_1000;
      run;
      quit;
proc datasets library=L0_2_16;
      copy in=S_L_0_2 out=L0_2_16;
            select L_10_2_1-L_10_2_1000;
      copy in=S_L_0_16 out=L0_2_16;
            select L_10_16_1-L_10_16_1000;
      run;
      quit;
proc datasets library=L0_2_8;
      copy in=S_L_0_2 out=L0_2_8;
            select L_10_2_1-L_10_2_1000;
      copy in=S_L_0_8 out=L0_2_8;
            select L_10_8_1-L_10_8_1000;
      run;
      quit;
proc datasets library=L0_2_4;
      copy in=S_L_0_2 out=L0_2_4;
            select L_10_2_1-L_10_2_1000;
      copy in=S_L_0_4 out=L0_2_4;
            select L_10_4_1-L_10_4_1000;
```

Appendix D10 (Continued)

```
        run;
        quit;
proc datasets library=L0_4_32;
        copy in=S_L_0_4 out=L0_4_32;
                select L_10_4_1-L_10_4_1000;
        copy in=S_L_0_32 out=L0_4_32;
                select L_10_32_1-L_10_32_1000;
        run;
        quit;
proc datasets library=L0_4_16;
        copy in=S_L_0_4 out=L0_4_16;
                select L_10_4_1-L_10_4_1000;
        copy in=S_L_0_16 out=L0_4_16;
                select L_10_16_1-L_10_16_1000;
        run;
        quit;
proc datasets library=L0_4_8;
        copy in=S_L_0_4 out=L0_4_8;
                select L_10_4_1-L_10_4_1000;
        copy in=S_L_0_8 out=L0_4_8;
                select L_10_8_1-L_10_8_1000;
        run;
        quit;
proc datasets library=L0_8_32;
        copy in=S_L_0_8 out=L0_8_32;
                select L_10_8_1-L_10_8_1000;
        copy in=S_L_0_32 out=L0_8_32;
                select L_10_32_1-L_10_32_1000;
        run;
        quit;
proc datasets library=L0_8_16;
        copy in=S_L_0_8 out=L0_8_16;
                select L_10_8_1-L_10_8_1000;
        copy in=S_L_0_16 out=L0_8_16;
                select L_10_16_1-L_10_16_1000;
        run;
        quit;
proc datasets library=L0_16_32;
        copy in=S_L_0_16 out=L0_16_32;
                select L_10_16_1-L_10_16_1000;
        copy in=S_L_0_32 out=L0_16_32;
                select L_10_32_1-L_10_32_1000;
        run;
        quit;
```

```
*****************************************************************;
proc datasets library=W4_2_32;
	copy in=S_W_4_2 out=W4_2_32;
		select W_4_2_1-W_4_2_1000;
	copy in=S_W_4_32 out=W4_2_32;
		select W_4_32_1-W_4_32_1000;
	run;
	quit;
proc datasets library=W4_2_16;
	copy in=S_W_4_2 out=W4_2_16;
		select W_4_2_1-W_4_2_1000;
	copy in=S_W_4_16 out=W4_2_16;
		select W_4_16_1-W_4_16_1000;
	run;
	quit;
proc datasets library=W4_2_8;
	copy in=S_W_4_2 out=W4_2_8;
		select W_4_2_1-W_4_2_1000;
	copy in=S_W_4_8 out=W4_2_8;
		select W_4_8_1-W_4_8_1000;
	run;
	quit;
proc datasets library=W4_2_4;
	copy in=S_W_4_2 out=W4_2_4;
		select W_4_2_1-W_4_2_1000;
	copy in=S_W_4_4 out=W4_2_4;
		select W_4_4_1-W_4_4_1000;
	run;
	quit;
proc datasets library=W4_4_32;
	copy in=S_W_4_4 out=W4_4_32;
		select W_4_4_1-W_4_4_1000;
	copy in=S_W_4_32 out=W4_4_32;
		select W_4_32_1-W_4_32_1000;
	run;
	quit;
proc datasets library=W4_4_16;
	copy in=S_W_4_4 out=W4_4_16;
		select W_4_4_1-W_4_4_1000;
	copy in=S_W_4_16 out=W4_4_16;
		select W_4_16_1-W_4_16_1000;
	run;
	quit;
proc datasets library=W4_4_8;
	copy in=S_W_4_4 out=W4_4_8;
		select W_4_4_1-W_4_4_1000;
```

Appendix D10 (Continued)

```
        copy in=S_W_4_8 out=W4_4_8;
                select W_4_8_1-W_4_8_1000;
        run;
        quit;
proc datasets library=W4_8_32;
        copy in=S_W_4_8 out=W4_8_32;
                select W_4_8_1-W_4_8_1000;
        copy in=S_W_4_32 out=W4_8_32;
                select W_4_32_1-W_4_32_1000;
        run;
        quit;
proc datasets library=W4_8_16;
        copy in=S_W_4_8 out=W4_8_16;
                select W_4_8_1-W_4_8_1000;
        copy in=S_W_4_16 out=W4_8_16;
                select W_4_16_1-W_4_16_1000;
        run;
        quit;
proc datasets library=W4_16_32;
        copy in=S_W_4_16 out=W4_16_32;
                select W_4_16_1-W_4_16_1000;
        copy in=S_W_4_32 out=W4_16_32;
                select W_4_32_1-W_4_32_1000;
        run;
        quit;
*************************************************************;
proc datasets library=W7_2_32;
        copy in=S_W_7_2 out=W7_2_32;
                select W_7_2_1-W_7_2_1000;
        copy in=S_W_7_32 out=W7_2_32;
                select W_7_32_1-W_7_32_1000;
        run;
        quit;
proc datasets library=W7_2_16;
        copy in=S_W_7_2 out=W7_2_16;
                select W_7_2_1-W_7_2_1000;
        copy in=S_W_7_16 out=W7_2_16;
                select W_7_16_1-W_7_16_1000;
        run;
        quit;
proc datasets library=W7_2_8;
        copy in=S_W_7_2 out=W7_2_8;
                select W_7_2_1-W_7_2_1000;
        copy in=S_W_7_8 out=W7_2_8;
```

```
            select W_7_8_1-W_7_8_1000;
      run;
      quit;
proc datasets library=W7_2_4;
      copy in=S_W_7_2 out=W7_2_4;
            select W_7_2_1-W_7_2_1000;
      copy in=S_W_7_4 out=W7_2_4;
            select W_7_4_1-W_7_4_1000;
      run;
      quit;
proc datasets library=W7_4_32;
      copy in=S_W_7_4 out=W7_4_32;
            select W_7_4_1-W_7_4_1000;
      copy in=S_W_7_32 out=W7_4_32;
            select W_7_32_1-W_7_32_1000;
      run;
      quit;
proc datasets library=W7_4_16;
      copy in=S_W_7_4 out=W7_4_16;
            select W_7_4_1-W_7_4_1000;
      copy in=S_W_7_16 out=W7_4_16;
            select W_7_16_1-W_7_16_1000;
```

Appendix D10 (Continued)

```
      run;
      quit;
proc datasets library=W7_4_8;
      copy in=S_W_7_4 out=W7_4_8;
            select W_7_4_1-W_7_4_1000;
      copy in=S_W_7_8 out=W7_4_8;
            select W_7_8_1-W_7_8_1000;
      run;
      quit;
proc datasets library=W7_8_32;
      copy in=S_W_7_8 out=W7_8_32;
            select W_7_8_1-W_7_8_1000;
      copy in=S_W_7_32 out=W7_8_32;
            select W_7_32_1-W_7_32_1000;
      run;
      quit;
proc datasets library=W7_8_16;
      copy in=S_W_7_8 out=W7_8_16;
            select W_7_8_1-W_7_8_1000;
      copy in=S_W_7_16 out=W7_8_16;
            select W_7_16_1-W_7_16_1000;
```

Appendix D10 (Continued)

```
        run;
        quit;
proc datasets library=W7_16_32;
        copy in=S_W_7_16 out=W7_16_32;
                select W_7_16_1-W_7_16_1000;
        copy in=S_W_7_32 out=W7_16_32;
                select W_7_32_1-W_7_32_1000;
        run;
        quit;
*******************************************************************;
proc datasets library=W0_2_32;
        copy in=S_W_0_2 out=W0_2_32;
                select W_10_2_1-W_10_2_1000;
        copy in=S_W_0_32 out=W0_2_32;
                select W_10_32_1-W_10_32_1000;
        run;
        quit;
proc datasets library=W0_2_16;
        copy in=S_W_0_2 out=W0_2_16;
                select W_10_2_1-W_10_2_1000;
        copy in=S_W_0_16 out=W0_2_16;
                select W_10_16_1-W_10_16_1000;
        run;
        quit;
proc datasets library=W0_2_8;
        copy in=S_W_0_2 out=W0_2_8;
                select W_10_2_1-W_10_2_1000;
        copy in=S_W_0_8 out=W0_2_8;
                select W_10_8_1-W_10_8_1000;
        run;
        quit;
proc datasets library=W0_2_4;
        copy in=S_W_0_2 out=W0_2_4;
                select W_10_2_1-W_10_2_1000;

        copy in=S_W_0_4 out=W0_2_4;
                select W_10_4_1-W_10_4_1000;
        run;
        quit;
proc datasets library=W0_4_32;
        copy in=S_W_0_4 out=W0_4_32;
                select W_10_4_1-W_10_4_1000;
        copy in=S_W_0_32 out=W0_4_32;
                select W_10_32_1-W_10_32_1000;
```

```
        run;
        quit;
proc datasets library=W0_4_16;
        copy in=S_W_0_4 out=W0_4_16;
                select W_10_4_1-W_10_4_1000;
        copy in=S_W_0_16 out=W0_4_16;
                select W_10_16_1-W_10_16_1000;
        run;
        quit;
proc datasets library=W0_4_8;
        copy in=S_W_0_4 out=W0_4_8;
                select W_10_4_1-W_10_4_1000;
        copy in=S_W_0_8 out=W0_4_8;
                select W_10_8_1-W_10_8_1000;
        run;
        quit;
proc datasets library=W0_8_32;
        copy in=S_W_0_8 out=W0_8_32;
                select W_10_8_1-W_10_8_1000;
        copy in=S_W_0_32 out=W0_8_32;
                select W_10_32_1-W_10_32_1000;
        run;
        quit;
proc datasets library=W0_8_16;
        copy in=S_W_0_8 out=W0_8_16;
                select W_10_8_1-W_10_8_1000;
        copy in=S_W_0_16 out=W0_8_16;
                select W_10_16_1-W_10_16_1000;
        run;
        quit;
proc datasets library=W0_16_32;
        copy in=S_W_0_16 out=W0_16_32;
                select W_10_16_1-W_10_16_1000;
        copy in=S_W_0_32 out=W0_16_32;
                select W_10_32_1-W_10_32_1000;
        run;
        quit;
```

Appendix D11

```
********************************************************************;
*************** Dissertation Simulation Primary program            *;
*************** Written by Deyab Almaleki                          *;
*************** Supervised by Dr. Applegate                        *;
*************** Code developed 2015                                *;
*************** Factorial invariance                              *;
********************************************************************;
**** Data Q2 file name;
libname scratch "C:\Users\dnp2969\Desktop\Generation\Data\Scratch";

libname H4_2_32 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\H\V-4\Merge S=2-32";
libname H4_2_16 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\H\V-4\Merge S=2-16";
libname H4_2_8  "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\H\V-4\Merge S=2-8";
libname H4_2_4  "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\H\V-4\Merge S=2-4";
libname H4_4_32 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\H\V-4\Merge S=4-32";
libname H4_4_16 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\H\V-4\Merge S=4-16";
libname H4_4_8  "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\H\V-4\Merge S=4-8";
libname H4_8_32 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\H\V-4\Merge S=8-32";
libname H4_8_16 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\H\V-4\Merge S=8-16";
libname H4_16_32"C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\H\V-4\Merge S=16-32";
******;
libname M4_2_32 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\M\V-4\Merge S=2-32";
libname M4_2_16 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\M\V-4\Merge S=2-16";
libname M4_2_8  "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\M\V-4\Merge S=2-8";
libname M4_2_4  "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\M\V-4\Merge S=2-4";
libname M4_4_32 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\M\V-4\Merge S=4-32";
libname M4_4_16 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\M\V-4\Merge S=4-16";
```

Appendix D11 (Continued)

```
libname M4_4_8  "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\M\V-4\Merge S=4-8";
libname M4_8_32 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\M\V-4\Merge S=8-32";
libname M4_8_16 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\M\V-4\Merge S=8-16";
libname M4_16_32"C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\M\V-4\Merge S=16-32";
********;
libname L4_2_32 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\L\V-4\Merge S=2-32";
libname L4_2_16 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\L\V-4\Merge S=2-16";
libname L4_2_8  "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\L\V-4\Merge S=2-8";
libname L4_2_4  "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\L\V-4\Merge S=2-4";
libname L4_4_32 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\L\V-4\Merge S=4-32";
libname L4_4_16 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\L\V-4\Merge S=4-16";
libname L4_4_8  "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\L\V-4\Merge S=4-8";
libname L4_8_32 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\L\V-4\Merge S=8-32";
libname L4_8_16 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\L\V-4\Merge S=8-16";
libname L4_16_32"C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\L\V-4\Merge S=16-32";
********;
libname W4_2_32 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\W\V-4\Merge S=2-32";
libname W4_2_16 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\W\V-4\Merge S=2-16";
libname W4_2_8  "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\W\V-4\Merge S=2-8";
libname W4_2_4  "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\W\V-4\Merge S=2-4";
libname W4_4_32 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\W\V-4\Merge S=4-32";
libname W4_4_16 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\W\V-4\Merge S=4-16";
libname W4_4_8  "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\W\V-4\Merge S=4-8";
```

Appendix D11 (Continued)

```
libname W4_8_32 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\W\V-4\Merge S=8-32";
libname W4_8_16 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\W\V-4\Merge S=8-16";
libname W4_16_32"C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\W\V-4\Merge S=16-32";

***** Clear all previous FIT datasets before running FIV;
proc datasets library=scratch nolist;
        delete fit fit1-fit1000;
        run;
*********************************************************************
****;
***** Evaluating same factor model in each of the groups and combined groups;
***** Model 0(CONFIGURAL INVARIANCE);
*********************************************************************
****;
%macro FIV_CONFIGURAL;
%do rep=1 %to 1000;
proc calis method=ml modification outfit=scratch.Fit&rep noprint;
        group 1 / data=W4_16_32.W_4_32_&rep;            * addapted line to call the
data;
        group 2 / data=W4_16_32.W_4_16_&rep;            * addapted line to call the
data;
        model 1 / group=1;
        factor
                factor1--->COL004 COL009 COL013 COL017,
                factor2--->COL023 COL027 COL034 COL039,
                factor3--->COL041 COL048 COL054 COL059,
                factor4--->COL063 COL069 COL072 COL080,
                factor5--->COL082 COL087 COL093 COL094;
        pvar
                Factor1 = 1.0,
                Factor2 = 1.0,
                Factor3 = 1.0,
                Factor4 = 1.0,
                Factor5 = 1.0,
                COL004 = e004,      COL023 = e023,      COL041 = e041,
        COL063 = e063,      COL082 = e082,
                COL009 = e009,      COL027 = e027,      COL048 = e048,
        COL069 = e069,      COL087 = e087,
                COL013 = e013,      COL034 = e034,      COL054 = e054,
        COL072 = e072,      COL093 = e093,
```

Appendix D11 (Continued)

```
                COL017 = e017,        COL039 = e039,        COL059 = e059,
        COL080 = e080,        COL094 = e094;
   cov
                Factor1 Factor2 = d12, Factor1 Factor3 = d13, Factor1 Factor4 = d14,
Factor1 Factor5 = d15,
                Factor2 Factor3 = d23, Factor2 Factor4 = d24, Factor2 Factor5 = d25,
                Factor3 Factor4 = d34, Factor3 Factor5 = d35,
                Factor4 Factor5 = d45;
        model 2 / group=2;
        refmodel 1 / AllNewParms;

                data scratch.Fit&rep;                                    * addapted
line to call the data;
                set scratch.Fit&rep;                                     * addapted
line to call the data;
                replication=&rep;
                *if IndexCode in (203,204,340,214,215,403);

run;
%end;
%mend;

***** execute FIV macro;
%FIV_CONFIGURAL;

***** Test for rolled-up FIT statistics dataset;
***** Creates it is not present;
%macro opends(name);
%let flg=%sysfunc(exist(scratch.&name,data));
%if &flg=1 %then %do;
                %put "Data set present";
        %end;
        %else %do;
                %put "Data set &name does not exist.";
                data W4_16_32.fit_CONFIGURAL;
        *this will create the initial dataset;
                        set scratch.Fit1;
                run;
        %end;
%mend opends;
%opends(fit);

%macro rollup;
%do rep=2 %to 1000;
```

Appendix D11 (Continued)

```
	proc datasets library=scratch nolist;
		append base=W4_16_32.fit_CONFIGURAL data=scratch.fit&rep; *
addapted line to save the data;
	run;
	quit;
%end;
%mend;

%rollup;

***********  Transpose data file ;
proc transpose data=W4_16_32.fit_CONFIGURAL(drop=IndexCode)
out=W4_16_32.FIT_CONFIGURAL_W4_16_32(drop=_name_ _label_);
	id FitIndex;
	by replication;
run;
**** CONFIGURAL invariance;
proc means data=W4_16_32.FIT_CONFIGURAL_W4_16_32 mean std;
	var Chi_Square
		Chi_Square_DF
		RMSEA_Estimate
		Bentler_Comparative_Fit_Index
		Bentler_Bonett_Non_normed_Index

		Standardized_RMR__SRMR_
		Goodness_of_Fit_Index__GFI_;
run;

***** Clear all previous FIT datasets before running FIV;
proc datasets library=scratch nolist;
	delete fit fit1-fit1000;
	run;


*************************************************************************
****;
***** Evaluating between-group equivalence of factor loadings;
***** Model 1a (WEAK INVARIANCE);
*************************************************************************
****;
%macro FIV_WEAK;
%do rep=1 %to 1000;
proc calis method=ml modification outfit=scratch.Fit&rep noprint;
```

Appendix D11 (Continued)

```
        group 1 / data=W4_16_32.W_4_32_&rep;            * addapted line to call the
data;
        group 2 / data=W4_16_32.W_4_16_&rep;            * addapted line to call the
data;
        model 1 / group=1;
        factor
                factor1--->COL004 COL009 COL013 COL017,
                factor2--->COL023 COL027 COL034 COL039,
                factor3--->COL041 COL048 COL054 COL059,
                factor4--->COL063 COL069 COL072 COL080,
                factor5--->COL082 COL087 COL093 COL094;
        pvar
                Factor1 = 1.0,
                Factor2 = 1.0,
                Factor3 = 1.0,
                Factor4 = 1.0,
                Factor5 = 1.0,
                COL004 = e004,      COL023 = e023,      COL041 = e041,
        COL063 = e063,      COL082 = e082,
                COL009 = e009,      COL027 = e027,      COL048 = e048,
        COL069 = e069,      COL087 = e087,
                COL013 = e013,      COL034 = e034,      COL054 = e054,
        COL072 = e072,      COL093 = e093,
                COL017 = e017,      COL039 = e039,      COL059 = e059,
        COL080 = e080,      COL094 = e094;
   cov
                Factor1 Factor2 = d12, Factor1 Factor3 = d13, Factor1 Factor4 = d14,
Factor1 Factor5 = d15,
                Factor2 Factor3 = d23, Factor2 Factor4 = d24, Factor2 Factor5 = d25,
                Factor3 Factor4 = d34, Factor3 Factor5 = d35,
                Factor4 Factor5 = d45;
        model 2 / group=2;
        refmodel 1;

        pvar
                Factor1 = g2_d1,
                Factor2 = g2_d2,
                Factor3 = g2_d3,
                Factor4 = g2_d4,
                Factor5 = g2_d5,
                COL004 = g2_e004,   COL023 = g2_e023,   COL041 = g2_e041,
        COL063 = g2_e063,   COL082 = g2_e082,
                COL009 = g2_e009,   COL027 = g2_e027,   COL048 = g2_e048,
        COL069 = g2_e069,   COL087 = g2_e087,
```

Appendix D11 (Continued)

```
                COL013 = g2_e013,   COL034 = g2_e034,   COL054 = g2_e054,
        COL072 = g2_e072,   COL093 = g2_e093,
                COL017 = g2_e017,   COL039 = g2_e039,   COL059 = g2_e059,
        COL080 = g2_e080,   COL094 = g2_e094;
   Cov

                Factor1 Factor2 = g2_d12, Factor1 Factor3 = g2_d13, Factor1 Factor4 =
g2_d14, Factor1 Factor5 = g2_d15,
                Factor2 Factor3 = g2_d23, Factor2 Factor4 = g2_d24, Factor2 Factor5 =
g2_d25,
                Factor3 Factor4 = g2_d34, Factor3 Factor5 = g2_d35,
                Factor4 Factor5 = g2_d45;

                data scratch.Fit&rep;                                   * addapted
line to call the data;
                set scratch.Fit&rep;                                    * addapted
line to call the data;
                replication=&rep;
                *if IndexCode in (203,204,340,214,215,403);
run;
%end;
%mend;

***** execute FIV macro;
%FIV_WEAK;

***** Test for rolled-up FIT statistics dataset;
***** Creates it is not present;
%macro opends(name);
%let flg=%sysfunc(exist(scratch.&name,data));
%if &flg=1 %then %do;
                %put "Data set present";
        %end;
        %else %do;
                %put "Data set &name does not exist.";
                data W4_16_32.fit_weak;
        *this will create the initial dataset;
                        set scratch.Fit1;
                run;
        %end;
%mend opends;
%opends(fit);

%macro rollup;
```

Appendix D11 (Continued)

```
%do rep=2 %to 1000;
	proc datasets library=scratch nolist;
		append base=W4_16_32.fit_weak data=scratch.fit&rep;	* addapted
line to save the data;
	run;
	quit;
%end;
%mend;

%rollup;
***********  Transpose data file ;
proc transpose data=W4_16_32.fit_weak(drop=IndexCode)
out=W4_16_32.FIT_weak_W4_16_32(drop=_name_ _label_);
	id FitIndex;
	by replication;
run;
**** weak invariance;
proc means data=W4_16_32.FIT_weak_W4_16_32 mean std;
	var Chi_Square
		Chi_Square_DF
		RMSEA_Estimate
		Bentler_Comparative_Fit_Index
		Bentler_Bonett_Non_normed_Index

		Standardized_RMR__SRMR_
		Goodness_of_Fit_Index__GFI_;
run;

***** Clear all previous FIT datasets before running FIV;
proc datasets library=scratch nolist;
	delete fit fit1-fit1000;
	run;

************************************************************;
***** Evaluating between-group equivalence of factor intercept;
***** Model 2 (Strong invariance);
************************************************************;

%macro FIV_STRONG;
%do rep=1 %to 1000;
proc calis method=ml modification outfit=scratch.Fit&rep noprint;
group 1 / data=W4_16_32.W_4_32_&rep;
group 2 / data=W4_16_32.W_4_16_&rep;
model 1 / group=1;
```

Appendix D11 (Continued)

```
		factor
			factor1--->COL004 COL009 COL013 COL017,
			factor2--->COL023 COL027 COL034 COL039,
			factor3--->COL041 COL048 COL054 COL059,
			factor4--->COL063 COL069 COL072 COL080,
			factor5--->COL082 COL087 COL093 COL094;
		pvar
			Factor1 = 1.0,
			Factor2 = 1.0,
			Factor3 = 1.0,
			Factor4 = 1.0,
			Factor5 = 1.0,
			COL004 = e004,	COL023 = e023,	COL041 = e041,
		COL063 = e063,	COL082 = e082,
			COL009 = e009,	COL027 = e027,	COL048 = e048,
		COL069 = e069,	COL087 = e087,
			COL013 = e013,	COL034 = e034,	COL054 = e054,
		COL072 = e072,	COL093 = e093,
			COL017 = e017,	COL039 = e039,	COL059 = e059,
		COL080 = e080,	COL094 = e094;
	cov
			Factor1 Factor2 = d12, Factor1 Factor3 = d13, Factor1 Factor4 = d14,
Factor1 Factor5 = d15,
			Factor2 Factor3 = d23, Factor2 Factor4 = d24, Factor2 Factor5 = d25,
			Factor3 Factor4 = d34, Factor3 Factor5 = d35,
			Factor4 Factor5 = d45;
		mean
			Factor1 Factor2 Factor3 Factor4 Factor5 = 0 0 0 0 0,
			COL004 = aCOL004, COL023 = aCOL023, COL041 = aCOL041,
		COL063 = aCOL063, COL082 = aCOL082,
			COL009 = aCOL009, COL027 = aCOL027, COL048 = aCOL048,
		COL069 = aCOL069, COL087 = aCOL087,
			COL013 = aCOL013, COL034 = aCOL034, COL054 = aCOL054,
		COL072 = aCOL072, COL093 = aCOL093,
			COL017 = aCOL017, COL039 = aCOL039, COL059 = aCOL059,
		COL080 = aCOL080, COL094 = aCOL094;
model 2 / group=2;
refmodel 1;
		pvar
			Factor1 = g2_d1,
			Factor2 = g2_d2,
			Factor3 = g2_d3,
			Factor4 = g2_d4,
			Factor5 = g2_d5,
```

Appendix D11 (Continued)

```
            COL004 = g2_e004,   COL023 = g2_e023,   COL041 = g2_e041,
        COL063 = g2_e063,   COL082 = g2_e082,
            COL009 = g2_e009,   COL027 = g2_e027,   COL048 = g2_e048,
        COL069 = g2_e069,   COL087 = g2_e087,
            COL013 = g2_e013,   COL034 = g2_e034,   COL054 = g2_e054,
        COL072 = g2_e072,   COL093 = g2_e093,
            COL017 = g2_e017,   COL039 = g2_e039,   COL059 = g2_e059,
        COL080 = g2_e080,   COL094 = g2_e094;
   cov
            Factor1 Factor2 = g2_d12, Factor1 Factor3 = g2_d13, Factor1 Factor4 =
g2_d14, Factor1 Factor5 = g2_d15,
            Factor2 Factor3 = g2_d23, Factor2 Factor4 = g2_d24, Factor2 Factor5 =
g2_d25,
            Factor3 Factor4 = g2_d34, Factor3 Factor5 = g2_d35,
            Factor4 Factor5 = g2_d45;
        mean
            Factor1 Factor2 Factor3 Factor4 Factor5 = g2_aFactor1 g2_aFactor2
g2_aFactor3 g2_aFactor4 g2_aFactor5;

            data scratch.Fit&rep;                                   * addapted
line to call the data;
            set scratch.Fit&rep;                                    * addapted
line to call the data;
            replication=&rep;
            *if IndexCode in (203,204,340,214,215,403);
run;
%end;
%mend;

***** execute FIV macro;
%FIV_STRONG;

***** Test for rolled-up FIT statistics dataset;
***** Creates it is not present;
%macro opends(name);
%let flg=%sysfunc(exist(scratch.&name,data));
%if &flg=1 %then %do;
            %put "Data set present";
        %end;
        %else %do;
            %put "Data set &name does not exist.";
            data W4_16_32.fit_Strong;
        *this will create the initial dataset;
                set scratch.Fit1;
```

Appendix D11 (Continued)

```
                run;
        %end;
%mend opends;
%opends(fit);

%macro rollup;
%do rep=2 %to 1000;
        proc datasets library=scratch nolist;
                append base=W4_16_32.fit_strong data=scratch.fit&rep;      * addapted
line to save the data;
        run;
        quit;
%end;
%mend;

%rollup;
***********  Transpose data file ;
proc transpose data=W4_16_32.fit_strong(drop=IndexCode)
out=W4_16_32.FIT_strong_W4_16_32(drop=_name_ _label_);
        id FitIndex;
        by replication;
run;
**** strong invariance;
proc means data=W4_16_32.FIT_strong_W4_16_32 mean std;
        var Chi_Square
                Chi_Square_DF
                RMSEA_Estimate
                Bentler_Comparative_Fit_Index
                Bentler_Bonett_Non_normed_Index

                Standardized_RMR__SRMR_
                Goodness_of_Fit_Index__GFI_;
run;
***** Clear all previous FIT datasets before running FIV;
proc datasets library=scratch nolist;
        delete fit fit1-fit1000;
        run;
*****************************************************************;
***** Evaluating between-group equivalence of intercepts for factors;
***** Model 3 (Structural mean invariance);
*****************************************************************;
%macro FIV_Structural_mean;
%do rep=1 %to 1000;
proc calis method=ml modification outfit=scratch.Fit&rep noprint;
```

Appendix D11 (Continued)

```
        group 1 / data=W4_16_32.W_4_32_&rep;            * addapted line to call the
data;
        group 2 / data=W4_16_32.W_4_16_&rep;            * addapted line to call the
data;
        model 1 / group=1;
        factor
                factor1--->COL004 COL009 COL013 COL017,
                factor2--->COL023 COL027 COL034 COL039,
                factor3--->COL041 COL048 COL054 COL059,
                factor4--->COL063 COL069 COL072 COL080,
                factor5--->COL082 COL087 COL093 COL094;
        pvar
                Factor1 = 1.0,
                Factor2 = 1.0,
                Factor3 = 1.0,
                Factor4 = 1.0,
                Factor5 = 1.0,
                COL004 = e004,      COL023 = e023,      COL041 = e041,
        COL063 = e063,      COL082 = e082,
                COL009 = e009,      COL027 = e027,      COL048 = e048,
        COL069 = e069,      COL087 = e087,
                COL013 = e013,      COL034 = e034,      COL054 = e054,
        COL072 = e072,      COL093 = e093,
                COL017 = e017,      COL039 = e039,      COL059 = e059,
        COL080 = e080,      COL094 = e094;
   cov
                Factor1 Factor2 = d12, Factor1 Factor3 = d13, Factor1 Factor4 = d14,
Factor1 Factor5 = d15,
                Factor2 Factor3 = d23, Factor2 Factor4 = d24, Factor2 Factor5 = d25,
                Factor3 Factor4 = d34, Factor3 Factor5 = d35,
                Factor4 Factor5 = d45;
        mean
                Factor1 Factor2 Factor3 Factor4 Factor5 = 0 0 0 0 0,
                COL004 = aCOL004, COL023 = aCOL023, COL041 = aCOL041,
        COL063 = aCOL063, COL082 = aCOL082,
                COL009 = aCOL009, COL027 = aCOL027, COL048 = aCOL048,
        COL069 = aCOL069, COL087 = aCOL087,
                COL013 = aCOL013, COL034 = aCOL034, COL054 = aCOL054,
        COL072 = aCOL072, COL093 = aCOL093,
                COL017 = aCOL017, COL039 = aCOL039, COL059 = aCOL059,
        COL080 = aCOL080, COL094 = aCOL094;
model 2 / group=2;
refmodel 1;
```

Appendix D11 (Continued)

```
        pvar
                Factor1 = g2_d1,
                Factor2 = g2_d2,
                Factor3 = g2_d3,
                Factor4 = g2_d4,
                Factor5 = g2_d5,
                COL004 = g2_e004,   COL023 = g2_e023,   COL041 = g2_e041,
        COL063 = g2_e063,   COL082 = g2_e082,
                COL009 = g2_e009,   COL027 = g2_e027,   COL048 = g2_e048,
        COL069 = g2_e069,   COL087 = g2_e087,
                COL013 = g2_e013,   COL034 = g2_e034,   COL054 = g2_e054,
        COL072 = g2_e072,   COL093 = g2_e093,
                COL017 = g2_e017,   COL039 = g2_e039,   COL059 = g2_e059,
        COL080 = g2_e080,   COL094 = g2_e094;
   cov
                Factor1 Factor2 = g2_d12, Factor1 Factor3 = g2_d13, Factor1 Factor4 =
g2_d14, Factor1 Factor5 = g2_d15,
                Factor2 Factor3 = g2_d23, Factor2 Factor4 = g2_d24, Factor2 Factor5 =
g2_d25,
                Factor3 Factor4 = g2_d34, Factor3 Factor5 = g2_d35,
                Factor4 Factor5 = g2_d45;


                data scratch.Fit&rep;                                   * addapted
line to call the data;
                set scratch.Fit&rep;                                    * addapted
line to call the data;
                replication=&rep;
                *if IndexCode in (203,204,340,214,215,403);
run;
%end;
%mend;
***** execute FIV macro;
%FIV_Structural_mean;
***** Test for rolled-up FIT statistics dataset;
***** Creates it is not present;
%macro opends(name);
%let flg=%sysfunc(exist(scratch.&name,data));
%if &flg=1 %then %do;
                %put "Data set present";
        %end;
        %else %do;
                %put "Data set &name does not exist.";
```

Appendix D11 (Continued)

```
                data W4_16_32.fit_Structural_mean;
                        *this will create the initial dataset;
                        set scratch.Fit1;
                run;
        %end;
%mend opends;
%opends(fit);

%macro rollup;
%do rep=2 %to 1000;
        proc datasets library=scratch nolist;
                append base=W4_16_32.fit_Structural_mean data=scratch.fit&rep; *
addapted line to save the data;
        run;
        quit;
%end;
%mend;

%rollup;
*********** Transpose data file ;

proc transpose data=W4_16_32.fit_Structural_mean(drop=IndexCode)
out=W4_16_32.FIT_Structural_mean_W4_16_32(drop=_name_ _label_);
        id FitIndex;
        by replication;
run;
**** Structural_mean_ invariance;
proc means data=W4_16_32.FIT_Structural_mean_W4_16_32 mean std;
        var Chi_Square
                Chi_Square_DF
                RMSEA_Estimate
                Bentler_Comparative_Fit_Index
                Bentler_Bonett_Non_normed_Index

                Standardized_RMR__SRMR_
                Goodness_of_Fit_Index__GFI_;
run;
```

Appendix D12

```
*********************************************************************;
*************** Dissertation Simulation Primary program              *;
*************** Written by Deyab Almaleki                            *;
*************** Supervised by Dr. Applegate                          *;
*************** Code developed 2015                                  *;
*************** Proportion Analysis                                 *;
*********************************************************************;
***** 4:1 VTF RATIOS;
libname H4_4_32 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\H\V-4\Merge S=4-32";
libname H4_4_16 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\H\V-4\Merge S=4-16";
libname H4_4_8  "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\H\V-4\Merge S=4-8";
libname H4_8_32 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\H\V-4\Merge S=8-32";
libname H4_8_16 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\H\V-4\Merge S=8-16";
libname H4_16_32"C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\H\V-4\Merge S=16-32";

libname M4_4_32 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\M\V-4\Merge S=4-32";
libname M4_4_16 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\M\V-4\Merge S=4-16";
libname M4_4_8  "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\M\V-4\Merge S=4-8";
libname M4_8_32 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\M\V-4\Merge S=8-32";
libname M4_8_16 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\M\V-4\Merge S=8-16";
libname M4_16_32"C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\M\V-4\Merge S=16-32";

libname L4_4_32 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\L\V-4\Merge S=4-32";
libname L4_4_16 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\L\V-4\Merge S=4-16";
libname L4_4_8  "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\L\V-4\Merge S=4-8";
libname L4_8_32 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\L\V-4\Merge S=8-32";
libname L4_8_16 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\L\V-4\Merge S=8-16";
```

Appendix D12 (Continued)

```
libname L4_16_32"C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\L\V-4\Merge S=16-32";

libname W4_4_32 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\W\V-4\Merge S=4-32";
libname W4_4_16 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\W\V-4\Merge S=4-16";
libname W4_4_8  "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\W\V-4\Merge S=4-8";
libname W4_8_32 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\W\V-4\Merge S=8-32";
libname W4_8_16 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\W\V-4\Merge S=8-16";
libname W4_16_32"C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\W\V-4\Merge S=16-32";

*************************************************************;
*** 7:1 VTF RATIOS;
libname H7_4_32 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\H\V-7\Merge S=4-32";
libname H7_4_16 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\H\V-7\Merge S=4-16";
libname H7_4_8  "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\H\V-7\Merge S=4-8";
libname H7_8_32 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\H\V-7\Merge S=8-32";
libname H7_8_16 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\H\V-7\Merge S=8-16";
libname H7_16_32"C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\H\V-7\Merge S=16-32";

libname M7_4_32 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\M\V-7\Merge S=4-32";
libname M7_4_16 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\M\V-7\Merge S=4-16";
libname M7_4_8  "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\M\V-7\Merge S=4-8";
libname M7_8_32 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\M\V-7\Merge S=8-32";
libname M7_8_16 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\M\V-7\Merge S=8-16";
libname M7_16_32"C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\M\V-7\Merge S=16-32";
```

Appendix D12 (Continued)

```
libname L7_4_32 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\L\V-7\Merge S=4-32";
libname L7_4_16 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\L\V-7\Merge S=4-16";
libname L7_4_8  "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\L\V-7\Merge S=4-8";
libname L7_8_32 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\L\V-7\Merge S=8-32";
libname L7_8_16 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\L\V-7\Merge S=8-16";
libname L7_16_32"C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\L\V-7\Merge S=16-32";

libname W7_4_32 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\W\V-7\Merge S=4-32";
libname W7_4_16 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\W\V-7\Merge S=4-16";
libname W7_4_8  "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\W\V-7\Merge S=4-8";
libname W7_8_32 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\W\V-7\Merge S=8-32";
libname W7_8_16 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\W\V-7\Merge S=8-16";
libname W7_16_32"C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\W\V-7\Merge S=16-32";

*************************************************************;
*** 10:1 VTF RATIOS;
libname H0_4_32 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\H\V-10\Merge S=4-32";
libname H0_4_16 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\H\V-10\Merge S=4-16";
libname H0_4_8  "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\H\V-10\Merge S=4-8";
libname H0_8_32 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\H\V-10\Merge S=8-32";
libname H0_8_16 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\H\V-10\Merge S=8-16";
libname H0_16_32"C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\H\V-10\Merge S=16-32";

libname M0_4_32 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\M\V-10\Merge S=4-32";
```

Appendix D12 (Continued)

```
libname M0_4_16 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\M\V-10\Merge S=4-16";
libname M0_4_8  "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\M\V-10\Merge S=4-8";
libname M0_8_32 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\M\V-10\Merge S=8-32";
libname M0_8_16 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\M\V-10\Merge S=8-16";
libname M0_16_32"C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\M\V-10\Merge S=16-32";
libname L0_4_32 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\L\V-10\Merge S=4-32";
libname L0_4_16 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\L\V-10\Merge S=4-16";
libname L0_4_8  "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\L\V-10\Merge S=4-8";
libname L0_8_32 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\L\V-10\Merge S=8-32";
libname L0_8_16 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\L\V-10\Merge S=8-16";
libname L0_16_32"C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\L\V-10\Merge S=16-32";
libname W0_4_32 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\W\V-10\Merge S=4-32";
libname W0_4_16 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\W\V-10\Merge S=4-16";
libname W0_4_8  "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\W\V-10\Merge S=4-8";
libname W0_8_32 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\W\V-10\Merge S=8-32";
libname W0_8_16 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\W\V-10\Merge S=8-16";
libname W0_16_32 "C:\Users\dnp2969\Desktop\Generation\Data\Primary\Data and
Analysis Q2\W\V-10\Merge S=16-32";
*******************************************************************;
data temp;
	set W0_16_32.FIT_Structural_mean_W0_16_32;
pvalue=round(Pr___Chi_Square,0.01); *not working as needed;
if pvalue>.05 then ChiTest=1;
	else ChiTest=0;
run;
proc freq data=temp;
	tables Chitest/bin(p=.05);
	run;
```