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TESTING THE INVARIANCE OF
THE TRANSTHEORETICAL MODEL
UTILIZING A POPULATION OF SMOKERS

BY
ROSE MARIE WARD

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE
REQUIREMENTS FOR THE DEGREE OF
MASTER OF ARTS
IN
PSYCHOLOGY

UNIVERSITY OF RHODE ISLAND

2001

Abstract

A crucial assumption in the development of a measure is that the measurement model is invariant. This means that the measurement model is the same in different populations and across different occasions. Utilizing data from a representative sample of smokers, we examined the invariance of the Decisional Balance Inventory and the Processes of Change. The sample consists of 4144 participants (44.3% male, 55.7% female, 95.7% White, mean age 40.7). After the number of factors for each scale was confirmed using Factor Analysis, the sample was partitioned into subgroups to test the invariance of the model. The scales were compared across two levels of gender (male and female), four levels of education (grade school, high school, college, and graduate school), two levels of race (white and black), and four levels of age (18-25, 26- 35, 36- 50, and 50+). Four different levels of invariance were evaluated. The first level, configural invariance, had no restrictions. The second level examined was the tau-equivalent model also known as weak factorial invariance and requires that the model loadings be proportional. The third level, pattern identity invariance requires the factor loadings to be equal. The fourth model tested is the most restrictive level also known strong factorial invariance. Strong factorial invariance requires that the loadings, error variances, means, and standard deviations be equal. The results indicated that the two TTM scales measure at high levels of invariance across the samples and across time. The research

supports the premise that the Decisional Balance and Processes of Change scales can be used in a variety of populations and in longitudinal studies.

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Preface

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Chapter 1:

Introduction and

Statement of the Problem

A critical step in the development and testing of a model involves operationalizing the constructs of the theory. Often this takes the form of selecting a set of observed variables that are good measures of the construct. The measurement model describes the relationship between these observed variables and the construct. In a factor analysis or structural equation model, the measurement is often illustrated by a figure where the squares (manifest variables) represent the observed variables and circles (latent variables or factors) represent the constructs. Data from a sample provide estimates of the loadings or correlations between the latent variables and the manifest variables.

A crucial assumption is that the measurement model is invariant. This means that the measurement model is the same in different populations and across different occasions. Even though the literature has argued for and against the various levels of factorial invariance, it seems that for longitudinal studies the minimum requirement must be configural invariance. We must maintain the same simple structure over time in order to justify our research. Without a structure that remains stable over time, the concept of longitudinal studies falls apart. Applying the same simple structure to samples insures that the scoring method is consistent. Rensvold and Cheung (1998) emphasize that a

researcher must determine that the simple structure underlying a study means the same thing for every sub-sample in the population. Without the invariance in the meaning, comparison between these groups (or using the same survey questions) becomes impossible.

What is Factorial Invariance?

Factor invariance is a concept developed by Thurstone (1947). At that time it meant comparing a simple structure across samples taken from different populations or sub-samples. Over the years numerous researchers have sought to describe and elaborate on the ideas of simple structure and factorial invariance.

Meredith (1964a, 1964b) concluded that a simple structure was evident in invariant structures of sub-samples when they are all taken from the same parent population. His theorems indicate that simple structure solutions can result even with non-chance restrictions on the sampling of the subjects. Meredith argues that "... a simple structure...is essentially defined by the zeroes... in the invariant factor pattern matrix rather than by the magnitude of the nonzero elements" (Meredith, 1964a, p 182). Horn, McArdle, & Mason (1983) extended Meredith's conclusion and stated that a researcher should expect the configuration (the zeros) and the salient (non-zeros) to remain stable.

Defining Factorial Invariance

Following Meredith (1964a), x is a measurable p -dimensional random variable that is related to a set of n factors (underlying latent variables). The relation can be expressed as:

$$(1) \quad x = \beta z + u$$

where

β is an $p \times m$ ($m < p$) factor pattern matrix,

z is an m -dimensional vector of common factor scores,

u is an p -dimensional vector of specific and/or error scores.

The factor analysis model is assumed to hold for the parent population indicating that

$$(2) \quad V = \beta C \beta' + \Delta$$

Where

V denotes the variance-covariance matrix of x ,

C denotes the variance-covariance matrix of z ,

and Δ denotes a diagonal matrix of variances and covariances of u .

To extend this formula to the concepts of factorial invariance, the following assumptions about the distributions must be made. y (a q -dimensional random variable) is chosen to be the selection variable such that the regression of each component of z (the m -dimensional vector of common factor scores) on y is linear and homoscedastic. Selection of y should also indicate that it is distributed independently of u . Meredith emphasizes (1964)

that “we don’t even need to know what the selection variables are, much less be able to observe them, in order for factorial invariance to hold.” Following Meredith, these conditions imply certain standards. The first condition is the linearity and homoscedasticity of the regression of x on y .

The variance-covariance matrix of x (denoted by V) in every subpopulation (for example, males and females) derived from the parent population by any type of selection on y can be expressed as

$$(3) \quad V_i = V + B (G_i - G) B'$$

where

B denotes the $p \times q$ matrix of regression weights for the regression of x on y ,

B' denotes the $m \times q$ matrix of weights providing the regression of z on y ,

V_i denotes the variance-covariance matrix of x in a subpopulation so derived,

and G and G_i denote the variance-covariance matrices of y in the parent and subpopulation, respectively.

In short, no matter which sub groups one selects through whatever manner the groups are selected, the variance-covariance matrix of the sub group can be represented by Equation 3.

Another extension of the formulas indicated above is

$$(4) \quad C_i = C + b (G_i - G) b'$$

where C_i denotes the variance-covariance matrix of z in the same subpopulation can be shown that

$$(5) \quad B = \beta b;$$

therefore if we substitute into Equation 3 the derived formulas for Equation 2, the result is

$$(6) \quad V_i = (\beta C \beta' + \Delta) + B (G_i - G) B'$$

and by substituting from Equation 5

$$(7) \quad V_i = (\beta C \beta' + \Delta) + \beta b (G_i - G) b' \beta' .$$

To simplify this equation further, we use Equation 4 to get

$$(8) \quad V_i = \beta (C + b (G_i - G) b') \beta' + \Delta$$

$$(9) \quad V_i = \beta (C_i) \beta' + \Delta.$$

Equation 9 holds true for every derivable subpopulation by the selection variable y .

Types of Factorial Invariance

Horn (1991) presented a version of factorial invariance that relaxed some of the requirements in exploratory factorial invariance. He defined two types of factorial invariance: configural and metric. Meredith (1993) presents the minimum requirements to satisfy factorial invariance at different levels of stringency.

To illustrate Meredith's definition of factorial invariance, consider the following four cases. Utilizing the factor pattern matrices from the two subgroups presented below, we will consider the four cases.

$$(10) \quad A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & 0 \\ a_{31} & 0 \\ 0 & a_{42} \end{bmatrix} \quad B = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & 0 \\ b_{31} & 0 \\ 0 & b_{42} \end{bmatrix}$$

Case I: Configural Invariance

Configural invariance is the minimum requirement for factorial invariance.

Configural invariance requires that the latent constructs have non-zero loadings occurring on the same variables across time or occasions. The two matrices presented above would demonstrate configural invariance when the non-zero loadings are left to vary while the zero loadings equivalent in both matrices or

$$(11) \quad \begin{aligned} a_{22} &= b_{22} = 0 \\ a_{32} &= b_{32} = 0 \\ a_{41} &= b_{41} = 0. \end{aligned}$$

Case II: Weak Factorial Invariance

The next level of factorial invariance is termed weak factorial invariance. It requires that the structure exhibit equality of the unstandardized factor loadings across time or groups. This level of invariance requires that the primary loading be on the same marker and magnitude of the loadings must be proportional. In the second case, we add this constraint to the constraint in Equation 11. In terms of the A and B matrices above, this can be denoted by

$$\begin{aligned}
 a_{11} &= k b_{11} \\
 a_{21} &= k b_{21} \\
 (12) \quad a_{31} &= k b_{31} \\
 a_{12} &= k b_{12} \\
 a_{42} &= k b_{42}.
 \end{aligned}$$

Case III: Pattern Identity Invariance

A stricter case, (termed pattern identity invariance by Horn), requires that factor loadings must be equal across group or time. Discussion of the technical aspects of pattern identity invariance can be found in Bentler and Bonnet (1980), Browne and Cudeck (1989, 1993), Butler (1969), Byrne, Shavelson, and Muthén (1989), Cunningham (1982), Horn (1991), Horn and McArdle (1992), Jöreskog (1979), Meredith (1964a, 1964b, 1993), Schaie and Hertzog (1985) and Thurstone (1947). Pattern identity invariance requires that all factor loadings are equal. In terms of the example matrices above

$$(13) \quad a_{ij} = b_{ij}$$

for all i and j .

Case IV: Strong Factorial Invariance

Meredith (1993) elaborated on the idea of strong factorial invariance. This level of invariance requires that the unique variances across group or time and the intercepts must be equal in addition to (13) above. In comparison to the three

previous mentioned cases, this case requires that more than the correlations must be examined. This fourth case requires the covariance matrices to be equal. This is the most restrictive type of invariance. In essence, this means that all parameters are restricted to be equal across groups (error variances, factor variances, factor covariances, and paths between factors).

Some researchers have employed this most restrictive form of factorial invariance. Jöreskog (1971) required that the covariance matrices involved be equal (strong factorial invariance). As Horn, McArdle, and Mason (1983) explain, this requirement is extremely stringent and may not be reasonable in many studies. In essence, this type of factorial invariance is frequently unobtainable because it requires subpopulations that are identical in every manner. Even though Horn et al. (1991) discouraged the stringency of the Jöreskog (1971) method, Bloxom (1972) supported the restrictive nature of the method.

Applications of Factorial Invariance

Factorial invariance has been applied to a variety of studies. Utilizing Thurstone's (1947) simple structure criteria, Ahmavaara (1954) examined whether a multivariate selection is reducible to univariate selections. Ahmavaara's work stresses the importance of working with variance/covariance structures instead of correlations. Puhan (1975) stressed the difference between factorial invariance and psychometric invariance. He states that "...factorial invariance studies ...see whether or not the nature of

psychological factors change across a specific dimension-developmental, cultural etc.” (Puhan, 1975, 295). The concept Puhan describes as psychometric invariance was defined by Horn et al. (1991) as metric invariance. Schaie et al. (1998) explored the invariance of various psychometric ability tests, which measure inductive reasoning, spatial orientation, perceptual speed, numeric facility, verbal ability, and verbal recall. Drasgow (1984, 1985) examined the invariance of various common psychological tests. Marsh and Hocevar (1985) investigated the invariance of studies concerning self-concept. Most recently, Cheung and Rensvold (1999) and Riordan and Vanderberg (1994) applied factorial invariance to cross-cultural sub-samples.

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Chapter 2:

The Factorial Invariance of the Short Form of the Decisional Balance Inventory

The Transtheoretical Model (TTM; Prochaska & DiClemente, 1983, Prochaska & Velicer, 1997; Velicer, Prochaska, Fava, Norman, & Redding, 1998) is a comprehensive model of behavior change that has been validated in numerous studies and applied to numerous behaviors (Prochaska et al., 1994) including alcohol use, quitting cocaine, safer sex, exercise, sunscreen use, and dietary fat reduction. Smoking cessation is the behavior that served as the initial basis for many of the innovations. It is the health behavior by which the primary constructs of the model were developed and where the greatest empirical support has been developed. The current study examines the invariance of the Decisional Balance Inventory, a widely used measure of one of the key constructs of the Transtheoretical Model, within this area of application.

Transtheoretical Model

The Transtheoretical Model is a model of intentional behavior change that focuses on the decision making of an individual. The Transtheoretical Model also involves a series of intermediate/ outcome measures. These constructs include the Pros and Cons from the Decisional Balance Scale, Self-efficacy or Temptation, the Processes of Change, and the target behavior. A more detailed presentation of this aspect of the model is provided elsewhere

(Prochaska & Velicer, 1997; Velicer, Prochaska, Fava, Rossi, Redding, Laforge, & Robbins, 2000; Velicer, Rossi, Prochaska, & DiClemente, 1996).

Measurement issues are central to applying a theoretical model to any problem. Assessing the constructs of the Transtheoretical Model involves a reliance on self-report. In the smoking area, self-report has been demonstrated to be very accurate under most circumstances (Velicer, Prochaska, Rossi, & Snow 1992). Accurate measurement requires a series of unambiguous items to which the individual will respond to accurately with little opportunity for distortion. One of the critical steps for the application of the model involves the development of short, reliable, and valid measures of the key constructs. This paper will focus on one of these key constructs, the Decisional Balance Inventory.

Describing the Decisional Balance Scale

The Decisional Balance scale was derived from Janis and Mann's (1977) decision-making model. Janis and Mann's model revolves around a conflict approach. This approach requires that a decision is made after the perusal of relevant considerations. The considerations are then compared on a "balance sheet" of gains and losses (Mann, 1972). Janis and Mann's decision-making model includes eight categories or factors of decision-making (gains or losses for self, gains or losses for significant others, self-approval or disapproval, and approval or disapproval of others).

Velicer, DiClemente, Prochaska, and Brandenburg (1985) developed a 20-item decisional balance measure for smoking cessation based on the Janis and Mann model. Following Janis and Mann (1977), a two factor, four factor, and eight-factor model were evaluated. A principal components analysis using Velicer's MAP criteria (Velicer, 1976; Zwick & Velicer, 1988) support two orthogonal components. The components were labeled the Pros of Smoking and the Cons of Smoking. Both scales successfully differentiated groups, which represented the stages of change. Other researchers have replicated this result with other health behaviors. Prochaska et al. (1994) reviews the generalizability of this structure across 12 problem areas. Velicer et al. (1985) concluded that the decisional balance scale provided predictive power when utilized in combination with the Transtheoretical model's Stages of Change.

Prochaska et al (1994) examined the relationship between Stages of Change and the Decisional Balance Inventory and determined that there are Strong and Weak Principles of Progress. The Strong Principle of Change is: PC $\rightarrow$ A $\cong$ 1 SD $\uparrow$ PROS. Progressing through the Stages of Change (specifically from Precontemplation through to Action) involves an increase of one standard deviation in the pros of changing. The Weak Principle of Change is: PC $\rightarrow$ A $\cong$ 0.5 SD $\downarrow$ CONS. Once again progression through the stages involves a 0.5 standard deviation decrease in the cons of changing. The implication of these findings is that an individual's pro of changing must

double as the cons of changing must be cut in half (Prochaska, 1994; Prochaska & Velicer, 1997; Prochaska, Velicer, et al., 1994).

The original reports on the Decisional Balance Measure focused on the 20-item long form of the measure. There is little published information about the psychometric properties of the 6-item short form. However, most intervention studies (Prochaska et al., in press; Prochaska, et al., 2001; Velicer, Prochaska, Fava, Laforge, & Rossi, 1999) have relied on this short form. The present study seeks to examine the factorial invariance of the Pro and Con scales across samples representing key demographic variables (gender, race, age, and education) and across time (baseline, 6 months, 12 months, and 18 months).

Levels of Invariance

Factor invariance is a concept developed by Thurstone (1947). Through time factor invariance has come to mean comparing a simple structure across samples (Meredith, 1964a) to determine if the structure remains invariant.

The current study examined four levels of invariance. The first and weakest level is *Configural Invariance*. This represents a minimum requirement for invariance. Configural Invariance requires that all the latent constructs have their primary non-zero loading on the same construct across groups or time occasions. It also requires that the constructs have equivalent zero loadings on constructs across groups or time occasions (Horn, McArdle, Mason, 1983; Meredith, 1964a, 1964b). The second level of invariance is *Weak*

Factorial Invariance. This level requires that the primary loading be on the same marker and magnitude of the loadings must be proportional. The third level of invariance is *Pattern Identity Invariance*. This third level requires that all the factor loadings be equal except for sampling fluctuations (Horn, 1991). The fourth case is *Strong Factorial Invariance*, which requires the covariance matrices to be equal. All other types of invariance can be applied to a set of standardized variables. Strong Factorial Invariance is the most restrictive type of invariance (Meredith, 1993).

The Present Study

Fava, Velicer, and Prochaska (1995) gathered data from a representative sample of smokers. The sample was recruited during the fall of 1990 to the spring of 1991. Participants provided information about their smoking habits in relation to items of the Transtheoretical Model. The study gathered information about the individuals' stage of change and decisional balance. The data was collected at 4 time points (baseline, 6 month, 12 month, and 18 month). The present study examined the level of factorial invariance of the decisional balance scales. Factorial invariance was assessed across four sets of demographic variables: (1) gender, (2) education, (3) race, and (4) age, employing the baseline assessment. If the structure was demonstrated to be invariant across subgroups, the invariance across the four assessment timepoints was investigated.

The current study hypothesized that the Decisional Balance Inventory will achieve a high level of invariance. Studies such as Prochaska et al. (1994) have noted the scale's stability and reliability. Due to the stable nature of the scale, pattern identity invariance is hypothesized.

Method

Participants

This study involved a secondary data analysis of data gathered for a smoking cessation study. All non-institutionalized adults between the ages of 18 and 75 years living in the state of Rhode Island were eligible for the study. Participants were identified by telephone using an adaptation of the two step Mitofsky-Waksberg random-digit-dialing (RDD) method (Waksberg, 1978). The first step in this method is to randomly generate four digit suffixes and assign them to three digit telephone exchanges. All 88 Rhode Island telephone exchanges were used in this step. These primary numbers were screened to ensure that they were residential numbers. In the second step, a random two-digit suffix was added to each prefix bank to create a secondary RDD.

Residences were screened to determine if an adult between the ages of 18 and 75 who regularly smoked resided there. If a household contained more than one eligible smoker, the individual who most recently celebrated their birthday was recruited for the study (Salmon & Nichols, 1983).

A total of 32,456 calls were made using random digit dialing procedures from steps one and two. Telephone interviews were conducted with 12,109 of the 14,266 (84.9%) eligible adults and over 35% of the interviews were conducted with self-identified smokers. Contact information was received from 96.5% of the interviewed smokers. For a detailed description of this recruitment procedure, refer to Fava et al. (1995).

Sample characteristics

Once the initial interviews were completed, an initial sample of 4,144 smokers was randomized to one of two treatment conditions. The mean age was 40.7 years. There were 44.3% males (N = 1836) and 55.7% females (N = 2308); the sample was 95.7% white (N = 3959), with a median income of 30-40 thousand dollars. 70.7% were employed. 53.5% were married. All participants were smokers with an average of 20.6 cigarettes per day. Table 2.1 presents the characteristics of the sample.

Insert Table 2.1 Here

Measurement Variables and Decisional Balance Inventory

Demographic Variables. For the first analysis, the sample was subdivided into two gender categories (Male; N = 1836 and Female; N = 2308). Sample size was adequate in both subgroups. For the second analysis, the sample was

divided into four age categories (18-25; N = 598, 26-35; N = 1061, 36-50; N = 1440, and 50+; N = 1039). Sample size was adequate in all four subgroups. For the third analysis, the sample was divided into four race categories (White; N = 3959, Black; N = 105, Asian; N = 16, and Other; N = 59). Sample size was adequate in only the White and Black subgroups. For the fourth analysis, the sample was divided into four levels of education (Grade School; N = 109, High School; N = 2348, College; N = 1464, and Graduate School; N = 223). Sample size was adequate in all four subgroups.

Decisional Balance Inventory. The original Decisional Balance measure consisted of 20-items (Velicer, DiClemente, Prochaska, & Brandenburg, 1985). The length of the measure combined with the other TTM measures produced a response burden on the participants during a phone interview (Fava, Rossi, Velicer, & Prochaska, 1991). Fava et al. (1991) reduced the long form of the scale using Principal Components Analysis and Structural Equation Modeling. The resulting 6-item short form correlated with the long form .93 and .91 (on the Pro and Cons scales respectively) indicating the two measures were comparable.

The Decisional Balance Inventory (short form) used in this study is comprised of 6 items involving smoking cessation. The inventory's six items form two sub-scales, the Pros of smoking and Cons of smoking (Velicer et al, 1985; Fava et al., 1991). Cronbach's Coefficient Alpha was calculated for each

of the two subscales by group (presented in Table 2.2). Figure 2.1 represents a model of the Decisional Balance Inventory.

Insert Table 2.2 & Figure 2.1 about here

Results

The factorial invariance of the Decisional Balance scale was examined across four demographic variables, (gender, education, race, and age), and across time (baseline, 6-month, 12-month, and 18-month). Structural Equation Modeling (SEM) was used to test items for factorial invariance.

Across Samples

Step One: A structural equation modeling program, EQS, (Bentler, 1989) was used to examine the relation between the six items and the two hypothesized factors for the total sample. This process utilized the baseline data.

Step Two: The sample was partitioned into groups based on the four demographic variables and structural equation modeling was employed to test the invariance of the structure across subgroups.

Step Three: The model was tested on four levels. The first and most restrictive model fit was the strong factorial invariance model. In this case, all

of the parameters were constrained to be equal. If this model fit, the procedure was terminated. The second model fit required the factor loadings to be equal (pattern identity invariance). If this model fit, the procedure was terminated. The third model tested was the weak factorial invariance model. If this model fit, the procedure was terminated. The fourth model tested had no restrictions. This is the congeneric or configural model. This model required that the nonzero loadings be equal between the samples.

All analyses were run on subgroups that had at least 100 participants. If less than a 100 participants was available, that subgroup was then eliminated. Structural equation modeling requires large numbers of cases in order for the model to converge. A minimum of one hundred has been suggested by multiple sources for evaluating measurement models (Boomsma, 1982; Gerbing & Anderson, 1983; Guadagnoli & Velicer, 1988; Velicer & Fava, 1998).

After determining the level of invariance (configural, weak, pattern identity, or strong), the level of invariance was tested across time. If invariance was not present across the subgroups, invariance across time was not assessed.

SEM was implemented utilizing the EQS (Bentler, 1989) computer program. SEM examines the variances and covariances of the data to determine the fit of the model. The best fitting model should excel in three aspects of fit: (1) Theoretical consistency; (2) Empirical evidence; and (3) Parsimony (Harlow and Rose, 1994). The first aspect, theoretical consistency implies that the model has a good basis in theory. Several criteria have been

suggested in the literature to evaluate empirical evidence. In this study, the following indices were employed: (a) the chi-square to degrees of freedom ratio, the Comparative Fit Index (CFI: Bentler, 1990); (b) the Normed Fit Index (NFI: Bentler- Bonett, 1980); (c) the Non-Normed Fit Index (NNFI: Tucker & Lewis, 1973); (d) the average absolute standardized residuals value (AASR); (e) root mean square error of approximation (RMSEA: Steiger & Lind, 1980); (f) the significance of individual parameters (e. g., factor loadings between latent constructs and indicators); and (g) the amount of explained variance (R^2). Empirical fit was evaluated by determining if the model falls within the following ranges for the indices: a chi square to degrees of freedom ratio of less than 5.0, a CFI, NFI, and NNFI greater than .90, the AASR and RMSEA less than .06, the measured parameters significant, and a good amount of explained variance (Harlow & Rose, 1994; Hoyle & Panter, 1995). Parsimony requires that the model that fits the data best have the fewest parameters.

Scale Reliabilities

Table 2 presents the reliabilities of the scales tested by sample sub group. Coefficient Alpha was determined to be between .51 and .67 for the Decisional Balance Scale.

Gender:

Sample size was adequate in both subgroups (Male; $N = 1836$ and Female; $N = 2308$). The highest level of invariance, Strong Factorial Invariance, provided a good fit to the model. Table 2.3 presents the sample size, overall

chi-square value, overall CFI, NFI, and NNFI values, AASR for each subgroup, RMSEA for the overall comparison, the chi-square to degrees of freedom ratio, the chi-square difference test, and the power for the model comparison. Power was calculated using the overall RMSEA (MacCallum, Browne, & Sugawara, 1996).

Insert Table 2.3 about here

The overall fit indices indicate that this model fits (CFI: .953; NFI: .943; NNFI: .951). The micro fit indices indicate that the model fits well across groups (Male AASR: .037; Female AASR .033). Figure 2.2 presents the parameter estimates for gender for the Decisional Balance Inventory.

Insert Figure 2.2 about here

Education

Sample size was adequate in all four subgroups (Grade School; N = 109, High School; N = 2348, College; N = 1315, and Graduate School; N = 223). The highest level of invariance, Strong Factorial Invariance, provided a good fit to the model. Table 3 presents the sample size, overall chi-square value, overall CFI, NFI, and NNFI values, AASR for each subgroup, RMSEA for the overall

comparison, the chi-square to degrees of freedom ratio, the chi-square difference test, and the power for the model comparison.

The overall fit indices indicate that this model fits (CFI: .959; NFI: .935; NNFI: .965). The micro level indices indicate that the model fits moderately well across groups (Grade school AASR: .100; High school AASR: .023; College AASR: .035; Graduate School AASR: .067). Figure 2.3 depicts the parameter estimates for education for the decisional balance inventory.

Insert Figure 2.3 about here

Race

Sample was adequate in only the White and Black subgroups (White; N = 3959 and Black; N = 105). The highest level of invariance, Strong Factorial Invariance, provided a good fit to the model. Table 3 presents the sample size, overall chi-square value, overall CFI, NFI, and NNFI values, AASR for each subgroup, RMSEA for the overall comparison, the chi-square to degrees of freedom ratio, the chi-square difference test, and the power for the model comparison.

The overall fit indices indicate that this model fits (CFI: .969; NFI: .959; NNFI: .968). The micro level indices indicate that the model fits moderately well across groups (White AASR: .019; Black AASR: .082). Figure 2.4 depicts the parameter estimates for race for the decisional balance inventory.

Insert Figure 2.4 about here

Age

Sample size was adequate in all four subgroups (18 - 25; N = 598, 26 - 35; N = 1061, 36 - 50; N = 1440, and 50+; N = 1039). The highest level of invariance, Strong Factorial Invariance, fit the model well. Table 2.3 presents the sample size, overall chi-square value, overall CFI, NFI, and NNFI values, AASR for each subgroup, RMSEA for the overall comparison, the chi-square to degrees of freedom ratio, the chi-square difference test, and the power for the model comparison.

The overall fit indices indicate that this model fits (CFI: .944; NFI: .920; NNFI: .953). The micro level indices indicate that the model fits well across age groups (18-25 AASR: .084; 26-34 AASR: .042; 35-50 AASR: .031; 50+ AASR: .051). Figure 2.5 depicts the parameter estimates for race for the Decisional Balance Inventory.

Insert Figure 2.5 about here

Across Time

Since factorial invariance was established across the subgroups, the model was assessed across time points. The model fit well across occasions.

The highest level of invariance, Strong Factorial Invariance, provided a good fit for the models. Table 2.3 presents the sample size, overall chi-square value, overall CFI, NFI, and NNFI values, AASR for each subgroup, RMSEA for the overall comparison, the chi-square to degrees of freedom ratio, the chi-square difference test, and the power for the model comparison.

The overall fit indices indicate that this model fit (CFI: .974; NFI: .970; NNFI: .969). The micro level indices indicate that the model fits well across age groups (Baseline AASR: .030; 6-month AASR: .028; 12-month AASR: .020; 18-month AASR: .026). Figure 2.6 presents the parameter estimates across time points for the Decisional Balance Inventory.

Insert Figure 2.6 about here

Discussion

Multiple sample analysis utilizing constraints or certain levels of invariance provides an opportunity to examine the performance of measurement models in our samples of interest. Tests of invariance using EQS provide insight concerning the areas in which our models may not be measuring or confirms that we are measuring the same construct across samples.

The present study was designed to examine measurement models for the Decisional Balance Scale across samples (Gender: Male, Female; Education Level: Grade School, High School, College, Graduate School; Race: White, Black; Age: 18-25, 26-35, 36-50, 50 and above). Pattern Identity invariance was postulated across samples. Analysis of the models, fit estimates, and parameters support this level for the Decisional Balance measure and actually provides evidence for a high level of invariance (specifically Strong Factorial Invariance).

In Structural Equation Modeling (SEM), a chi-square test is employed to assess the model's overall fit (Bentler, 1989). A significant chi-square indicates that the model is significantly different than the data. In short, when using SEM, one wants a non-significant chi-square indicating that the model fits the data well. In the event that the data provides many cases or participants (i.e. a couple hundred cases), SEM will indicate that the model does not fit the data well even when this is not the case. In essence, the large sample size has made the model extremely powerful. In this case, to assess model fit, one must examine the alternative overall fit indices (CFI, NFI, & NNFI) while also exploring the micro fit indices or the parameter fit indices (AASR, parameter estimates, & parameter reliabilities).

In the current study, power was calculated for the measurement models at the various levels of invariance (using RMSEA and the MacCullum et al. 1996 SAS program). With few exceptions, the power of the models was

determined to be .99 or above indicating that these measurement models were very sensitive. Power for each model is reported in Table 2.3.

Analyses illustrate a consistent pattern for the relationships among the factor Pros and Cons of smoking and the Pro and Con items. For the confirmatory factor analysis (CFA) multi sample analysis of the scale, strong factorial invariance was achieved for the sample comparisons and across time comparisons.

Gender. For the male/female comparison the overall fits indices (CFI, NFI, NNFI) indicate that the model fits well even all the most constrained level. The AASRs indicate that the model fits well in both groups individually even with this high level of constraint.

Education Level. Concerning the comparison between participants who had an eighth grade education or less (grade school), who had some high school education (high school), who indicated having some education beyond high school (college), and who reported education beyond 4 years of college (graduate school), the highest level of invariance was achieved. The overall fit indices indicate that the model fits well. The AASRs information regarding the different sample sizes for each group. The grade school ($N = 109$) population has an AASR of .10 and the graduate school sample ($N = 223$) has an AASR of .067 which are both above the .06 cutoff for good model fit. This difference indicates that for the grade school and graduate school samples were not as

strongly represented as the high school and college samples, which had greater sample sizes.

Race. For the white and black samples, the overall model fit indices reveal that strong factorial invariance was achieved. While the CFIs, NFIs, and NNFI provide information regarding the overall fit, the AASRs provide insight about the models' fit for each sample. Among the participants' who reported being black (N = 105), the model did not achieve the desired AASR level (AASR = .082). As mentioned in the educational CFA multi sample analyses, a non-fitting AASR highlights the largely different sample sizes used for this comparison (white, N = 3959 and Black, N = 105).

Age. For the comparison between age groups (18-25, 26-35, 36-50, and 50+), strong factorial invariance was achieved. The overall fit indices indicate that the model fits well at the most constrained level. The micro fit indices indicate that at the strong factorial invariance level the model fits well across different age groups.

Across Time: After achieving invariance across samples, the measurement model was tested across time points. This analysis revealed that the measurement model continued to hold at the highest level of invariance across time points. The achievement of strong factorial invariance supports the use of the Decisional Balance Inventory in longitudinal studies.

Conclusions: The Decisional Balance Scale holds extremely well across samples. The measurement model held up across the strictest form of

invariance. It appears that this scale can be applied across a variety of age groups, education levels, and with males and females.

The present study provides evidence supporting the use of the TTM's Decisional Balance Inventory across samples in longitudinal studies. Future research may want to examine the Decisional Balance scales across smoking intervention studies. Research in this area would confirm the present studies results and provide further evidence into the utilization of the scale.

Additional research may wish to examine a more ethnically diverse sample of participants. The current study was limited to individuals who identified themselves as white or black due to sample size. Researchers seeking to establish the validity of the measure may also examine the scale across behaviors to determine if the same measurement model exists.

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Table 2.1

Characteristics of the sample

Variable	COUNTIES			Total Sample
	Kent	Washington /Newport	Providence / Bristol	
SAMPLE SIZE	1418 (34.2%)	1299 (31.3%)	1427 (34.4%)	4144
MEAN AGE	40.6	40.5	40.9	40.7
GENDER				
Males	626 (44.1%)	612 (47.1%)	598 (41.8%)	1836 (44.3%)
Females	792 (55.9%)	686 (52.9%)	830 (58.2%)	2308 (55.7%)
EDUCATION				
Mean Grade Level	12.7	13.0	12.5	12.7
Median Grade Level	12.0	12.0	12.0	12.0
ETHNICITY				
White	1393 (98.4%)	1243 (95.8%)	1323 (92.7%)	3959 (95.7%)
Black	9 (0.6%)	28 (2.2%)	68 (4.8%)	105 (2.5%)
Asian	4 (0.3%)	7 (0.5%)	5 (0.4%)	16 (0.4%)
Other	9 (0.6%)	19 (1.5%)	31 (2.2%)	59 (1.4%)
HOUSEHOLD INCOME				
Median	\$30-\$40K	\$30-\$40K	\$30-\$40K	\$30-\$40K

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Other	9 (0.6%)	19 (1.5%)	31 (2.2%)	59 (1.4%)
HOUSEHOLD INCOME				
Median	\$30-\$40K	\$30-\$40K	\$30-\$40K	\$30-\$40K

EMPLOYED	1035	908	986	2929
Yes	(73.0%)	(69.9%)	(69.1%)	(70.7%)
MARITAL STATUS				
Married & Living	798	684	734	2216
With Spouse	(56.3%)	(52.8%)	(51.5%)	(53.5%)
Living With Partner	57	70	79	206
	(4.0%)	(5.4%)	(5.5%)	(5.0%)
Never Married	206	235	262	703
	(14.5%)	(18.1%)	(18.4%)	(17.0%)
Divorced	229	191	209	629
	(16.2%)	(14.7%)	(14.7%)	(15.2%)
Separated	46	44	45	135
	(3.2%)	(3.4%)	(3.2%)	(3.3%)
Widowed	75	63	89	227
	(5.3%)	(4.9%)	(6.2%)	(5.5%)
Other	6	9	8	23
	(0.4%)	(0.7%)	(0.6%)	(0.6%)

Table 2.2
Reliabilities for the decisional balance scales by sub population

Scale	Subgroup	Category	Cronbach's Alpha	Scale Mean	Scale SD
Pros	Total Sample		.61	7.34	2.86
	Gender	Male	.62	7.00	2.87
		Female	.60	7.61	2.86
	Education	Grade School	.67	7.63	3.10
		High School	.63	7.41	2.89
		College	.59	7.22	2.75
		Graduate School	.60	7.25	3.00
	Race	White	.61	7.35	2.84
		Black	.66	7.19	3.25
	Age	18-25	.56	7.11	2.54
		26-35	.60	7.01	2.75
		36-50	.62	7.53	2.94
		Above 50	.63	7.59	3.00
Cons	Total Sample		.59	8.86	3.05
	Gender	Male	.57	8.36	2.99
		Female	.60	9.26	3.05
	Education	Grade School	.51	8.43	3.05
		High School	.61	8.76	3.09
		College	.59	9.04	3.01
		Graduate School	.53	8.97	2.89
	Race	White	.60	8.88	3.06
		Black	.52	9.01	3.00
	Age	18-25	.56	8.27	2.89
		26-35	.61	8.94	3.02
		36-50	.58	9.03	3.03
		Above 50	.56	8.85	3.10

Table 2.3

Strong factorial invariance for the decisional balance scale across samples

	N	χ^2	CFI	NFI	NNFI	AASR	RMSEA	χ^2/DF	χ^2 diff. test	Power
Gender		156.568	.953	.943	.951		.033	5.40	43.99/7/***	>.99
Male	1836					.037				
Female	2308					.033				
Education		187.225	.959	.935	.965		.020	2.64	32.29/21/ NS	>.99
Grade	109					.10				
School										
High School	2348					.023				
College	1315					.035				
Graduate	223					.067				
Race		114.379	.969	.959	.968		.027	3.94	10.87/7/ NS	>.99
White	3959					.019				
Black	105					.082				
Age		223.973	.944	.920	.953		.023	3.15	60.60/21/***	>.99
18-25	598					.083				
26-34	1061					.042				
35-50	1440					.031				
Above 50	1039					.051				
Across Time		495.251	.960	.954	.961		.027	7.99	155.50/12/***	>.99
Baseline	2351					.077				
6-month	2351					.029				
12-month	2351					.029				
18-month	2351					.049				

CFI=Comparative Fit Index, Bentler, (1990); NFI=Normed Fit Index, Bentler-Bonnet (1980); NNFI=Non Normed Fit Index, Tucker-Lewis (1973); AASR= Average Absolute Standardized Residual; RMSEA=Root Mean Squared Error of Approximation, Steiger & Lind (1980).

Figure 2.1 A Model of the Decisional Balance Inventory

Figure 2.2 Strong Factorial Invariance Model for Gender (Males, N = 1836 and Females, N = 2308).

Note: * $p < .05$, ** $p < .001$, *** $p < .001$, NS non-significant

Figure 2.3 Strong Factorial Invariance Model for Education
(Grade School, N = 109, High School, N = 2348, College, N = 1315, and Graduate School, N = 223).

Note: * p<.05, ** p<.001, *** p<.001, NS non-significant

Figure 2.4 Strong Factorial Invariance Model for Race (White, N = 3959, and Black, N = 105).

Note: * $p < .05$, ** $p < .001$, *** $p < .001$, NS non-significant

Figure 2.5 Strong Factorial Invariance Model for Age
(18 - 25, N = 598, 26 - 35, N = 1061, 36 - 50, N = 1440, and 50+, N = 1039).

Note: * p<.05, ** p<.001, *** p<.001, NS non-significant

Figure 2.6 A Conceptual Model of the Decisional Balance Across Time

Figure 2.7 Strong Factorial Invariance Model for Across Time Points
(Baseline, 6-Months, 12-Months, and 18-Months N = 2351).

Note: * $p < .05$, ** $p < .001$, *** $p < .001$, NS non-significant

Chapter 3:

The Factorial Invariance of the Short Form of the Processes of Change Inventory

The Transtheoretical Model (TTM; Prochaska & DiClemente, 1983, Prochaska & Velicer, 1997; Velicer, Prochaska, Fava, Norman, & Redding, 1998) is a comprehensive model of behavior change that has been validated in numerous studies and applied to numerous behaviors (Prochaska et al., 1994) including addictive behaviors such as alcohol use and quitting cocaine; adoption behaviors such as safer sex, exercise, and sunscreen use; and dietary behaviors such as dietary fat reduction and fruit and vegetable consumption. Smoking cessation is the behavior that served as the initial basis for many of the innovations. It is the behavior on which the primary constructs of the model were developed and where the greatest empirical support exists. The current study examines the invariance of the Processes of Change Inventory, a widely used measure of one of the key group of constructs of the Transtheoretical Model, applied to this area of study.

Transtheoretical Model

The Transtheoretical Model is a model of intentional behavior change that focuses on the decision making of the individual. The Transtheoretical Model also involves a series of intermediate/outcome measures. These constructs include the Pros and Cons from the Decisional Balance Scale, Self-efficacy or Temptation, the Processes of Change, and the target behavior. A

more detailed presentation of this aspect of the model is provided elsewhere (Prochaska & Velicer, 1997; Velicer, Prochaska, Fava, Rossi, Redding, Laforge, & Robbins, 2000; Velicer, Rossi, Prochaska, & DiClemente, 1996).

Measurement issues are central to applying a theoretical model to any problem. Assessing the constructs of the Transtheoretical Model involves a reliance on self-report. In smoking area, self-report has been demonstrated to be very accurate under most circumstances (Velicer, Prochaska, Rossi, & Snow 1992). Accurate measurement requires a series of unambiguous items that the individual can respond to accurately with little opportunity for distortion. One of the critical steps for the application of the model involves the development of short, reliable, and valid measures of the key constructs. This paper will focus on one of these key constructs, the Processes of Change Inventory.

Describing the Process of Change Inventory

The Processes of Change as (Prochaska & DiClemente, 1983; Prochaska & DiClemente, 1992; Prochaska, Velicer, DiClemente, & Fava, 1988) are covert and overt activities that individuals use to progress through the stages of behavior change. The Processes of Change inventory measures five experiential and five behavioral activities.

Consciousness Raising (CR) is the process, which involves being primed for information. Individuals using this process become aware of new facts, ideas, and tips, which provide support for their behavioral change. Individuals who are in the earlier stages of change primarily use this process.

Dramatic Relief (DR) involves experiencing increased emotional responses accompanied by reduced affect. Individuals using this process are effected by the media, ad campaigns, personal testimonies, and role-playing.

Self-Reevaluation (SR) is akin to image evaluation. Individuals endorsing this process assess their identity in respect to the behavior change.

Environmental Reevaluation (ER) is similar to social impact. The individual using this process evaluates the impact of their behavior change on his or her proximal social and physical environment.

Self-liberation (SEL) is making a commitment to change. Many individuals use this process around the New Year.

Helping Relationships (HR) involves building an alliance with others. This support network allows for encouragement, rapport building, and social support for the behavioral change.

Counterconditioning (CC) includes the process of learning how to substitute. Individuals endorsing this process substitute healthier behaviors or cognitions to counter the behavior that they are attempting to change.

Reinforcement Management (RM) is the process of rewards and punishments. The individual employs rewards for the healthy behavior and attempts to decrease the rewards for the unhealthy behavior.

Stimulus Control (SC) is a process that individuals in the later stages of change use. This process involves restructuring one's environment to promote

behavior change and adding cues or reminders to avoid problem behavior. For example, smokers using this process will throw out all of their cigarettes.

Social Liberation (SOL) is realizing that society is making changes to support the behavior change. For example, individuals involved in smoking cessation may notice how many restaurants and public arenas are banning smoking.

The relationship between stages and process is not linear. In Precontemplation, process use is at its lowest. While an individual is in the decision making stages (preparation and action), the process use is at a maximum. As the individual progresses through the stage (into maintenance), process use diminishes. Typically, processes known as the experiential processes (Consciousness Raising, Dramatic Relief, Environmental Reevaluation, Social Liberation, and Self-Reevaluation) are used more in the earlier stages. The processes known as the behavioral process (Stimulus Control, Helping Relationships, Counterconditioning, Reinforcement Management, and Self Liberation) tend to peak later in their use as compared to the experiential processes (Velicer, Prochaska, Fava, Norman, & Redding, 1998).

Levels of Invariance

Factor invariance is a concept developed by Thurstone (1947). Through time, factor invariance has come to mean comparing a simple structure across samples (Meredith, 1964a) to determine if the structure remains invariant.

The current study examined four levels of invariance. The first and weakest level is *Configural Invariance*. This represents a minimum requirement for invariance. It requires that all the latent constructs have their primary non-zero loading on the same construct across groups or time occasions. It also requires that the constructs have equivalent zero loadings on constructs across groups or time occasions (Horn, McArdle, Mason, 1983; Meredith, 1964a, 1964b). The second level of invariance is *Weak Factorial Invariance*. This requires that the primary loading be on the same marker and magnitude of the loadings must be proportional. The third level of invariance is *Pattern Identity Invariance*. This requires that all the factor loadings be equal except for sampling fluctuations (Horn, 1991). The fourth case is *Strong Factorial Invariance*. This requires the covariance matrices to be equal. All other types of invariance can be applied to a set of standardized variables. This is the most restrictive type of invariance (Meredith, 1993).

The Present Study

Fava, Velicer, and Prochaska (1995) gathered data from a representative sample of smokers. The sample was recruited during the fall of 1990 to the spring of 1991. Participants provided information about their smoking habits in relation to items of the Transtheoretical Model. The study gathered information about the individuals' stage of change and process of change. The data was collected at 4 time points (baseline, 6 month, 12 month, and 18 month). This study examined the level factorial invariance of the Processes of Change scales.

Factorial invariance was assessed across four sets of demographic variables: (1) gender, (2) education, (3) race, and (4) age, employing the baseline assessment data. If the structure was demonstrated to be invariant across subgroups, the invariance across the four assessments was investigated.

The current study hypothesized that the Processes of Change Inventory will achieve a high level of invariance. Studies such as Prochaska, Velicer, DiClemente, and Fava (1988) have noted the scale's stability and reliability. Due to the stable nature of the scale, pattern identity invariance is hypothesized.

Method

Participants

This study involved a secondary data analysis of data gathered for a smoking cessation study. All non-institutionalized adults between the ages of 18 and 75 years living in the state of Rhode Island were eligible for the study. Participants were identified by telephone using an adaptation of the two step Mitofsky-Waksberg random-digit-dialing (RDD) method (Waksberg, 1978). The first step in this method is to randomly generate four digit suffixes and assign them to three digit telephone exchanges. All 88 Rhode Island telephone exchanges were used in this step. These primary numbers were screened to ensure that they were residential numbers. In the second step, a random two-digit suffix was added to each prefix bank to create a secondary RDD.

Residences were screened to determine if an adult between the ages of 18 and 75 who regularly smoked resided there. If a household contained more than one eligible smoker, the individual who most recently celebrated their birthday was recruited for the study (Salmon & Nichols, 1983).

A total of 32,456 calls were made using random digit dialing procedures from steps one and two. Telephone interviews were conducted with 12,109 of the 14,266 (84.9%) eligible adults, and over 35% of the interviews were conducted with self-identified smokers. Contact information was received from 96.5% of the interviewed smokers. For a detailed description of this recruitment procedure, refer to Fava et al. (1995).

Sample characteristics

Once the initial interviews were completed, an initial sample of 4,144 smokers was randomized to one of two treatment conditions. The mean age was 40.7 years. There were 44.3% males (N = 1836) and 55.7% females (N = 2308); the sample was 95.7% white (N = 3959), with a median income of thirty to forty thousand dollars. Approximately 70 percent were employed and 53.5% were married. All participants were smokers with an average of 20.6 cigarettes per day. Table 3.1 presents the characteristics of the sample.

Insert Table 3.1 Here

Measure and Measurement Variables

Demographic Variables. For the first analysis, the sample was subdivided into two gender categories (Male; N = 1836 and Female; N = 2308). Sample size was adequate in both subgroups. For the second analysis, the sample was divided into four levels of education (Grade School; N = 109, High School; N = 2348, College; N = 1464, and Graduate School; N = 223). Sample size was adequate in all four subgroups. For the third analysis, the sample was divided into four race categories (White; N= 3959, Black; N = 105, Asian; N = 16, and Other; N = 59). Sample size was adequate in only the White and Black subgroups. For the fourth analysis, the sample was divided into four age categories (18-25; N = 598, 26-35; N = 1061, 36-50; N = 1440, and 50+; N = 1039). Sample size was adequate in all four subgroups.

Processes of Change. The Processes of Change inventory is comprised of five experiential and five behavioral subscales that measure the frequency of various strategies (Prochaska et al., 1988) smokers characteristically utilize when attempting to change their smoking behavior. The experiential processes include the following: Consciousness Raising, Environmental Reevaluation, Self-Reevaluation, Social Liberation, and Dramatic Relief. Helping Relationships, Self-Liberation, Counterconditioning, Reinforcement Management, and Stimulus Control comprise the behavioral processes. Fava et al. (1995) utilized the 20-item short form of this inventory. Cronbach's Coefficient Alpha was calculated for the 10 subscales. Table 3.2 presents the

Alpha, mean, and standard deviation for each sub-scale in the total sample and in each subgroup. Coefficient Alpha was determined to be between .24 and .85 for the Process of Change Inventory subscales. Figure 3.1 depicts the hypothesized hierarchical model of the Processes of Change Inventory.

Insert Table 3.2 and Figure 3.1 Here

Results

The factorial invariance of the Processes of Change scale was examined across four demographic variables, (gender, education, race, and age), and across time (baseline, 6-month, 12-month, and 18-month). Structural Equation Modeling (SEM) was used to test items for factorial invariance using the EQS program (Bentler, 1989).

Across Samples

Step One: The hypothesized structural equation model was fit to the whole sample to examine the relation between the 20 observed variables and the ten primary factors and between the 10 primary factors and the two second order factors. This process utilized the baseline data.

Step Two: The sample was partitioned into groups based on the four demographic variables and structural equation modeling was employed to test the invariance of the structure across subgroups.

The model was tested on four levels. The first and most restrictive model fit was the strong factorial invariance model. In this case, all of the parameters constrained to be equal. If this model fit, the procedure was terminated. The second model fit required the factor loadings to be equal (pattern identity invariance). If this model fit, the procedure was terminated. The third model tested was the weak factorial invariance model. If this model fit, the procedure was terminated. The fourth model tested had no restrictions. This is the congeneric or configural model.

All analyses were run only subgroups that had at least 100 participants. If fewer were available, that subgroup was then eliminated. Structural equation modeling requires large numbers of cases in order for the model to converge. A minimum of one hundred has been suggested by multiple sources for evaluating measurement models (Boomsma, 1982; Gerbing & Anderson, 1983; Guadagnoli & Velicer, 1988; Velicer & Fava, 1998).

Step Three: After determining the level of invariance (configural, weak, pattern identity, or strong), the level of invariance was tested across time. If invariance was not present across the subgroups, invariance across time was not assessed.

SEM Fitting

SEM was implemented utilizing the EQS (Bentler, 1989) computer program. SEM examines the variances and covariances of the data to determine the fit of the model. The best fitting model should excel in three aspects of fit:

(1) Theoretical consistency; (2) Empirical evidence; and (3) Parsimony (Harlow and Rose, 1994). The first aspect, theoretical consistency implies that the model has a good basis in theory. Several criteria have been suggested in the literature to evaluate empirical evidence. In this study, the following indices were employed: (a) the chi-square to degrees of freedom ratio, the Comparative Fit Index (CFI: Bentler, 1990); (b) the Normed Fit Index (NFI: Bentler- Bonett, 1980); (c) the Non-Normed Fit Index (NNFI: Tucker & Lewis, 1973); (d) the average absolute standardized residuals value (AASR); (e) root mean square error of approximation (RMSEA: Steiger & Lind, 1980); (f) the significance of individual parameters (e. g., factor loadings between latent constructs and indicators); and (g) the amount of explained variance (R^2). Empirical fit was evaluated by determining if the model falls within the following ranges for the indices: a chi square to degrees of freedom ratio of less than 5.0, a CFI, NFI, and NNFI greater than .90, the AASR and RMSEA less than .06, the measured parameters significant, and a vast amount of explained variance (Harlow & Rose, 1994; Hoyle & Panter, 1995). Parsimony requires that the model that fits the data best have the fewest parameters.

Measurement Model in the Total Sample

While Figure 3.1 presents the hierarchical model for the Processes of Change Inventory, Figure 3.2 presents the fully correlated model. While the first model represents the theoretical model for the scale, the second model presents the testable measurement model. The second model was chosen due

to its applicability in intervention studies. It is more common for studies to provided intervention utilizing the subscale scores for each participant (Velicer et al., 1993). The model depicted in Figure 3.2 was utilized for the following model comparisons.

Insert Figure 3.2 here

Gender.

Sample size was adequate in both subgroups (Male; N = 1836 and Female; N = 2308). The highest level of invariance, Strong Factorial Invariance, provided a good fit to the model. Table 3.3 presents the sample size, overall chi-square value, overall CFI, NFI, and NNFI values, AASR for each subgroup, RMSEA for the overall comparison, the chi-square to degrees of freedom ratio, the chi-square difference test, and the power for the model comparison. Power was calculated using the overall RMSEA (MacCallum, Browne, & Sugawara, 1996).

Insert Table 3.3 about here

The overall fit indices indicate that this model fits (CFI: .955; NFI: .943; NNFI: .949). The chi-square to degrees of freedom ratio is 4.39. The micro fit indices indicate that the model fits well across groups (Male AASR: .037;

Female AASR: .028). Figure 3.3 presents the parameter estimates for gender for the Processes of Change inventory. Table 3.4 presents the correlation matrix for the relationships between the factors.

Insert Figure 3.3 and Table 3.4 about here

Education.

Sample size was adequate in all four subgroups (Grade School; N = 109, High School; N = 2348, College; N = 1315, and Graduate School; N = 223). The highest level of invariance, Strong Factorial Invariance, provided a good fit to the model. Table 3.3 presents the sample size, overall chi-square value, overall CFI, NFI, and NNFI values, AASR for each subgroup, RMSEA for the overall comparison, the chi-square to degrees of freedom ratio, the chi-square difference test, and the power for the model comparison. Power was calculated using the overall RMSEA (MacCallum, Browne, & Sugawara, 1996).

The overall fit indices indicate that this model fits (CFI: .958; NFI: .931; NNFI: .958). The micro fit indices indicate that the model fits well across groups (Grade School AASR: .109; High School AASR: .026; College AASR: .039; Graduate School AASR: .075). Figure 3.4 presents the parameter estimates for gender for the Processes of Change Inventory. Table 3.5 provides the correlation matrix for the relationship between the factors.

Insert Figure 3.4 and Table 3.5 about here

Race.

Sample size was adequate in only the White and Black subgroups (White; N= 3959 and Black; N = 105). The highest level of invariance, Strong Factorial Invariance, provided a good fit to the model. Table 3.3 presents the sample size, overall chi-square value, overall CFI, NFI, and NNFI values, AASR for each subgroup, RMSEA for the overall comparison, the chi-square to degrees of freedom ratio, the chi-square difference test, and the power for the model comparison. Power was calculated using the overall RMSEA (MacCallum, Browne, & Sugawara, 1996).

The overall fit indices indicate that this model fits (CFI: .964; NFI: .933; NNFI: .960). The micro fit indices indicate that the model fits well across groups (White AASR: .018; Black AASR: .089). Figure 3.5 presents the parameter estimates for race for the Processes of Change Inventory and Table 3.6 provides the correlation matrix for the relationships between subscales.

Insert Figure 3.5 and Table 3.6 about here

Age

Sample size was adequate in all four subgroups (18 - 25; N = 598, 26 - 35; N = 1061, 36 - 50; N = 1440, and above 50; N = 1039). The highest level of invariance, Strong Factorial Invariance, provided a good fit to the model. Table 3.3 presents the sample size, overall chi-square value, overall CFI, NFI, and NNFI values, AASR for each subgroup, RMSEA for the overall comparison, the chi-square to degrees of freedom ratio, the chi-square difference test, and the power for the model comparison. Power was calculated using the overall RMSEA (MacCallum, Browne, & Sugawara, 1996).

The overall fit indices indicate that this model fits (CFI: .960; NFI: .933; NNFI: .960). The micro fit indices indicate that the model fits well across groups (18 - 25 AASR: .043; 26 - 35 AASR: .029; 36 - 50 AASR: .025; 50+ AASR: .039). Figure 3.6 presents the parameter estimates for age for the Processes of Change Inventory and Table 3.7 provides the correlation matrix for the relationships between subscales.

Insert Figure 3.6 and Table 3.7 about here

Across Time Points.

Since factorial invariance was established across the subgroups, the model was assessed across time points. The model was fit across occasions. The highest level of invariance, Strong Factorial Invariance, provided a good fit

to the model. Table 3.3 presents the sample size, overall chi-square value, overall CFI, NFI, and NNFI values, AASR for each subgroup, RMSEA for the overall comparison, the chi-square to degrees of freedom ratio, the chi-square difference test, and the power for the model comparison. Power was calculated using the overall RMSEA (MacCallum, Browne, & Sugawara, 1996). The model used for the across time comparisons mimics the structural model used for the aforementioned across group comparisons. It restricts the whole population at every time point to the same model.

The overall fit indices indicate that this model fits (CFI: .955; NFI: .948; NNFI: .954). The micro fit indices indicate that the model fits well across groups (Baseline AASR: .033; 6-month AASR .027; 12-month AASR .026; 18-month AASR .037). Figure 3.7 presents the parameter estimates for the across time comparison for the Processes of Change Inventory, and Table 3.8 provides the correlation matrix for the subscales.

Insert Figure 3.7 and Table 3.8 about here

Discussion

Analyses illustrate a consistent pattern for the relationships among the Processes of Change sub scales (Helping Relationships, Consciousness Raising, Self Reevaluation, Environment Reevaluation, Stimulus Control, Social

Liberation, Counter Conditioning, Self Liberation, Reinforcement Management, and Dramatic Relief) and the subscale items. For the confirmatory factor analysis (CFA) multi-sample analysis of the inventory, strong factorial invariance was achieved for all sample comparisons. The results of the study confirm previous research (Bellis & Rossi, 1990).

As mentioned earlier, the chi-square test may be inappropriate to review these models due to the large sample size. Power analysis of the models indicates a high level of sensitivity therefore making it almost impossible to get a non-significant chi-square. Due to the sensitivity of the models, alternative fit indices will be emphasized.

The chi-square to degrees of freedom ratio is also difficult to interpret with large sample sizes. It is difficult to evaluate with a highly specified model and a large sample. Alternative fit indices were included in conjunction with this evaluation of fit. The chi-square to degrees of freedom ratios can be found in Table 3.3.

Gender. The overall fit indices indicate that the model fits well at the most restrictive level across the samples of males and females. The micro fit indices confirm the overall fit indices (AASRs .037 and .028 for males and females respectively).

Education. After examining the overall fit indices (CFI, NFI, NNFI) and the chi-square difference test, it appears that the model fits the data well. The grade school and graduate school samples failed to meet the AASR .06

requirement for a good fitting model (.109 and .075 respectively). This reflects their relatively small sample sizes. The AASR statistic reflects the residuals standardized over sample size. The smaller sample sizes were not able to compete with the other larger sample (specifically the college and high school samples). The smaller samples could not perform as well as the larger samples which accounted for more variance.

Race. The macro fit indices (CFI, NFI, NNFI) indicate that the model fits well across groups at the most stringent level of invariance. The micro fit index (AASR) also reveals that the black sample did not fit at the desired level (.089). This slip in fit can be accounted, again by the great difference in sample sizes (White = 3959 and Black = 105). The chi-square difference test indicates that the strong factorial model is significantly different than the pattern identity model ($p < .001$).

Age. Comparisons among the different age groups provided a good overall fit for the measurement model. The CFIs, NFIs, and NNFIs were all in the .90s. The AASRs indicate the model fit well in all groups.

Across Groups. A high level of invariance was achieved for across samples and groups for the Process of Change Inventory. A pattern identity factorial invariance was postulated while strong factorial invariance was achieved. These results suggest that the Process of Change inventory can be utilized across populations with little concern about question reliabilities. All parameters were significant at the $p < .001$ level.

Across Time Points

A comparison of the scales across time provides a look at the measurement models across four time points. The measurement models for the process of change inventory held across time at the most constrained level of invariance. It is hypothesized that a longitudinal model incorporating the participant's stage may account for more of the variance and model the data slightly better.

Conclusions. The results of the Process of Change Inventory mimic those found in the Decisional Balance Scale. As mentioned above, the scale held up well for each individual time point as shown by significant and reliable parameters, and preformed equally well across time. As mentioned in the previous section, model which incorporate the Stage of Change of the participants might be able to model the relationship across time better. The methods of longitudinal model and cross-lagged panel designs might also provide further insights concerning the Processes of Change Inventory across time.

It is possible to conclude that for high levels of invariance, the measurement models hold true across samples for the Processes of Change Inventories.

It is a premise of the TTM that people use different processes of change, have differing levels of temptation, and have differing levels of Pros and Cons depending on stage. These scales are stage dependent. Until a structural

equation model is available which incorporates all aspects of the TTM, it will be difficult to explore these concepts across time.

The current study confirms that the Processes of Change Inventory incorporates solid, reliable scales and can be applied to different levels of education, age, with male and female populations, and across many time points. Further research should examine the scales across a more ethnically diverse population. For the ease of model convergence, samples of 100 or more were used. Sufficient samples were not available for racial categories beyond white and black. Even with over a hundred participants in the black category, the results cannot be completely trusted when they are being compared to over 3900 white individuals. Future research may want to take a random sample of individuals from the white sample and compare them to the other ethnic samples.

Another direction that future research can take is examining the Processes of Change Inventory with respect to Stage of Change. If Stage is covaried out of the model, the measurement model may perform better across samples. By incorporating stage into the analysis, extreme scores may not be such a problem. Stage might account for the differential use of processes across time.

To confirm the reliability and applicability of these scales, future research may want to examine the measurement models from this smoking sample to other behaviors in which the TTM has been applied. For example,

one might examine the Processes of Change measurement model for exercise or a measurement model for alcohol use across groups and time points.

In summary, researchers using the Processes of Change Inventory should be confident that they measure works well in a population of smokers. Future extensions of this research could examine the same concepts across other samples of smokers and across other behavior change interventions.

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Table 3.1

Characteristics of the sample

Variable	COUNTIES			Total Sample
	Kent	Washington /Newport	Providence / Bristol	
SAMPLE SIZE	1418 (34.2%)	1299 (31.3%)	1427 (34.4%)	4144
MEAN AGE	40.6	40.5	40.9	40.7
GENDER				
Males	626 (44.1%)	612 (47.1%)	598 (41.8%)	1836 (44.3%)
Females	792 (55.9%)	686 (52.9%)	830 (58.2%)	2308 (55.7%)
EDUCATION				
Mean Grade Level	12.7	13.0	12.5	12.7
Median Grade Level	12.0	12.0	12.0	12.0
ETHNICITY				
White	1393 (98.4%)	1243 (95.8%)	1323 (92.7%)	3959 (95.7%)
Black	9 (0.6%)	28 (2.2%)	68 (4.8%)	105 (2.5%)
Asian	4 (0.3%)	7 (0.5%)	5 (0.4%)	16 (0.4%)
Other	9 (0.6%)	19 (1.5%)	31 (2.2%)	59 (1.4%)
HOUSEHOLD INCOME				
Median	\$30-\$40K	\$30-\$40K	\$30-\$40K	\$30-\$40K

EMPLOYED Yes	1035 (73.0%)	908 (69.9%)	986 (69.1%)	2929 (70.7%)
MARITAL STATUS				
Married & Living With Spouse	798 (56.3%)	684 (52.8%)	734 (51.5%)	2216 (53.5%)
Living With Partner	57 (4.0%)	70 (5.4%)	79 (5.5%)	206 (5.0%)
Never Married	206 (14.5%)	235 (18.1%)	262 (18.4%)	703 (17.0%)
Divorced	229 (16.2%)	191 (14.7%)	209 (14.7%)	629 (15.2%)
Separated	46 (3.2%)	44 (3.4%)	45 (3.2%)	135 (3.3%)
Widowed	75 (5.3%)	63 (4.9%)	89 (6.2%)	227 (5.5%)
Other	6 (0.4%)	9 (0.7%)	8 (0.6%)	23 (0.6%)

Table 3.2

Reliabilities for the processes of change scales by sub population

Scale	Subgroup	Category	Cronbach's Alpha	Scale Mean	Scale SD
Con. Rais.	Total Sample		.49	5.71	2.12
	Gender	Male	.48	5.47	2.11
		Female	.48	5.89	2.12
	Education	Grade School	.45	5.33	2.15
		High School	.47	5.61	2.14
		College	.50	5.89	2.09
		Graduate School	.60	5.76	2.15
	Race	White	.49	5.71	2.12
		Black	.51	5.68	2.29
	Age	18-25	.46	5.40	2.08
		26-35	.50	5.71	2.16
		36-50	.50	5.83	2.10
		Above 50	.46	5.68	2.15
Dram Rel.	Total Sample		.72	5.03	2.30
	Gender	Male	.68	4.62	2.21
		Female	.73	5.35	2.32
	Education	Grade School	.69	5.14	2.65
		High School	.70	4.97	2.30
		College	.74	5.12	2.29
		Graduate School	.73	4.99	2.14
	Race	White	.72	5.03	2.30
		Black	.61	5.37	2.23
	Age	18-25	.74	4.67	2.21
		26-35	.74	5.06	2.27
		36-50	.72	5.14	2.26
		Above 50	.66	4.98	2.37

Table 3.2 continued.

Self Reev.	Total Sample		.79	5.64	2.63
	Gender	Male	.77	5.30	2.57
		Female	.80	5.91	2.65
	Education	Grade School	.81	5.46	2.89
		High School	.79	5.50	2.67
		College	.79	5.85	2.56
		Graduate School	.79	5.83	2.46
	Race	White	.79	5.65	2.63
		Black	.74	5.81	2.61
	Age	18-25	.73	5.11	2.46
		26-35	.79	5.73	2.60
		36-50	.79	5.82	2.62
		Above 50	.80	5.59	2.75
Env. Reev.	Total Sample		.83	5.36	2.56
	Gender	Male	.81	4.72	2.48
		Female	.83	5.86	2.51
	Education	Grade School	.83	5.16	2.75
		High School	.83	5.44	2.59
		College	.83	5.28	2.51
		Graduate School	.84	5.00	2.40
	Race	White	.83	5.33	2.55
		Black	.67	6.12	2.43
	Age	18-25	.84	5.39	2.54
		26-35	.83	5.40	2.54
		36-50	.82	5.25	2.52
		Above 50	.84	5.40	2.65

Table 3.2 continued.

Self Lib.	Total Sample		.72	5.84	2.47
	Gender	Male	.70	5.77	2.45
		Female	.73	5.91	2.48
	Education	Grade School	.68	5.81	2.63
		High School	.72	5.82	2.49
		College	.72	5.88	2.43
		Graduate School	.67	5.87	2.43
	Race	White	.72	5.84	2.46
		Black	.72	6.06	2.55
	Age	18-25	.67	6.21	2.40
		26-35	.72	5.99	2.45
		36-50	.70	5.66	2.40
		Above 50	.73	5.68	2.57
Help. Rel.	Total Sample		.77	4.81	2.63
	Gender	Male	.77	4.67	2.58
		Female	.78	4.93	2.67
	Education	Grade School	.75	4.39	2.59
		High School	.78	4.77	2.66
		College	.76	4.93	2.61
		Graduate School	.74	4.71	2.53
	Race	White	.77	4.83	2.63
		Black	.66	4.44	2.46
	Age	18-25	.80	5.54	2.71
		26-35	.79	5.05	2.64
		36-50	.76	4.70	2.58
		Above 50	.74	4.26	2.49

Table 3.2 continued.

Coun. Cond.	Total Sample		.40	4.47	1.88
	Gender	Male	.34	4.32	1.82
		Female	.44	4.58	1.92
	Education	Grade School	.24	4.14	1.87
		High School	.39	4.41	1.90
		College	.44	4.56	1.85
		Graduate School	.34	4.54	1.88
	Race	White	.40	4.46	1.88
		Black	.31	4.32	1.91
	Age	18-25	.30	4.61	1.77
		26-35	.40	4.62	1.86
		36-50	.38	4.38	1.86
		Above 50	.40	4.23	1.94
Reinf. Mgt.	Total Sample		.76	3.89	2.32
	Gender	Male	.72	3.62	2.14
		Female	.78	4.11	2.44
	Education	Grade School	.82	4.45	2.86
		High School	.75	3.94	2.37
		College	.78	3.80	2.22
		Graduate School	.73	3.73	2.13
	Race	White	.76	3.89	2.31
		Black	.76	4.46	2.69
	Age	18-25	.81	4.34	2.46
		26-35	.76	4.03	2.36
		36-50	.76	3.80	2.26
		Above 50	.70	3.58	2.20

Table 3.2 continued.

Stim. Cntl.	Total Sample		.65	2.95	2.64
	Gender	Male	.60	2.80	1.44
		Female	.67	3.06	1.75
	Education	Grade School	.60	2.69	1.59
		High School	.64	2.90	1.61
		College	.67	3.03	1.67
		Graduate School	.64	2.98	1.53
	Race	White	.65	2.94	1.62
		Black	.64	3.21	1.94
	Age	18-25	.63	2.84	1.46
		26-35	.63	3.03	1.66
		36-50	.68	2.97	1.64
		Above 50	.58	2.84	1.59
Social Lib.	Total Sample		.54	7.54	2.07
	Gender	Male	.52	7.15	2.14
		Female	.53	7.85	1.96
	Education	Grade School	.65	6.69	2.44
		High School	.55	7.35	2.14
		College	.51	7.84	1.92
		Graduate School	.30	7.88	1.77
	Race	White	.54	7.55	2.06
		Black	.62	7.06	2.33
	Age	18-25	.53	7.02	2.14
		26-35	.51	7.49	2.01
		36-50	.54	7.74	1.99
		Above 50	.53	7.59	2.11

Table 3.3

Strong Factorial Invariance for the Processes of Change Inventory across Samples and across Time

	N	χ^2	CFI	NFI	NNFI	AASR	RMSEA	χ^2/DF	χ^2 diff. test	Power
Gender		1470.790	.955	.943	.949		.029	4.39	145.14/20/ ***	>.99
Male	1836					.037				
Female	2308					.028				
Education		1853.038	.958	.931	.958		.019	2.43	157.24/60/ ***	>.99
Grade School	109					.109				
High School	2348					.026				
College	1315					.039				
Graduate	223					.075				
Race		1248.402	.964	.952	.960		.026	3.73	67.84/20/ ***	>.99
White	3959					.018				
Black	105					.089				
Age		1799.736	.960	.933	.960		.018	2.38	175.15/60/ ***	>.99
18-25	598					.043				
26-34	1061					.029				
35-50	1440					.025				
Above 50	1039					.039				
Time		5360.039	.955	.948	.954		.021	7.10	1392.34/60/ ***	>.99
Baseline	4144					.033				
6-month	3465					.027				
12-month	2956					.026				
18-month	2641					.037				

Note: CFI=Comparative Fit Index, Bentler, (1990); NFI=Normed Fit Index, Bentler-Bonnet (1980); NNFI=Non Normed Fit Index, Tucker-Lewis (1973); AASR= Average Absolute Standardized Residual; RMSEA=Root Mean Squared Error of Approximation, Steiger & Lind (1980).

Table 3.4

Correlation Matrix for Strong Factorial Invariance across Gender

Sub Scale	1	2	3	4	5	6	7	8	9	10
1. Counter Conditioning	1.00									
2. Self Liberation	.558	1.00								
3. Social Liberation	.277	.289	1.00							
4. Consciousness Raising	.584	.681	.591	1.00						
5. Reinforcement Management	.381	.324	.246	.499	1.00					
6. Environmental Reevaluation	.438	.432	.299	.640	.386	1.00				
7. Dramatic Relief	.454	.510	.335	.812	.405	.606	1.00			
8. Self Reevaluation	.421	.561	.395	.812	.381	.507	.813	1.00		
9. Stimulus Control	.717	.407	.185	.582	.449	.402	.507	.476	1.00	
10. Helping Relationships	.478	.376	.250	.534	.432	.311	.323	.313	.360	1.00

Note: All correlations significant at the $p < .001$ level.

Table 3.5

Correlation Matrix for Strong Factorial Invariance across Education Level

Sub Scale	1	2	3	4	5	6	7	8	9	10
1. Counter Conditioning	1.00									
2. Self Liberation	.556	1.00								
3. Social Liberation	.286	.291	1.00							
4. Consciousness Raising	.586	.678	.595	1.00						
5. Reinforcement Management	.394	.327	.279	.513	1.00					
6. Environmental Reevaluation	.452	.430	.350	.654	.402	1.00				
7. Dramatic Relief	.464	.508	.365	.817	.418	.624	1.00			
8. Self Reevaluation	.428	.561	.407	.814	.395	.524	.816	1.00		
9. Stimulus Control	.718	.408	.195	.585	.458	.414	.513	.481	1.00	
10. Helping Relationships	.476	.377	.253	.534	.438	.316	.327	.316	.361	1.00

Note: All correlations significant at the $p < .001$ level.

Table 3.6

Correlation Matrix for Strong Factorial Invariance across Race

Sub Scale	1	2	3	4	5	6	7	8	9	10
1. Counter Conditioning	1.00									
2. Self Liberation	.559	1.00								
3. Social Liberation	.287	.293	1.00							
4. Consciousness Raising	.589	.673	.610	1.00						
5. Reinforcement Management	.393	.322	.268	.507	1.00					
6. Environmental Reevaluation	.450	.423	.348	.651	.398	1.00				
7. Dramatic Relief	.468	.507	.370	.818	.413	.618	1.00			
8. Self Reevaluation	.438	.563	.417	.819	.388	.519	.815	1.00		
9. Stimulus Control	.721	.405	.203	.582	.452	.406	.513	.485	1.00	
10. Helping Relationships	.480	.375	.255	.537	.437	.317	.329	.321	.364	1.00

Note: All correlations significant at the $p < .001$ level.

Table 3.7

Correlation Matrix for Strong Factorial Invariance across Age

Sub Scale	1	2	3	4	5	6	7	8	9	10
1. Counter Conditioning	1.00									
2. Self Liberation	.553	1.00								
3. Social Liberation	.307	.302	1.00							
4. Consciousness Raising	.599	.686	.596	1.00						
5. Reinforcement Management	.382	.320	.282	.518	1.00					
6. Environmental Reevaluation	.448	.427	.344	.654	.402	1.00				
7. Dramatic Relief	.470	.513	.357	.815	.426	.625	1.00			
8. Self Reevaluation	.439	.569	.405	.814	.401	.524	.815	1.00		
9. Stimulus Control	.719	.408	.203	.587	.454	.410	.513	.484	1.00	
10. Helping Relationships	.468	.371	.277	.551	.423	.316	.337	.331	.362	1.00

Note: All correlations significant at the $p < .001$ level.

Table 3.8

Correlation Matrix for Strong Factorial Invariance across Time Points

Sub Scale	1	2	3	4	5	6	7	8	9	10
1. Counter Conditioning	1.00									
2. Self Liberation	.604	1.00								
3. Social Liberation	.231	.300	1.00							
4. Consciousness Raising	.529	.598	.532	1.00						
5. Reinforcement Management	.331	.324	.253	.476	1.00					
6. Environmental Reevaluation	.397	.392	.332	.611	.390	1.00				
7. Dramatic Relief	.443	.500	.357	.771	.420	.602	1.00			
8. Self Reevaluation	.377	.559	.390	.742	.379	.482	.780	1.00		
9. Stimulus Control	.689	.457	.199	.592	.413	.412	.520	.499	1.00	
10. Helping Relationships	.399	.375	.264	.483	.475	.299	.336	.319	.358	1.00

Note: All correlations significant at the $p < .001$ level.

Figure 3.1 A Hierarchical Model of the Processes of Change Inventory

Figure 3.2 A Model of the Processes of Change Inventory - Factors Fully Correlated

Figure 3.3 Strong Factorial Invariance Model for Gender (Males, N = 1836 and Females, N = 2308).

Note: * p<.05, ** p<.001, *** p<.001, NS non-significant

Figure 3.4 Strong Factorial Invariance Model for Education

(Grade School, N = 109, High School, N = 2348, College, N = 1315, and Graduate School, N = 223).

Note: * $p < .05$, ** $p < .001$, *** $p < .001$, NS non-significant

Figure 3.5 Strong Factorial Invariance Model for Race (White, N = 3959, and Black, N = 105).

Note: * p<.05, ** p<.001, *** p<.001, NS non-significant

Figure 3.6 Strong Factorial Invariance Model for Age
(18 - 25, N = 598, 26 - 35, N = 1061, 36 - 50, N = 1440, and 50+, N = 1039).

Note: * $p < .05$, ** $p < .001$, *** $p < .001$, NS non-significant

Figure 3.7 A Conceptual Model of the Processes of Change across Time

Figure 3.8 Strong Factorial Invariance Model for Across Time

(Baseline, N = 4,144, 6-Month, N = 3465, 12-Month, N = 2956, and 18-Month, N = 2641).

Note: * p<.05, ** p<.001, *** p<.001, NS non-significant

Chapter 4:

Conclusions and Summary

It is possible to conclude that for high levels of invariance, the measurement models hold true across samples and across time points for the Decisional Balance and Processes of Change Inventories. This current study confirms that the Decisional Balance Scales and the Processes of Change Inventory are solid, reliable scales and can be applied to the previously mentioned sub populations.

The present study examined the factorial invariance of the measurement models of the aforementioned scales. The models were assessed using Meredith's definitions for levels of invariance (Meredith, 1964a, 1964b, 1993). Each model was examined using EQS (Bentler, 1990) and assessed for each level of invariance.

The present study also employed use of the short forms for each of these scales. The short forms were more desirable for the study due to the common use in intervention studies. Fava et al. (1991) confirmed the short forms comparability to the previously published long forms.

The Decisional Balance Scale

The Decisional Balance Inventory, one of the scales in the Transtheoretical Model (TTM; Prochaska & DiClemente, 1983, Prochaska & Velicer, 1997; Velicer, Prochaska, Fava, Norman, & Redding, 1998) held at the

highest level of invariance across samples and across time. This reflects the stability and reliability of the measurement model. While the chi-square tests of these models were significant, the overwhelming support for model fit suggests the unreliability of the chi-square test while examining extremely large sample sizes ($n > 4000$). Power analysis also supported this claim by indicating that the models were highly sensitive to model discrepancies.

A high level of fit was support by omnibus fit indices for the most part above .95 when .90 is considered good fit. Model fit was also confirmed by the Root Means Square Error of Approximation (RMSEA) being below the .05 indicating good fit.

Processes of Change Inventory

The Processes of Change Inventory's measurement model also fit for Strong Factorial Invariance. This finding replicates the findings of Bellis and Rossi (1990) in another sample. The fit of the model was supported through the use of the CFI, NFI, and NNFI fit indices. As mentioned in the Decisional Balance section, the chi-square test seems unreliable in models with large sample sizes. The Process of Change measurement models utilized large samples as well. Power analysis of these models also indicated the measurement models were high sensitive to model misfit. The model misfit may have been even further emphasized by the largely unequal samples sizes used for comparison.

As in the Decisional Balance results, the Process of Change Inventory yielded excellent model fit between groups. The macro fit indices indicated the measurement model fit well across groups. This fit was above .95 for most model comparisons when .90 is considered a well fitting model. A high level of fit is also confirmed with the chi-square to degrees of freedom ratio. With the exception of the across time comparison, all of the ratios were below the 5.0 requirement for good fit. The large ratio for the across time comparison reflects the large sample comparison. All of the groups for this comparison were greater than 2,500 people.

Implications for Use of these Scales

There are a couple implications for using these scales. The results from the present study support the use of the scales in diverse samples. The results also support utilizing the scale for longitudinal intervention studies. The present study confirms that the scales remain highly invariant across time and sample. It seems apparent from the present study's ability to achieve Strong Factorial invariance that two of the TTM's scales provide a venue for assessment in a variety of populations. The finding of Strong Factorial invariance across samples and time points provides insight into the stringent process the scales went through to be developed.

Limitations

The current study was limited in terms of diverse racial sampling. The current sample was mostly white. Due to inefficient sample sizes, the scales were not assessed across a variety of racial categories.

The present study also only examined the TTM scales in the context of smoking research. To ensure the applicability of the scales across behaviors, additional research examining the scales in a similar manner is necessary.

Future Research

Further research should examine the scales across a more ethnically diverse population. For the ease of model convergence, samples of 100 or more were used. Sufficient samples were not available for racial categories beyond white and black. Even with over a hundred participants in the black category, the results can not be completely trusted when they are being compared to over 3900 white individuals.

If a sufficient sample exists subsequent analyses might examine the Decisional Balance Scale and the Process of Change Inventory by sample (gender, race, age, and education level) and by stage (precontemplation, contemplation, preparation, action, and maintenance). Such analyses would examine the invariance of the stage constructs across time and across scale.

To further confirm the validity and applicability of these scales, future research may want to examine similar measurement models from this smoking sample in other behaviors in which the TTM has been applied. For example,

one might examine the decisional balance measurement model for exercise or a measurement model for alcohol use across samples and across time points.

Consequently, researchers using the Decisional Balance Scale and the Processes of Change Inventory should be confident that the measure works well in a population of smokers. Future extensions of this research could examine the same concepts across smoking samples and across other behavior change interventions.

Conclusion

While Strong Factorial invariance has been reported as an unobtainable goal for researchers (Horn et al., 1991), the TTM's Decisional Balance Scale and the Processes of Change Inventory provide strong measurement models, which work well across the aforementioned sub populations of smokers. The present study supports using these measures with male and female participants, across age groups, across education level, and across various time points.

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