Chapter 5

Confirmation of Identified Factor Structure and Identification of Relationships between the Constructs through Structural Equation Modeling

5.1 Introduction

The Exploratory Factor Analysis conducted in the previous chapter has been able to identify five factors or constructs. However, identification, not being the end in a pursuit of exploration requires that the factors or constructs be confirmed and then seek if causal relations exist between them. Exploratory Factor Analysis explores the underlying variables and groups it into a number of constructs wherein the researcher has limited control over the allocation of variables to the factors whereas in the case of SEM the researcher has absolute control over the specification of indicators for each factor. There are two models of Structural Equation Modeling (SEM) – Measurement Model and Structural Model. The multivariate procedure used in this chapter will initially test the construct validity among the constructs which have been represented by multiple observable variables. In this explorations, Structural Equation Modeling has been used.

5.2 Assessment of Normality

Multivariate Normality is a significant assumption in the conduct of SEM studies using AMOS (Arbuckle, 2007).The skewness value and kurtosis value are less than 3 and 7, respectively, in our study, suggesting that the data is normally distributed. The Mardia's co-efficient (multivariate kurtosis) value is 4.842 and the corresponding critical value is 1.651, which is less than the threshold value of 7, suggesting a multivariate normality of the data in our study. According to Curran et al. (1996), a kurtosis value > 7 and a skewness value > 3 suggest a deviation from normality. Similarly, West et al. (1995) have proposed that a kurtosis value greater than 7 suggests a significant deviation from normality. Thus, the data in our analysis is normally distributed for continuing further studies.

5.3 Confirmatory Factor Analysis

Confirmatory factor analysis (CFA) confirms the measurement model developed using the exploratory factor analysis. Even though both EFA and CFA is based on the common factor model, EFA is used for the development of a measure while CFA is used to confirm the factor structure identified. CFA confirms whether the structure of measures fits in the new population. It provides enhanced control over unidimensionality and has more construct validity than EFA. CFA is conducted before proceeding to SEM. Further, it is not only conducted to confirm or reject the model but is also used to revise, refine and retest the CFA model using a prescribed set of criteria.

The Measurement Model describes the extent to which the observed variable contributes to the latent variable and focuses on the validity of the model. It is represented by Confirmatory Factor Analysis. The Measurement model also helps to determine the reliability and validity of the measuring instrument. Confirmatory Factor Analysis has been performed using AMOS 20. The results of the Confirmatory Factor Analysis is given below in Figure 5.1 and Table 5.1

In figure 5.1, Factor I - Liquidity Aspects has been shown as LIQA, Factor II - Commission Aspects as COMA, Factor III – Training Aspects as TRAA, Factor IV - Technical Aspects as TECA and Factor V – Intention to Continue Aspects as INTA respectively.

Figure: 5.1 Confirmatory Factor Analysis – Measurement Model

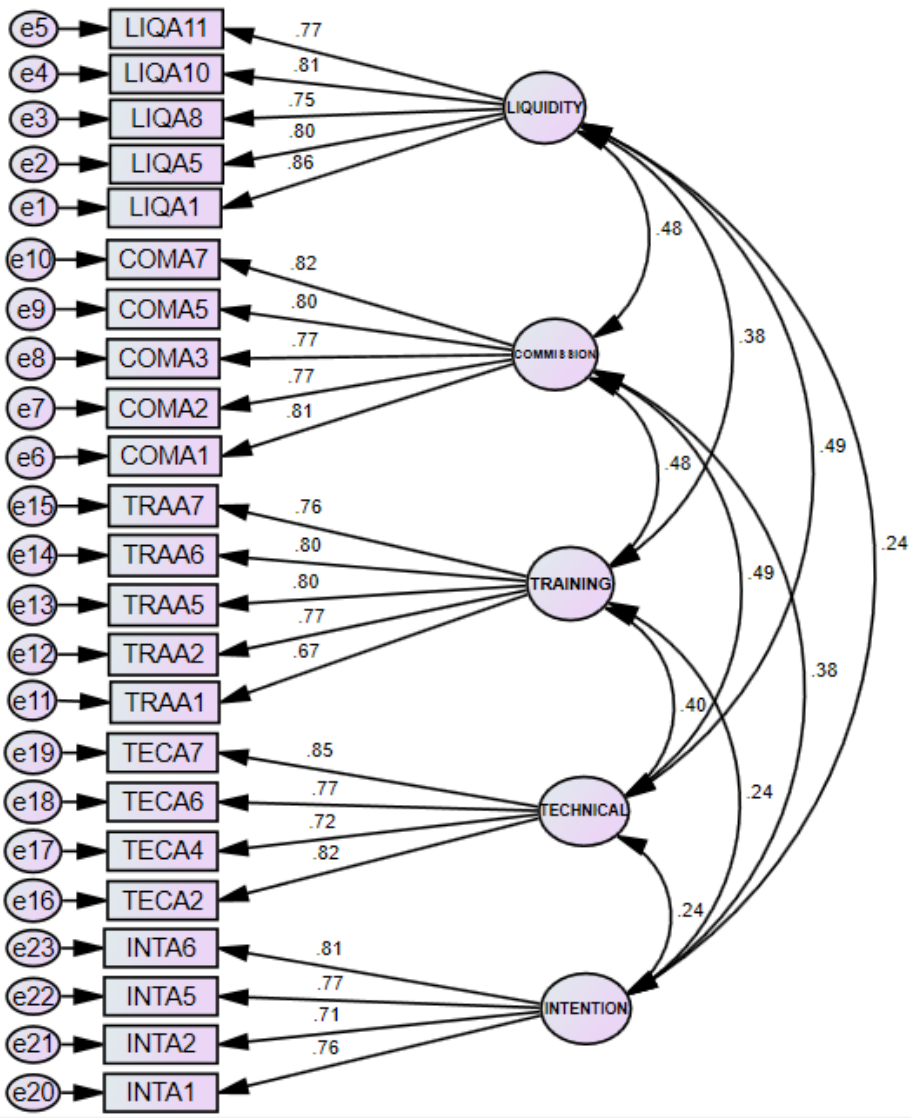


Table – 5.1 Confirmatory Factor Analysis – Standardized Factor loadings, Construct Reliability and Average Variance Extracted

LABELS	LIQUIDITY ASPECT	COMMISSION ASPECT	TRAINING ASPECT	TECHNICAL ASPECT	INTENTION TO CONTINUE ASPECT
LIQA1	0.86				
LIQA5	0.8				
LIQA8	0.75				
LIQA10	0.81				
LIQA11	0.77				

COMA1		0.81			
COMA2		0.77			
COMA3		0.77			
COMA5		0.8			
COMA7		0.82			
TRAA1			0.67		
TRAA2			0.77		
TRAA5			0.8		
TRAA6			0.8		
TRAA7			0.76		
TECA2				0.82	
TECA4				0.72	
TECA6				0.77	
TECA7				0.85	
INTA1					0.76
INTA2					0.71
INTA5					0.77
INTA6					0.81
CR	0.899	0.847	0.871	0.869	0.894
AVE	0.64	0.582	0.576	0.624	0.629

5.3.1 Assessment of the Measurement Model Validity

Validity check was conducted to test the validity of the instrument used in the study. It is a process where the data collection instruments measure accurately what it was actually designed to measure (Saunders & Thornbill, 2003). The following are the validity assessments:

5.3.1.1 Construct Validity

Construct Validity is refer to the extent where the set of measured items reflects the latent factor which they are designed to measure. The construct validity provides confidence wherein it states that the sample item taken for measurement actually represents the true score in the population.

(a) Convergent Validity

Each item that are indicators of a construct should converge or share a high proportion of variance in common is known as Convergent Validity. It can be examined using three different methods i.e. factor loading, average variance extracted (AVE) and Construct Reliability (CR).

(i) **Factor loading** – Factor loading size is one of the important consideration, high factor loading indicates that the item representing one construct converge on a common point leading towards high convergent validity. Since, all the factor loading is greater than 0.5 and is significant at 0.05 significance level as reflected in Table 5.1, thus it supports the convergent validity.

(ii) **Average Variance extracted (AVE)** – It measures the explained variance of a construct. It ranges from 0 to 1 where AVE greater than 0.5 suggests adequate convergence. AVE can be calculated using the formulae specified by Fornell & Larcker (1981) which is as follows:

Average Variance Explained =

$$\frac{\text{Sum of squared standardised factor loading}}{\text{Sum of squared standardised factor loading} + \text{Sum of factor measurement error}}$$

The calculated value of AVE as shown in Table 5.1 for all the factors is above 0.5 suggesting adequate convergent validity.

iii. **Construct Reliability (CR)** – It is also an important indicator of convergent validity. It is defined as the degree to which measurement are free from errors and thus yield consistent results. The value of construct reliability should be greater than 0.7. It can be calculated using the formulae specified by Fornell and Larcker (1981) which is as follows:

Construct Reliability =

$$\frac{(\text{Sum of standardised factor loading})2}{(\text{Sum of standardised factor loading})2 + (\text{Sum of factor measurement error})}$$

The calculated value of CR for all the construct is greater than 0.7 and the value of CR>AVE as per the Table 5.1

(b) Discriminant Validity –

It is the extent to which a construct is truly different from other constructs. High discriminant validity ensures that a construct is completely unique and captures specific phenomena. It should explain better the variance of its construct indicator than the variance of other constructs. Discriminant validity can be confirmed if AVE>MSV; AVE>ASV and Square root of each construct should be greater than the off-diagonal value of all the correlation coefficient.

As seen from the factor correlation matrix in Table 5.2 the lowest value of the square root of AVE is 0.759 which is greater than inter-construct correlation and thus illustrates that the construct is different from each other (Fornell & Larcker, 1981) satisfying the discriminant validity of the model.

Table 5.2 Factor Matrix showing Discriminant Validity

Constructs	CR	AVE	MSV	TRA	TEC	LIQ	COM	INT
TRAINING	0.871	0.576	0.227	**0.759**				
TECHNICAL	0.869	0.624	0.242	0.398	**0.790**			
LIQUIDITY	0.899	0.640	0.235	0.379	0.485	**0.800**		
COMMISSION	0.847	0.582	0.142	0.241	0.240	0.236	**0.763**	
INTENTION TO CONTINUE	0.894	0.629	0.242	0.476	0.492	0.483	0.377	**0.793**

Note: Diagonal are the square root of the Average variance extracted of each construct.

5.2.2 Overall Fit of the Measurement Model

The measurement model has five constructs i.e. Liquidity aspect, Commission aspect Technical aspect, Training aspect and Intention to continue aspect. Each construct is measured by 4 or 5 observed variables. Only those observed variables were considered whose factor loading was 0.7 or above. Further, all the five constructs are highly inter-correlated. The fitness between observed sample data and estimated covariance matrices is found through the chi-square test. All the model fit indices satisfy the criteria required. The value of CMIN/df = 1.747; GFI = 0.899; AGFI = 0.873; CFI = 0.957; IFI = 0.958; TLI = 0.951 exceeds the criteria required for a good model fit (Hair et al., 2010). Similarly, RMSEA = 005 is less than 0.08. Thus, the model fit satisfies the criteria required for adequate fit to the data. The summary of the CFA model fit indices are shown in Table – 5.3

Table: 5.3 CFA Model Fit Indices

Indices	Criteria	Model fit Indices
Chi Square	-	384.281
Degree of freedom	-	220
CMIN/df	< 5	1.747
Probability	0.05	0.00
GFI	≥ 0.80	0.899
AGFI	≥ 0.80	0.873
CFI	> 0.90	0.957
IFI	> 0.90	0.958
TLI	> 0.90	0.951
RMSEA	< 0.08	0.050

5.2.3 Measurement Model: Goodness of Fit

Goodness of Fit measures how well the model reproduced the observed covariance matrix among the indicative items. It also measures how well the researcher theory fits the sample data. The various indicators for the goodness of fit are as follows:

(a) **Chi-square statistics** – It is one of the most fundamental absolute fit indexes. The value of chi-square should be as less as possible which implies that theoretical concept and data collected differences are less. The chi-square value of 0 means the data is perfectly fit into the model. According to Byrne (2010), the CMIN value for the goodness of fit should be less than 3. The CMIN value given in table 5.3 is 1.747 which signifies that the model is fit.

(b) **Goodness of Fit Index (GFI) and Adjusted Goodness of Fit Index (AGFI)** – The Goodness of Fit index calculates the proportion of variance accounted for by the estimated population covariance. It was the first standardised fit index conceptualized during 1981. The range of GFI values is 0 to 1, with higher values

closer to 1 indicating a better fit. Adjusted Goodness of Fit Index (AGFI) has some similar features of the Goodness of fit index. The main difference being the adjustment of the number of degrees of freedom in the case of AGFI. The obtained values for GFI and AGFI was 0.899 and 0.873 as shown in Table 5.3 which is in the acceptable level for the goodness of fit.

(c) **Normed Fit Index (NFI)** – It is one of the original incremental fit index. It compares the Chi square value of models with the corresponding value of the null model. The value falls between 0 and 1. The NFI value equal to or above 0.90 is considered as a good fit with 1 being a perfect fit. The obtained value was 0.906 shown in Table 5.3 which is higher than 0.90 indicating that it is at the acceptable level.

(d) **Tucker Lewis Index (TLI)** – It is similar to the Normed Fit Index. It is actually a comparison of normed chi-square value for null and specified models taking into account model complexity. The threshold value above 0.90 is considered as good. The obtained value of 0.906 shown in Table 5.3 which suggests a better model fit.

(e) **Comparative Fit Index (CFI)** – CFI is an incremental fit index which is an improved version of the normed fit index. It is one of the most widely used index. The value of 1 indicates a perfect fit while the value above 0.90 is acceptable goodness of fit measure. The Amos output result in Table 5.3 shows Comparative Fit Index (CFI) value of 0.957 which is above the threshold limit signifying that the model is fit.

(f) **Root Mean Square Error of Approximation (RMSEA)** – RMSEA represents how well the hypothesized model fits a population. Lower value indicates a better fit with RMSEA value of 0 indicates a perfect fit model. The value of less than 0.08

is indicative of a good fit. The obtained value of RMSEA was 0.05 which indicates that we can generalize the hypothesized model to the population.

5.3 The Structural Model

Once CFA is performed, Structural Equation Model is used to find out the relationship between the endogenous and exogenous variables. Structural model defines the relationship among the unobserved variables and shows the relationship among the construct. Structural Equation Modeling (SEM) is a multivariate statistical technique that helps the researcher to explain the relationship between the observed variables. It is also used to test the theoretical model or validate it along with its in-depth analysis supported through statistical efficiency using empirical data. Confirmatory factor analysis identifies and confirms the common factor in the study whereas SEM establishes a relationship among those common factors (Phakiti et al. 2018). CFA has been used to confirm the five constructs obtained through EFA. It helps to test the hypothesis wherein it states that there exists a relationship between the observed variable and the underlying construct. Thus, based on prior research and participatory observational research, the following structural relationship is proposed and the following hypothesis of the model is built which are as follows:

H_1 – Liquidity of BC Agents have a positive influence on their commission earned

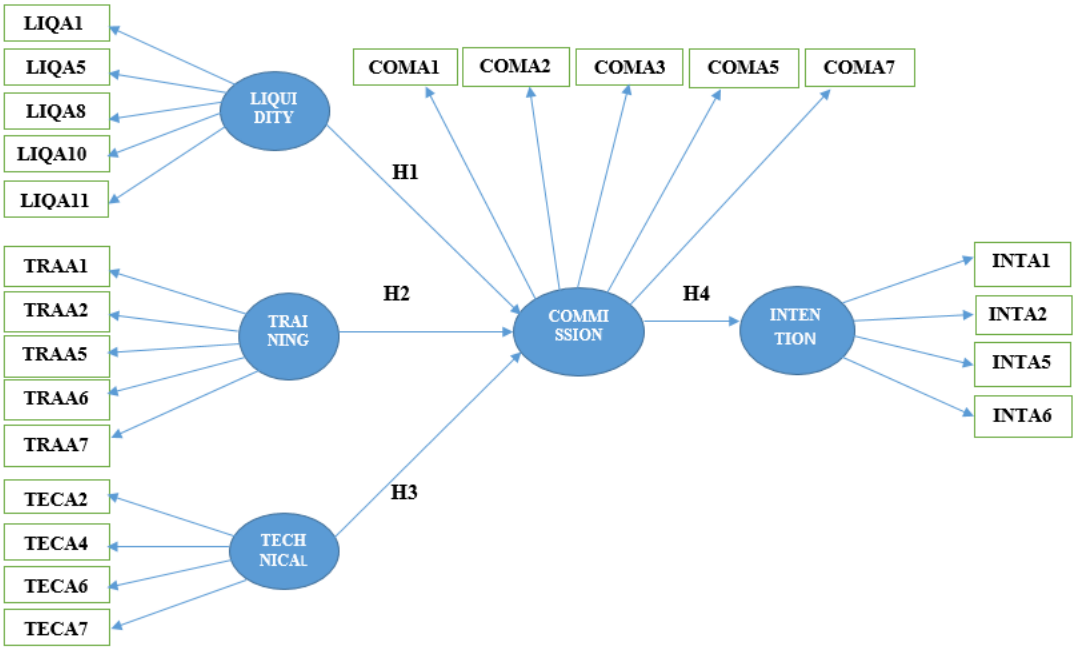
H_2 – Training of the BC Agents have a positive influence on their commission earned

H_3 – Technical ease in conducting banking operations of BC Agents have a positive influence on their commission earned

H_4 - There is a positive influence of commission earned on the Intention to continue their agency banking business as Business Correspondents Agents

The Hypothesized Model is shown in the following diagram -

Figure: 5.2 Path Diagram showing Specified Structural Relationships & Measurement Specifications



5.3.1 Assessing the Structural Model Validity – Goodness of Fit

SPSS Amos specify the Default model, Saturated Model and Independence model wherein the default model contains fit statistics for the model specified in AMOS Graphics diagram. The fit statistics for the default model is reported in Table 5.4.

Table – 5.4 Goodness-of-Fit Measures for Intention to Continue

Absolute Measures	**Model Fit Indices**
CMIN (Chi-Square)	386.392
df for CMIN	223
Probability	0.00
NPAR (No of parameters)	53
CMIN/df	1.733
RMR	0.036
GFI	0.898
RMSEA	0.049

Incremental Fit Measures	
NFI	0.906
CFI	0.958
RFI	0.893
TLI or NNFI	0.952
Parsimony Measures	
PNFI	0.798
AGFI	0.874
PCFI	0.844

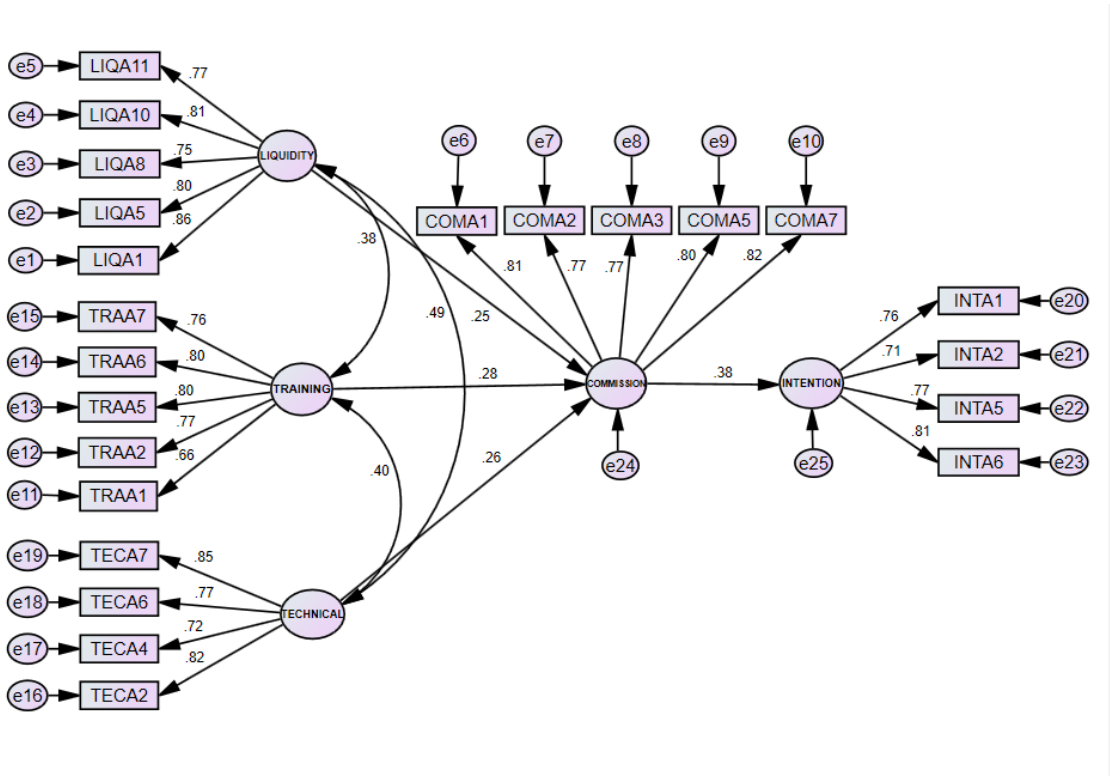
Note: Detailed results are given in Appendix 4

The structural model fit indices provide a reasonable model fit. CFI obtained is 0.958, GFI is 0.898, AGFI is 0.874, IFI is 0.958, TLI is 0.952 and RMSEA is 0.049. Hence, it signifies that the hypothesized research model fits the data satisfactorily.

5.3.2 Examining the Standardized Path Estimates for the Model

Since this model fits well and is theoretically consistent, it would be rationale now to examine the path estimates and individual tests of significance of each path estimate. AMOS provides two ways to examine path estimates. One method uses the path diagram output to visually display the path estimates while the other approach uses tables with tests of significance. In this case, both methods have been used.

Figure 5.3 -- Standardized Path Estimates for Liquidity, Training, Technical, Commission and Intention to Continue Aspects



The hypotheses path was tested through standardised regression weight output value comparing it with the p-value. Based on p-value, the hypotheses is specified whether it is significant or insignificant. The result of the hypotheses tested are shown in Table 5.5

Table: 5.5 Structural Parameter (Path) Estimates for the Model

Structural Relationship	Unstandardized Parameter	Standard Error	t-value	Standardized Parameter	Supported
H1 : LIQ => COM	.223	.057	3.879	0.254	**Yes**
H2 : TRA => COM	.309	.071	4.374	0.279	**Yes**
H3 : TEC => COM	.250	.064	3.873	0.261	**Yes**
H4 : COM => INT	.329	.056	5.855	0.384	**Yes**

All the hypotheses are accepted. The standardised parameter estimates for H1, H2, H3 and H4 are statistically significant at p = 0.05. The standardised path coefficient are estimated from correlation. Standardised path co-efficient for the latent variables

indicate direct and positive of the exogenous construct to be a cause on the endogenous latent construct. Path co-efficient are standardised because they are estimated from correlations. The standardised parameter shows that if liquidity aspect increases by one standard deviation then the commission increases by 0.254. Similarly, if training aspect increases by one standard deviation then commission increases by 0.279 standard deviation. Furthermore, if technical aspect, increases by one standard deviation then commission increases by 0.261.Finally, if the commission aspect increases by one standard deviation then the intention to continue the business as BCs increases by 0.384 standard deviation respectively.

5.4 Conclusion

The empirical analysis carried out in the previous section has been able to confirm the factors and establish structural and dependence relationships among them. The findings here are a mirror to reality because the amount of commission earned by the BCs depend on smooth transactions of different varieties. Absence of glitches in technology and liquidity and capacity building through training does increase the efficiency of agency banking operations and provides opportunities of better livelihoods for the BCs through enhanced commission earnings. There may have been other factors, but those were not found to be significant through rigorous filtration of observable variables in chapter four and confirmation of the factors in this chapter. The findings of this chapter will therefore lead in making suitable policy prescriptions.

Chapter References:

i. Arbuckle, J. L. (2007). *AMOS Users' Guide*. Chicago: SPSS

ii. Byrne, B. M. (2010). *Structural Equation Modeling with AMOS: Basic Concepts, Applications and Programming.* New York: Routledge.

iii. Curran, P.S., West, S. G. and Finch, J. F. (1996). The Robustness of Test Statistics to Non- Normality and Specification Error in Confirmatory Factor Analysis. *Psychological Methods*, 1(1), 16-29.

iv. Fornell, C. and Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, 18, 39-50.

v. Phakiti, A., De Costa, P., Plonsky, L and Starfield, S. (Eds.). (2018). *The Palgrave Handbook of Applied Linguistics Research Methodology*. London: Palgrave Macmillan.

vi. Saunders, M. and Thornhill, A. (2003). Organisational Justice, Trust and the Management of Change - An Exploration. *Personnel Review*, 32 (3), 360-375.

vii. West, S. G., Finch, J. F., & Curran, P. J. (1995). *Structural Equation Models with Non-Normal Variables: Problems and Remedies.* In R. H. Hoyle (Ed.), Structural Equation Modeling: Concepts, Issues, and Applications (p. 56–75). Sage Publications, Inc.