STRUCTURAL EQUATION MODELLING

by

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DECLARATION

I declare that **STRUCTURAL EQUATION MODELLING** is my own work and that all the sources that I have used or quoted have been indicated and acknowledged by means of complete references.

.... 30/1/98 ....

SIGNATURE DATE

(Mr P Mohanlal)

DEDICATION

This dissertation is dedicated to my late father, who provided me with the motivation and inspiration to pursue higher education.

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SUMMARY

Over the past two decades there has been an upsurge in interest in structural equation modelling (SEM). Applications abound in the social sciences and econometrics, but the use of this multivariate technique is not so common in public health research. This dissertation discusses the methodology, the criticisms and practical problems of SEM. We examine actual applications of SEM in public health research. Comparisons are made between multiple regression and SEM and between factor analysis and SEM. A complex model investigating the utilization of antenatal care services (ANC) by migrant women in Belgium is analysed using SEM. The dissertation concludes with a discussion of the results found and on the use of SEM in public health research. Structural equation modelling is recommended as a tool for public health researchers with a warning against using the technique too casually.

KEY TERMS

Structural equation modelling; Measurement model; Structural model; Latent variable; Multivariate statistical techniques; Theory based model; Path diagram; Identification; Specification error; Multiple regression; Exploratory factor analysis; Confirmatory factor analysis; Utilization of antenatal care services

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CHAPTER 1

INTRODUCTION

Over the past two decades there has been an upsurge in interest in structural equation modelling (SEM) especially in the fields of social science and econometrics. Applications of this technique include modelling macroeconomic formulation, racial discrimination in employment, evaluation of social action programs, voting behaviour, studies of genetic and cultural effects, scholastic achievement, and many other phenomena.

The history of SEM shows that there is no one person who invented this technique, but rather it developed over time. From the early work of Sewall Wright (1918) on path analysis and the work of factor analysis initiated by Spearman (1904), structural equation modelling developed in leaps and bounds in the early 1970's and 1980's. Jöreskog (1973), Keesling (1972), Wiley (1973) and others were instrumental in the conceptual synthesis of latent variable and measurement models. The late 1970's and early 1980's saw the development of estimation procedures which in turn led to the development of computer software. However it was the work of Jöreskog and Sörbom on the LISREL (Linear Structural Relations) software that popularized the spread of this technique in the social sciences.

The development of structural equation modelling was seen as a solution to the problems of:

1. estimation of multiple and interrelated dependence relationships, and

2. representing unobserved concepts.

These problems are common in the social sciences and that is the reason for SEM being so popular in this field.

Epidemiological methods have traditionally been seen as the best methods of studying public health problems. Most epidemiological research has been focused on establishing the etiology of disease, but recently the view developed that disease is a result of a complex mix of social, economic, political and environmental factors. As public health has broadened from its focus on medical and behavioural problems to incorporate a more socio-environmental approach, so the questions asked by public health researchers have become more complex, more embedded in social, political and economic factors. Epidemiological methods are not designed to cope with the complexities of public health research while the social sciences offer a range of methods that have evolved to deal with the complex questions being asked by public health researchers. One such tool is structural equation modelling. With the change of focus in public health research and the complexity of the research questions being asked, methodologies for health research should be diverse. Adopting methodologies that evolved in the social sciences is one option to diversify public health research.

Structural equation modelling presents one such possible methodology which can be used to great effect in the public health environment. From as early as 1974, Goldsmith and Berglund (1974) presented tentative path diagrams for:

1. childhood asthma and bronchitis,
2. adult bronchitis and emphysema,

3. respiratory functional impairment in children and adolescents, and

4. cancer of the lungs.

These they proposed as areas for further research but applications of either path analysis or SEM have been limited. More recently Buncher et al. (1991) showed the merits of using SEM in environmental epidemiology. In this dissertation, SEM will be applied to selected problems, to show that there are benefits in using this technique to analyse complex problems that would otherwise be difficult to solve using the standard statistical techniques.

The aim of this dissertation is to show the benefits of using SEM when investigating complex causal relationships and also to discuss some criticisms, problems and shortcomings of this technique when applied in the public health environment.

Chapter 2 gives an overview of structural equation modelling, taking us through the methodology and mathematical notation of SEM and discussing some criticisms and practical problems of the technique. Throughout this chapter the "low-birth weight example", which examines the relationship of acculturation (a process of social change caused by the interaction of significantly diverse cultures) and a number of other variables with low-birth weight status of women, will be used to explain and illustrate the structural equation modelling methodology. This example will also be used to explain definitions and terminologies. The model (revised from that which was analysed by Cobas et al. (1996)) is given in Figure 2.1.

In Chapter 3 similarities and differences between SEM and multiple regression and between SEM and factor analysis are discussed. The purpose of this chapter is to highlight the similarities and differences between SEM and other multivariate techniques. For each one of these techniques a data set is analysed in SEM and the related technique and the results are compared. In §3.1 the HATCO data set from Hair et al. (1992, pp. 536-537) serves as the data for analysis. The HATCO example looks at the effects of specific parameters on the level of satisfaction of their customers. In §3.2 the example comes from Huba et al. (1981) and concerns the drug usage rates of 1634 Los Angeles teenagers.

A complex model investigating the utilization of antenatal care services by migrant Turkish women in Belgium is analysed using SEM in Chapter 4. The aim of this chapter is mainly to see how SEM is applied to a complex data set which has multiple interrelated regression equations which incorporate latent variables and to show the strengths and limitations of structural equation modelling.

Chapter 5 is a general discussion on structural equation modelling. It includes advantages and disadvantages of the methodology, a discussion on criticisms and recommendations on the use of SEM. Included are also problems which were experienced when conducting the analyses.

CHAPTER 2

STRUCTURAL EQUATION MODELLING

2.1 OVERVIEW

Multivariate statistical techniques have been used for decades and have emerged as a powerful tool in research, primarily for the exploration of data rather than testing of causal theories. One technique has recently become very popular especially in the fields of econometrics, psychology, sociology and educational research for testing causal theories, namely structural equation modelling (SEM).

Structural equation modelling, though similar in some ways to the multivariate linear model, differs quite markedly in others. Multivariate linear models include multivariate analysis-of-variance models, multivariate analysis-of-covariance models, and multivariate regression models. Multivariate linear models must not be confused with multivariate analysis. The field of multivariate analysis covers a wide variety of other techniques not covered by the multivariate linear model.

The multivariate linear model is written as:

$$Y = XB + E$$

where, **Y** is a (n x k) matrix of observed values of k independent variables of responses

X is a (n x m) matrix of n observations on the m independent variables (which may contain dummy variables)

B is an (m x k) matrix of regression coefficients or parameters. Each column of **B** is a vector of coefficients corresponding to each of the k dependent variables, and each row contains the coefficients associated with each of m independent variables.

E is the (n x k) matrix of the n random errors, each column corresponding to each of the dependent variables.

Structural equation modelling can be shown to embody the multivariate linear model (Bollen, 1989, pp. 2-4), but there are differences between these techniques. In the multivariate analysis-of-variance (MANOVA) we allow for multiple dependent variables but we cannot model multiple interrelated dependent relationships as SEM does. Similarly multiple regression can only examine relationships with a single dependent variable (Hair et al., 1992, p. 426). This is a severe restriction when modelling complex relationships. For MANOVA we minimise the F ratio, while in SEM the fitting function is minimised. The fitting function will be discussed under the topic of "estimation" on pages 20 to 23.

Very often in research complex relationships need to be tested and the multivariate linear model is not suitable.

Let us consider the following example, which will be referred to as the "low-birth weight example", which examines the relationship of acculturation (a process of social change caused by the interaction of significantly diverse cultures) and a number of variables with low-birth weight. The model (revised from that which was analysed by

Cobas et al.(1996)) is depicted in Figure 2.1. I will use this example to illustrate the concepts, methodology and the notation which is used in SEM. In the low birth weight example, Cobas et al used structural equation modelling to re-analyse data employed by Scribner and Dwyer in their 1987 study of the effects of acculturation on mothers' low birth weight status. The analysis was based on the Mexican American portion of the Hispanic Health and Nutritional Survey conducted by Scribner and Dwyer. The model examined in Figure 2.1 included only women who had experienced at least one live birth. Other variables included in the model, which are theoretically justified in Cobas et al. (1996), are education, age, size of the community, language spoken, preferred language, language read better, language written better, respondent's ethnic identity, mother's ethnic identity, father's ethnic identity, place of birth, food energy intake, calcium intake, iron intake, smoking status, parity (number of live births) and low birth weight status. More details on the variables and how they were derived and measured can be obtained from Scribner and Dwyer (1989) and Cobas et al. (1996). The revised model is given in Figure 2.1 below.

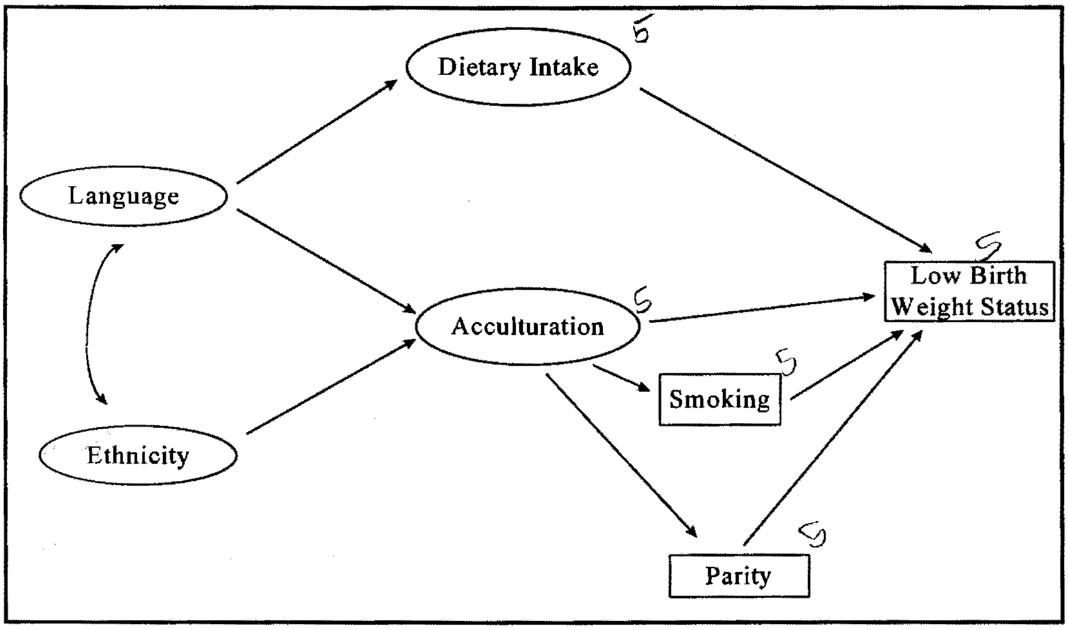


Figure 2.1: Relationship between the variables in the low birth weight example.

One strength of SEM lies in its ability to deal with multiple relationships simultaneously in a straightforward manner while still providing statistical efficiency. Structural equation modelling estimates a series of separate but interdependent multiple regression equations simultaneously. Figure 2.1 clearly illustrates five relationships. The first, illustrating the relationship between Dietary Intake and Language. The second showing the relationship between Ethnicity, Language and Acculturation. The third relationship is between Acculturation and Parity. The fourth relationship is between Acculturation and Smoking and the fifth relationship is between Dietary Intake, Acculturation, Smoking, Parity and Low Birth Weight Status. In an interdependent relationship, some dependent variables (Smoking and Parity) will be used as independent variables in subsequent relationships. Many of the same variables will affect each of the dependent variables but with differing effects. This type of model is called a structural model. In the low-birth weight example, Parity is a dependent variable which is related to Acculturation, but is also used as an independent variable when predicting Low Birth Weight Status.

The other strength of SEM is its ability to incorporate latent variables into the analysis. A latent variable or construct is an unobserved concept that can only be approximated by observed variables often called manifest variables, measures, indicators or proxies (these terms will be used interchangeably throughout this dissertation). The model given in Figure 2.1 has four latent variables or constructs, represented by Language, Ethnicity, Dietary Intake and Acculturation. Table 2.1 illustrates the manifest variables or indicators which approximate the latent variables.

Table 2.1: Table of Latent variables and Manifest variables.

LATENT VARIABLES	MANIFEST VARIABLES
Language	Language Spoken
	Preferred Language
	Language Read Better
	Language Written Better
Ethnicity	Respondent's Ethnic ID
	Mother's Ethnic ID
	Father's Ethnic ID
	Birth Place
Dietary Intake	Food Energy
	Calcium
	Iron
Acculturation	Education
	Age
	Size of the Community
	Birth Place

Constructs or latent variables are the basis for forming causal relationships as they make possible the representation of concepts. They can be defined with varying degrees of specificity, ranging from quite narrow concepts to complex or abstract concepts. Using latent variables has both practical and theoretical advantages, for example improving statistical estimation by accounting for measurement error. Measurement error is not always caused by inaccurate responses but is also present when very abstract concepts are used. Structural equation modelling accounts for measurement error through the use of the measurement model.

The measurement model is a submodel in SEM that:

1. specifies the indicators for each construct,
2. assesses the reliability of each construct for use in causal relationships, and
3. measures the variance extracted by each of the constructs.

The measurement model is very similar to factor analysis and is often referred to as confirmatory factor analysis (CFA) (Bentler, 1983; Bollen, 1989, p. 223; Jöreskog & Sörbom, 1976).

Traditional statistical techniques involve the analysis and modelling of individual observations or cases. In order to understand SEM we need to look at the analysis of the data in a different light and divorce ourselves from the idea that data can only be analysed as individual cases. We need to look at the data as a matrix of covariances rather than cases.

2.2 METHODOLOGY

The benefits of SEM come from using the structural and measurement models simultaneously. To ensure that the models are correctly specified and the results are valid, Hair et al. (1992, p. 435) recommend a seven step approach. The steps are as follows:

1. development of a theoretically based model,
2. constructing a path diagram of causal relationships,
3. converting the path diagrams into a set of structural equations and measurement model,
4. choosing the input matrix type and estimation of the proposed model,
5. assessing the identification of the model equations,
6. model evaluation, and
7. modifying the model if necessary and if theoretically justified.

Other authors suggest a similar approach, only involving five steps (Jöreskog, 1976; Bentler & Weeks, 1980; Long, 1994). The seven steps are now explained, using the descriptions given by Hair et al. (1992, pp. 435-452).

2.2.1 Development of a Theory Based Model

Structural equation modelling, like most multivariate techniques, is based on causal relationships, where a change in one variable results in the change of another variable. A model is formulated on the basis of one's theory or past research in the area of interest. Palloni (1987) discusses the relationship between theories, models and causal inferences. He defines a theory as an organized set of propositions reducing a particular set of phenomena to an abstract network of concepts, created with a causal language that makes explicit the existence of causal factors and causal mechanisms.

In order to draw valid inferences about causal relationships, the theory is translated into a model using a path diagram. At this stage the researcher chooses to emphasize certain aspects of the theory and de-emphasize others (Levin et al., 1989), and may also decide to simplify the relations implied by the theory.

A critical error to be avoided in SEM as in all theoretically based models, is the omission of one or more key predictors, often called specification error (Jöreskog, 1976; Hair et al., 1992, p. 436). Omitting key predictors will bias the importance of other variables. This does not mean that all variables must be included even though not theoretically justified. This will have practical limitations in terms of interpretation. We should always keep at the back of our minds the benefits of parsimonious and concise models.

While theory is often a primary objective of academic research, researchers often propose or develop a set of relationships that are interrelated and quite complex. It is here that researchers can benefit from the unique analytical tools presented in structural equation modelling.

2.2.2 Constructing a Path Diagram

A path diagram is a pictorial representation of a system of simultaneous equations. It effectively communicates the basic conceptual ideas of the model. However, the path diagram can do more than that. If the diagram is drawn correctly and includes sufficient detail, it can represent exactly the corresponding algebraic equations of the model and the assumptions about the error terms in the equations.

The following conventions are generally used in literature for path diagrams (Everitt, 1984, pp. 10-11; Li, 1975, pp. 106-108; Loehlin, 1987, pp. 2-8). Reference will be made to the variables depicted in Figure 2.2.2.

1. Observed variables, such as Language Spoken, Preferred Language, Language Read Better, Language Written Better, Respondent's Ethnic ID, Mother's Ethnic ID, Father's Ethnic ID, Birth Place, Food Energy, Calcium, Iron, Education, Age, Size of the Community, Parity, Smoking and Low Birth Weight Status, are enclosed in squares or rectangles. Latent variables, such as Language, Ethnicity, Dietary Intake and Acculturation, are enclosed in circles or ellipses. Error variables are included but are not enclosed.
2. A one-way straight arrow between two variables indicates a direct influence. The one-way arrow between Parity and Low Birth Weight Status indicates a direct influence of Parity on Low Birth Weight Status.
3. All direct influences of one variable on another must have a one-way arrow, so that an absence of an arrow means that there is no assumed direct relationship. For example there is no direct relationship between Iron and Low Birth Weight Status and therefore the absence of a one-way arrow between these two variables.
4. A curved two-way arrow indicates just a correlation. The curved arrow between Language and Ethnicity indicates that the two constructs are

correlated. While the curved two-way arrow between Education and Age indicates that the two manifest variables are correlated without any direct relationship.

The path diagram in Figure 2.2.2 depicts the relationships for the low birth weight example and indicates the conventions which are generally used.

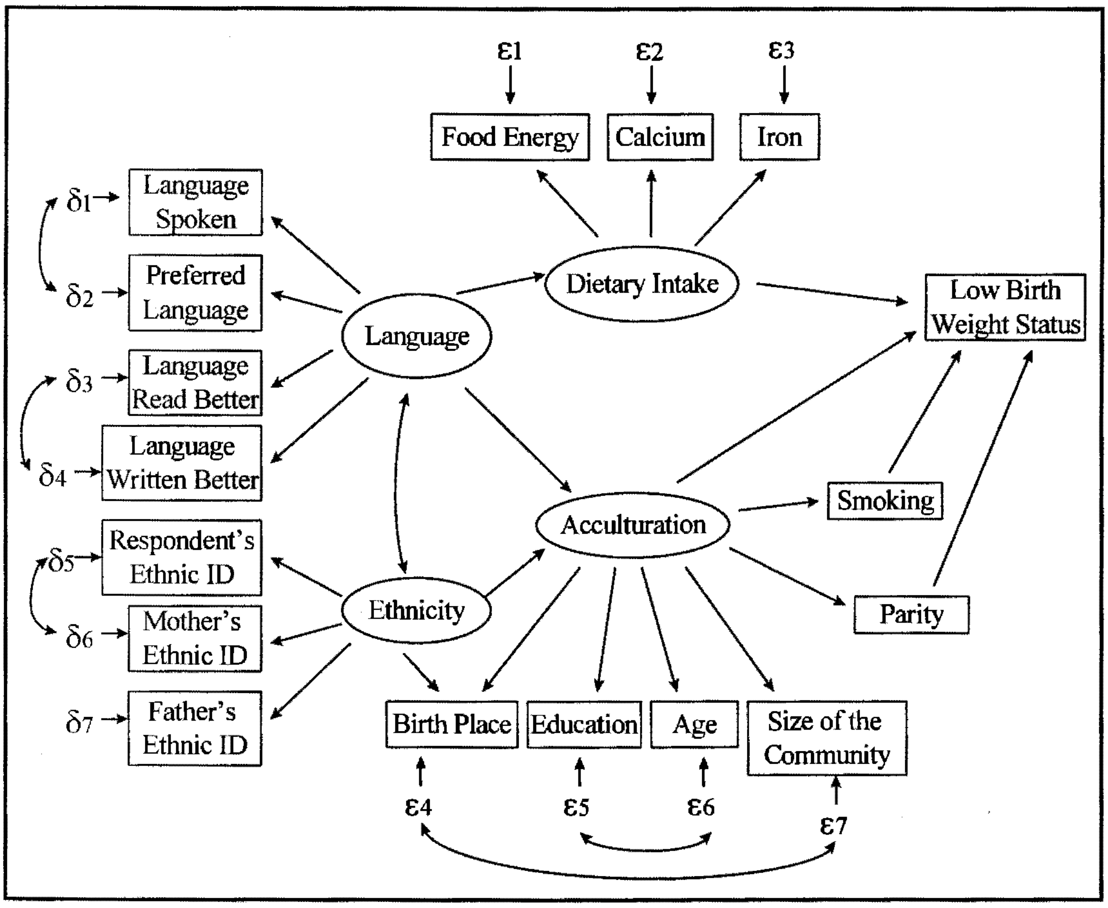


Figure 2.2.2: Path Diagram for the low birth weight example.

Path diagrams are extremely helpful in visually or diagramatically depicting causal relationships. In SEM, path diagrams are critical as they provide a means of arriving at the algebraic equations.

2.2.3 Converting the Path Diagram into a set of Structural Equations to specify the Measurement Model

Once the path diagram has been drawn, the model can be specified in terms of a series of equations which define:

1. the structural equation linking constructs,
2. the measurement model defining which variables measure which construct, and
3. a set of matrices indicating any hypothesized correlation of the constructs or variables.

2.2.3.1 Structural Model

The structural model specifies the causal relationship among the latent variables and describes the causal effects and the amount of unexplained variance. Here we translate the path diagram into a series of structural equations. Each endogenous construct will be the dependent variable in one equation, and the exogenous constructs are the independent variables. Each equation will contain at least one endogenous variable and one or more exogenous variables with an error. For the low birth weight example, the following nine coefficients need to be estimated in the structural equations and are expressed in the Table 2.2.3.1. This table clearly indicates the endogenous and the exogenous constructs and how they are related.

Table 2.2.3.1: Table of Structural Coefficients.

	Exogenous Constructs		Endogenous Constructs/Variables			
Endogenous Variable	Language	Ethnicity	Dietary Intake	Acculturation	Smoking	Parity
Dietary Intake	β_1					
Acculturation	β_2	β_3				
Smoking				β_4		
Parity				β_5		
Low Birth Weight Status			β_6	β_7	β_8	β_9

2.2.3.2 Measurement Model

The measurement model specifies how the latent variables or hypothetical constructs are measured in terms of the observed variables. The relationship between the latent variables (Language, Ethnicity, Dietary Intake and Acculturation) and the manifest variables (Language Spoken, Preferred Language, Language Read Better, Language Written Better, Respondent's Ethnic ID, Mother's Ethnic ID, Father's Ethnic ID, Birth Place, Food Energy, Calcium, Iron, Education, Age, Size of the Community) for the low birth weight example is represented in Table 2.1 and depicted in the form of a path diagram in Figure 2.2.2. Measurement models are important when one tries to measure abstract concepts. The procedure is very similar to factor analysis, but is much more powerful. Most of the indicators of the constructs contain a sizeable amount of measurement error and the measurement model takes this measurement error into account. Ignoring measurement error leads to inconsistent estimators and inaccurate assessment of the relation between the underlying latent variables. Once the measurement model has been specified, the analyst must then provide measures of reliability of the constructs and estimate the variance extracted by the latent variables.

2.2.4 Choosing the Input Matrix Type

As mentioned earlier the focus in structural equation modelling is not on the individual cases but rather on the correlation or covariance matrix. Most SEM programs can read data of the following types:

1. raw data,
2. covariance matrix,
3. product moment correlation matrix, or
4. a correlation matrix consisting of any of the correlations such as tetrachoric, polychoric, biserial, polyserial or canonical correlations based on raw scores or normal scores.

The following guidelines can be used to choose the input matrix type:
Whenever a true "test of theory" (Hair et al., 1992, p. 442) is being produced the covariance matrix should be used, as this type of input matrix satisfies the assumptions of SEM and is the appropriate form of the data for validating causal relationships. Correlations of the types, tetrachoric, polychoric, biserial or polyserial are generally used when the data is ordinal or categorical. However, many authors caution against the interpretation and generalization of the results obtained by using any form of correlation matrix as these are standardized coefficients (Greenland et al., 1986; Rothman, 1986, p. 303). This will be discussed further in Section 2.4.

Once the input matrix has been selected, the computer program must be chosen for estimation. Frequently analysts use whichever computer program is available but there are differences in their abilities. The most common computer program used today is LISREL (Linear Structural Relations). This name has become almost synonymous with SEM. Other computer packages are available. These include:

EQS (BMDP) which was developed by Peter Bentler (Bentler, 1985).

PLS (Partial Least Squares) which was developed by Herman Wold. It is known primarily for its unique estimation method.

AMOS which was developed by James Arbuckle and is distributed by SmallWaters Corporation (Hox, 1995, and Ridgon, 1996).

RAMONA which was developed by Michael Browne and is now distributed as part of SYSTAT. More details on the application of RAMONA can be found in Kirby (1993).

LISCOMP which was developed by Bength Muthén (Muthén, 1987) and is now distributed by Scientific Software, Inc.

COSAN which was developed by Colin Fraser and Roderick McDonald (McDonald, 1978, 1980).

PROC CALIS (Covariance Analysis and Linear Structural equations) of the SAS software package which was developed by Wolfgang Hartman (SAS Institute Inc., (1989).

Mx which is a combination of a matrix algebra interpreter and a numerical optimizer that was developed by Michael Neale (Neale, 1995). It includes built-in fit functions to enable structural equation modelling and other types of statistical modelling of data, including maximum likelihood estimation.

The TETRAD II software which is designed as a tool to assist the development of causal models. It analyses conditional probability relationships, prepares Monte-Carlo generated samples. To estimate linear models, the program will generate input files CALIS, EQS or LISREL (Scheines et al., 1994).

Throughout this dissertation the CALIS (Covariance Analysis of Linear Structural Equations) procedure in SAS will be used for the SEM solutions to the examples in Chapters 3 and 4. The CALIS procedure can be used for analysis of covariance structures, fitting systems of linear structural equations and path analysis. This procedure estimates parameters and tests the appropriateness of linear structural models using covariance structure analysis (SAS Institute Inc., 1989, p. 246). The raw data, correlation matrix or covariance matrix can be used as input. Normality of the dependent variables is a critical assumption and poor estimates can be expected if there are large deviations from normality. In CALIS, parameters can be estimated using the criteria of least squares, generalized least squares or maximum likelihood for multivariate normal data. The output obtained is very similar to all the other programs. All programs contain very similar goodness-of-fit measures. They all provide the observed matrix together with the predicted and residual matrix. Also given are standardized and unstandardized solutions and a plot of normalized residuals.

It is not uncommon to find numerical problems in the optimization process. It is in these optimization algorithms where the CALIS procedure differs from LISREL. The CALIS procedure offers several optimization algorithms including, Levenberg-Marquardt and Newton-Raphson implementations to various quasi Newton, dual quasi- Newton, and conjugate gradient algorithms (SAS Institute Inc., 1989, pp. 295-298). LISREL on the other hand uses Fletcher and Powell's minimization procedures. Unlike the Newton-Raphson method, the Fletcher-Powell one does not require the inverse of the analytic second partial derivatives in each iteration. Instead, this matrix is built up through adjustments after each iteration.

The general structural equation model uses several methods to estimate the unknown parameters, so that the implied covariance matrix, Σ, is close to the sample covariance matrix, S. Many fitting functions are used to minimise the difference between Σ and S (Bollen, 1989, pp. 106-107). The choice of the estimation technique, and hence the fitting function, is often determined by the distributional properties of the variables being analysed. Both LISREL and the CALIS procedure offer the following three estimation methods:

1. Maximum Likelihood (ML)

   This is to date the most widely used method. The fitting function that is minimised is,

$$F = \log|\Sigma(\theta)| + \mathrm{tr}(S\,\Sigma^{-1}(\theta)) - \log|S| - (p+q)$$

where, θ is the vector that contains the model parameters,

$\Sigma(\theta)$ is the covariance matrix written as a function of θ, and

S is the sample covariance matrix

p is the number of exogenous indicators, and

q is the number of endogenous indicators.

This function may be used even if the distribution of the observed variables deviate from normality (Jöreskog and Sörbom, 1989, p. 21). The asymptotic distribution of (N-1) F is a χ^2 distribution with $\{(1/2)(p + q)(p + q + 1) - t\}$ degrees of freedom, where t is the number of free parameters and F is the value of the fitting function evaluated at the final estimates (Bollen, 1989, p. 110).

The maximum likelihood fitting function is derived from the maximum likelihood principle based on the assumption that the observed variables have a multinormal probability distribution (Jöreskog, 1989, p. 21).

The likelihood function is given below:

$$L(\theta) = (2\pi)^{-N(p+q)/2} |\Sigma(\theta)|^{-N/2} \exp[(-1/2)\sum_{i=1}^{N} z_i' \Sigma^{-1}(\theta) z_i]$$

where, z is a $(p \times q) \times 1$ vector formed by combining multinormal random variables **y** and **x**,

N is the number of observations,

p is the number of random variables of **y**, and

q is the number of random variables of **x**.

The derivation of $L(\theta)$ can be found in Bollen (1989, pp. 133-135).

2. Unweighted Least Squares (ULS)

The ULS fitting function is,

$$F = (1/2)\ \mathrm{tr}\ [(S - \Sigma\ (\theta))^2]$$

The function for ULS is justified when all variables are measured in the same units. This is the most simple fitting function and leads to consistent estimators. However, ULS does not lead to the asymptotically most efficient estimator. The values of the fitting function differ when correlation instead of covariance matrices are analysed, or it can differ with a change of scale (Bollen, 1989, p. 113).

3. Generalized Least Squares (GLS)

The fitting function for GLS is,

$$F = (1/2)\ \mathrm{tr}\ [(I - S^{-1}\Sigma\,(\theta))^2]$$

GLS and ML have similar asymptotic properties. Under the assumption of multivariate normality, both estimators are optimal in the sense of being most precise in large samples (Jöreskog and Sörbom, 1989, p. 21). This fit function may also be used when the distribution of the observed variables deviate from normality. The asymptotic distribution of (N-1) F evaluated at the final estimates is chi-square. The degrees of freedom are $(1/2)(p + q)(p + q +1) - t$ } where t is the number of free parameters (Bollen, 1989, p. 115).

In addition to the above three estimation methods, LISREL offers the following methods of estimation:

1. two-stage least squares (TSLS)
2. generally weighted least squares (WLS), and
3. diagonally weighted least squares.

More details on the above three methods of estimation can be found in the LISREL manual.

2.2.5 Assessing the Identification of the Structural Model

Jöreskog (1976) defines an identification problem as the inability of the proposed model to generate unique estimates. In SEM it becomes difficult to ensure that a model is identified. One approach to ensure that your model is identified, is to look at possible symptoms of an identification problem. These include:

1. very large standard errors for one or more coefficients,
2. inability of the program to invert the information matrix,
3. unreasonable estimates such as negative error variances, and
4. high correlation (approx. 0.90) among the estimated coefficients.

Different starting values can be used to assess identification. If the starting values do not converge to the same point each time, then identification should be examined thoroughly.

If an identification problem is indicated, one can look at three common sources:

1. a large number of estimated coefficients relative to the number of covariances or correlations, indicated by a small number of degrees of freedom (similar to the problem of overfitting the data),
2. the use of reciprocal effects (two-way causal arrows between two constructs), and
3. failure to fix the measurement error variances of constructs.

The only solution is to define more constraints on the model (Bollen, 1989, p. 99; Long, 1994). If over-identification still exists, then the researcher must reformulate the model to provide more constructs relative to the number of causal relationships examined.

2.2.6 Model Evaluation

To evaluate the results we assess the degree to which the data and proposed model meet the assumptions of structural equation modelling. Once the assumptions are all met the results are accepted and then the goodness-of-fit must be assessed at several levels: first for the overall model (§2.2.6.1) and then for the measurement (§2.2.6.2) and structural (§2.2.6.3) models separately.

The assumptions which must be met are:

1. independence of the observations,
2. random sampling of the respondents,
3. linearity of all relationships, and
4. multivariate normality.

Generalized least squares (GLS) is often used to overcome some of these problems but caution must be taken when the models become large and complex. Departures from multivariate normality may cause severe problems because this can substantially inflate the chi-square statistic and thus bias the critical values for determining significance of the coefficients.

Once the assumptions have been checked, the results are examined for estimated coefficients that exceed acceptable limits, called offending estimates. Common examples are :

1. negative error variances or non-significant error variances for any construct,
2. standardized coefficients exceeding or very close to 1.0, or
3. very large standard errors for the estimates.

2.2.6.1 Overall Model Fit

Once all the assumptions are met and there are no offending estimates, we need to assess the overall fit of the model using one or more measures of goodness-of-fit. There are three types of goodness-of-fit measures, overall model fit measures, incremental fit measures and parsimonious fit measures:

2.2.6.1.1 Absolute fit

This determines the degree to which the overall model predicts the observed covariance or correlation matrix. There are three absolute measures of fit commonly used in structural equation modelling:

1. Chi-square Statistic

This is the only measure of goodness-of-fit available in SEM, which has known distributional properties (Hair et al., 1992, pp. 489-490). A large chi-square relative to the degrees of freedom implies that the observed and estimated matrices differ to a large degree. Thus low chi-square values, which result in significance levels greater than 0.05 or 0.1, indicate that the difference between the actual and predicted matrices are not statistically significant.

§2.2.4 discussed the Maximum Likelihood fitting function and the Generalised Least Squares fitting function. Both of these are used as estimators of chi-square to test the hypothesis that the actual and predicted covariance matrices are equal.

An important criticism of the chi-square measure is that it is too sensitive to sample size differences. It is sensitive to both small and large sample sizes and to departures from multivariate normality of the observed variables.

2. Goodness-of-Fit Index (GFI)

The goodness-of-fit index (GFI) is another measure commonly used by most computer packages. This measure ranges in value from 0 (poor fit) to 1.0 (perfect fit). Higher values indicate a better fit, but there is no absolute threshold level for acceptability.

3. Root Mean Square Residual (RMSR)

The RMSR is also provided by most packages. It is the root of the mean square residuals. If covariances are used it is the average residual covariance while if a correlation matrix is used then it is in terms of an average residual correlation.

2.2.6.1.2 Incremental Fit Measure

This measure compares the proposed model to a comparison model, often referred to as the null model. The null model is the most simple model that can be theoretically justified. The most common example of a null model is a single construct model related to all indicators with no measurement error. Throughout §2.2.6.1.2 we will refer to the chi-square for the null and the proposed models. These are the likelihood ratio chi-square statistics for the null and proposed models, respectively. In other sections the chi-square statistics are the statistics for the proposed model. There are two incremental fit measures:

1. Tucker-Lewis Index (TLI) (Tucker & Lewis, 1973)

TLI combines a measure of parsimony into a relative index between the proposed and null models, resulting in values ranging from 0 to 1.0. It is expressed as:

$$TLI = \frac{[\chi^2_{null}/df_{null}] - [\chi^2_{proposed}/df_{proposed}]}{[\chi^2_{null}/df_{null}] - 1}$$

where, χ^2_{null} is the chi-square statistic for the null model,

$\chi^2_{proposed}$ is the chi-square statistic for the proposed model,

df_{null} is the degrees of freedom for the null model, and

$df_{proposed}$ is the degrees of freedom for the proposed model.

The recommended value is 0.90 or greater.

2. Normed Fit Index (NFI) (Bentler & Bonnet, 1980)

This is probably the most popular measure. The values range from 0 (poor fit) to 1.0 (perfect fit). It is expressed as:

$$NFI = \frac{[\chi^2_{null} - \chi^2_{proposed}]}{\chi^2_{null}}$$

Once again, there is no indicator of what constitutes an acceptable level of fit, and the recommended values are the same as the TLI.

2.2.6.1.3 Parsimonious Fit Measures

There are four measures which are measures of parsimonious fit and their basic objective is to diagnose whether model fit has been achieved by "overfitting" the data with too many coefficients. These measures are:

1. Adjusted Goodness-of-Fit Index (AGFI)

The AGFI is an extension of the GFI (defined on page 26) but is adjusted by the ratio of degrees of freedom for the proposed model to the degrees of freedom for the null model. The recommended level of acceptance is 0.90 or greater.

2. Normed Chi-square (Jöreskog, 1969)

This method adjusts the χ^2 and it is simply the Chi-square divided by the degrees of freedom.

3. Parsimonious Fit Index (PFI) (James, Muliak & Brett, 1982, p. 155)

This is a modification of the NFI. The PFI is given by:

$$PFI = (d.f_{proposed} / d.f_{null}) \times (NFI)$$

Higher values of PFI are better and it is used mainly for comparison of models with different degrees of freedom.

4. Akaike's Information Criterion (Akaike, 1987)

The final measure is the AIC. It is very similar to the PFI and is calculated as follows:

$$AIC = \chi^2/2 - (\text{number of estimated coefficients})$$

AIC values closer to zero indicate better fit.

2.2.6.1.4 Summary

In evaluating the set of measures, some general criteria are applicable and indicate models with acceptable fit:

1. non-significant χ^2 (at least $p > 0.05$, perhaps 0.10 or 0.20),
2. incremental fit indices (NFI & TLI) greater than 0.90,
3. parsimonious indices that indicate the model to be more parsimonious than alternative models, and
4. low RMSR based on the use of correlation or covariances.

2.2.6.2 Measurement Model Fit

Once the overall model fit is evaluated, the measurement of each construct can be assessed, by

1. examining the indicator loadings for statistical significance, and
2. assessing the construct's reliability and variance extracted.

The Construct's reliability is given by:

Construct Reliability = [(Sum of | standardised loadings |)^2] /

[(Sum of | standardised loadings |)^2 + (Sum of indicator measurement error)]

The Variance extracted is given by:

Variance Extracted = (Sum of squared standardized loadings) /

[(Sum of squared standardized loadings) + (Sum of indicator measurement error)]

2.2.6.3 Structural Model Fit

Examination of the structural model involves testing the significance of the estimated coefficients. Structural equation modelling methods provide the estimated coefficients together with standard errors and calculated t-values for each coefficient. Standardized solutions can be examined. An overall coefficient of determination R^2 is also calculated for each endogenous equation. This provides a measure of fit for the entire structural equation and gives an indication of the amount of variation or correlation of the endogenous variable accounted for by the exogenous variables. It also provides a relative measure of fit for each structural equation.

2.2.7. Interpreting and Modifying the Model

Once the model is acceptable, we must examine possible modifications to improve both the theoretical explanations and the goodness-of-fit of the model. Examination of the residuals of the predicted covariance or correlation matrix is a good indicator that model modifications may be required (Hair et al., 1992, p. 474). Normalized residuals in excess of approximately 2.0 can be regarded as statistically significant at the 5% level and indicate prediction error. Modification indices also aid in assessing the fit of a model. If no further modifications are necessary the results can be interpreted.

2.3 MATHEMATICAL NOTATION

Understanding the methodology of structural equation modelling is helped by having a knowledge of the notation used. The intention in this section is to give an introduction to the mathematical notation and to express the low birth weight example in the notation which is commonly used. Bollen (1989, p. 10) and Jöreskog & Sörbom (1976, pp. 3-14) give an in-depth discussion on this topic, with most using the LISREL notation. I will therefore use the LISREL notation.

The structural equation methodology requires a reorientation. The procedure emphasizes covariances rather than cases. Instead of minimising functions of observed and predicted individual values, we minimise the difference between the sample covariances and the covariances predicted by the model. The fundamental hypothesis for these structural equation procedures is that the covariance matrix of the observed variables is a function of a set of parameters. If the model were correct and we knew the parameters, the population covariance matrix would be exactly reproduced. Hence SEM is all about testing the hypothesis:

$$\Sigma = \Sigma(\theta) \qquad \text{......... 2.3.1}$$

where, Σ is the population covariance matrix of observed variables,

θ is the vector that contains the model parameters, and

$\Sigma(\theta)$ is the covariance matrix written as a function of θ.

Suppose that there are *m* exogenous constructs, *n* endogenous constructs, *p* exogenous indicators and *q* endogenous construct indicators. If we let:

ξ indicate the exogenous construct, such as Language and Ethnicity from the low birth weight example.

η indicate the endogenous construct, such as Dietary Intake and Acculturation.

x be the indicator of exogenous construct, such as Language Spoken, Preferred Language, Language Read Better, Language Written Better, Respondent's Ethnic ID, Mother's Ethnic ID, Father's Ethnic ID, and Birth Place.

y be the indicator of endogenous construct, Food Energy, Calcium, Iron, Education, Age, Birth Place, and Size of the Community.

The basic equation for the **structural model** is given as:

$$\eta = \mathbf{B}\,\eta + \Gamma\,\xi + \zeta, \qquad \text{......... 2.3.2}$$

where,

B (n*n) is a coefficient matrix of latent endogenous variables,

η (n*1) is a vector of latent endogenous variables,

Γ (n*m) is a coefficient matrix of latent exogenous variables,

ξ (m*1) is a vector of latent exogenous variables, and

ζ (n*1) is a random vector of residuals.

The correlations among the exogenous constructs in the structural model are represented by PHI Φ, i.e. Φ(m*m) is the correlation matrix of ξ.

$$
\begin{array}{c} \xi_1 \\ \xi_2 \\ \vdots \\ \xi_m \end{array}
\overset{\begin{array}{ccccc} \xi_1 & \xi_2 & \cdots & \cdots & \xi_m \end{array}}{\begin{bmatrix} - & & & & \\ \Phi_{12} & - & & & \\ \vdots & \vdots & - & & \\ \Phi_{1m} & \Phi_{2m} & \cdots & \cdots & - \end{bmatrix}}
$$

The correlations among the error terms of the endogenous constructs in the structural model are represented by PSI Ψ, i.e. $\Psi(n*n)$ is the correlation matrix of ζ.

$$
\begin{array}{c} \eta_1 \\ \eta_2 \\ \vdots \\ \eta_n \end{array}
\overset{\begin{array}{ccccc} \eta_1 & \eta_2 & \cdots & \cdots & \eta_n \end{array}}{\begin{bmatrix} - & & & \\ \Psi_{12} & - & & \\ \vdots & & - & \\ \Psi_{1n} & \Psi_{2n} & & - \end{bmatrix}}
$$

The basic equations for the measurement model are given as:

$$x = \Lambda_x \xi + \delta, \qquad \text{.................. 2.3.3}$$

$$y = \Lambda_y \eta + \varepsilon, \qquad \text{.................. 2.3.4}$$

where,

x $(p*1)$ is a vector of observed indicators of ξ,

y $(q*1)$ is a vector of observed indicators of η,

δ $(p*1)$ is a vector of measurement errors of x,

ε $(q*1)$ is a vector of measurement error of y,

Λ_x $(p*m)$ is a coefficient matrix relating x to ξ, and

Λ_y $(q*n)$ is a coefficient matrix relating y to η.

The correlations among the error terms of the exogenous indicators in the measurement model are given by THETA-DELTA Θ_δ, i.e. $\Theta_\delta(p*p)$ is the correlation matrix of δ.

$$\begin{array}{c} \\ X_1 \\ X_2 \\ \vdots \\ X_p \end{array} \begin{array}{c} \begin{array}{cccc} X_1 & X_2 & \cdots & X_p \end{array} \\ \left[\begin{array}{cccc} - & & & \\ \Theta_{\delta 21} & - & & \\ \vdots & & - & \\ \Theta_{\delta p1} & \Theta_{\delta p2} & \cdots & - \end{array} \right] \end{array}$$

The correlations among the error terms of the error terms of the endogenous indicators in the measurement model are given by THETA-EPSILON Θ_ε, i.e. $\Theta_\varepsilon(q*q)$ is the correlation matrix of ε.

$$\begin{array}{c} \\ Y_1 \\ Y_2 \\ \vdots \\ Y_q \end{array} \begin{array}{c} \begin{array}{cccc} Y_1 & Y_2 & \cdots & Y_q \end{array} \\ \left[\begin{array}{cccc} - & & & \\ \Theta_{\varepsilon 21} & - & & \\ & & & \\ \Theta_{\varepsilon q1} & \Theta_{\varepsilon q2} & \cdots & - \end{array} \right] \end{array}$$

The elements of **B** represent direct effects of η- variables on other η- variables and the elements of Γ represents direct effects of ξ- variables on ξ- variables. ε, δ and ζ are vectors of error terms.

The main assumptions are:

1. $E(\eta) = E(\xi) = E(\zeta) = E(\varepsilon) = E(\delta) = 0$,
2. ζ is uncorrelated with ξ,

3. ε is uncorrelated with η and ξ,

4. δ is uncorrelated with ξ, η,

5. ζ, ε and δ are mutually uncorrelated, and

6. **I-B** is non-singular.

More details on the mathematics involved in SEM are provided by Jöreskog (1979, pp. 105-127), Browne (1982) and Bollen (1989, pp. 10-20).

If we look at the low birth weight example, depicted in the form of the path diagram in Figure 2.2.2, the actual equations (structural and measurement) will comprise, two exogenous constructs (Language and Ethnicity), two endogenous constructs (Dietary Intake and Acculturation) and three endogenous variables (Parity, Smoking and Low Birth Weight Status). Two of the endogenous variables, Parity and Smoking, are intermediate variables (this variable is a response in one equation and a predictor in another), while Low Birth Weight Status is the response variable. We will represent these equations in a straightforward manner, i.e. as the actual equations and then we shall represent them in matrix notation. The first step would be to construct structural equations into a series of structural equations for each endogenous variable and then to represent the path diagram (Figure 2.2.2) into a series of structural equations for the exogenous and endogenous constructs.

The structural equations for the endogenous constructs/variables are represented in Table 2.3.1 below.

Table 2.3.1: Structural Equations

Endog. cons./var. =		Exog. cons./var. +		Endog. cons./var.	+ Error
		Language	Ethnicity	Dietary Intake Accul. Smoking Parity	
Dietary Intake	=	β_1 Lang.			$+ \varepsilon_1$
Acculturation	=	β_2 Lang. +	β_3 Ethnic.		$+ \varepsilon_2$
Smoking	=			β_4 Accul.	$+ \varepsilon_3$
Parity	=			$\beta 5$ Accul.	$+ \varepsilon 4$
Low Birth Weight Status	=			β_6 Diet + β_7 Accul. + β_8 Smoke + β_9 Parity	$+ \varepsilon_5$

The structural model linking the endogenous constructs to the exogenous constructs is given as follows:

$$\eta_1 = \gamma_{11}\, \xi_1 + \zeta_1$$

$$\eta_2 = \gamma_{21}\, \xi_1 + \gamma_{22}\, \xi_2 + \zeta_2$$

The measurement model equations representing the relationship between the 8 exogenous indicators (Language Spoken, Preferred Language, Language Read Better Language Written Better, Respondent's Ethnic ID, Mother's Ethnic ID, Father's Ethnic ID and Birth Place) and the 2 exogenous constructs (Language and Ethnicity), and the relationship between the 7 endogenous indicators (Food Energy, Calcium, Iron, Education, Age, Size of the Community and Birth Place) and the two endogenous constructs (Dietary Intake and Acculturation), now needs to be constructed. This relationship between the indicators and the constructs or latent variables is indicated in Table 2.1. The measurement model equations for the exogenous and endogenous constructs are given in Table 2.3.2 and Table 2.3.3, respectively.

Table 2.3.2: Measurement model equations for the exogenous constructs

Exogenous Indicators		Exogenous Constructs			
		ξ_1 (Language)	ξ_2 (Ethnicity)	Error	
Language Spoken	=	$\lambda^x_{11}\xi_1$		+	δ_1
Preferred Language	=	$\lambda^x_{21}\xi_1$		+	δ_2
Language Read Better	=	$\lambda^x_{31}\xi_1$		+	δ_3
Language Written Better	=	$\lambda^x_{41}\xi_1$		+	δ_4
Respondent's Ethnic ID	=		$\lambda^x_{52}\xi_2$	+	δ_5
Mother's Ethnic ID	=		$\lambda^x_{62}\xi_2$	+	δ_6
Father's Ethnic ID	=		$\lambda^x_{72}\xi_2$	+	δ_7
Birth Place	=		$\lambda^x_{82}\xi_2$	+	δ_8

Table 2.3.3: Measurement model equations for the endogenous constructs

Endogenous Indicators		Endogenous Constructs			
		η_1 (Dietary Intake)	η_2 (Acculturation)	Error	
Food Energy	=	$\lambda^y_{11}\eta_1$		+	ε_1
Calcium	=	$\lambda^y_{21}\eta_1$		+	ε_2
Iron	=	$\lambda^y_{31}\eta_1$		+	ε_3
Birth Place	=		$\lambda^y_{42}\eta_2$	+	ε_4
Education	=		$\lambda^y_{52}\eta_2$	+	ε_5
Age	=		$\lambda^y_{62}\eta_2$	+	ε_6
Size of the Community	=		$\lambda^y_{72}\eta_2$	+	ε_7

The exogenous constructs (Language and Ethnicity) are correlated with each other. This is indicated by the curved arrows between these two constructs in Figure 2.2.2, so that the corresponding structural equation correlation among the two exogenous constructs can be represented by the PHI matrix given below,

$$
\begin{array}{c} \\ \xi_1 \\ \xi_2 \end{array}
\begin{array}{cc} \xi_1 & \xi_2 \\ \end{array}
\begin{bmatrix} - & \\ \Phi_{12} & - \end{bmatrix}
$$

There are no correlations between the error terms of the two endogenous constructs, so that the PSI matrix does not exist.

The measurement errors for Language Spoken and Preferred Language are correlated, so too are the measurement errors for Language Read Better and Language Written Better. The measurement errors for Respondent's Ethnic ID and Mother's Ethnic Id are correlated. So too are the measurement errors for Mother's Ethnic Id and Father's Ethnic ID. These measurement errors are not indicated on the path diagram (Figure 2.2.2) but the curved arrows are indicated on the path diagram . The measurement error correlation between the two exogenous indicators , is depicted by the theta-delta matrix below.

	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8
X_1	-							
X_2	$\Theta_{\delta 12}$	-						
X_3			-					
X_4			$\Theta_{\delta 34}$	-				
X_5					-			
X_6					$\Theta_{\delta 56}$	-		
X_7							-	
X_8								-

where,

X_1 - Language Spoken

X_2 - Preferred Language

X_3 - Language Read Better

X_4 - Language Written Better

X_5 - Respondent's Ethnic ID

X_6 - Mother's Ethnic ID

X_7 - Father's Ethnic ID

X_8 - Birth Place

The measurement error correlation between the two endogenous indicators, is depicted by the theta-epsilon matrix below.

	Y_1	Y_2	Y_3	X_8	Y_5	Y_6	Y_7
Y_1	-						
Y_2		-					
Y_3			-				
X_8				-			
Y_5					-		
Y_6					$\Theta_{\varepsilon 65}$	-	
Y_7				$\Theta_{\varepsilon 74}$			-

where,

Y_1 - Food Energy

Y_2 - Calcium

Y_3 - Iron

X_8 - Birth Place

Y_5 - Education

Y_6 - Age

Y_7 - Size of the Community

The path diagram in Figure 2.2.2 can now be represented in LISREL notation. This is done in Figure 2.3.1 below.

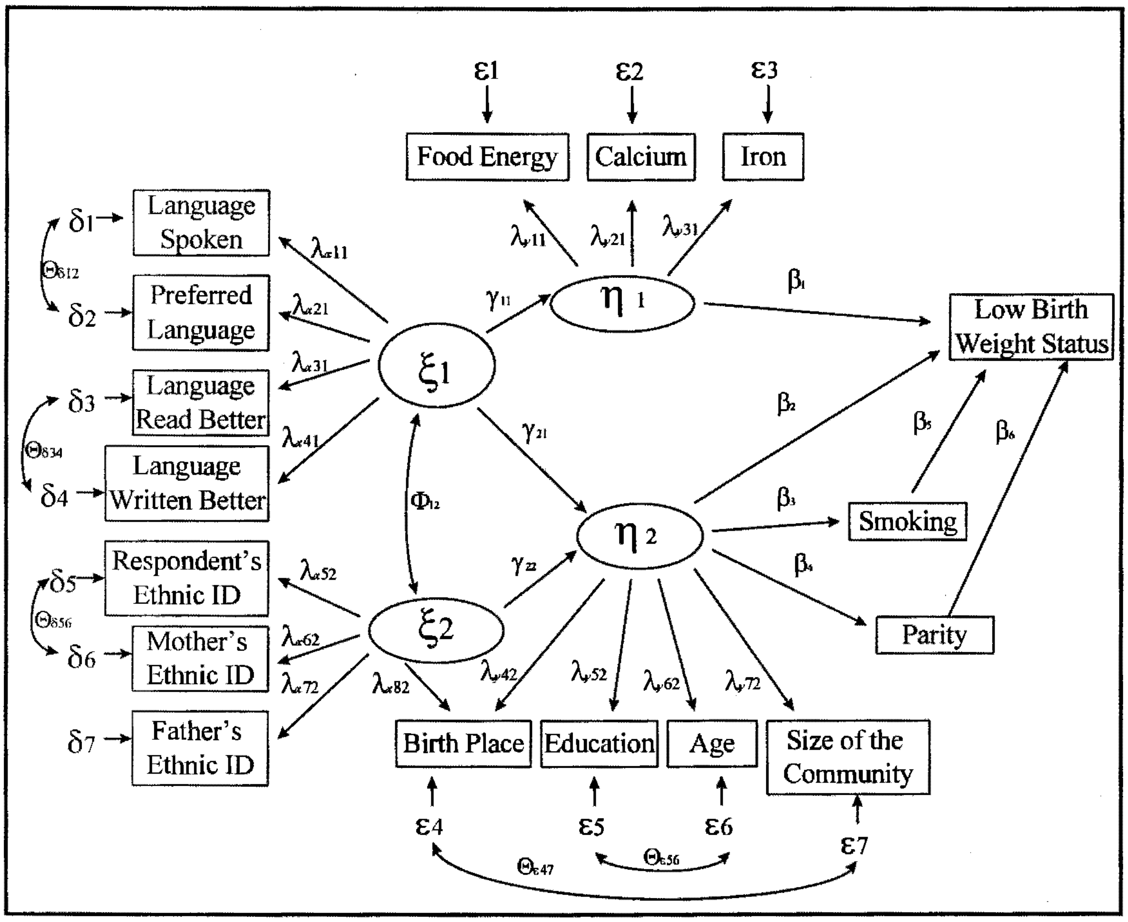


Figure 2.3.1: Path Diagram with the LISREL notation for the low birth weight example.

It should be remembered that the terms *exogenous* and *endogenous* are model specific. It may be that an exogenous variable in one model is endogenous in another. Specifications of any causal relationship can be incorporated directly into one of the eight matrices discussed in this section.

2.4 PRACTICAL PROBLEMS OF SEM

Although there has not been much criticism of the statistical theory which underlies structural equation models, people have criticised the application of the technique.

Categorical data can be a problem if not handled in the proper manner. The most common procedure that is adopted for dealing with categorical data is to compute some form of correlation matrix, and then to proceed as if the data had been obtained from continuous variables. Popular correlation matrices used are the Pearson correlation, polychoric and polyserial correlations. The polychoric correlation matrix is used when a categorical variable is correlated with another categorical variable and the polyserial correlation matrix is used when a categorical variable is correlated with a continuous variable. When there are more than two categorical variables, the numerical computation involved in producing this matrix becomes considerable (Dunn, Everitt and Pickles, 1993, p. 171).

Structural equation models have been criticised in that if the observed variables do not have a multivariate normal distribution then the model has no value. This is a valid criticism, but SEM methods are being developed for handling discrete and other non-normal data. Non-linear relationships within the data can severely affect the elements of the covariance matrix. Another source of difficulty can be outliers. Outliers are observations with values that are distinct or distant from the bulk of the data. When outliers are present, the covariances provide a misleading summary of the association between most of the cases and lead to large residuals. Detecting outliers should be done using univariate summary measures and bivariate graphical techniques. Gallini and

Casteel (1993) demonstrate the effects of outliers on parameter estimates in a structural equation model using an empirical data set. If outliers are suspected, whether due to improperly identified samples, incorrect measurement, data contamination or other factors, some approach to reducing the effects of the outliers should be considered. Some approaches are given by Gallini and Casteel (1993).

Strong criticisms have been made on the use of standardised regression coefficients, correlations and path coefficients. Greenland et al. (1986) argue about the "Fallacy of Employing Standardized Regression Coefficients as Measures of Effect.". This is not a direct attack on structural equation modelling. It basically argues against all correlation type techniques as measures of effect. The implication is that correlation type techniques are subject to distortion, and furthermore, offer no meaningful biological or public health interpretation. For example, how does one transcribe a path coefficient or estimate of model fit in terms of disease risk to an individual or group of individuals. Rothman (1986, p. 303) argues that techniques relying on path coefficients or related estimates should be avoided in epidemiology.

CHAPTER 3

COMPARISON OF SEM TO RELATED TECHNIQUES

3.1 INTRODUCTION

The purpose of this chapter is to highlight the similarities of and differences between structural equation modelling and other related multivariate techniques. Structural equation modelling is compared to multiple regression and is also compared to factor analysis. In each section a simple data set is analysed and the results obtained from the two techniques are compared.

It is easy to show how regression and factor analysis is related to SEM. Simple examples from Bollen (1989, pp. 2-3) will illustrate how regression and factor analysis are similar to structural equation modelling. Consider the simple regression equation $y = \gamma x + \zeta$, where γ is the regression coefficient, ζ is the disturbance variable which is uncorrelated with x, and the expected value of ζ, $E(\zeta)$, is zero. Then x, y, and ζ are random variables. This regression model can now be written in terms of (2.3.1) as follows:

$$\begin{bmatrix} VAR(y) & COV(x,y) \\ COV(x,y) & VAR(x) \end{bmatrix} = \begin{bmatrix} \gamma^2 VAR(x) + VAR(\zeta) & \gamma VAR(x) \\ \gamma VAR(x) & VAR(x) \end{bmatrix}$$

where VAR ( ) and COV ( ) refer to the population variances and covariances of the elements in parentheses. In the matrices above, the left-hand side is Σ and the right-hand side is Σ (θ), with θ containing γ, VAR (x), and VAR (ζ) as parameters. The equation implies that each element on the left-hand side equals its corresponding element on the right-hand side. This example could be modified to include multiple regression, by adding explanatory variables, or more equations and other variables could be added to make a simultaneous equations system. Both cases can be represented as special cases of equation (2.3.1).

Now suppose we have two random variables, x_1 and x_2, that are indicators of a factor (or latent variable), denoted as ξ. The dependence of the variables on the factor is $x_1 = \xi + \delta_1$ and $x_2 = \xi + \delta_2$, where δ_1 and δ_2 are random disturbance terms, which are uncorrelated with ξ and with each other, and $E(\delta_1) = E(\delta_2) = 0$. Equation (2.3.1) can now be written as :

$$\begin{bmatrix} VAR\ (x_1) & COV\ (x_1, x_2) \\ COV\ (x_1, x_2) & VAR\ (x_2) \end{bmatrix} = \begin{bmatrix} \phi + VAR\ (\delta_1) & \phi \\ \phi & \phi + VAR\ (\delta_2) \end{bmatrix}$$

where ϕ is the variance of the latent variable ξ. Hence θ consists of three elements: ϕ, VAR (δ_1), and VAR (δ_2). The covariance matrix of the observed variables is a function of three parameters. More indicators and latent variables could be added and we could allow for factor loadings and correlated disturbances, thus creating a general factor analysis model. It could be easily shown that this represents a special case of the covariance structure equation (2.3.1).

3.2 MULTIPLE REGRESSION & SEM

Multiple regression analysis is by far the most widely used and versatile multivariate dependence technique, applicable in most fields of research (Hair et al., 1992, p. 19; Lewis-Beck, 1993, p. 39). It is applicable in most types of research, both experimental and observational. ANOVA, Regression and ANCOVA can be looked at within the framework of the General Linear Model. When we discuss multiple regression, this will refer to all of the above techniques.

Multiple regression analysis can be viewed as a special case of structural equation modelling. Multiple regression is specialised in that it assumes that the explanatory variables are measured without error. Regression has four basic assumptions. First, it consists of one equation examining a single relationship. Second, this equation specifies a directional relationship between two sets of variables, the dependent variable and a set of independent variables. The variation in the dependent variable is explained by means of a weighted combination of the values of the independent variables, called regression coefficients. Thirdly, the independent variables are assumed to be measured without error. Fourthly, the independent variables are assumed to be linearly related to the dependent variable.

Goldberger (1973) gives three situations in which structural equation modelling has advantages over regression analysis:

1. when the observed variables contain measurement errors,
2. when there is interdependence among the observed response variables, and
3. when important explanatory variables have not been measured.

Farrel (1994) gives one more area where SEM has the edge over regression analysis: The simplicity with which longitudinal data can be analysed and interpreted, although now there are regression techniques for handling longitudinal data (Von Eye, 1990; Diggle et al., 1994). In a recent study, Cole et al. (1993), argued in favour of SEM over multivariate analysis of variance (MANOVA) when multiple indicators for the constructs are involved but warn against choosing too casually one technique over the other.

Although SEM does have some advantages over regression analysis, lots of work still has to be done in the areas of goodness-of-fit and diagnostics. Assessing the overall goodness-of-fit for SEM is not as straightforward as with other multivariate dependence techniques. Structural equation modelling does not have a single statistical test that best describes the "strength" of the models' predictions (Bentler, 1980). Analysts therefore have to assess goodness-of-fit based on a number of measures. Up to now there exists only one statistically based goodness-of-fit measure in SEM. Regression diagnostics are also much more advanced than the diagnostics in SEM. Multivariate normality is difficult to assess in both regression and SEM and tests of univariate normality and bivariate graphical display techniques will have to be performed using the data. It is however impossible to carry out these tests if the raw data is not available. Testing for multicollinearity can be done using the variance inflation factor (VIF) and tolerance (Kleinbaum et al., 1988, p. 210) in regression and the diagnostics are excellent. This cannot be done in SEM unless the variables which are linearly related are specified in the path diagrams. Multicollinearity poses great difficulties for measurement models (Bollen, 1989, p. 59). Detecting outliers is also an easy task in regression but is difficult in SEM, where the residual covariance or correlation matrix is used.

Structural equation models can incorporate interaction effects in a similar manner to regression analysis. The interaction effect is defined as a new variable that is a combination of two or more variables and is included as an independent variable. However finding interactions between two factors with a large number of levels does create a problem as this would result in creating a large number of dummy variables. Obtaining the intercept term in SEM is a little more complicated. Most statistical software automatically provides the intercept in regression but is not so easily available in SEM. Bollen (1989, pp. 129-130) outlines how to obtain the intercept using LISREL VI.

In structural equation models each equation represents a causal link rather than a more empirical association. In a regression model, on the other hand, each equation represents the conditional mean of a dependent variable as a function of explanatory variables. It is this distinction that makes conventional regression analysis an inadequate tool for estimating structural equation models, but the appropriateness of each technique will depend on the questions that are being asked in the investigation.

Example 3.2:

The following hypothetical example from Hair et al. (1992, pp. 15-17) will serve as the data set for analysis in this section. This data set is given in Table 1 in Appendix A. In order to predict HATCO's Customer Satisfaction Level (X10), we use the seven independent variables, Delivery Speed (X1), Price Level (X2), Price Flexibility (X3), Manufacturer's Image (X4), Overall Service (X5), Sales Force Image (X6) and the Product Quality (X7). The database consists of 100 observations on 14 separate variables. Two classes of information were collected. The first class is the importance of seven benefits identified in past studies as most influential in the choice of suppliers. The second class of information contains evaluations of each respondent's satisfaction with HATCO, the percentage of their product purchases made from HATCO, and general characteristics of the purchases made from HATCO. For purposes of analyses the following variables will be used:

X1	-	Delivery Speed
X2	-	Price Level
X3	-	Price Flexibility
X4	-	Manufacturer's Image
X5	-	Service
X6	-	Sales Force Image
X7	-	Product Quality
X9	-	Product Usage Level
X10	-	Customer Satisfaction Level

3.2.1 Regression Solution

To demonstrate the use of multiple regression, we will show the procedures used by HATCO to attempt to predict the satisfaction level of their customers from measures obtained from a survey.

Below is a list of the variables used in the analysis and their descriptive statistics, which includes the mean, the standard deviation and the minimum and maximum values. All these variables showed little deviation from univariate normality.

Descriptive Statistics

Variable	N	Mean	Std Dev	Sum	Minimum	Maximum
X1	100	3.515	1.321	351.500	0	6.100
X2	100	2.436	1.312	243.600	0.200	8.000
X3	100	7.894	1.387	789.400	5.000	10.000
X4	100	5.248	1.131	524.800	2.500	8.200
X5	100	2.916	0.751	291.600	0.700	4.600
X6	100	2.665	0.771	266.500	1.100	4.600
X7	100	6.971	1.585	697.100	3.700	10.000
X9	100	46.100	8.989	4610.000	25.000	65.000
X10	100	4.771	0.856	477.100	3.200	6.800

The product moment correlations among the 8 independent variables and their correlations with the dependent variable (X10) appear below. Examination of the correlation matrix indicates that X10 is strongly correlated with X9, X5 and X1. These should be significant predictors of X10 provided that multicollinearity is not a problem.

Correlation Analysis

Pearson Correlation Coefficients / N = 100

	X1	X2	X3	X4	X5	X6	X7	X9	X10
X1	1.000	-0.306	0.509	0.050	0.610	0.077	-0.631	0.676	0.651
X2	-0.306	1.000	-0.428	0.290	0.415	0.165	0.370	0.049	0.047
X3	0.509	-0.428	1.000	-0.116	0.067	-0.034	-0.448	0.559	0.524
X4	0.050	0.290	-0.116	1.000	0.299	0.788	0.200	0.224	0.476
X5	0.612	0.415	0.067	0.299	1.000	0.241	-0.055	0.701	0.631
X6	0.077	0.165	-0.034	0.788	0.241	1.000	0.177	0.256	0.341
X7	-0.483	0.370	-0.448	0.200	-0.055	0.177	1.000	-0.192	-0.283
X9	0.676	0.049	0.559	0.224	0.701	0.256	-0.192	1.000	0.711
X10	0.651	0.047	0.525	0.476	0.631	0.341	-0.283	0.711	1.000

Initially the model with the eight predictors and two interaction terms (X1*X3 and X1*X2) was fitted. Both the interaction terms were not significant at the 5% level of significance, so the model with only the first order terms is fitted. This model with the 8 predictors (X1, X2, ..., X7, X9) is used to predict the levels of customer satisfaction of HATCO's customers.

Model: **MODEL1**

Dependent Variable: X10

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	8	57.95427	7.24428	45.428	0.0001
Error	91	14.51163	0.15947		
C Total	99	72.46590			

Root MSE	0.39934	R-square	0.7997
Dep Mean	4.77100	Adj R-sq	0.7821
C.V.	8.37005		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEPT	1	-0.510511	0.45238863	-1.128	0.2621
X1	1	0.099293	0.07037809	1.411	0.1617
X2	1	0.024512	0.05421285	0.452	0.6522
X3	1	0.289622	0.04867033	5.951	0.0001
X4	1	0.417447	0.06015913	6.939	0.0001
X5	1	0.421993	0.13500131	3.126	0.0024
X6	1	-0.187581	0.08661249	-2.166	0.0329
X7	1	-0.040589	0.03220567	-1.260	0.2108
X9	1	-0.001127	0.00940589	-0.120	0.9049

Variable	DF	Tolerance	Variance Inflation
INTERCEPT	1	-	0.00000000
X1	1	0.18643995	5.36365731
X2	1	0.3185504	3.13922038
X3	1	0.35372851	2.82702684
X4	1	0.34769113	2.87611593

X5	1	0.15659792	6.38578101
X6	1	0.36135446	2.76736587
X7	1	0.61799404	1.61813858
X9	1	0.22534047	4.43772930

These 8 predictors account for 79.97% of the variation of X10, with X3 ($p<0.001$), X4 ($p<0.001$), X5 ($p=0.0024$), X6 ($p=0.0329$) significant. All the other predictors are not significant at either the 5% or 10% levels of significance. The adjusted R^2 for this model is 0.7821.

Collinearity Diagnostics(intercept adjusted)

Number	Eigen.	Condition Index	Var Prop X1	Var Prop X2	Var Prop X3	Var Prop X4	Var Prop X5	Var Prop X6
1	2.879	1.000	0.018	0.001	0.018	0.003	0.009	0.003
2	2.397	1.096	0.001	0.028	0.013	0.037	0.005	0.031
3	1.159	1.576	0.001	0.068	0.014	0.055	0.028	0.090
4	0.639	2.123	0.008	0.003	0.130	0.015	0.004	0.002
5	0.494	2.415	0.079	0.203	0.170	0.003	0.013	0.000
6	0.203	3.763	0.014	0.000	0.042	0.836	0.000	0.776
7	0.149	4.400	0.215	0.173	0.415	0.050	0.011	0.098
8	0.080	6.012	0.664	0.524	0.198	0.001	0.930	0.000

Number	Var Prop X7	Var Prop X9
1	0.017	0.021
2	0.034	0.001
3	0.003	0.004
4	0.540	0.045
5	0.229	0.005
6	0.031	0.027
7	0.128	0.712
8	0.018	0.185

All predictors for which the tolerance is less than 0.10 and consequently the variance inflation factor (VIF) is greater than 10, should be scrutinized (Kleinbaum et al., 1988, p. 210). If we look at the VIF and the tolerance, none of the predictors have a tolerance smaller than 0.15 and VIF greater than 6.39. This together with the small condition numbers indicate that multicollinearity is not a problem.

We now investigate a model which excludes three predictors which are not significant, X2, X7 and X9. This model is now presented.

Model: **MODEL2**
Dependent Variable: X10

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	5	57.64391	11.52878	73.115	0.0001
Error	94	14.82199	0.15768		
C Total	99	72.46590			

Root MSE	0.39709	R-square	0.7955
Dep Mean	4.77100	Adj R-sq	0.7846
C.V.	8.32300		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEPT	1	-0.824473	0.34772640	-2.371	0.0198
X1	1	0.106411	0.04779724	2.226	0.0284
X3	1	0.292538	0.03596684	8.134	0.0001
X4	1	0.419373	0.05930494	7.071	0.0001
X5	1	0.430139	0.07557319	5.692	0.0001
X6	1	-0.203758	0.08451788	-2.411	0.0179

Parameter	DF	Tolerance	Variance Inflation
INTERCEPT	1	.	0.00000000
X1	1	0.39967964	2.50200384
X3	1	0.64046858	1.56135684
X4	1	0.35376816	2.82670998
X5	1	0.49411737	2.02381066
X6	1	0.37523293	2.66501133

Dropping X2, X7 and X9 from the model has a very small effect on the mean square error (MSE), reducing it from 0.39934 to 0.39709. The coefficient of determination (R^2)

also reduced from 79.97% to 79.55% while the adjusted R^2 increased to 0.7846 from 0.7821. This tells us that X2, X7 and X9 are not important when predicting X10. All the remaining predictors (X1, X3, X4, X5 and X6) are significant.

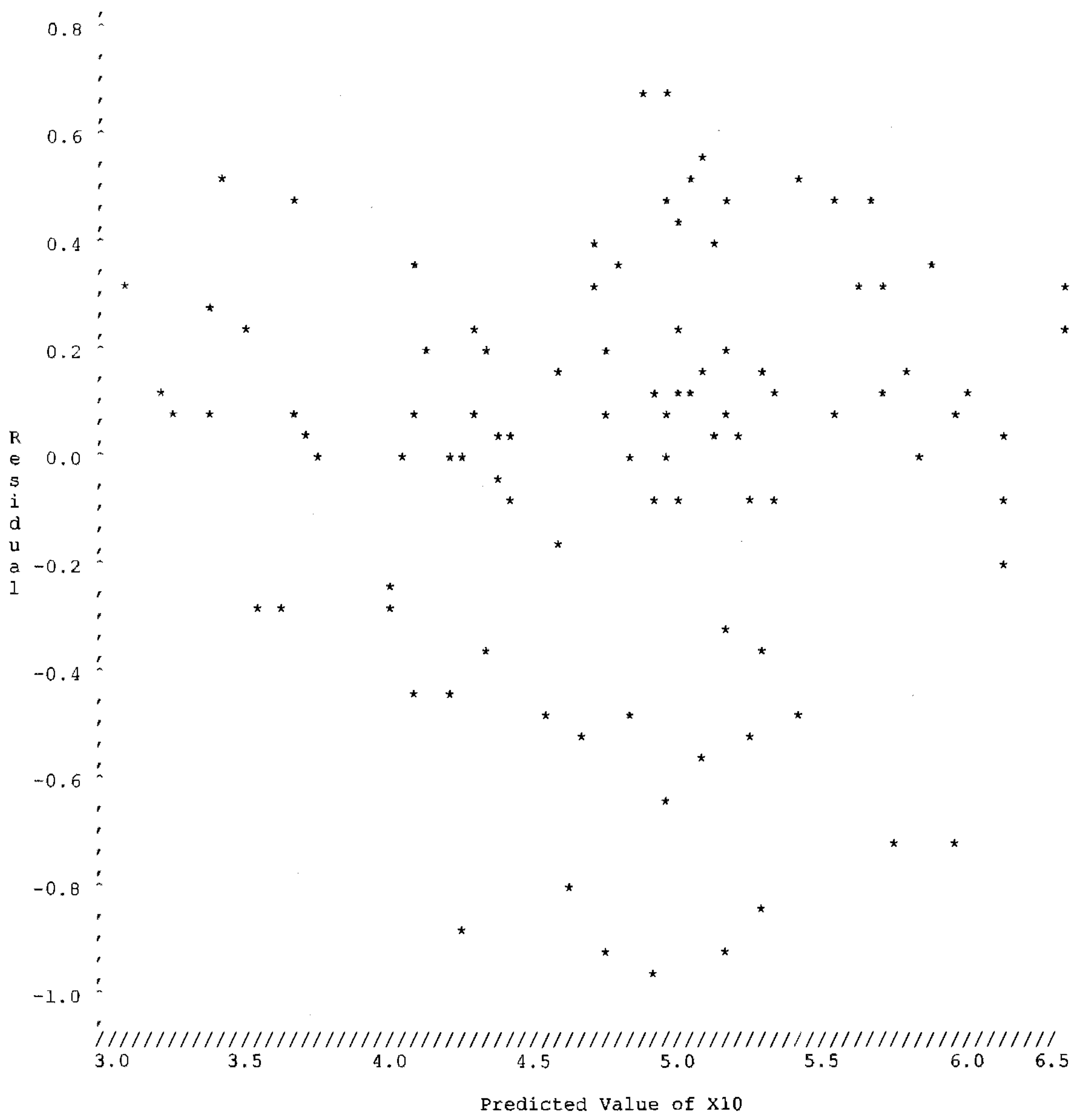
Collinearity Diagnostics(intercept adjusted)

Number	Eigenvalue	Condition Index	Var Prop X1	Var Prop X3	Var Prop X4	Var Prop X5	Var Prop X6
1	2.08145	1.00000	0.0344	0.0077	0.0460	0.0612	0.0482
2	1.65798	1.12045	0.0730	0.1152	0.0401	0.0149	0.0364
3	0.82691	1.58655	0.0051	0.3856	0.0109	0.2223	0.0426
4	0.23458	2.97878	0.7362	0.4710	0.0804	0.5193	0.1529
5	0.19908	3.23345	0.1513	0.0205	0.8226	0.1823	0.7198

Once again the tolerance for the predictors are all well above 0.10 and the VIF for the predictors are well below 10 to conclude that multicollinearity is not a problem in this data set (Kleinbaum et al., 1988, p. 210). The condition numbers from the collinearity diagnostics supports this conclusion.

There are however a few outliers. These are observations numbered 31, 34, 50, 56, 72 and 91. Removing these outliers would improve the fit of the model but there is no evidence supporting or rejecting the omission of these outliers and for the purpose of this dissertation the outliers are included in the analysis. The residuals are presented in Table 1 in Appendix C. The plot of the residuals against the predicted values does not indicate any unusual patterns, suggesting acceptable model fit.

Plot of RESID*PRED. Symbol used is '*'.



The regression model is therefore:

$$X10 = -0.824 + 0.106\ X1 + 0.293\ X3 + 0.419\ X4 + 0.430\ X5 - 0.204\ X6$$

Hence customer satisfaction can be predicted using only five (Delivery Speed, Price Flexibility, Manufacturer's Image, Service and Sales Force Image) of the 8 parameters. These are very important characteristics to consider in determining the satisfaction of HATCO customers. The faster products are delivered the more satisfied are the customers. Increased, price flexibility, manufacturer's image and service, all increase the satisfaction level. While increased sales force image decreases the level of satisfaction. If HATCO is to increase their customer satisfaction levels they need to focus on their delivery speed, price flexibility, manufacturer's image and service. Their customers are not interested in the image of the sales force.

3.2.2 SEM Solution

HATCO believes that certain of the explanatory variables measure the same characteristics and therefore proposed a model which has two factors or latent variables and a series of structural relationships which would help in their understanding of customer satisfaction in their industry. The proposed model is given below in Figure 3.2.1 and the SAS program is in Program 1 in Appendix B.

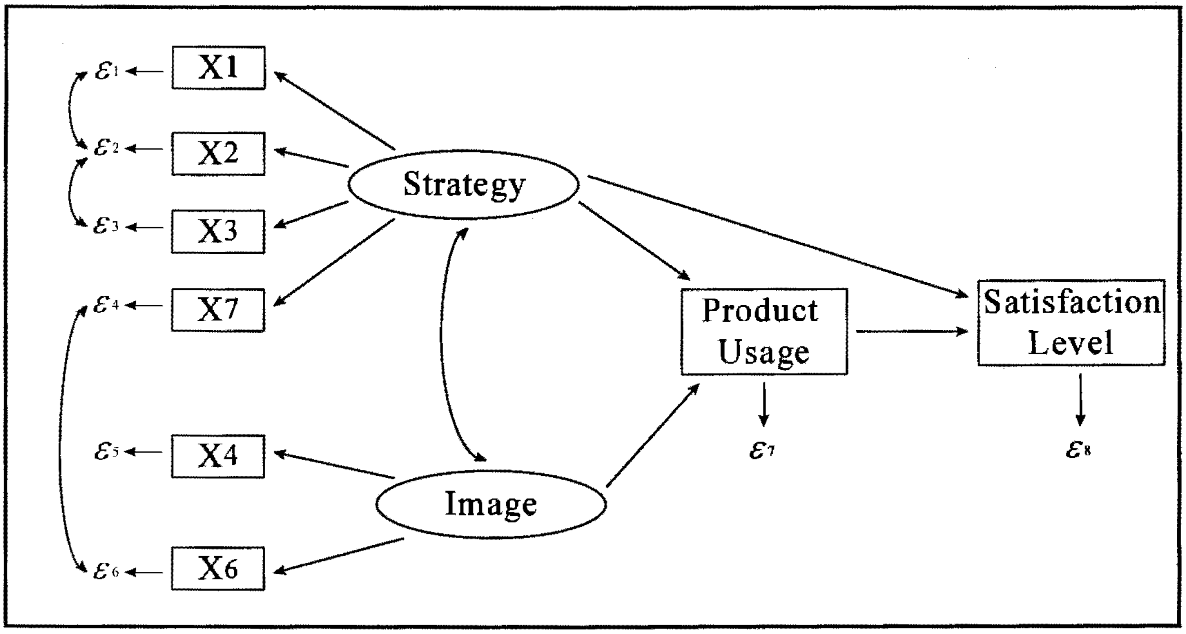


Figure 3.2.1: Path Diagram for the HATCO example.

From the path diagram it is evident that there are two exogenous constructs (Strategy and Image) with six manifest variables (X1, X2, X3, X7, X4 and X6) and two endogenous variables (Product Usage and Satisfaction Level). Product Usage is an intermediate variable as it is an endogenous variable which is related to the exogenous constructs and is also an exogenous variable when explaining the satisfaction level of HATCO's customers.

The covariance matrix and the residual matrix are given below. The residual matrix provides an indication that the model is not going to fit very well. Both the average absolute residual (0.1891) and the average off-diagonal absolute residual (0.2324) are not as low as would be expected for a model which fits well.

Covariance Matrix

	X1	X2	X3	X4	X6	X7	X9	X10
X1	1.744	-0.531	0.933	0.075	0.079	1.010	8.031	0.735
X2	-0.531	1.721	-0.778	0.430	0.167	0.769	0.582	0.053
X3	0.933	-0.778	1.922	-0.182	-0.037	-0.985	6.967	0.623
X4	0.075	0.430	-0.182	1.280	0.687	0.359	2.280	0.461
X6	0.079	0.167	-0.037	0.687	0.594	0.217	1.774	0.225
X7	-1.010	0.769	-0.985	0.359	0.217	2.513	-2.743	-0.384
X9	8.031	0.582	6.967	2.280	1.774	-2.743	80.798	5.466
X10	0.735	0.053	0.623	0.461	0.225	-0.384	5.466	0.732

Residual Matrix

	X1	X2	X3	X4	X6	X7	X9	X10
X1	0.000	0.100	-0.104	-0.056	-0.028	-0.314	-0.056	0.001
X2	0.100	-0.294	0.152	0.419	0.158	0.830	-0.130	-0.012
X3	-0.104	0.152	0.000	-0.292	-0.126	-0.403	0.207	0.009
X4	-0.056	0.419	-0.292	0.000	0.004	0.433	0.098	0.351
X6	-0.028	0.158	-0.126	0.004	0.005	0.256	0.007	0.136
X7	-0.314	0.830	-0.403	0.433	0.256	0.001	1.799	0.028
X9	-0.056	-0.130	0.207	0.098	0.007	1.799	0.000	0.000
X10	0.001	-0.012	0.009	0.351	0.136	0.028	0.000	0.000

Average Absolute Residual = 0.1891

Average Off-diagonal Absolute Residual = 0.2324

Goodness-of-Fit Measures

```
Goodness of Fit Index (GFI) . . . . . . . . . . .     0.8415
GFI Adjusted for Degrees of Freedom (AGFI). . . .     0.5925
Root Mean Square Residual (RMR) . . . . . . . . .     0.3761
Chi-square = 97.5931       df = 14     Prob>chi**2 = 0.0001
Null Model Chi-square:     df = 28                 470.7755
RMSEA Estimate  . . . . . .  0.2456  90%C.I.[0.2009, 0.2927]
Bentler's Comparative Fit Index . . . . . . . . .     0.8112
Akaike's Information Criterion. . . . . . . . . .    69.5931
Schwarz's Bayesian Criterion. . . . . . . . . . .    33.1207
Bentler & Bonett's (1980) NFI . . . . . . . . . .     0.7927
```

The goodness-of-fit measures now need to be examined. The chi-square is significant with a value of 97.5931 on 14 degrees of freedom ($p<0.001$) and there is strong evidence of lack of fit. This although not significant is a big improvement from the chi-square for the null model. However based on the chi-square statistic this model has to be rejected. All the other goodness-of-fit measures are well below the acceptable limits of 0.90. The GFI (0.8415) is not high enough. The root mean square residual (RMR=0.3761) is not low enough. The NFI (0.7927), the AIC (69.5931) and the SBC (33.12), provide very little in support of this model.

Although this model is rejected it is important to analyse the measurement and the structural models in order to re-specify the model. The construct loadings are now given below.

Construct Loadings (t values in parenthesis)

Indicator	Strategy	Image
X1	0.8430 (9.42)	
X2	0.0691 (0.61)	
X3	0.6713 (7.08)	
X4		0.8119 (6.32)
X6		0.9688 (6.99)
X7	-0.3945 (-4.045)	

Correlations Between the Latent Variables

	STRATEGY	IMAGE
STRATEGY	1.000000000	0.128855598
IMAGE	0.128855598	1.000000000

The construct loadings and their associated t-values of Image are relatively large. For the other exogenous construct, Strategy, all the loadings are large except for X2, which is not significant. There is also a strong indication that Strategy and Image are not correlated as postulated. The correlation between these two latent variable is just 0.129. Hence we might consider dropping X2 and the correlation between Strategy and Image when respecifying the measurement model. Although the t-value for X7 is significant, the factor loading is low and we might also consider dropping X7 as well. For this model I would not calculate the reliability of the two constructs and the variance extracted by the constructs as this model does not fit well enough.

The coefficients for the two endogenous variables (X9 and X10) from the structural model now need to be estimated.

Endogenous Variable Equations

```
X9        =    7.0752*F_STRAT + 1.4641*F_IMAGE + 0.5665 E7
Std Err        0.7804 BETA1     0.5600 BETA2
t Value        9.0659           2.6143

X10       =    0.0241*X9      + 0.4840*F_STRAT + 0.6196 E8
Std Err        0.0143 BETA4     0.1342 BETA3
t Value        1.6889           3.6064
```

Variances of Exogenous Variables

Variable	Parameter	Estimate	Standard Error	t Value
E7	EPS1	25.926764	5.488327	4.724
E8	EPS2	0.280972	0.044013	6.384

Squared Multiple Correlations

	Variable	Error Variance	Total Variance	R-squared
1	X9	25.926764	80.797980	0.679116
2	X10	0.280972	0.731979	0.616147

This component fits very well and 61.61% of the variation of X10 is accounted for by Strategy and X9 and 67.91% of the variation of X9 is accounted for by Strategy and Image. The error terms for both these equations are significant. This together with the R^2, tells us that a fair amount of variation of X10 is not accounted for by variables not included in the two equations and can be attributed to measurement error.

I now re-specify the model by dropping two manifest variables (X2 and X7) and add Image as a predictor of X10. There are two correlations amongst the error terms in this model (between ε_1 and ε_2 and between ε_7 and ε_8). The path diagram for the re-specified model is given below.

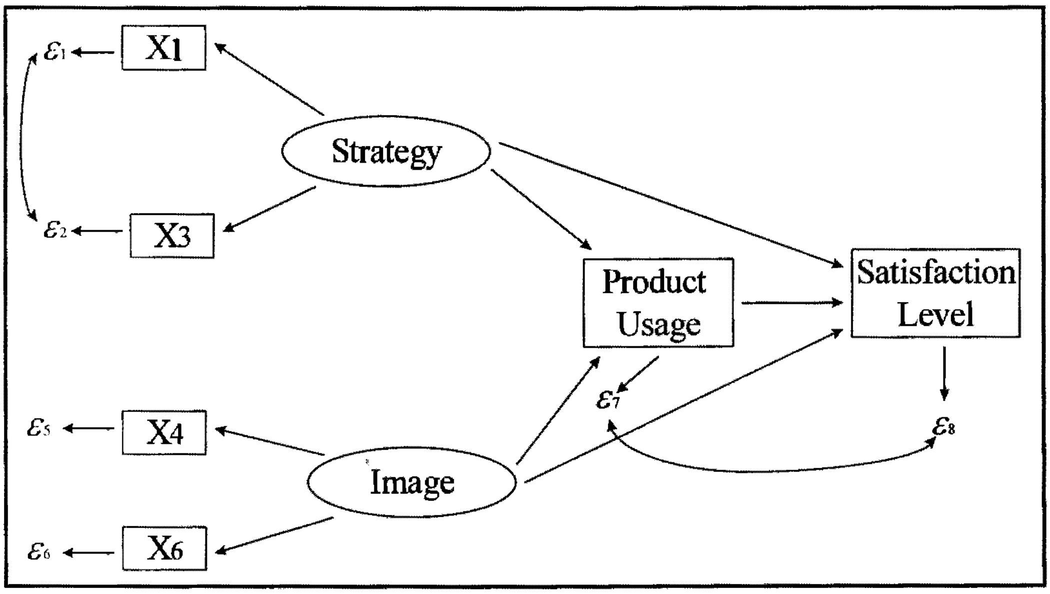


Figure 3.2.2: Path Diagram for the re-specified HATCO model.

In the revised model the two exogenous constructs are measured by four manifest variables. Strategy is measured by X1 (Delivery Speed) and X3 (Price Flexibility) and the other exogenous construct, Image, is measured by X4 (Manufacturer's Image) and X6 (Sales Force Image). The intermediate variable, X9 (Product Usage) is still in the re-specified model and X10 (Customer Satisfaction Level) is now related to X9, Strategy and Image. The two latent variables are no longer correlated.

Maximum likelihood estimation is used to arrive at the parameter estimates and the covariance matrix is analysed. This matrix together with the residual matrix is presented below.

Covariance Matrix

	X1	X3	X4	X6	X9	X10
X1	1.744	0.933	0.075	0.079	8.031	0.735
X3	0.933	1.922	-0.182	-0.037	6.967	0.623
X4	0.075	-0.182	1.280	0.687	2.280	0.461
X6	0.079	-0.037	0.687	0.594	1.774	0.225
X9	8.031	6.967	2.280	1.774	80.798	5.466
X10	0.735	0.623	0.461	0.225	5.466	0.732

Determinant = 4.231 (Ln = 1.442)

Residual Matrix

	X1	X3	X4	X6	X9	X10
X1	-.020	0.015	0.075	0.079	0.150	-.001
X3	0.015	0.004	-.182	-.037	-.199	-.047
X4	0.075	-.182	0.000	0.000	-.135	-.013
X6	0.079	-.037	0.000	0.000	0.186	0.017
X9	0.150	-.199	-.135	0.186	0.161	-.096
X10	-.001	-.047	-.013	0.017	-.096	-.019

Average Absolute Residual = 0.06835

Average Off-diagonal Absolute Residual = 0.08205

Most of the residuals are small and the average absolute residual is 0.068 and the average off-diagonal absolute residual is 0.082. These values give an early indication that the model fits well. The distribution of normalised residuals given below also gives an indication of good fit. None of the normalised residuals exceed 2.0 and the distribution is symmetric and centred around zero.

Distribution of Normalised Residuals

(Each * represents 1 residuals)

-1.25000 -	-1.00000	1	4.76%	|	*
-1.00000 -	-0.75000	0	0.00%	|	
-0.75000 -	-0.50000	0	0.00%	|	
-0.50000 -	-0.25000	2	9.52%	|	**
-0.25000 -	0	7	33.33%	|	*******
0 -	0.25000	8	38.10%	|	********
0.25000 -	0.50000	2	9.52%	|	**
0.50000 -	0.75000	0	0.00%	|	
0.75000 -	1.00000	1	4.76%	|	*

We now need to look at the goodness-of-fit measures to assess the fit of the model.

Goodness-of-fit Measures

```
Goodness of Fit Index (GFI) . . . . . . . . . . .        0.9853
GFI Adjusted for Degrees of Freedom (AGFI). . . .        0.9228
Root Mean Square Residual (RMR) . . . . . . . . .        0.0976
Chi-square = 4.5448         df = 4       Prob>chi**2 = 0.3373
Null Model Chi-square:      df = 15                  353.8163
RMSEA Estimate . . . . . . . . . 0.0371  90%C.I.[., 0.1603]
Bentler's Comparative Fit Index . . . . . . . . .        0.9984
Akaike's Information Criterion. . . . . . . . . .       -3.4552
Schwarz's Bayesian Criterion. . . . . . . . . . .      -13.8758
Bentler & Bonett's (1980) NFI . . . . . . . . . .        0.9872
```

The three absolute fit measures, the χ^2 = 4.545 (p=0.3378), the GFI (0.9853) and the RSMR (0.0976) indicates acceptable fit. The chi-square value of 4.545 is not significant and is a huge reduction from the χ^2 for the null model (353.82). The GFI is much higher than the acceptable threshold of 0.90 and the root mean square residual is low enough to suggest acceptable fit. The RMSEA estimate (0.0371) is also very low, again an indication of acceptable fit. The NFI value of 0.9872, the AIC (-3.46) and the SBC (-13.8753), also suggest good fit of the model.

Based on these goodness-of-fit measures, there is no indication of lack of fit and the model cannot be rejected.

The measurement model now needs to be assessed to see if the manifest variables are good indicators of Strategy and Image and to see if a fair amount of variation of these latent variables are accounted for. The construct loadings are now presented below.

Construct Loadings (t values in parenthesis)

Indicator	Strategy	Image
X1	0.9857 (10.62)	
X3	0.8598 (8.58)	
X4		0.9035 (5.81)
X6		0.8724 (5.78)

The construct loadings and the associated t-values for both Strategy and Image are all very high and are therefore important in describing the latent variables.

The reliability of both the constructs as well as the variance extracted now need to be presented.

Sum of |Standardised Loadings|:

Strategy = (0.9857 + 0.8598) = 1.8455

Image = (0.9035 + 0.8724) = 1.7759

Sum of Measurement Error:

Strategy = $(1 - 0.9857^2) + (1 - 0.8598^2) = 0.2891$

Image = $(1 - 0.9035^2) + (1 - 0.8724^2) = 0.4226$

Reliability:

Strategy = $(1.8455)^2 / \{(1.8455)^2 + 0.2891\} = 0.9218$

Image = $(1.7759)^2 / \{(1.7759)^2 + 0.4226\} = 0.8818$

Sum of Squared Standardised Loadings:

Strategy = $(0.9857^2 + 0.8598^2) = 1.7109$

Image = $(0.9035^2 + 0.8724^2) = 1.5774$

Variance:

Strategy = $(1.7109) / \{1.7109 + 0.2891\} = 0.8555$

Image = $(1.5774) / \{1.5774 + 0.4226\} = 0.7887$

In terms of reliability both Strategy and Image exceed the suggested level of 0.70 and are therefore very reliable. In terms of variance extracted both exogenous constructs exceed the threshold value of 0.50. Thus for both constructs, the indicators are sufficient in terms of how the measurement model in now specified.

The structural model comprises of two equations where the endogenous variable, X9 and X10 are predicted. These equations together with their coefficients and t-values are presented.

Endogenous Variable Equations

X9	=	7.7435*F_STRAT +	2.4013*F_IMAGE +	0.6940 E7	
Std Err		0.0815 BETA1	0.3100 BETA2		
t Value		95.0159	7.7458		

X10	=	0.0373*X9 +	0.4345*F_STRAT +	0.2241*F_IMAGE +	0.6169 E8
Std Err		0.0075 BETA4	0.0871 BETA3	0.0762 BETA5	
t Value		5.0064	4.9865	2.9397	

Variances of Exogenous Variables

Variable	Parameter	Estimate	Standard Error	t Value
E7	EPS1	38.835556	5.137715	7.559
E8	EPS2	0.285933	0.042122	6.788

Covariances among Exogenous Variables

Parameter			Estimate	Standard Error	t Value
E3	E1	COV13	-0.641125	0.128156	-5.003
E8	E5	COV58	0.157894	0.061303	2.576

Squared Multiple Correlations

	Variable	Error Variance	Total Variance	R-squared
5	X9	38.835556	80.637319	0.518392
6	X10	0.285933	0.751285	0.619408

It is evident that all the predictors are highly significant and are important in explaining both X9 (Product Usage) and X10 (Customer Satisfaction). 51.84% of the variation of

Product Usage is accounted for by both the exogenous constructs, Strategy and Image, and 61.94% of the variation of Customer Satisfaction is accounted for by Strategy, Image and Product Usage. This together with significant error terms e7 and e8 indicate that a fair amount of variation can be accounted for by measurement error and variables not included in the model. All the predictors of Customer Satisfaction are significant at the 5% level. An increase in Product Usage is expected to lead to increased Customer Satisfaction. Increased strategy of HATCO is expected to lead to higher satisfaction levels and a higher image perception of HATCO also leads to increased satisfaction levels. In order for HATCO to increase their satisfaction levels, they need to focus on increasing their delivery speed and their price flexibility which are strategic elements of their campaign. They would also have to increase the manufacturers image and their sales force image. While it is true that HATCO must focus on the above aspects of their business, they must not ignore the other aspects such as price levels, service and product quality.

3.2.3 Conclusions

The regression solution arrives at five predictors (Delivery Speed, Price Flexibility, Manufacturer's Image, Service and Sales Force Image) of Customer Satisfaction. Increased, delivery speed, price flexibility, service and manufacturer's image, increases the level of customer satisfaction of HATCO's customers. HATCO should therefore focus on these four aspects in their campaign to increase their customer satisfaction. However, they should not ignore other aspects of their business which might impact on customer satisfaction in future.

The structural equation model which is proposed (Figure 3.2.2), includes two latent variables which explain the concepts of Strategy and Image which HATCO has decided to focus on. The Strategy component is measured by Delivery Speed and Price Flexibility and the Image component is measured by Manufacturer's Image and Sales Force Image. The two indicators of Strategy load highly and so does the indicators of Image and are very important variables when measuring these two concepts. The reliability of both constructs and the variance extracted by the Strategy and Image are well above the acceptable thresholds, thus giving further evidence of the importance of the indicators.

The SEM solution gives a better understanding of the factors and variables which would help in increasing the levels of customer satisfaction of HACTO customers. This model includes Product Usage, which is absent in the regression model. The structural equation model provides strong evidence that Delivery Speed and Price Flexibility measure the same concept and that Manufacturer's Image and Sales Force Image measure another concept. This is the strength of SEM, it incorporates these factors with a regression model and analyses the data simultaneously, whereas the regression model includes the above indicators as independent variables. Furthermore, the interrelationship of all the factors and the variables is taken into consideration in this model thus giving the HATCO management a better understanding of the process which they need to follow to increase their customer satisfaction levels. The path diagram outlines the causal process involved in predicting customer satisfaction. This is not possible in regression.

An added advantage of using structural equation modelling for this example, is that the accepted model can be tested over time to see if the same factors and variables are still important in explaining customer satisfaction or whether a new model needs to be tested. This will help HATCO in assessing the strategic direction that needs to be followed. Hence this model should be re-assessed on a regular basis to keep up with the changes which are experienced in the environment they operate in.

3.3 EXPLORATORY FACTOR ANALYSIS & CONFIRMATORY FACTOR ANALYSIS

As mentioned in the previous chapter, structural equation modelling is made up of two components, the measurement model and the structural model. The measurement model relates the manifest variables to the latent variables or constructs. This component is identical to confirmatory factor analysis. The discussion from here on will focus on the comparison of exploratory factor analysis (EFA) and confirmatory factor analysis (CFA).

The primary goal of factor analysis is to explain the covariances or correlations between many observed variables by means of relatively few underlying latent variables. It can therefore be classified as a data reduction technique. Factor analysis can be approached in two ways, an exploratory and a confirmatory approach. Exploratory factor analysis (EFA) is the more traditional approach. The most distinctive feature of EFA, is that a model specifying the relationship between the latent variables and the manifest variables is not required. The number of latent variables need not be predetermined, the measurement errors are not allowed to be correlated, and under-identification (occurs when unique parameter estimates cannot be generated) is common (Bollen, 1989, pp. 226-232).

On the other hand, depending upon the knowledge of the researcher, factor analysis can be used as a means of testing hypotheses. When factor analysis is used as a means of testing specific hypotheses rather than exploring underlying dimensions, we refer to the technique as confirmatory factor analysis (CFA) (Everitt, 1984, pp. 13-14). In contrast to EFA, in CFA a model is constructed in advance, clearly identifying relationships and errors. The number of latent variables is set by the researcher, measurement errors are allowed to be correlated and parameter identification is required. In practice though, the distinction between the two approaches is not always clear-cut.

Everitt (1984, pp. 13-14) and Bollen (1989, pp. 226-232) discuss some of the problems of EFA and their limits. Firstly, the technique does not allow the researcher to constrain some of the factor loadings to zero. In EFA each latent variable influences all of the manifest variables. Secondly, EFA does not allow correlated errors of measurement. Situations arise frequently when measurement errors may be correlated because they come from the same source, or because of response bias in survey questions, or for other reasons. This may lead to ambiguous or misleading solutions. The third problem is that of determining the number of factors. This becomes a problem no matter which selection criterion is used.

These problems or limits reflect the inability of EFA to accommodate theoretical knowledge. Confirmatory factor analysis overcomes these shortcomings, but the strengths of CFA can only be exploited once the model is expertly formulated. Once the model is constructed, it can be estimated, and its fit to the data can be assessed using the measures discussed in the previous chapter.

We can therefore conclude that confirmatory factor analysis provides a much more powerful tool in confirmatory research than exploratory factor analysis.

Example 3.3:

The following example comes from Huba et al. (1981) and concerns the drug usage rates of 1634 students. The Pearson product-moment correlation matrix is in Table 2 in Appendix A.

The participants in the study were 1634 students in the seventh through to ninth grades in 11 schools in the greater metropolitan area of Los Angeles. The schools were selected from a larger sample initially contacted through their district offices during the spring of 1975. Each participant in the study completed a questionnaire about the number of times particular substances had ever been used. Responses were recorded on a five point scale:

1. Never tried
2. Only once
3. A few times
4. Many times
5. Regularly

Of the 1634 students providing usable responses 35.6% were male and 64.4% were female. White students comprised 56.4% of the sample, with Hispanic, Black and Asian students comprising 14.8%, 23.6% and 5.2% respectively. Seventh graders represent 38.7% of the sample, eight graders 37.2% and ninth graders 24.1%. More detailed characteristics of the sample are given in Huba et al. (1979).

The data will be analysed using the two techniques discussed above. In the exploratory factor analysis (EFA), the data will be analysed to investigate how many latent variables explain the usage of the 13 different drugs. While in the confirmatory factor analysis (CFA) a model will be tested.

3.3.1 Exploratory Factor Analysis Solution

Exploratory factor analysis (EFA) is now performed on the product moment correlation matrix. The principal component is used to estimate the loading matrix. The number of factors extracted or retained influences how well the off-diagonal elements of the correlation matrix can be reproduced by the EFA model. Using a large number of factors defeats the purpose of factor analysis, namely to describe the variables in terms of only a few factors. Although principal factor analysis is the most commonly used method of factor analysis, maximum likelihood (ML) factor analysis is also used in practice. The ML method provides tests to ensure that an adequate numbers of factors is retained in the analysis. However, for the purposes of this dissertation, principal factor analysis will be used.

In this analysis, I used the "Percentage of the total correlation criterion" and require 75% of the total correlation to be accounted for by the factors extracted. This is however not the only criterion which can be used. Others which can be used are the "number of factors criterion", the "eigenvalue criterion" and the "scree plot". Using the"Percentage of total correlation criterion", 7 factors will be retained as these account for at least 75% of the total correlation, in fact, the first 7 principal components accounts for 79% of the total correlation. The number of factors retained is large but I will nevertheless interpret the results.

Eigenvalues of the Correlation Matrix: Total = 13 Average = 1

	1	2	3	4	5	6	7	8	9	10	11	12	13
Eigenvalue	4.39	2.05	0.95	0.82	0.76	0.68	0.64	0.61	0.56	0.40	0.39	0.38	0.36
Difference		2.33	1.10	0.13	0.06	0.08	0.04	0.03	0.05	0.16	0.01	0.02	0.02
Proportion	0.34	0.16	0.07	0.06	0.06	0.05	0.05	0.05	0.04	0.03	0.03	0.03	0.03
Cumulative	0.34	0.50	0.57	0.63	0.69	0.74	0.79	0.84	0.88	0.91	0.94	0.97	1.00

7 factors will be retained by the **PROPORTION** criterion.

Factor Pattern

	F1	F2	F3	F4	F5	F6	F7	
V9	0.710	-0.232	-0.229	-0.095	0.313	-0.138	-0.113	Marijuana
V10	0.688	0.075	-0.347	-0.107	0.234	0.186	0.101	Hashish
V13	0.687	0.333	-0.228	-0.241	-0.179	0.021	-0.115	Amphetamines
V4	0.665	-0.462	0.048	0.052	-0.150	0.149	0.004	Liquor
V6	0.613	0.371	-0.169	0.076	-0.108	0.055	-0.442	Tranquilizers
V2	0.599	-0.565	0.123	0.086	-0.152	0.140	0.095	Beer
V1	0.585	-0.406	-0.047	0.027	0.243	-0.385	-0.104	Cigarettes
V11	0.578	0.243	0.308	-0.174	0.061	-0.437	0.366	Inhalants
V12	0.519	0.471	-0.108	-0.264	-0.306	0.131	0.330	Hallucinogenics
V3	0.558	-0.563	0.210	0.123	-0.258	0.133	0.052	Wine
V7	0.368	0.271	0.711	-0.296	0.222	0.217	-0.267	Drug store
V5	0.435	0.412	0.052	0.538	0.390	0.275	0.241	Cocaine
V8	0.421	0.451	0.143	0.480	-0.308	-0.298	-0.133	Heroin

Variance explained by each factor

F1	F2	F3	F4	F5	F6	F7
4.384976	2.050142	0.952309	0.817589	0.761744	0.683972	0.643355

The estimated loading matrix is now given on the previous page and all the variables from Cigarettes to Amphetamines are reordered according to their factor loadings. The factor loading of Marijuana is the highest of all for the first factor (F1) followed by Hashish etc. However, the factor patterns are not very clear since many factor loadings take on moderate values. Of the 7 factors, the first two explain the major proportion of the correlation.

The matrix of residual correlations provides a good indication that a major proportion of the total correlation is explained by this EFA model; most of the off-diagonal elements of this matrix are very small. If 9 factors were retained 88% of the total correlation would be accounted for and the off-diagonal elements would be much closer to zero. The root mean square off-diagonal residuals (0.0637) is very close to zero, indicating that the model fits the data well.

Residual Correlations With Uniqueness on the Diagonal

	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	
V1	0.27	-0.03	0.01	-0.05	0.05	-0.01	0.03	-0.04	-0.15	-0.06	-0.12	0.15	0.01	**Cigarette**
V2	-0.03	0.25	-0.13	-0.11	-0.01	0.02	0.00	0.01	0.00	0.00	0.01	-0.02	0.01	**Beer**
V3	0.01	-0.13	0.23	-0.12	0.02	0.02	-0.01	-0.04	0.00	0.01	0.01	-0.01	0.02	**Wine**
V4	-0.05	-0.11	-0.12	0.29	0.00	0.00	-0.01	-0.01	-0.01	-0.03	0.05	-0.04	-0.02	**Liquor**
V5	0.05	-0.01	0.02	0.00	0.06	0.03	-0.02	-0.08	-0.02	-0.12	0.01	0.01	0.07	**Cocaine**
V6	-0.01	0.02	0.02	0.00	0.03	0.24	-0.07	-0.16	-0.07	-0.06	0.14	-0.02	-0.09	**Tranquilizers**
V7	0.03	0.00	-0.01	-0.01	-0.02	-0.07	0.03	0.06	0.02	0.04	-0.06	0.04	-0.02	**Drugstore**
V8	-0.04	0.01	-0.04	-0.01	-0.08	-0.16	0.06	0.17	0.08	0.14	-0.09	0.02	-0.04	**Heroine**
V9	-0.15	0.00	0.00	-0.01	-0.02	-0.07	0.02	0.08	0.25	-0.06	-0.04	0.05	-0.05	**Marijuana**
V10	-0.06	0.00	0.01	-0.03	-0.12	-0.06	0.04	0.14	-0.06	0.29	0.01	-0.08	-0.09	**Hashish**
V11	-0.12	0.01	0.01	0.05	0.01	0.14	-0.06	-0.09	-0.04	0.01	0.15	-0.13	0.00	**Inhalants**
V12	0.15	-0.02	-0.01	-0.04	0.01	-0.02	0.04	0.02	0.05	-0.08	-0.13	0.21	-0.11	**Hallucinogen**
V13	0.01	0.01	0.02	-0.02	0.07	-0.09	-0.02	-0.04	-0.05	-0.09	0.00	-0.11	0.26	**Amphetamine**

Root Mean Square Off-diagonal Residuals: Over-all = 0.06373300

To make the results in the loading matrix easier to interpret, the Varimax method of orthogonal rotation is used. The new loading matrix provides the factor loadings with the variables reordered in terms of their loadings. The factor patterns are now much clearer.

Rotation Method: Varimax

Rotated Factor Pattern

	F1	F2	F3	F4	F5	F6	F7	
V3	**0.867**	0.020	0.113	0.062	-0.014	0.047	0.050	Wine
V2	**0.835**	0.067	0.209	-0.020	0.044	0.017	0.058	Beer
V4	**0.771**	0.187	0.268	0.043	0.042	0.048	0.001	Liquor
V12	0.070	**0.797**	-0.144	0.092	0.123	0.033	**0.327**	Hallucinogenics
V13	0.104	**0.754**	0.264	0.262	-0.002	0.127	0.070	Amphetamines
V10	0.120	**0.575**	**0.460**	-0.088	**0.349**	0.005	0.009	Hashish
V9	**0.308**	0.264	**0.753**	0.002	0.109	0.048	0.060	Marijuana
V1	**0.383**	-0.054	**0.725**	0.107	-0.029	-0.008	0.202	Cigarettes
V8	0.047	0.154	-0.020	**0.852**	0.188	0.017	0.213	Heroin
V6	0.050	**0.530**	0.296	**0.535**	0.106	0.216	-0.206	Tranquilizers
V5	0.018	0.143	0.071	0.219	**0.920**	0.104	0.082	Cocaine
V7	0.073	0.115	0.020	0.062	0.094	**0.957**	0.150	Drug store
V11	0.097	0.253	0.229	0.171	0.095	0.198	**0.801**	Inhalants

For the first factor, Wine, Beer and Liquor load highly while Marijuana and Cigarettes load moderately and all the variables which load highly relate to alcohol use and I therefore call this factor (F1) Alcohol Use. Hallucinogenics, Amphetamines, Hashish and Tranquilizers load highly on factor 2 (F2). These variables give a good indication of hard drug usage and I therefore call F2, Hard Drug Use. Factor 3 relates to cannabis use as Marijuana and Cigarettes load highly while Hashish loads moderately on this factor. It is therefore called Cannabis Use. Heroin and Tranquilizers load highly on F4. I would rather refer to this factor as Heroin Use. Cocaine loads highly for factor 5 while Hashish loads moderately. This factor I call Cocaine Use. Drug Store and Inhalants are the only variables which load highly on factors 6 and 7 respectively and I call these factors Drug Store Usage and Inhalant Use, respectively.

The present 7 factor model retains a large number of factors and I therefore try a 5 factor model using the NFACTOR criterion. These 5 factors accounts for 69% of the total correlation. The residual matrix is only marginally worse than that of the 7 factor model. This is expected as a lower percentage of the total correlation is accounted for by these 5 factors. The root mean square off-diagonal residuals (=0.0717) is not much different from the 0.0637 of the 7 factor model and is also fairly close to zero, indicating an acceptable fit of the data to the model.

The factor loadings for the 5 factor model after using Varimax rotation is now give below.

Rotated Factor Pattern

	F1	F2	F3	F4	F5	
V3	**0.86335**	0.03934	0.04340	0.02556	0.06682	Wine
V2	**0.82699**	0.04803	0.18403	0.00966	0.05356	Beer
V4	**0.77082**	0.17001	0.23926	0.03489	0.04909	Liquor
V12	0.00183	**0.79291**	0.02975	0.07495	0.17706	Hallucinogenics
V13	0.12837	**0.78167**	0.27267	0.08941	0.12378	Amphetamines
V6	0.10216	**0.60424**	0.21254	**0.36622**	0.06200	Tranquilizers
V9	**0.39332**	0.21824	**0.71107**	0.04952	0.08497	Marijuana
V10	0.16627	**0.44111**	**0.65064**	0.13608	0.03812	Hashish
V1	**0.52784**	-0.00045	**0.52906**	0.05486	0.08950	Cigarettes
V5	-0.07149	0.06597	**0.32522**	**0.81126**	0.17346	Cocaine
V8	0.14058	**0.41155**	-0.23285	**0.69184**	0.06822	Heroin
V7	0.04637	0.10587	0.01433	0.08601	**0.91133**	Drug store
V11	0.17458	**0.37021**	0.16117	0.17090	**0.54632**	Inhalants

Variance explained by each factor

F1	F2	F3	F4	F5
2.568832	2.201774	1.608421	1.347064	1.240668

For the first factor (F1), Wine, Beer, Cigarettes and Liquor load highly while Marijuana load moderately. This factor is almost identical to that of the 7 factor model and I therefore retain the name Alcohol Use. The second factor (F2) has Hallucinogenics, Amphetamines and Tranquilizers loading highly and Hashish, Heroin and Inhalants loading moderately. This is also similar to factor 2 of the previous model. The variables of F2 give a good indication of hard drug usage and is given the name Hard Drug Use. Factor 3 (F3) has Marijuana, Hashish and Cigarettes loading highly and Cocaine loading moderately. This factor is called Cannabis Use as the variables which load highly give a good indication of cannabis use. Factor 4 (F4) has Cocaine and Heroin loading highly while Tranquilizers load moderately. This factor is therefore called Cocaine & Heroin Use. Drug Store and Inhalants load highly on F5, with Drug Store loading exceptionally high. I therefore call this factor Drug Store Use.

The 5 factor model is accepted as the results are very similar to the 7 factor model and has the benefit of two less factors.

3.3.2 Confirmatory Factor Analysis Solution

A three factor model was postulated to explain the observed correlations and the Factors being Alcohol Use (F1), Cannabis Use (F2) and Hard Drug Use (F3). The path diagram depicting the model is given below in Figure 3.3.1:

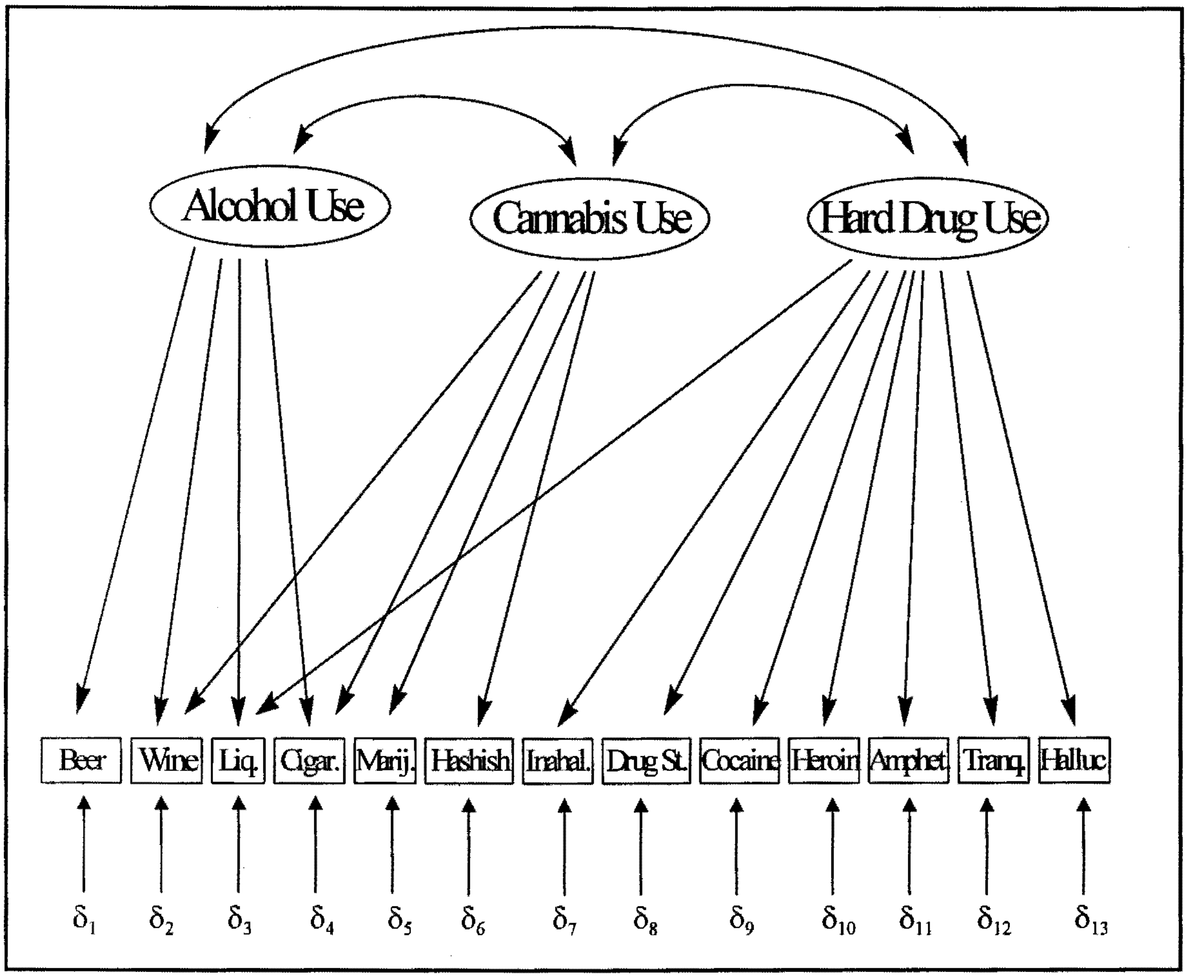


Figure 3.3.1: Initial Model for the Teenage Drug Usage

The initial model with correlated errors between Drug store and Inhalants, Cocaine and Amphetamines, Heroin and Tranquilizers and between Amphetamines and Tranquilizers had to be rejected as being fully adequate for representing the correlations among the 13 drug use variables, chi-square (54) = 213.9 (Table 3.3.2). On the other hand the individual parameter estimates are all highly significant. Furthermore the model's observed chi-square to degree of freedom ratio indicates that for this large sample there is not really that much discrepancy between the correlations obtained and those predicted from the model (Table 3.3.1). The Average Absolute Residual is also very small giving a further indication of the small discrepancy between the observed and the predicted correlation matrices. All the other indicators of goodness-of-fit are well above 0.95 (Table3.3.2) indicating that all the correlations among the measures are explained by the model.

Table 3.3.1: Residual Matrix for the Initial Model

	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13
V1	-.000	-.009	.018	-.014	-.028	.031	-.000	-.044	.004	-.021	.101	-.068	.032
V2	-.009	.000	.001	.006	-.058	-.007	.022	-.049	-.012	.027	.075	-.062	.010
V3	.018	.001	-.000	-.006	-.048	.017	.045	-.023	-.003	.006	.081	-.046	.033
V4	-.014	.006	-.006	-.000	-.063	.043	.008	-.060	.009	.032	.081	-.046	.033
V5	-.028	-.058	-.048	-.063	-.000	.020	.034	.081	-.049	-.002	-.003	-.044	.001
V6	.031	-.007	.017	.043	.020	-.001	.009	-.005	.031	.008	-.010	-.024	-.006
V7	-.000	.022	.045	.008	.034	.009	-.000	.047	-.001	-.033	-.000	.024	-.030
V8	-.044	-.049	-.023	-.060	.081	-.005	.047	.000	-.054	-.050	.045	.035	-.046
V9	.004	-.012	-.003	.009	-.049	.031	-.001	-.054	-.000	-.001	.063	-.076	.041
V10	-.021	.027	.006	.032	-.002	.008	-.033	-.050	-.001	.000	-.007	.006	.011
V11	.101	.075	.081	.075	-.003	-.010	-.000	.045	.063	-.007	-.000	.013	-.020
V12	-.068	-.062	-.046	-.072	-.044	-.024	.024	.035	-.076	.006	.013	-.000	.027
V13	.032	.010	.033	.027	.001	-.006	-.030	-.046	.041	.011	-.020	.027	-.000

Average Absolute Residual = 0.02588

Average Off-diagonal Absolute Residual = 0.03018

V1 = Cigarettes
V2 = Beer
V3 = Wine
V4 = Liquor
V5 = Cocaine
V6 = Tranquilizers
V7 = Drug store
V8 = Heroin
V9 = Marijuana
V10 = Hashish
V11 = Inhalants
V12 = Hallucinogenics
V13 = Amphetamines

Table 3.3.2: Indicators of Goodness-of-fit for the Initial Model

Goodness of Fit Index (GFI)		0.9808
GFI Adjusted for Degrees of Freedom (AGFI). . . .		0.9677
Root Mean Square Residual (RMR)		0.0359
Chi-square = 213.9032 df = 54		Prob>chi**2 = 0.0001
Null Model Chi-square: df = 78		6635.8126
RMSEA Estimate . . . . . . 0.0426 90%C.I.[0.0367, 0.0486]		
Probability of Close Fit		0.9786
Bentler's Comparative Fit Index		0.9756
Akaike's Information Criterion.		105.9032
Schwarz's Bayesian Criterion.		-185.6643
Bentler & Bonett's (1980) Non-normed Index. . . .		0.9648
Bentler & Bonett's (1980) NFI		0.9678

Although the fit of the initial model was good, improvements can be made by removing Wine as an indicator of Cannabis Use and removing Liquor as an indicator of Hard Drug Use. A few more correlated errors (which are theoretically justified) are added. A list of all these correlated errors can be viewed in Appendix B (Program 2, Revised Model).

The path diagram for the revised model is now given below in Figure 3.3.2.

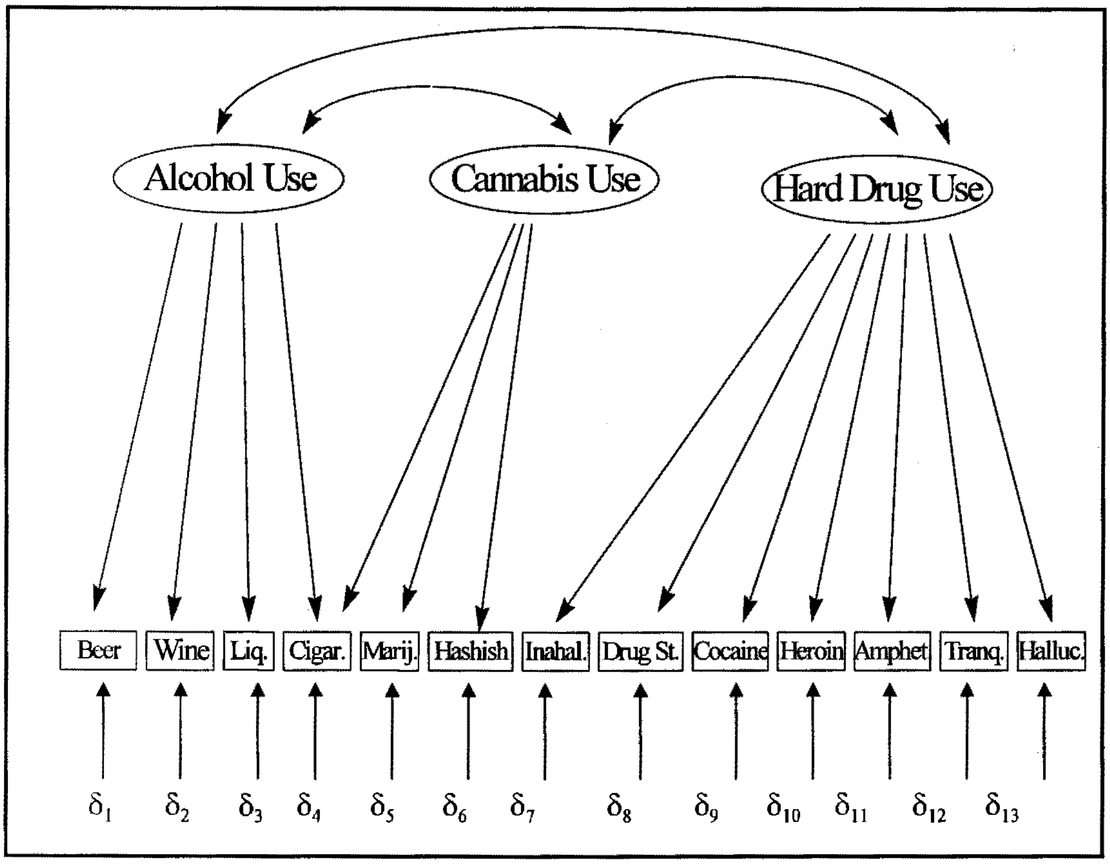


Figure 3.3.2: Path Diagram for the Revised Model

These improvements on the initial model do not improve the Chi-square (211.7503) and has minor improvements on the other Goodness-of-fit indices (Table 3.3.3). All the goodness-of-fit measures for the revised model exceed 0.95. Once again indicating that all the correlations among the measures are explained by the model. Furthermore the model's observed chi-square to degree of freedom ratio indicates that for this large sample there is not really that much discrepancy between the correlations obtained and those predicted from the model. Even though the chi-square is significant, the model results in a huge reduction in the χ^2 for the null model (6618.42).

Table 3.3.3: Indicators of Goodness-of-fit for the Revised Model

Goodness of Fit Index (GFI)	0.9813
GFI Adjusted for Degrees of Freedom (AGFI). . . .	0.9672
Root Mean Square Residual (RMR)	0.0356
Chi-square = 211.7503 df = 52	Prob>chi**2 = 0.0001
Null Model Chi-square: df = 78	6618.4166
RMSEA Estimate	0.0434 90%C.I.[0.0374, 0.0495]
Probability of Close Fit	0.9620
Bentler's Comparative Fit Index	0.9756
Akaike's Information Criterion.	107.7503
Schwarz's Bayesian Criterion.	-173.0184
Bentler & Bonett's (1980) Non-normed Index. . . .	0.9634
Bentler & Bonett's (1980) NFI	0.9680

Table 3.3.4: Residual Matrix for the revised model.

	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	
V1	.007	.006	.006	.006	-.032	.012	-.002	-.030	.014	-.023	.044	-.075	0.01	Cigarettes
V2	.006	.000	.019	-.016	-.067	-.031	.017	-.041	.001	.023	.066	-.075	-.020	Beer
V3	.006	.019	.000	-.002	-.074	-.028	.029	-.032	-.054	-.038	.054	-.080	-.022	Wine
V4	.006	-.016	-.002	.000	-.017	.086	.038	-.004	.049	.080	.122	-.020	.080	Liquor
V5	-.032	-.067	-.074	-.016	.000	.017	.047	.001	-.048	.011	.015	-.027	-.000	Cocaine
V6	.012	-.031	-.028	.086	.017	.000	.009	-.003	.009	-.006	-.014	-.034	.007	Tranquiliz.
V7	-.002	.017	.029	.038	.047	.009	.000	.077	.000	-.024	.005	.037	-.031	Drug Store
V8	-.030	-.041	-.032	-.004	.001	-.003	.077	-.001	-.026	-.005	.013	-.006	-.001	Heroin
V9	.014	.001	-.054	.049	-.048	.009	.000	-.026	.004	-.002	.063	-.030	.014	Marijuana
V10	-.023	.023	-.038	.080	.011	-.006	-.024	-.005	-.002	.000	.005	.015	-.007	Hashish
V11	.044	.066	.054	.122	.015	-.014	.005	.013	.063	.005	.001	.030	-.025	Inhalants
V12	-.075	-.075	-.080	-.020	-.027	-.034	.036	-.006	-.030	.015	.030	-.000	.015	Hallucinog.
V13	.009	-.020	-.022	.080	-.000	.007	-.031	-.001	.014	-.007	-.025	.015	.000	Amphet.

Average Absolute Residual = 0.02453

Average Off-diagonal Absolute Residual = 0.02843

There is not really that much discrepancy between the correlations obtained and those predicted from the revised model and the Average Absolute Residual (0.02453) is not much lower than that of the initial model (0.02588). The Average Off-diagonal Absolute Residuals (0.02843) is also marginally lower than that of the initial model (0.03018).

Distribution of Asymptotically Standardized Residuals

(Each * represents 1 residuals)

-5.25000 -	-5.00000	1	1.10%	*
-5.00000 -	-4.75000	0	0.00%	
-4.75000 -	-4.50000	0	0.00%	
-4.50000 -	-4.25000	0	0.00%	
-4.25000 -	-4.00000	1	1.10%	*
-4.00000 -	-3.75000	3	3.30%	***
-3.75000 -	-3.50000	1	1.10%	*
-3.50000 -	-3.25000	2	2.20%	**
-3.25000 -	-3.00000	1	1.10%	*
-3.00000 -	-2.75000	3	3.30%	***
-2.75000 -	-2.50000	2	2.20%	**
-2.50000 -	-2.25000	0	0.00%	
-2.25000 -	-2.00000	0	0.00%	
-2.00000 -	-1.75000	3	3.30%	***
-1.75000 -	-1.50000	3	3.30%	***
-1.50000 -	-1.25000	8	8.79%	********
-1.25000 -	-1.00000	3	3.30%	***
-1.00000 -	-0.75000	2	2.20%	**
-0.75000 -	-0.50000	0	0.00%	
-0.50000 -	-0.25000	4	4.40%	****
-0.25000 -	0	4	4.40%	****
0 -	0.25000	10	10.99%	**********
0.25000 -	0.50000	2	2.20%	**
0.50000 -	0.75000	10	10.99%	**********
0.75000 -	1.00000	1	1.10%	*
1.00000 -	1.25000	2	2.20%	**
1.25000 -	1.50000	2	2.20%	**
1.50000 -	1.75000	3	3.30%	***
1.75000 -	2.00000	0	0.00%	
2.00000 -	2.25000	4	4.40%	****
2.25000 -	2.50000	1	1.10%	*
2.50000 -	2.75000	2	2.20%	**
2.75000 -	3.00000	0	0.00%	
3.00000 -	3.25000	2	2.20%	**
3.25000 -	3.50000	0	0.00%	
3.50000 -	3.75000	3	3.30%	***
3.75000 -	4.00000	0	0.00%	
4.00000 -	4.25000	1	1.10%	*
4.25000 -	4.50000	0	0.00%	
4.50000 -	4.75000	1	1.10%	*
4.75000 -	5.00000	0	0.00%	
5.00000 -	5.25000	2	2.20%	**
5.25000 -	5.50000	1	1.10%	*
5.50000 -	5.75000	1	1.10%	*
5.75000 -	6.00000	2	2.20%	**

The maximum likelihood estimates for the loadings and correlations, standard errors and the student's t-statistic are given for each estimate in Table 3.3.5. In all cases the parameter estimates are significant at the nominal 5% level, indicating that the parameters are necessary and important when determining drug usage patterns amongst teenagers.

Table 3.3.5: (Parameter estimates, standard errors and t-values for the final Model)

	Alcohol Use			Cannabis Use			Hard Drug Use		
Drug	Estimate	SE	t-value	Estimate	SE	t-value	Estimate	SE	t-value
Cigarettes	0.347	0.035	9.95	0.337	0.035	9.59	0.000[f]		
Beer	0.797	0.023	35.47	0.000[f]			0.000[f]		
Wine	0.752	0.023	32.88	0.000[f]			0.000[f]		
Liquor	0.777	0.023	34.32	0.000[f]			0.000[f]		
Cocaine	0.000[f]			0.000[f]			0.503	0.027	18.46
Tranquilizers	0.000[f]			0.000[f]			0.659	0.024	27.52
Drug store	0.000[f]			0.000[f]			0.322	0.026	12.21
Heroin	0.000[f]			0.000[f]			0.387	0.028	14.02
Marijuana	0.000[f]			0.908	0.032	28.86	0.000[f]		
Hashish	0.000[f]			0.396	0.031	12.98	0.378	0.030	12.69
Inhalants	0.000[f]			0.000[f]			0.511	0.025	20.34
Hallucinogenics	0.000[f]			0.000[f]			0.608	0.024	24.87
Amphetamines	0.000[f]			0.000[f]			0.816	0.023	35.06

Factor Correlations

	F1	F2	F3
F1	1.0000[f]	0.6129	0.3362
F2	0.6129	1.0000[f]	0.5127
F3	0.3362	0.5127	1.0000[f]

[f] Parameter fixed at indicated value

This model can be summarized as follows. There are positive loadings for Beer, Wine, Liquor and Cigarettes on the first latent variable of Alcohol Use. The second latent variable of Cannabis Use has positive loadings for Marijuana, Hashish and Cigarettes. The third latent variable of Hard Drug Use has significant positive loadings for Cocaine, Tranquilizers, Drugstore Medication, Heroin, Hashish, Inhalants, Hallucinogenics and Amphetamines. The three latent variables are substantially intercorrelated in a positive manner. All the indices of goodness-of-fit does not indicate lack of fit and suggest an acceptance of this model but the chi-square value of 211.75 on 52 df (p-value < 0.001) rejects this model. This chi-square value may be unreliable and can be attributed to a "few heavy" user adolescents with peculiar patterns of co-use. This is confirmed by the Distribution of Asymptotically Standardized Residuals on page 85.

The reliability of the three constructs are now calculated together with the variance extracted for each construct.

Sum of | Standardized Loadings |:

Alcohol Use = (0.3481 + 0.7972 + 0.7521 + 0.7774)

= 2.6748

Cannabis Use = (0.3382 + 0.9102 + 0.3962)

= 1.6446

Hard Drug Use = (0.5031 + 0.6594 + 0.3218 + 0.3862 + 0.3777 + 0.5108 + 0.6075 + 0.8162)

= 4.1827

Sum of Measurement Error:

Alcohol Use = 2.073

Cannabis Use = 1.900

Hard Drug Use = 5.621

Sum of Squared Standardized Loadings:

Alcohol Use	= 1.927
Cannabis Use	= 1.100
Hard Drug Use	= 2.379

RELIABILITY:

Alcohol Use	$= (2.6748)^2 / \{(2.6748)^2 + 2.073\} = 0.775$
Cannabis Use	$= (1.6446)^2 / \{(1.6446)^2 + 1.900\} = 0.587$
Hard Drug Use	$= (4.1827)^2 / \{(4.1827)^2 + 5.621\} = 0.757$

VARIANCE EXTRACTED:

Alcohol Use	$= (1.927) / \{1.927 + 2.073\} = 0.482$
Cannabis Use	$= (1.100) / \{1.100 + 1.900\} = 0.367$
Hard Drug Use	$= (2.379) / \{2.379 + 5.621\} = 0.297$

In terms of reliability, Alcohol Use (0.775) and Hard Drug Use (0.757) are above the suggested level of 0.70 while Cannabis Use (0.587) is well below the recommended level. Hence Cannabis Use is not very reliable but Alcohol Use and Hard Drug Use are fine even though there are a few indicators which load moderately for these factors. The variance extracted for Cannabis Use (36.7%) and Hard Drug Use (29.7%) are much lower than the recommended value of 50% while the variance extracted for Alcohol Use (48.2%) is only marginally lower than the suggested value.

Although this model is acceptable, the inclusion of one or two more factors might lead to a better model to explain drug usage patterns amongst teenagers. This is evident by some low parameter estimates for Cannabis Use and Hard Drug Use.

3.3.3 Conclusions

Factor 1 (F1) of the exploratory factor analysis (EFA) has Beer (0.83), Wine (0.86), Cigarettes (0.53) and Liquor (0.77) loading high and Marijuana (0.39) loading moderately and is named Alcohol Use. The latent variable also named Alcohol Use in the confirmatory factor analysis (CFA), has Beer (0.80), Wine (0.75) and Liquor (0.78) loading very high and Cigarettes (0.35) loading moderately. The indicators and loadings of factor one (F1) from the EFA and the latent variable (Alcohol Use) from the CFA are almost identical. There is also a close resemblance of factor two (F2) from the EFA and the latent variable, Hard Drug Use, from the CFA. In the EFA, Hallucinogenics (0.79), Amphetamines (0.78) and Tranquilizers (0.60) load high and Hashish (0.44), Heroin (0.41) and Inhalants (0.37) load moderately while in the CFA, Hallucinogenics (0.61), Amphetamines (0.82), Inhalants (0.51), Cocaine (0.50) and Tranquilizers (0.66) load high and Hashish (0.38), Heroin (0.39) and Drug Store (0.32) load moderately. The latent variable, Cannabis Use, has Marijuana (0.91) loading very high and Cigarettes (0.34) and Hashish (0.40) loading moderately. This latent variable bears close resemblance with factor three (F3) of the EFA, which has Marijuana (0.71), Hashish (0.65) and Cigarettes (0.53) loading high and Cocaine (0.33) loading moderately.

The EFA model with five factors seems to explain the drug usage patterns amongst teenagers better than the CFA model. The CFA model lacks one or two more latent variables to give a better understanding of the drug usage patterns. Huba et al. (1981) have shown that a few adolescents with a peculiar pattern of co-use is impacting on the CFA model. Leaving out these individuals would significantly improve the model. However, it is not possible to identify these individuals as the raw data is not available.

Confirmatory factor analysis has the advantage of providing tests of significance of the parameters, and indicators of goodness-of-fit which assists the analyst in selecting a suitable model. There are also measures, such as reliability and variance extracted, which guide in re-specifying the model. All these are absent in exploratory factor analysis where we have to rely on arbitrary cut-off points for the factor loadings..

Frequently analysts have latent variables to contend with in their regression analysis, they calculate the principal components and use these in the regression analysis. These are however difficult to interpret and the analysts resort to using the original variables in the regression analysis. Structural equation model provides a dynamic way of combining regression and factor analysis. For example, if the researcher wants to relate the three factors from the CFA model to say teenage delinquency, then SEM would be more powerful than either EFA alone or regression alone.

CHAPTER 4

ANALYSIS OF ANC UTILIZATION DATA

A better understanding of structural equation modelling (SEM) and the methodology requires the application of the technique to a real data set. Chapter 2 introduced us to the methodology of SEM. In Chapter 3 simple data sets were analysed using SEM and alternative techniques and the results obtained were compared. A complex data set will now be analysed using SEM, showing the strengths and limitations of this technique.

4.1 INTRODUCTION

Health problems occur frequently during pregnancy. Low education and socio-economic levels are also associated with an increased risk of morbidity in pregnancy, of complaints during labour and in the postpartum period. Other known risk factors are age, parity and gravida. Parity is the number of live births by the women and gravida is the number of times the woman was pregnant.

Migrant women in Belgium frequently belong to a high risk group because of their low education and/or socio-economic status and/or their multigravidity. Belgian practitioners noticed differences between migrant and western women. For migrant women they noticed late first prenatal consultation, diminished contact rates and reserved attitudes towards prenatal examination in general and gynaecological investigation in particular (da Silveria et al., 1988).

The prenatal behaviour of migrant women is a very complex matter. On the one hand, the western care providers have established certain norms and a routine prenatal care that is inspired by the existing concepts of health and disease in West-European culture and based on biomedical sciences. On the other hand migrants have no other choice than to attend the western antenatal care, although antenatal care is set up from a western point of view and is not necessarily the most appropriate for them.

The general consensus is that pregnant migrant women have different preventive health service utilization behaviour which is assessed as "inappropriate" in comparison to Belgian women. The underlying hypothesis is that an adequate utilization of the antenatal services by the migrant pregnant women will decrease their probability of having serious complications during pregnancy and delivery and improve the health of the pregnant women.

A conceptual model was proposed by da Silveria et al. (1988) to study the utilization of antenatal services by migrant Turkish women in Belgium. This model is now given in Figure 4.1.1 and was analysed using a general multiple regression approach by Levin et al. (1989). Levin et al. (1989) also suggested an alternative method of analysis, "the structural analysis", where the modelling procedure itself is suggested by the conceptual model. The results from the structured analysis was very similar to that obtained from the general approach. Although a marginally higher value of R^2 for the structured analysis model than the model using the general regression model was found, this cannot be interpreted as a statistically better model, since in both cases regression was used as a descriptive tool, rather than trying to find the "best" model. Specifically this meant that variables which were thought to be important from prior knowledge, were included in the model.

The biggest shortcomings of the approach adopted by Levin et al. (1989) is that it was too arbitrary and that the data analysis was time consuming. This is a general problem in all of the traditional techniques, they cannot directly incorporate and analyse factors or latent variables in a simultaneous manner.

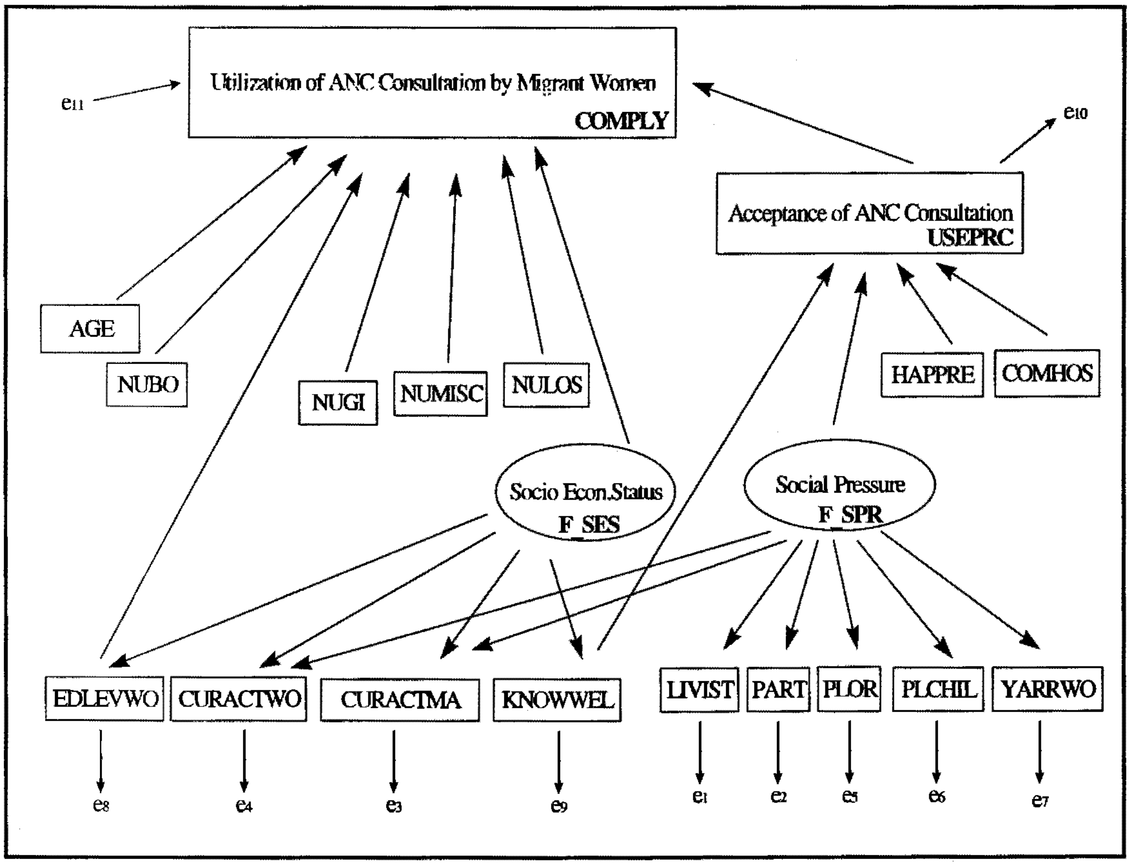


Figure 4.1.1: Path Diagram for the ANC model

The definitions of all the variables used in this model are on page 97.

4.2 THE PROCESS OF BUILDING THE MODEL

The model was developed in three stages:

1. brainstorming session,
2. first draft of the model, and
3. interactive process.

In the first stage a team consisting of Anthropologists, Demographers, Epidemiologists, Family Practitioners, Gynaecologists, Nurses, Nutritionists, Psychologists, Public Health Specialists and Sociologists met with the objective:

1. of defining the problems related to the utilization behaviour of antenatal services by migrant women,
2. to provide a list of markers which are supposed to have influence on the antenatal behaviour,
3. to interrelate determinants in "causal" pathways, and
4. to grade the determinants according to their relative priority.

All the individuals in the team were either directly involved in the health environment or actually involved with migrants.

The second stage involved developing an initial conceptual model and depicting it in the form of a path diagram. The final stage involved presenting the initial model to a research group on migrant studies and modifying the model. The new draft was once again presented to that research group and approved. Further information on the development and the uses of the conceptual model in the study of antenatal service utilization by migrant women in Belgium can be found in da Silveria et al. (1988).

4.3 THE USES OF THE MODEL

The model would be used,

1. to guide the choice of an adequate study design,
2. in the preparation of the questionnaire,
3. in the preparation of instruments for the measurement of facts and/or attitudes,
4. as a basis for statistical modelling,
5. in the detection of unexplored areas in the study of the determinants,
6. in the detection of causal mechanisms involved,
7. as a basis for mathematical model development, and
8. help for a holistic view of antenatal care.

4.4 METHODOLOGY

After the development of the conceptual model, two questionnaire instruments were developed for a survey of pregnant Turkish women. The model identified factors to be investigated by a factual questionnaire, and by an attitude questionnaire, which aimed at finding the women's opinions about pregnancy, childbirth and the family.

The survey was then carried out on a sample of 115 recently delivered Turkish women who had given birth between 15th and 30th of September 1987 in 3 maternity hospitals - Sint Franciscus (Zolder), Sint Etienne (Brussels) and Middelheim (Antwerp) - that are frequently used by the migrant population. The interviews were conducted in Turkish by Turkish females who had been specially trained for the job outside the normal visiting hours, i.e. in the absence of any one familiar with the interviewee, and they took about 60 minutes. None of the selected women refused to participate.

4.5 THE ANALYSIS OF THE DATA

The main aim of the data analysis was to determine which covariates significantly influenced the utilization of antenatal care. In their analysis of the data, Levin et al. (1989) split the conceptual model into 5 sub-models to facilitate analysis. The data was then analysed in a structured manner by a series of regression equations. This was found to be time consuming and highlighted one of the shortcomings of not analyzing the data using the equations simultaneously.

As a measure of utilization of antenatal care a compliance score was developed as follows: If a woman had no medical consultation in the first trimester of her pregnancy, she was given a score of -3, otherwise she was given a score of 1. For the second trimester, no visit resulted in a score of -2, and each visit earned a score of 1 up to a maximum of 3. For the third trimester, no visit was given a score of -1 and each visit earned a score of 1 up to a maximum of 8. The compliance score was then defined as a sum of the scores for the three trimesters, and thus lay between -6 (for a non-complier) and 12 (for an excellent complier). It was recognised that there was a degree of arbitrariness in this definition of the compliance score, so Levin et al. (1989) tried a slightly different score. The resulting model was very similar to the model with the original compliance score given above and it was decided to use the original compliance score as the response variable.

The following variables are considered in the model:

COMPLY	- Compliance score of the woman
COMHOS	- Means of communication with the doctor
CURACTMA	- Current activity of the man
CURACTWO	- Current activity of the woman
EDLEVWO	- Educational level of the woman
HAPPRE	- Was the woman happy when she found out about the pregnancy
KNOWWEL	- Knowledge of a Western language
LIVIST	- Actual living situation
NUBO	- Number of boys born to the woman
NUGI	- Number of girls born to the woman
NULOS	- Number of children lost
NUMISC	- Number of miscarriages
PART	- Relationship to the partner
PLCHIL	- Place where the woman spent most of her childhood
PLOR	- Place where the woman was born
USEPRC	- Was it useful to follow antenatal care
YARRWO	- Year the woman arrived in Belgium
AGE	- Age of the woman
F_SPR	- Social pressure of hostile environment and ghetto
F_SES	- Socio-economic Status of the woman

There are two latent variables in the model, F_SES (Socio-economic Status) and F_SPR (Social pressure of hostile environment and ghetto). The exogenous construct, F_SES, is measured by four manifest variables; namely, CURACTMA, CURACTWO, EDLEVWO and KNOWWEL. The other exogenous construct, F_SPR, is measured by seven manifest variables; namely, LIVIST, PART, CURACTMA, CURACTWO, PLOR, PLCHIL and YARRWO. There is one intermediate variable in the model, USEPRC (acceptance of the ANC consultation), which has four predictors (COMHOS, HAPPRE, KNOWWEL & F_SPR). The other endogenous variable is COMPLY (measuring the utilization of the ANC consultation by the migrant women). COMPLY has eight predictors, which comprises of six variables (EDLEVWO, AGE, NUBO, NUGI, NUMISC and NULOS), one latent variable (F_SES) and the intermediate variable (USEPRC).

Maximum likelihood estimation is used to arrive at the parameter estimates and the covariance matrix is analysed. The observed covariance matrix is given in Table 2 in Appendix C and the normalized residual matrix is in Table 3 in Appendix C. The values of the residual matrix should be relatively small and evenly spread among the variables if the model is a reasonable one for the data. Large residuals associated with specific variables are an indication of poor fit. The residual matrix gives an early indication of poor fit as there are numerous residuals that are large. These large residuals would impact on the chi-square statistic. The average normalized residual (0.7373) and the average normalized off-diagonal residual (0.8223) are both high, indicating unacceptable fit. This is supported by the number of large residuals given in the distribution of asymptotically standardized residuals. Ideally the distribution of asymptotically standardized residuals should be symmetric and centred around zero.

Distribution of Asymptotically Standardized Residuals

(Each * represents 2 residuals)

-3.00000 -	-2.75000	2	1.17%	*
-2.75000 -	-2.50000	2	1.17%	*
-2.50000 -	-2.25000	2	1.17%	*
-2.25000 -	-2.00000	2	1.17%	*
-2.00000 -	-1.75000	4	2.34%	**
-1.75000 -	-1.50000	2	1.17%	*
-1.50000 -	-1.25000	5	2.92%	**
-1.25000 -	-1.00000	7	4.09%	***
-1.00000 -	-0.75000	12	7.02%	******
-0.75000 -	-0.50000	6	3.51%	***
-0.50000 -	-0.25000	11	6.43%	*****
-0.25000 -	0	15	8.77%	*******
0 -	0.25000	59	34.50%	*****************************
0.25000 -	0.50000	11	6.43%	*****
0.50000 -	0.75000	2	1.17%	*
0.75000 -	1.00000	5	2.92%	**
1.00000 -	1.25000	6	3.51%	***
1.25000 -	1.50000	3	1.75%	*
1.50000 -	1.75000	1	0.58%	
1.75000 -	2.00000	7	4.09%	***

Before evaluating the structural and measurement models, the overall fit of the model needs to be assessed. The goodness-of-fit measures discussed in Chapter 2 will now be interpreted.

Goodness-of-fit Measures

Goodness of Fit Index (GFI)	0.7671
GFI Adjusted for Degrees of Freedom (AGFI). . . .	0.6277
Root Mean Square Residual (RMSR)	1.1027
Chi-square = 248.0253 df = 107	Prob>chi**2 = 0.0001
Null Model Chi-square: df = 153	584.5382
RMSEA Estimate . . . . . . 0.1353 90%C.I.[0.1133, 0.1574]	
Bentler's Comparative Fit Index	0.6732
Akaike's Information Criterion.	34.0253
Schwarz's Bayesian Criterion.	-211.0539
Bentler & Bonett's (1980) NFI	0.5757

ABSOLUTE FIT MEASURES: All three of the absolute fit measures are provided in the output. The chi-square value of 248.03 with 107 degrees of freedom is statistically significant ($p < 0.001$). This model clearly cannot be accepted based on the chi-square statistic. However, the chi-square test becomes more sensitive as the number of indicators rises and we therefore need to look at other measures. The GFI value of 0.7671 is lower than the recommended 0.90 and the RMSR value of 1.1027 and the RMSEA estimate (0.1353) are too high. The RMSR value must be evaluated in light of the large number of high residuals. Thus based solely on the above three measures, the model has to be rejected.

INCREMENTAL FIT MEASURES: The model is now evaluated relative to the null model. The null model has a chi-square value of 584.54 with 153 degrees of freedom. Although a substantial reduction in the χ^2 is gained, the NFI (0.5757) provides little to support this model.

PARSIMONIOUS FIT INDICES: The AGFI (0.6277), AIC (34.03) and Schwarz's Bayesian Criterion (-211.05), all provide very little in support of this model.

All three types of overall fit indices reveal that the model has to be rejected.

Measurement Model Fit

Although there is little to support this model, valuable information can be gained as to which factors are important in understanding the utilization of antenatal care (ANC) consultation by migrant women in Belgium. The results are also very important when re-specifying the model. We can therefore proceed with the interpretation of the results. The first stage is to examine the indicator loadings, which are given below.

Construct Loadings (t value in parenthesis)

INDICATORS	F_SPR	F_SES
LIVIST	0.4568	
	(4.3526)	
PART	0.0845	
	(0.7190)	
PLOR	0.0559	
	(0.4746)	
PLCHIL	-0.6892	
	(-8.9255)	
YARRWO	0.9995	
	(82.5519)	
CURACTMA	-0.0885	-0.1165
	(-0.4235)	(-0.5342)
CURACTWO	-0.2850	0.4682
	(-1.3720)	(2.1931)
EDLEVWO		0.3487
		(2.880)
KNOWWEL		-0.9409
		(-5.5641)

Covariance Among the Latent Variables

(t values in parentheses)

	F_SPR	F_SES
F_SPR	0.4763	-0.4161
		(-4.117)
F_SES	-0.4161	0.5933
	(-4.117)	

The construct loadings and the associated t values for F_SES are relatively large except for the variable CURACTMA. For the exogenous construct F_SPR, most of the variables load lowly, except for the variables LIVIST, PLCHIL and YARRWO.

Normally the variables that load lowly will be deleted and the model will be re-estimated. This we must keep in mind when re-specifying the model.

The reliability of the two constructs, F_SPR and F_SES are now calculated together with the variance extracted for each construct.

Sum of | Standardized Loadings | :

F_SPR = 2.6594

F_SES = 1.8743

Sum of Measurement Error:

F_SPR = 5.2180

F_SES = 2.7603

RELIABILITY:

$$F\_SPR = (2.6594)^2 / \{(2.6594)^2 + 5.2180\} = 0.5754$$

$$F\_SES = (1.8743)^2 / \{(1.8743)^2 + 2.7603\} = 0.5600$$

Sum of Squared Standardized Loadings:

F_SPR = 1.7820

F_SES = 1.2397

VARIANCE EXTRACTED:

$$F\_SPR = (1.7820) / \{1.7820 + 5.2180\} = 0.2546$$

$$F\_SES = (1.2397) / \{1.2397 + 2.7603\} = 0.3099$$

In terms of reliability, both exogenous constructs are well below the suggested level of 0.70 and are not very reliable. The variance extracted for each exogenous construct is also very low and well below the recommended level of 0.50. Thus the two constructs are not specified properly in this model.

Structural Model Fit

There are two endogenous variables in the structural model, USEPRC and COMPLY. USEPRC is also an exogenous variable and is therefore called an intermediate variable.

The endogenous variable equations are now given below. It is evident that there are a number of significant predictors of both USEPRC and COMPLY.

Endogenous Variable Equations

USEPRC =	- 0.1982*KNOWWEL	- 0.0954*COMHOS	+ 0.1499*HAPPRE	+ 0.4170*F_SPR
Std Err	0.1024 BETA3	0.0389 BETA2	0.0439 BETA16	0.1375 BETA4
t Value	-1.9365	-2.4529	3.4157	3.0335
	+ 0.8649 E10			

COMPLY =	0.6629*EDLEVWO	- 0.3677*USEPRC	+ 0.2788*AGE	- 0.7645*NUBO
Std Err	0.3363 BETA1	0.5673 BETA11	0.0916 BETA5	0.4517 BETA6
t Value	1.9710	-0.6481	-3.0428	-1.6926
	- 1.5395*NUGI	+ 0.6576*NUMISC	+ 1.4618*NULOS	+ 1.6823*F_SES
Std Err	0.3497 BETA7	0.5116 BETA8	0.5270 BETA9	0.2847 BETA10
t Value	-4.4026	1.2853	2.7737	5.9086
	+ 0.7342 E11			

Squared Multiple Correlations

	Variable	Error Variance	Total Variance	R-squared
1	USEPRC	0.296202	0.395939	0.251901
2	COMPLY	8.305703	15.406419	0.460893

Estimates of Error Terms

Variable	Parameter	Estimate	Standard Error	t Value
E10	THETA10	0.296202	0.049381	5.998
E11	THETA11	8.305703	1.422585	5.838

Only 25.19% of the variation of USEPRC is accounted for by KNOWWEL, COMHOS, HAPPRE and the latent variable F_SPR. For this endogenous variable COMHOS, HAPPRE and F_SPR are all statistically significant while KNOWWEL is only marginally not significant at the 5% level. Acceptance of ANC consultation is expected to increase by 0.1499 units for those women who were happy when they found out about their pregnancy and is not expected to increase for those women who were not happy. Social pressure of the hostile environment and ghettos are expected to increase the acceptance of ANC consultation. It is expected to increase by 0.4170 units for every unit increase in F_SPR. On average the acceptance of ANC consultation is 0.1982 points lower for women who knew a western language well than for those women who did not have a good knowledge of a western language. The acceptance of ANC consultation is also expected to decrease by 0.0954 units for those women who have a

means of communicating with the doctor as opposed to those who have no means of communication.

For COMPLY, AGE, NUGI, NULOS AND F_SES are all significant while USEPRC, EDLEVWO and NUMISC are not significant. Women who have lost children are also more prone to have higher compliance scores than women who have not lost children. In fact the compliance score is expected to increase by 1.4618 units for each child lost. The compliance score decreased by 0.7645 units for every boy the woman had given birth to and decreased by 1.5395 units for every girl the woman had given birth to. Women who have a higher socio-economic status have higher compliance scores than those who are of a lower socio-economic status. In fact the compliance score increases by 1.6823 units for every unit of F_SES. The compliance score increases by 0.2788 per unit increase in age for each woman. Although NUMISC is not significant, every miscarriage is expected to increase the compliance score by 0.6576 units. On average the compliance score increases by 0.6629 units for every unit increase in the educational level of the women. The acceptance of ANC consultation decreases the compliance score and is not significant.

The R^2 for this relationship is 0.461, indicating that 46.1% of the total variation is accounted for by the variables listed above. The estimates of the error terms, E10 and E11, for both endogenous equations are statistically significant. This together with the R^2 tells us that a fair amount of variation is due to variables not included in the model and to measurement error.

In order to improve the model, the non-significant exogenous variables, non-significant exogenous constructs and the indicators which load lowly are dropped from the model. These include USEPRC, NUBO, NUMISC, F_SPR and CURACTMA. Hence the revised model now has COMPLY as the only endogenous variables, F_SES as the only exogenous construct, three indicators which are CURACTWO, EDLEVWO and KNOWWEL. There are also four exogenous variables, namely, AGE, NUGI, NULOS and EDLEVWO.

The path diagram depicting the relationship of all the variables given above with COMPLY is now given in Figure 4.5.1.

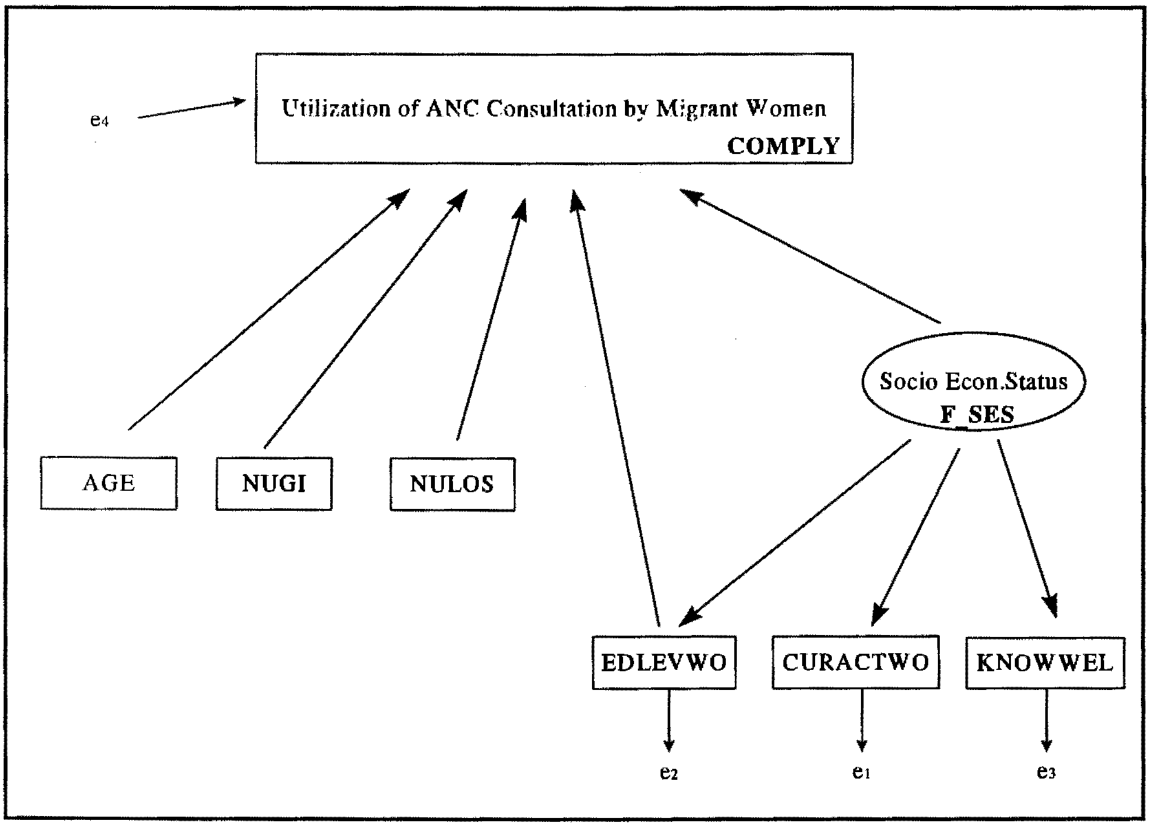


Figure 4.5.1: Path Diagram for the Revised ANC Model.

Maximum likelihood estimation is used to arrive at the parameter estimates and the covariance matrix is analysed. The observed covariance matrix is given in Table 4.5.1 below and the normalized residual matrix is in Table 4.5.2 below.

Table 4.5.1: Covariance Matrix

	EDLEVWO	CURACTWO	KNOWWEL	COMPLY	NUGI	NULOS	AGE
EDLEVWO	1.1964	0.2755	-0.3940	1.5245	-0.3099	-0.1093	-0.9183
CURACTWO	0.2755	0.5638	-0.4829	0.9791	-0.0827	-0.0453	-0.1209
KNOWWEL	-0.3940	-0.4829	0.8185	-1.4742	0.0545	0.0107	-0.4028
COMPLY	1.5245	0.9791	-1.4742	16.2209	-1.3030	0.7596	4.4209
NUGI	-0.3099	-0.0827	0.0545	-1.3030	1.2962	0.1145	2.2113
NULOS	-0.1093	-0.0453	0.0107	0.7596	0.1145	0.4970	1.2738
AGE	-0.9183	-0.1209	-0.4028	4.4209	2.2113	1.2738	23.4209

Determinant = 20.08 (Ln = 3.000)

Table 4.5.2: Normalized Residual Matrix

	EDLEVWO	CURACTWO	KNOWWEL	COMPLY	NUGI	NULOS	AGE
EDLEVWO	0.0000	-0.0541	-0.0214	0.0220	-2.0818	-1.1855	-1.4514
CURACTWO	-0.0541	0.0000	0.0000	0.0724	-0.8094	-0.7156	-0.2784
KNOWWEL	-0.0214	0.0000	0.0000	-0.3249	0.4429	0.1399	-0.7697
COMPLY	0.0220	0.0724	-0.3249	0.1217	-0.6352	-0.3505	-0.1909
NUGI	-2.0818	-0.8094	0.4429	-0.6352	0.0000	0.0000	0.0000
NULOS	-1.1855	-0.7156	0.1399	-0.3505	0.0000	0.0000	0.0000
AGE	-1.4514	-0.2784	-0.7697	-0.1909	0.0000	0.0000	0.0000

Average Normalized Residual = 0.3453

Average Off-diagonal Normalized Residual = 0.4546

The normalized residuals are all low except for that between EDLEVWO and NUGI. The average normalized residual is 0.3453 and the average normalized off-diagonal residual is 0.4546. These are relatively low. This together with the distribution of normalized residuals give an indication of good fit.

Distribution of Normalized Residuals
(Each * represents 1 residuals)

-2.25000 -	-2.00000	1	3.57%	*
-2.00000 -	-1.75000	0	0.00%	
-1.75000 -	-1.50000	0	0.00%	
-1.50000 -	-1.25000	1	3.57%	*
-1.25000 -	-1.00000	1	3.57%	*
-1.00000 -	-0.75000	2	7.14%	**
-0.75000 -	-0.50000	2	7.14%	**
-0.50000 -	-0.25000	3	10.71%	***
-0.25000 -	0	3	10.71%	***
0 -	0.25000	14	50.00%	**************
0.25000 -	0.50000	1	3.57%	*

Now the goodness-of-fit measures need to be assessed so that the overall fit of the model can be checked.

Goodness-of-fit Measures

Goodness of Fit Index (GFI)			0.9656
GFI Adjusted for Degrees of Freedom (AGFI). . . .			0.8930
Root Mean Square Residual (RMSR)			0.2402
Chi-square = 9.1993	df = 9		Prob>chi**2 = 0.4191
Null Model Chi-square:	df = 21		133.4405
RMSEA Estimate . . . . . . 0.0178 90%C.I.[., 0.1364]			
Bentler's Comparative Fit Index			0.9982
Akaike's Information Criterion.			-8.8007
Schwarz's Bayesian Criterion.			-29.1648
Bentler & Bonett's (1980) NFI			0.9311

ABSOLUTE FIT MEASURES: The chi-square value of 9.199 with 9 degrees of freedom is not statistically significant (p = 0.4191). The GFI value of 0.9656 is well above the recommended value of 0.90 and the RMSR value of 0.2402 and the RMSEA estimate of 0.0178 are low enough to be regarded as acceptable.

INCREMENTAL FIT MEASURES: The model is now evaluated relative to the null model. The null model has a chi-square value of 133.4405 with 21 degrees of freedom and a substantial reduction in the χ^2 is gained by the re-specified ANC model. The NFI (0.9311) is also above the recommended threshold of 0.90.

PARSIMONIOUS FIT INDICES: The AGFI (0.8930), AIC (-8.8007) and Schwarz's Bayesian Criterion (-29.1648), all indicate a parsimonious model.

All three types of overall fit indices are favourable and indicate a model which cannot be rejected.

Measurement Model Fit

Now that acceptable model fit has be achieved, the measurement model can be interpreted. There is just one latent variable and three manifest variables which make up this model. The indicator loadings together with their associated t-values are given below.

Construct Loadings (t value in parenthesis)

INDICATORS	F_SES
CURACTWO	0.7844
	(4.4918)
EDLEVWO	0.4363
	(3.243)
KNOWWEL	-0.9062
	(-4.3124)

The construct loadings and the associated t values for F_SES are relatively large. All the t-values are significant at the 5% level. The reliability of F_SES now needs to be calculated together with the variance extracted for F_SES.

Sum of | Standardized Loadings | :

F_SES = 2.1269

Sum of Measurement Error:

F_SES = 1.3732

RELIABILITY:

$$F\_SES = (2.1269)^2 / \{(2.1269)^2 + 1.3732\} = 0.7671$$

Sum of Squared Standardized Loadings:

F_SES = 1.6268

VARIANCE EXTRACTED:

$$F\_SES = (1.6268) / \{1.6268 + 1.3732\} = 0.5423$$

In terms of reliability, the exogenous construct is above the suggested level of 0.70 and is therefore reliable. The variance extracted for the exogenous construct is also above the recommended level of 0.50. Thus the construct is specified properly in this model.

Structural Model Fit

This model comprises of one endogenous variable, COMPLY, four exogenous variables, EDLEVWO, NUGI, NULOS and AGE, and one exogenous construct, F_SES. The endogenous variable equation is now given below.

Endogenous Variable Equations

COMPLY =	0.7652*EDLEVWO	- 1.2902*NUGI	+ 1.4271*NULOS	+ 0.2523*AGE
Std Err	0.3805 BETA7	0.3478 BETA3	0.5546 BETA5	0.0873 BETA1
t Value	2.0108	-3.7093	2.5732	2.8904

	+ 2.9757*F_SES	+ 0.7524 E4
Std Err	0.4860 BETA6	
t Value	6.1232	

Squared Multiple Correlations

Variable	Error Variance	Total Variance	R-squared
1 COMPLY	8.997630	15.893909	0.433894

Estimates of Error Terms

Variable	Parameter	Standard Estimate	Error	t Value
E4	THETA4	8.997630	1.569905	5.731

All the predictors of COMPLY are significant and these predictors account for 43.39% of the variation of COMPLY. On average the compliance score increases by 0.7652 units for every unit increase in the educational level of the woman. The compliance score is expected to decrease by 1.2902 units for every girl the woman had given birth to. Women who have lost children can be expected to have a higher compliance score than women who have not lost children. In fact the compliance score is expected to increase by 1.4271 units for each child lost. The compliance score increases by 0.2523 units per unit increase in age for each woman. Women who have a higher socio-economic status have higher compliance scores than those who are of a lower socio-economic status. In fact the compliance score increases by 2.9757 units for every unit of increase in F_SES.

The R^2 for this relationship is 0.434, indicating that 43.4% of the total variation is accounted for by the variables listed above. The estimates of the error term, E4, for the endogenous equation is statistically significant. This together with the R^2 tells us that a fair amount of variation is due to variables not included in the model and by measurement error.

Although, the results obtained point to a very good model, these results must be viewed with suspicion. This model fits the available data well but may perform badly with a different dataset. Cross validation or replication for an independent sample is an important step in building confidence in the model (Bollen, 1989, p. 305). The cross validation method has been advocated by Cudeck and Browne (1983) to assess overall model fit. It is one of many methods used to assess overall model fit. Cross validation begins by randomly splitting a sample in half and forming two sample covariance matrices $\mathbf{S}_1$ and $\mathbf{S}_2$. Then a model is fitted to $\mathbf{S}_1$ and results in an estimated covariance matrix. The cross validation step does not involve estimation of a new model but, instead, calculates a fitting function, F, when $\mathbf{S}_2$, and the estimated covariance matrix are substituted for **S** and Σ, respectively, in the fitting function. This procedure is repeated for several models. The model with the smallest value of F in the validation half of the sample has the best fit.

The method of cross validation was used to test the fit of the Revised Model as compared to the Initial Model. To do this the original data set was randomly split into samples. One comprising of a third of the observations and the other containing two thirds of the observations. The sample with two thirds of the observations from the original data set shall be called the **analysis sample** and the smaller sample will be called the **validation sample**. Both the models were analysed using the analysis sample and the validation sample and the goodness of fit index, together with the value of the Maximum Likelihood fitting function are presented below in Table 4.5.3.

Table 4.5.3: Goodness-of-fit Indices

	Initial Model		**Revised Model**	
	Analysis Sample	Validation Sample	Analysis Sample	Validation Sample
GFI	0.7125	0.611	0.9182	0.9377
AGFI	0.5405	0.3783	0.7454	0.8062
RMSR	1.3026	1.0019	0.3326	0.5529
RMSEA	0.1546	0.2385	0.1289	0
Chi-square	0.0001	0.0001	0.0664	0.8002
CFI	0.6616	0.4152	0.9196	1
NFI	0.5529	0.3693	0.8521	0.8744
AIC	13.1573	26.8775	-1.9763	-12.6225
SBC	-187.06	-94.6204	-27.8172	-31.8419
R^2 (Comply)	0.4664	0.6459	0.4491	0.422

Fitting Function	9.9344	-0.7164

The results indicate that the revised model performs far better than the initial model. The value of the fitting function for the revised model is much lower than that of the initial model. This value is very close to zero indicating a well specified model. For both the analysis sample and the validation sample, the results are very similar and indicate a model which fits the data well.

Thus the cross validation together with the goodness-of-fit indices for the revised model on page 108 indicates an acceptable model.

4.6 CONCLUSIONS

The initial ANC model (MODEL_1) was incorrectly specified, hence leading to a complex model which did not fit well. The revised ANC model (MODEL_2), although simple, fits very well.

Table 4.6.1: Comparison of Goodness-of-fit measures for MODEL_1 and MODEL_2.

	MODEL_1	MODEL_2
GFI	0.7671	0.956
AGFI	0.6277	0.8930
RMSR	1.1027	0.2402
RMSEA	0.1353	0.0178
χ^2	248.0253 (df = 107)	9.9199 (df = 9)
CFI	0.6732	0.9982
NFI	0.5757	0.9311
AIC	34.0253	-8.8007
SBC	-211.0539	-29.1648
R^2 (COMPLY)	0.4609	0.4339

A comparison of the goodness-of-fit measures for MODEL_1 and MODEL_2, reveals a significant improvement on the revised ANC model from the initial ANC model. Every goodness-of-fit measure in MODEL_2 points to an acceptable model with favourable fit while, all the measures in MODEL_1 indicate a model which does not fit well and can be improved. Although the coefficient of determination (R^2) is marginally higher for MODEL_1 than MODEL_2, it is expected to be. This is largely due to a decrease in the number of predictors of COMPLY in MODEL_2 than in MODEL_1.

Table 4.6.2: Comparison of the Measurement model for MODEL_1 and MODEL_2

	MODEL_1	MODEL_2
Reliability		
F_SES	0.5600	0.7671
F_SPR	0.2062	
Variance Extracted		
F_SES	0.3100	0.5423
F_SPR	0.2546	

Table 4.6.2 gives us a good indication of the improvement on the measurement model from MODEL_1 to MODEL_2. There is a significant improvement on the reliability and the variance extracted for F_SES in MODEL_2 from MODEL_1.

We now compare the parameter estimates from MODEL_1, MODEL_2 and those given in Levin et al. (1989). These are given together with the standard errors for each of the parameters in Table 4.6.3.

Table 4.6.3: Parameter estimates from the three models.

	MODEL_1	MODEL_2	LEVIN MODEL
AGE	0.2788 (0.0916)	0.2523 (0.0873)	0.26 (0.11)
EDLEVWO	0.6629 (0.3363)	0.7652 (0.3805)	
F_SES	1.6823 (0.2847)	2.9757 (0.4860)	
KNOWWEL			2.45 (1.63)
NUBO	-07645 (0.4517)		-0.94 (0.61)
NUGI	-1.5395 (0.3497	-1.2902 (0.3478)	-1.74 (0.47)
NULOS	1.4618 (0.5270)	1.4271 (0.5546)	
NUMISC	0.6576 (0.5116)		0.5
USEPRC	-0.3677 (0.5673)		

The parameter estimates of those variables common in MODEL_1 and MODEL_2 (AGE, EDLEVWO, F_SES, NULOS and NUGI) are very similar. The only large difference is in F_SES, with MODEL_1 much lower than MODEL_2. The estimates of the LEVIN MODEL do not vary from those in MODEL_1 or MODEL_2. Levin et al. (1989) have identified multicollinearity between KNOWWEL and EDLEVWO and therefore only included KNOWWEL in the LEVIN MODEL. This variable is not significant. However, the SEM analysis in MODEL_2 have identified EDLEVWO as a significant parameter.

Although MODEL_2 has shown acceptable fit, further improvement can be achieved in future studies. Greater thought must be given to the variables which explain Socio-economic status. This is evident from the variance extracted for this latent variable. In the structural model, a few important variables are absent and have not been measured in this study. Adding more variables that would impact on the compliance would further improve our understanding of the utilization of ANC consultation by migrant women in Belgium.

There are a large number of cases with missing data. In fact of the 115 women interviewed only 69 had complete information on all the variables analysed. This small sample size impacts on the results and hence the poor fit of the more complex SEM model (MODEL_1). If a more complex model is to be investigated, a larger sample size is necessary. For this example it is more advantageous to use SEM than multiple regression. With SEM one has the option of using pairwise deletion. In pairwise deletion a sample covariance matrix is formed, by using all cases with non-missing values to compute each covariance or variance (Bollen, 1989, pp. 370-371). Multiple regression uses only observations with no missing information. The use of pairwise deletion in SEM represents a significant advantage for SEM over traditional models. Pairwise deletion does have drawbacks, however. First, the sample covariance matrix may not be positive-definite (Browne, 1982, p. 88). Second, the choice of the sample size in a covariance structure analysis of the sample covariance matrix plays a role in the chi-square tests of the model fit and the estimated asymptotic standard errors of the parameter estimates. Questions have been raised about the appropriateness of using the uncorrected standard errors and chi-square tests that result from analysing the sample covariance matrix (Bollen, 1989, p. 39). This is not a trivial problem and it may be safer to use listwise deletion of missing cases.

Structural equation modelling is particularly useful in this example because it provides a mechanism of analyzing the measurement model and the structural model simultaneously. Not being able to analyse the data simultaneously was highlighted as one of the shortcomings of the analysis in Levin et al. (1989). The other advantage of using SEM for this example is due to the inclusion of latent variables in the analysis. Socio-economic status could not be directly measured and therefore had to be approximated by other measured variables. MODEL_1, which included latent variables and interdependent relationships, is very complex, although not impossible, to analyse using multiple regression. Structural equation modelling could be easily applied to this problem as the model was developed based on theory and past research in the area of antenatal care and on migrant women.

The conceptual model, to which MODEL_1 is an approximation, was developed by a multidisciplinary team and it was hoped that by integrating several disciplines, the model proposed could be used to obtain a holistic view of the antenatal care of migrant women in Belgium. However, on the basis of the results, MODEL_1 fails to achieve this objective but valuable information is gained as to the determinants of the utilisation of antenatal care of migrant women. Even MODEL_2 cannot be used to obtain a holistic view of the antenatal care of migrant women in Belgium. Due to the fact that this is the first time work of this nature has been carried out so extensively, MODEL_1 can be used as a basis for further work in understanding the behavioural patterns of migrant women. It can also be used in the preparation of questionnaires in future studies.

Future studies should impose more structure on the survey instrument because this study lacked structure in the questionnaire. Levin et al. (1989) recognised that there was a degree of arbitrariness in the definition of the compliance score. The research team must give more thought on how best to measure the utilization of ANC amongst migrant women or a better method of quantifying compliance. The main problem with this particular study was that some of the variables identified in the conceptual model weren't measured in the questionnaire. Some latent variables can be avoided by directly measuring that variable.

Notwithstanding the problems experienced in this study, the structural equation model (MODEL_2) provided very good results which were easily interpreted.

CHAPTER 5

CONCLUSIONS

5.1 INTRODUCTION

This Chapter gives a general discussion on structural equation modelling (SEM). It includes advantages and disadvantages of the methodology, a discussion of the criticisms of SEM, and recommendations on the use of SEM. Also included is a discussion on the technical problems of SEM and a theoretical discussion on the methodology.

5.2 TECHNICAL DISCUSSION

Throughout this dissertation, the essential modelling concepts, terminologies and techniques of the structural equation modelling approached have been discussed. However, in applying this methodology to new models and data, researchers are likely to encounter a number of additional issues and problems that have not yet been discussed.

Specification error can be viewed simply as "using the wrong model". Researchers often propose wrong models, so that specification errors are common, though not often and easily recognised.

We can seldom be sure that we have a correct model. Although we can sometimes be nearly certain, on the basis of empirical evidence, that we have been using the wrong model. What is true is that we can never have a perfect model. Hence we may never be able to compare our model to a perfect model. Some precautions can however be taken to ensure that we do not totally misspecify a model, like giving careful thought to developing a model based on theory and not omitting important variables from the model.

The initial confirmatory factor analysis model in §3.2, although it was not rejected, tended to show elements of misspecification. This was evident in the low factor loadings for some of the variables. A few "heavy" user teenagers with peculiar patterns of co-use did impact, to some degree, on the model leading to these signs of specification errors. In Chapter 4, the initial ANC model was rejected, largely due to specification errors in the measurement model, where the reliability of the latent variables were well below 0.7 and the variance extracted was below 50% for both the latent variables. Key predictors were also omitted from the structural model.

Correctly specifying a model is not the only criterion for not rejecting a model. Other important criteria such as design of survey, sample size and measurement error are also important.

In analyzing the data a few problems were encountered with the CALIS procedure. Constructing a path diagram using SAS is impossible and Microsoft PowerPoint had to be used. Although EQS does have the facility to construct path diagrams, from where the structural and measurement model parameters are estimated. Other SEM packages such as AMOS, RAMONA, and LISREL also have this facility. SAS, however does not have this graphical interface and hence the path diagram had to be constructed using other software and the equations has to be specified in the SAS program so that the parameters in the measurement and structural models can be estimated. It is therefore my recommendation that future work on the CALIS procedure should incorporate graphical interfaces.

In assessing the measurement model it is crucial to have an indication of the reliability of the latent variables and also the variance extracted by the latent variables. Obtaining these estimates is not very difficult by using the formulae given in Chapter 2, however the SAS output using the CALIS procedure does not estimate these indices. These have to be calculated manually and can become problematic when the number of constructs and manifest variables are large.

Assessing the goodness-of-fit of the structural equation models is not as straightforward as with other multivariate dependence techniques like regression, MANOVA and discriminant analysis. Presently there is only one goodness-of-fit measure with known distributional properties, namely the chi-square statistic, and there is no single statistical test which best describes the "strength" of the model's prediction, instead a number of measures are used. All the other goodness-of-fit measures have a recommended threshold level of 0.90 and greater. However it is frequently found that models with measures in excess of 0.90 are rejected. With these subjective levels there is uncertainty as to what is acceptable fit and unacceptable fit and it is left to the researcher to determine whether fit is acceptable rather than being based on some statistical test. However, the choice of the cutoffs for fit indices can be influenced by the standards set by prior work. If other analyses of the same or similar variables with the same baseline have cutoffs of 0.90 or higher, then a 0.85 or 0.90 cutoff may be regarded as unacceptable. Alternatively, if models in other research have fit indices typically below 0.80, then values of 0.85 or higher can be regarded as an important improvement over the existing work and a threshold of 0.80 may be regarded as acceptable.

These goodness-of-fit measures have also been criticised. The chi-square measure is too sensitive to both small and large sample sizes and to departures from multivariate normality of the observed variables. This measure of fit has serious disadvantages, particularly in the social and behavioural sciences, where models are perhaps best regarded as approximations to reality rather than as exact statements of truth. As a consequence any model is likely to be rejected if the sample size is sufficiently large, simply because of the difference between corresponding elements of the observed and predicted covariance matrices. The RMSEA is also unfavourable for use when sample sizes are small and the comparative fit index (CFI) would be preferable when the sample size is small. However the CFI is suitable in more exploratory contexts, while the RMSEA is more suited to confirmatory situations. The RMSEA is also good at detecting model misspecifications. With this in mind care must be taken when interpreting the goodness-of-fit measures as there are no strict rules to adhere to.

5.3 THEORETICAL DISCUSSION

The purpose of certain statistical techniques is to assist in establishing the plausibility of a theoretical model and to estimate the effects of the various explanatory variables (exogenous variables) on the dependent variable (endogenous variable). Various forms of regression are used for this purpose. Regression analysis and structural equation modelling (SEM) are two such techniques. The important difference between these techniques is the shift towards causal modelling in SEM.

In considering possible statistical models, it may be useful to distinguish between exploratory and confirmatory stages in investigating relationships. The exploratory approach is particularly useful in the absence of a relevant theoretical model. What is needed at this stage are statistical procedures that allow us to see the relative usefulness of different predictors or sets of predictors as well as what confounding is occurring among the independent variables, and what differences there are among different possible models for the data. Confounding occurs when a factor is causally related to both the cause and the effect. At the exploratory stage, the data analysis should suggest ways in which the theoretical model can be modified, how the measures might be combined or separated, or which variables can be deleted or ignored. As more convincing models are specified, applying structural equation modelling as a technique of analysis would be more appropriate.

The initial model investigating the utilization of antenatal care (ANC) consultation by migrant women in Belgium is a much more complex model than the initial HATCO example of Example 3.1. Regression analysis can be applied to the ANC model but does not have the same effect as SEM does. This model has two endogenous variables, two latent variables and one manifest variable. The benefit of SEM comes from incorporating these latent variables and the manifest variable in the model and therefore being able to analyse all the relationships simultaneously. When simple research questions like Example 3.1 are asked i.e. single linear relationships need to be tested, regression will be an appropriate tool but more complex causal models will need a more complex procedure. Models which incorporate latent variables can best be analysed using SEM.

It is often the case in research that researchers' knowledge of statistical procedures will be a guide to the complexity of the research question. What is also true, is that certain disciplines require more complex models than others and therefore applications of SEM would be more common in some than in others. Hence the type of technique should depend solely on the type of research question at hand and not vice versa.

Most applications of structural equation models use observational data and most statistical analyses of experimental data employ ANOVA or regression techniques. However both ANOVA and regression are special cases of structural equation models. Both procedures are specialized in that they assume that the explanatory variables are measured without error. Costner (1971), Miller (1971) and other authors have over the years suggested that analysis of experimental data could benefit from structural equations that allow for measurement error, multiple indicators and tests for confounding variables. In a recent study, Cole et al. (1993), argued in favour of SEM over MANOVA when multiple indicators for the constructs are involved and recommended SEM as an alternative approach to the detection of multivariate mean differences in between-group designs. They however warn against choosing too casually one technique over another and encourage researchers to give careful thought to the variables under study before making their choice.

Experimental design utilizes a powerful means of control. It minimizes the effects of confounding variables through randomization. In observational studies, control through randomization is unavailable. These studies use statistical control by entering into the model the variables suspected to be causally related to the dependent variable. This can at times lead to elaborate models. It is in these elaborate models where SEM is beneficial. In experimental studies, the primary objective is often not to solve complex models but rather to test simpler effects, where ANOVA and regression would be far simpler to employ than SEM.

Although it is evident that SEM can be applied to experimental data, applications of this technique are limited to the psychological and psychiatric environments. While it is true that SEM is applicable to some experimental data, the true value of SEM with experimental data cannot be gauged until more applications in different environments are seen.

Structural equation modelling is a very familiar tool for most sociologists. This is largely due to the nature of the problems they try to solve where many of the concepts or constructs they work with are not directly measurable. Concepts like socio-economic status, aspiration, motivation, attitudes, intelligence and income are common but these concepts are not restricted to sociology. It is not uncommon to find these concepts being used in public health research. In South Africa, socio-economic status, educational level and income are common constructs used in trying to solve public health issues. These would be increasingly useful where diseases of poverty are common.

Although there has not been much criticism of the statistical theory which underlies structural equation models, people have criticized the application of the technique. Criticism has been advanced on three facets, namely the falsifiability of models, the use of latent variables and the distributional assumptions.

The first criticism suggests that structural equation models cannot be disproved since a researcher cannot disconfirm a false causal assumption, regardless of the sample size or evidence, so long as the variables alledged to be causally related are correlated (Ling, 1983). There are numerous tests used to test the overall fit and model fit. This allows certain models to be disproved. Furthermore it is common to find two variables which are correlated, have no relationship once other variables are controlled. Establishing causality is a general problem, not restricted to SEM. Furthermore, SEM, although it proposes "causal models" cannot by itself prove causality. The second criticism is that structural equation models are not believable because they incorporate latent variables and that their constructs are abstract and have no scientific validity. There is a tendency for researchers to assign names to factors, and, subsequently, to imply that these factors have a reality of its own over and above the manifest variables. This tendency continues with the use of the term latent variables since it suggests that they are existing variables and that there is simply a problem of how they should be measured. However, latent variables will never be anything more than is contained in the observed variables and will never be anything beyond what is specified in the model. If we were to accept the argument that structural equation models are not believable, then we would eliminate much of contemporary science and statistics. The third criticism is that estimates of structural equation models have no value if the observed variables do not have a multivariate normal distribution. This is a valid criticism, but methods are being developed for handling discrete and other non-normal data.

5.4 OVERALL CONCLUSIONS

Although there are still some problems with SEM, there are numerous advantages of employing this technique when faced with the research problems discussed in this dissertation. It can be particularly effective in public health research where relationships involving constructs and intermediate variables need to be tested. It is therefore my recommendation that SEM be used more for confirmatory type of work and leave the exploratory work for other multivariate techniques. Complex models which include latent variables and interdependent relationships, like the initial ANC model from Chapter 4, can benefit from the analytical tools available in SEM, whilst single relationships would be easily analysed using regression.

There is also the danger that SEM might be used too casually by researchers who are not familiar with the technique and therefore careful thought must be given to the choice of the technique based on the research question at hand. Consideration must also be given to the nature of the variables before choosing one technique over another.

As public health has broadened from its focus on medical and behavioural problems, the questions asked by public health researchers have become more complex, more embedded in social, political, economic and environmental factors. It is in these complex research questions that SEM can be particularly beneficial. Public health researchers can certainly benefit from using structural equation modelling.

APPENDIX A

DATA SETS

Table 1: HATCO data set for example 3.1:

id	x1	x2	x3	x4	x5	x6	x7	x8	x9	x10	x11	x12	x13	x14
1	4.1	0.6	6.9	4.7	2.4	2.3	5.2	0	32	4.2	1	0	1	1
2	1.8	3	6.3	6.6	2.5	4	8.4	1	43	4.3	0	1	0	1
3	3.4	5.2	5.7	6	4.3	2.7	8.2	1	48	5.2	0	1	1	2
4	2.7	1	7.1	5.9	1.8	2.3	7.8	1	32	3.9	0	1	1	1
5	6	0.9	9.6	7.8	3.4	4.6	4.5	0	58	6.8	1	0	1	3
6	1.9	3.3	7.9	4.8	2.6	1.9	9.7	1	45	4.4	0	1	1	2
7	4.6	2.4	9.5	6.6	3.5	4.5	7.6	0	46	5.8	1	0	1	1
8	1.3	4.2	6.2	5.1	2.8	2.2	6.9	1	44	4.3	0	1	0	2
9	5.5	1.6	9.4	4.7	3.5	3	7.6	0	63	5.4	1	0	1	3
10	4	3.5	6.5	6	3.7	3.2	8.7	1	54	5.4	0	1	0	2
11	2.4	1.6	8.8	4.8	2	2.8	5.8	0	32	4.3	1	0	0	1
12	3.9	2.2	9.1	4.6	3	2.5	8.3	0	47	5	1	0	1	2
13	2.8	1.4	8.1	3.8	2.1	1.4	6.6	1	39	4.4	0	1	0	1
14	3.7	1.5	8.6	5.7	2.7	3.7	6.7	0	38	5	1	0	1	1
15	4.7	1.3	9.9	6.7	3	2.6	6.8	0	54	5.9	1	0	0	3
16	3.4	2	9.7	4.7	2.7	1.7	4.8	0	49	4.7	1	0	0	3
17	3.2	4.1	5.7	5.1	3.6	2.9	6.2	0	38	4.4	1	1	1	2
18	4.9	1.8	7.7	4.3	3.4	1.5	5.9	0	40	5.6	1	0	0	2
19	5.3	1.4	9.7	6.1	3.3	3.9	6.8	0	54	5.9	1	0	1	3
20	4.7	1.3	9.9	6.7	3	2.6	6.8	0	55	6	1	0	0	3
21	3.3	0.9	8.6	4	2.1	1.8	6.3	0	41	4.5	1	0	0	2
22	3.4	0.4	8.3	2.5	1.2	1.7	5.2	0	35	3.3	1	0	0	1
23	3	4	9.1	7.1	3.5	3.4	8.4	0	55	5.2	1	1	0	3
24	2.4	1.5	6.7	4.8	1.9	2.5	7.2	1	36	3.7	0	1	0	1
25	5.1	1.4	8.7	4.8	3.3	2.6	3.8	0	49	4.9	1	0	0	2
26	4.6	2.1	7.9	5.8	3.4	2.8	4.7	0	49	5.9	1	0	1	3
27	2.4	1.5	6.6	4.8	1.9	2.5	7.2	1	36	3.7	0	1	0	1
28	5.2	1.3	9.7	6.1	3.2	3.9	6.7	0	54	5.8	1	0	1	3
29	3.5	2.8	9.9	3.5	3.1	1.7	5.4	0	49	5.4	1	0	1	3
30	4.1	3.7	5.9	5.5	3.9	3	8.4	1	46	5.1	0	1	0	2
31	3	3.2	6	5.3	3.1	3	8	1	43	3.3	0	1	0	1
32	2.8	3.8	8.9	6.9	3.3	3.2	8.2	0	53	5	1	1	0	3
33	5.2	2	9.3	5.9	3.7	2.4	4.6	0	60	6.1	1	0	0	3
34	3.4	3.7	6.4	5.7	3.5	3.4	8.4	1	47	3.8	0	1	0	1
35	2.4	1	7.7	3.4	1.7	1.1	6.2	1	35	4.1	0	1	0	1
36	1.8	3.3	7.5	4.5	2.5	2.4	7.6	1	39	3.6	0	1	1	1
37	3.6	4	5.8	5.8	3.7	2.5	9.3	1	44	4.8	0	1	1	2
38	4	0.9	9.1	5.4	2.4	2.6	7.3	0	46	5.1	1	0	1	3
39	0	2.1	6.9	5.4	1.1	2.6	8.9	1	29	3.9	0	1	1	1
40	2.4	2	6.4	4.5	2.1	2.2	8.8	1	28	3.3	0	1	1	1
41	1.9	3.4	7.6	4.6	2.6	2.5	7.7	1	40	3.7	0	1	1	1
42	5.9	0.9	9.6	7.8	3.4	4.6	4.5	0	58	6.7	1	0	1	3
43	4.9	2.3	9.3	4.5	3.6	1.3	6.2	0	53	5.9	1	0	0	3
44	5	1.3	8.6	4.7	3.1	2.5	3.7	0	48	4.8	1	0	0	2
45	2	2.6	6.5	3.7	2.4	1.7	8.5	1	38	3.2	0	1	1	1
46	5	2.5	9.4	4.6	3.7	1.4	6.3	0	54	6	1	0	0	3

47	3.1	1.9	10	4.5	2.6	3.2	3.8	0	55	4.9	1	0	1	3
48	3.4	3.9	5.6	5.6	3.6	2.3	9.1	1	43	4.7	0	1	1	2
49	5.8	0.2	8.8	4.5	3	2.4	6.7	0	57	4.9	1	0	1	3
50	5.4	2.1	8	3	3.8	1.4	5.2	0	53	3.8	1	0	1	3
51	3.7	0.7	8.2	6	2.1	2.5	5.2	0	41	5	1	0	0	2
52	2.6	4.8	8.2	5	3.6	2.5	9	1	53	5.2	0	1	1	2
53	4.5	4.1	6.3	5.9	4.3	3.4	8.8	1	50	5.5	0	1	0	2
54	2.8	2.4	6.7	4.9	2.5	2.6	9.2	1	32	3.7	0	1	1	1
55	3.8	0.8	8.7	2.9	1.6	2.1	5.6	0	39	3.7	1	0	0	1
56	2.9	2.6	7.7	7	2.8	3.6	7.7	0	47	4.2	1	1	1	2
57	4.9	4.4	7.4	6.9	4.6	4	9.6	1	62	6.2	0	1	0	2
58	5.4	2.5	9.6	5.5	4	3	7.7	0	65	6	1	0	0	3
59	4.3	1.8	7.6	5.4	3.1	2.5	4.4	0	46	5.6	1	0	1	3
60	2.3	4.5	8	4.7	3.3	2.2	8.7	1	50	5	0	1	1	2
61	3.1	1.9	9.9	4.5	2.6	3.1	3.8	0	54	4.8	1	0	1	3
62	5.1	1.9	9.2	5.8	3.6	2.3	4.5	0	60	6.1	1	0	0	3
63	4.1	1.1	9.3	5.5	2.5	2.7	7.4	0	47	5.3	1	0	1	3
64	3	3.8	5.5	4.9	3.4	2.6	6	0	36	4.2	1	1	1	2
65	1.1	2	7.2	4.7	1.6	3.2	10	1	40	3.4	0	1	1	1
66	3.7	1.4	9	4.5	2.6	2.3	6.8	0	45	4.9	1	0	0	2
67	4.2	2.5	9.2	6.2	3.3	3.9	7.3	0	59	6	1	0	0	3
68	1.6	4.5	6.4	5.3	3	2.5	7.1	1	46	4.5	0	1	0	2
69	5.3	1.7	8.5	3.7	3.5	1.9	4.8	0	58	4.3	1	0	0	3
70	2.3	3.7	8.3	5.2	3	2.3	9.1	1	49	4.8	0	1	1	2
71	3.6	5.4	5.9	6.2	4.5	2.9	8.4	1	50	5.4	0	1	1	2
72	5.6	2.2	8.2	3.1	4	1.6	5.3	0	55	3.9	1	0	1	3
73	3.6	2.2	9.9	4.8	2.9	1.9	4.9	0	51	4.9	1	0	0	3
74	5.2	1.3	9.1	4.5	3.3	2.7	7.3	0	60	5.1	1	0	1	3
75	3	2	6.6	6.6	2.4	2.7	8.2	1	41	4.1	0	1	0	1
76	4.2	2.4	9.4	4.9	3.2	2.7	8.5	0	49	5.2	1	0	1	2
77	3.8	8	8.3	6.1	2.2	2.6	5.3	0	42	5.1	1	0	0	2
78	3.3	2.6	9.7	3.3	2.9	1.5	5.2	0	47	5.1	1	0	1	3
79	1	1.9	7.1	4.5	1.5	3.1	9.9	1	39	3.3	0	1	1	1
80	4.5	1.6	8.7	4.6	3.1	2.1	6.8	0	56	5.1	1	0	0	3
81	5.5	1.8	8.7	3.8	3.6	2.1	4.9	0	59	4.5	1	0	0	3
82	3.4	4.6	5.5	8.2	4	4.4	6.3	0	47	5.6	1	1	1	2
83	1.6	2.8	6.1	6.4	2.3	3.8	8.2	1	41	4.1	0	1	0	1
84	2.3	3.7	7.6	5	3	2.5	7.4	0	37	4.4	1	1	0	1
85	2.6	3	8.5	6	2.8	2.8	6.8	1	53	5.6	0	1	0	2
86	2.5	3.1	7	4.2	2.8	2.2	9	1	43	3.7	0	1	1	1
87	2.4	2.9	8.4	5.9	2.7	2.7	6.7	1	51	5.5	0	1	0	2
88	2.1	3.5	7.4	4.8	2.8	2.3	7.2	0	36	4.3	1	1	0	1
89	2.9	1.2	7.3	6.1	2	2.5	8	1	34	4	0	1	1	1
90	4.3	2.5	9.3	6.3	3.4	4	7.4	0	60	6.1	1	0	0	3
91	3	2.8	7.8	7.1	3	3.8	7.9	0	49	4.4	1	1	1	2
92	4.8	1.7	7.6	4.2	3.3	1.4	5.8	0	39	5.5	1	0	0	2
93	3.1	4.2	5.1	7.8	3.6	4	5.9	0	43	5.2	1	1	1	2
94	1.9	2.7	5	4.9	2.2	2.5	8.2	1	36	3.6	0	1	0	1
95	4	0.5	6.7	4.5	2.2	2.1	5	0	31	4	1	0	1	1
96	0.6	1.6	6.4	5	0.7	2.1	8.4	1	25	3.4	0	1	1	1
97	6.1	0.5	9.2	4.8	3.3	2.8	7.1	0	60	5.2	1	0	1	3
98	2	2.8	5.2	5	2.4	2.7	8.4	1	38	3.7	0	1	0	1
99	3.1	2.2	6.7	6.8	2.6	2.9	8.4	1	42	4.3	0	1	0	1
100	2.5	1.8	9	5	2.2	3	6	0	33	4.4	1	0	0	1

Table 2: Factor analysis data set for section 3.2: (Product Moment Correlation Matrix *1000)

Drug	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*
1 Cigarettes	-												
2 Beer	447	-											
3 Wine	422	619	-										
4 Liquor	436	604	583	-									
5 Cocaine	114	068	053	115	-								
6 Tranquillizers	203	146	139	258	349	-							
7 Drugstore	091	103	110	122	209	221	-						
8 Heroin	082	063	066	097	321	355	201	-					
9 Marijuana	513	445	365	482	186	316	150	154	-				
10 Hashish	304	318	240	368	303	377	163	219	534	-			
11 Inhalants	245	203	183	255	272	323	310	288	301	302	-		
12 Hallucinogenics	101	088	074	139	279	367	232	320	204	368	340	-	
13 Amphetamines	245	199	184	293	278	545	232	314	394	467	392	511	-

Table 3: Data set for Utilization of ANC consultation in Chapter 4.

1	5	2	1	0	1	3	2	1	1	12	81	10	11	59	0	1	0	0	5
2	5	4	1	0	1	3	2	3	2	12	69	8	11	60	2	1	0	2	5
3	5	3	1	0	1	3	5	3	1	21	66	8	11	66	0	1	0	0	1
4	5	2	2	3	1	3	2	1	1	11	80	4	11	65	1	2	0	1	3
5	5	4	3	3	2	1	2	1	2	12	82	9	11	64	0	2	0	1	5
6	5	1	2	4	1	2	3	3	2	12	76	8	13	46	1	1	1	0	5
7	5	4	1	0	1	1	5	3	2	12	76	6	11	69	0	1	0	0	5
8	5	2	1	4	1	1	2	1	2	12	70	6	10	62	1	2	0	0	5
9	5	2	2	3	1	4	2	1	1	12	82	0	10	62	0	2	0	0	5
10	5	2	2	4	1	1	3	3	2	12	71	5	12	61	1	3	1	0	5
11	5	1	3	3	1	1	2	1	1	11	76	9	12	59	2	1	1	3	5
12	4	1	3	3	1	2	4	1	2	12	76	6	13	55	1	5	1	2	5
13	5	2	1	0	1	3	3	2	1	11	73	8	11	58	1	2	0	0	5
14	5	1	0	4	1	3	4	1	2	12	73	9	13	51	4	1	0	0	5
15	5	2	3	4	1	1	4	1	1	11	79	8	8	58	3	1	0	0	5
16	5	5	1	0	1	4	2	2	1	11	79	9	11	59	1	1	1	0	5
17	1	1	3	4	1	1	4	1	1	12	72	10	11	49	3	3	2	1	1
18	5	2	3	4	2	1	2	1	1	11	76	9	11	52	3	1	2	0	5
19	5	5	3	3	1	1	2	3	2	12	81	2	11		1	1	0	0	5
20	5	2	2	3	1	4	4	1	2	12	74	5	9	57	2	1	1	1	5
21	5	2	3	3	1	4	2	1	2	12	78	2	10	59	2	1	0	0	2
22	5	2	3	3	1	4	2	1	2	12	85	9	12	54	2	1	1	0	3
23	5	4	2	3	2	2	2	1	1	11	85	3	9	70	0	1	2	0	5
24	5	4	1	0	1	1	2	2	2	21	66	9	15	60	0	2	0	0	4
25	4	2	3	3	2	2	3	1	2	12	85	-2	16	67	1	0	0	0	3
26	5	2	3	3	2	2	3	1	1	11	86	10	14	69	0	1	1	0	5
27	5	3	3	3	2	3	3	1	2	12	80	-2	16	64	0	2	0	0	5
28	4	3	1	0	1	3	2	3	2	12	69	7	12	66	3	0	1	0	3
29	5	3	2	4	1	2	2	3	2	12	71	7	11	62	2	1	0	0	5
30	5	1	3	0	1	1	3	1	2	12	82	-4	12	67	2	2	0	0	1
31	5	2	3	0	2	1	3	1	1	11	86	1	12	70	0	1	0	0	5
32	5	1	3	0	2	1	3	1	2	12	85	-3	17	68	1	0	0	0	3
33	2	1	3	4	1	1	3	1	2	12	76	-3	12	61	1	5	2	0	1
34	5	4	2	3	1	3	3	1	2	12	80	5	11	63	0	2	0	0	1
35	5	2	1	0	1	3	3	2	2	12	78	8	16	61	3	1	0	0	3
36	5	3	3	3	1	2	0	1	1	12	79	8	13	61	2	1	0	0	4
37	5	1	3	4	2	1	2	1	2	12	87	5	12	70	1	0	0	0	5
38	5	3	1	0	1	3	3	1	1	11	69	5	14	58	2	3	0	1	5
39	5	3	0	4	1	3	2	3	2	12	72	5	12	59	1	2	0	0	5
40	5	4	3	3	2	4	2	1	2	12	86	5	9	66	0	1	0	0	5
41	5	2	2	3	1	3	4	1	2	12	75	-1	10	56	1	3	0	0	2
42		1							2		86	3	10	69	1	0			
43		3							2		85	3	11	63	0	3			
44		2							1		80	7	12	65	1	1			
45		3							1		65	2	11	60	2	1			
46		4							1		86	2	11	61	1	2			
47		1							1		86	9	11	68	1	0			
48		2							2		85	1	15	67	1	0			
49		4							2		85	3	12	69	1	1			
50		4							1		86	7	14	65	0	1			
51		3							2		64	9	12	64	1	0			

52		2							1		84	9	14	63	2	0			
53		2							2		86	8	13	68	0	1			
55		3							2		74	7	10	63	0	2			
56		2							2		86	9	12	68	1	0			
57		1							1		69	9	12	53	1	4			
58		2							2		73	8	12	57	3	1			
59		3							1		86	4	8	71	0	1			
60		2							2		79	5	12	65	1	1			
61		3							1		86	10	14	59	1	2			
63		2							1		80	9	14	60	2	3			
64		4							1		64	8	10	64	2	0			
65		4							1		71	5	10	64	1	0			
66		3							2		69	8	14	60	1	1			
67		2							2		86	5	14	70	1	0			
68		5							2		72	0	13	64	1	2			
69		1							2		78	7	11	61	3	1			
70		1							2		80	5	12	60	1	3			
71		5							2		86	2	13	63	1	0			
72		2							2		78	6	14	59	2	1			
73		4							2		70	10	10	65	1	0			
74		3							2		71	1	12	67	0	1			
75		2							2		87	0	10	68	0	1			
76		2							2		74	-1	15	58	2	1			
77		3							2		74	4	16	65	2	2			
78		3							2		70	4	13	69	1	0			
79		4							2		67	4	14	61	1	2			
80		1							2		79	4	16	53	0	6			
81		2							1		86	9	13	68	0	1			
82		1							2		65	2	11	55	2	3			
83	5	3	1	0	1	4	2	2	1	21	64	9	13	56	3	0	3	1	5
84	5	1	2	4	1	1	2	1	2	12	79	9	11	58	1	2	1	2	5
85	5	1	3	4	1	1	2	1	2	12	86	9	11	62	1	0	1	0	5
86	5	3	3	4	1	1	2	1	1	11	80	9	11	54	1	2	1	2	5
87	5	1	1	0	1	1	3	3	2	12	68	9	10	56	2	2	0	0	5
88	5	2	2	4	1	1	2	1	1	11	86	9	12	65	1	0	0	0	5
89	5	4	1	0	1	1	3	3	2	21	64	9	11	63	1	2	2	0	5
90	5	3	1	0	2	1	2	2	1	21	64	10	11	59	2	0	2	1	5
91	5	3	1	0	2	1	3	1	2	21	70	9	11	69	0	1	0	0	0
92	5	4	1	0	1	3	2	2	1	21	64	9	9	63	1	0	0	0	5
93	5	3	3	0	2	2	2	1	2	12	86	8	10	70	0	0	0	0	2
94	5	4	3	3	2	1	5	1	1	11	86	8	11	65	1	0	0	0	5
95	4	4	1	0	1	1	2	2	2	21	61	9	12	63	1	1	0	0	3
96	5	4	1	0	1	1	2	2	1	21	66	6	12	65	1	0	0	0	5
97	4	3	1	0	2	2	3	3	2	21	69	10	12	69	0	1	0	0	5
98	5	3	1	0	1	2	2	3	2	21	71	8	11	69	0	1	0	0	5
99	5	2	3	3	2	1	3	1	2	12	84	5	12	68	0	1	0	0	5
100	5	4	2	0	2	4	2	1	2	12	82	9	10	62	0	2	1	0	5
101	5	1	3	0	2	2	2	1	2	12	84	1	10	69	0	2	0	0	1
102	5	2	3	0	1	2	3	1	2	12	79	-1	11	62	2	2	1	0	1
103	5	2	3	0	1	3	3	1	2	12	81	1	11	59	2	2	0	0	1
104	4	2	3	3	2	4	3	1	2	12	85	2	11	66	2	0	0	0	3
105	5	2	3	3	2	4	3	1	2	12	79	-1	9	61	2	2	0	0	3
106	5	2	3	3	2	4	5	1	1	11	78	4	9	62	1	4	0	0	4
107	5	1	2	3	1	4	2	1	2	12	77	8	9	59	2	1	2	0	5

108	5	5	2	3	1	4	4	1	2	12	79	7	9	59	1	2	0	0	5
109	5	2	3	3	2	4	3	1	2	12	86	6	8	68	1	0	1	0	5
110	5	4	3	3	2	4	2	1	2	12	82	9	9	67	1	0	0	0	5
111	5	2	3	3	1	1	5	1	2	12	87	-2	9	64	0	1	0	0	5
112	5	2	3	3	2	1	2	1	2	12	84	0	9	63	1	1	0	0	5
113	5	2	2	4	1	4	4	1	1	11	76	9	9	61	3	1	0	3	5
114	5	3	3	3	2	4	2	1	1	11	86	5	9	70	0	1	0	0	5
115	5	1	2	3	1	1	2	1	2	11	79	-1	10	61	1	4	0	0	2

The data is separated by at least one space and the names of the variables are listed below in the order which the data is captured.

id, edlevwo, comhos, part, curactwo, useprc, knowwel, livist, curactma, plor, plchil, yarrwo, comply, x5, ybirwo, nubo, nugi, numisc, nulos, happre.

APPENDIX B

SEM PROGRAMS

Program 1 (Example 3.1)

/*The Program does a Structural Equation Analysis for the HATCO example in section 3.1 of Chapter 3*/

```
 data hatco;
  filename hat1 'c:\sas\data\hatco.dat';
  infile hat1 missover;
  input id 1-4 x1 8-13 x2 15-22 x3 23-30 x4 31-38 x5 39-46 x6 48-54 x7 55-63 x8 64-69
         x9 72-78 x10 80-86 x11 87-94 x12 95-102 x13 104-110 x14 111-117;

      label x1='Delivery Speed'  x2='Price Level'  x3='Price Flexibility'
          x4='Manufacturers Image'  x5='Service'   x6='Sales Force Image'
          x7='Product Quality'   x8='Size of the Firm'   x9='Usage Level'
          x10='satisfaction Level'   x11='Specification Level'
        x12='Structure of procurement'   x13='Type of industry'
        x14='Type of buying situation';
```

/*Initial Model*/

```
 proc calis cov all;
   lineqs
         x1 = gamma1 f_strat + e1,
         x2 = gamma2 f_strat + e2,
         x3 = gamma3 f_strat + e3,
         x7 = gamma4 f_strat + e4,
         x4 = gamma5 f_image + e5,
         x6 = gamma6 f_image + e6,

         x9 = beta1 f_strat + beta2 f_image + e7,
         x10 = beta3 f_strat + beta4 x9 + e8;

   std
         e1-e6=delta1-delta6,
         e7-e8=eps1-eps2,
         f_strat f_image=2*1.0;
```

```
cov
        f_strat f_image=cov1,
        e1 e2=cov2,
        e2 e3=cov3,
        e4 e6=cov4;
run;
```

/*Revised Model*/

```
proc calis cov method=ml all;
  lineqs
        x1 = gamma1 f_strat + e1,
        x3 = gamma3 f_strat + e3,
        x4 = gamma5 f_image + e5,
        x6 = gamma6 f_image + e6,
        x9 = beta1 f_strat + beta2 f_image + e7,
        x10 = beta3 f_strat + beta4 x9 + beta5 f_image + e8;

    std
        e1=0.05,
        e5=delta5,
        e3=0.5,
        e6=delta6,
        e7=delta7,
        e8=delta8,
        f_strat=eps1,
        f_image=eps2;
    cov
        e5 e8=cov15,
        e1 e3=cov3;
run;
```

Program 2 (Confirmatory Factor Analysis)

```
/*The Program does the Confirmatory Factor Analysis in section 3.2 of Chapter 3*/

data cfa (type=corr);
 _type_='corr';
 filename cfa 'a:\fact.dat';
 infile cfa missover;
input _name_ $ v1-v13;
    label v1='Cigarettes' v2='Beer' v3='Wine' v4='Liquor' v5='Cocaine'
          v6='Tranquilizers' v7='Drug store' v8='Heroin' v9='Marijuana'
          v10='Hashish' v11='Inhalants' v12='Hallucinogenics' v13='Amphetamines';

/*Initial Model*/
proc calis corr data=cfa method=ml edf=1634 all;
 title "Confirmatory factor analysis of Huba et al data";
  lineqs
          v1=lambda f1 + lambda1 f2 + e1,
          v2=lambda2 f1 + e2,
          v3=lambda31 f1 + lambda32 f2 + e3,
          v4=lambda41 f1 + lambda43 f3 + e4,
          v5=lambda5 f3 + e5,
          v6=lambda6 f3 + e6,
          v7=lambda7 f3 + e7,
          v8=lambda8 f3 + e8,
          v9=lambda9 f2 + e9,
          v10=lambd102 f2+ lambd103 f3+ e10,
          v11=lambda11 f3 + e11,
          v12=lambda12 f3 + e12,
          v13=lambda13 f3 + e13;
  std
          e1-e13=theta1-theta13,
          f1-f3=3*1.0;
  cov
          e1 e11=gamma111,
          e1 e10=gamma110,
          e1 e12=gamma112,
          e2 e10=gamma210,
          e3 e7=gamma37,
```

```
        e3 e13=gamma313,
        e4 e10=gamma410,
        e4 e12=gamma412,
        e4 e6=gamma46,
        e5 e8=gamma58,
        e5 e9=gamma59,
        e9 e11=gamma911,
        e9 e12=gamma912,
        e7 e10=gamma710,
        e7 e13=gamma713,
        e7 e8=gamma78,
        e8 e11=gamma811,
        e8 e12=gamma812,
        e10 e12=gamm1012,
        e11 e12=gamm1112,
        e5 e13=gamma513,
        e6 e8=gamma68,
        e6 e13=gamma613,
        e7 e11=gamma711,
        f1 f2=alpha12,
        f1 f3=alpha13,
        f2 f3=alpha23;
  run;
```

/*Revised Model*/

```
 proc calis data=drug method=ml edf=1634 all;
  title "Confirmatory Factor Analysis for Drug Usage Model";
   lineqs
        v1=lambda11 f1 + lambda12 f2 + e1,
        v2=lambda21 f1 + e2,
        v3=lambda31 f1 + e3,
        v4=lambda41 f1 + e4,
        v5=lambda53 f3 + e5,
        v6=lambda63 f3 + e6,
        v7=lambda73 f3 + e7,
        v8=lambda83 f3 + e8,
        v9=lambda92 f2 + e9,
        v10=lambd102 f2 + lambd103 f3 + e10,
        v11=lambd113 f3 + e11,
```

```
    v12=lambd123 f3 + e12,
    v13=lambd133 f3 + e13;

  std
    e1-e13=theta1-theta13,
    f1-f3=3*1.0;
  cov
    e1 e11=cov111,
    e5 e8=cov58,
    e5 e13=cov513,
    e6 e8=cov68,
    e7 e11=cov711,
    e8 e11=cov811,
    e8 e12=cov812,
    e9 e12=cov912,
    f1 f2=phi12,
    f1 f3=phi13,
    f2 f3=phi23;
run;
```

Program 3 (Chapter 4: Utilization of Antenatal Care by Migrant women in Belgium)

```
/*The Program does the Structural Equation Analysis for the ANC data of Chapter 4*/

/*MODEL_1*/
data migrant;
  filename migrant 'a:\migrant.dat';
  infile migrant missover;
  input id 1-3 edlevwo 7 comhos 11 part 15 curactwo 19 useprc 5 knowwel 9 livist 13
       curactma 17 plor 21 plchil 23-24 yarrwo 26-27 comply 29-30 ybirwo 35-36
       nubo 38 nugi 40 numisc 42 nulos 44 happre 46;
label     useprc = 'Was it useful to follow antenatal care'
          edlevwo = 'Educational level of the woman'
          knowwel = 'Knowledge of an Western language'
          comhos = 'Means of communication with the doctor'
          livist = 'Actual living situation'
          part = 'Relationship with the partner'
          curactma = 'Current activity of the man'
          curactwo = 'Current activity of the woman'
          plor = 'Place where the woman was born'
          plchil = 'Place where the woman spent most of her childhood'
          yarrwo = 'Year the woman arrived in Belgium'
          ybirwo = 'Year of birth of the woman';

age=97-ybirwo;

  proc calis cov all;
    lineqs
          livist = gamma1 f_spr + e1,
          part = gamma2 f_spr + e2,
          curactma = gamma3 f_spr + gamma31 f_ses + e3,
          curactwo = gamma4 f_spr + gamma41 f_ses + e4,
          plor = gamma5 f_spr + e5,
          plchil = gamma6 f_spr + e6,
          yarrwo = gamma7 f_spr + e7,
          edelvwo = gamma8 f_ses + e8,
          knowwel = gamma9 f_ses + e9,

          useprc = beta2 comhos + beta16 happre + beta3 knowwel + beta4 f_spr + e10,
```

```
comply = beta5 age + beta6 nubo + beta7 nugi + beta8 numisc + beta9 nulos +
        beta10 f_ses + beta11 useprc + beta1 edelvwo + e11;

std
    e1-e6=theta1-theta6,
    e7=0.05,
    e8-e11=theta8-theta11,
    f_spr f_ses=psi1;
cov
    f_spr f_ses=cov1;
run;

/*MODEL_2*/
data migrant1;
 filename migrant1 'a:\migrant1.dat';
 infile migrant1 missover;
input id 1-3 edlevwo 7 comhos 11 part 15 curactwo 19 useprc 5 knowwel 9 livist 13
    curactma 17 plor 21 plchil 23-24 yarrwo 26-27 comply 29-30  ybirwo 35-36
    nubo 38 nugi 40 numisc 42 nulos 44 happre 46;

age=97-ybirwo;

 proc calis cov all;
  lineqs
    curactwo = gamma41 f_ses + e1,
    edelvwo = gamma8 f_ses + e2,
    knowwel = gamma9 f_ses + e3,

    comply = beta1 age + beta3 nugi + beta5 nulos +  beta6 f_ses + beta7 edelvwo + e4;

std
    e1-e4=theta1-theta4,
    f_ses=cov1;
run;
```

APPENDIX C

RESULTS

Table 1. Residual Diagnostics for the Revised HATCO Model in Chapter 3

<table>
<tr><th>Obs</th><th>Dep Var X10</th><th>Predict Value</th><th>Std Err Predict</th><th>Residual</th><th>Std Err Residual</th><th>Student Residual</th><th>-2-1-0 1 2</th><th>Cook's D</th></tr>
<tr><td>1</td><td>4.2000</td><td>4.1651</td><td>0.093</td><td>0.0349</td><td>0.386</td><td>0.090</td><td>| | |</td><td>0.000</td></tr>
<tr><td>2</td><td>4.3000</td><td>4.2382</td><td>0.101</td><td>0.0618</td><td>0.384</td><td>0.161</td><td>| | |</td><td>0.000</td></tr>
<tr><td>3</td><td>5.2000</td><td>5.0205</td><td>0.114</td><td>0.1795</td><td>0.380</td><td>0.472</td><td>| | |</td><td>0.003</td></tr>
<tr><td>4</td><td>3.9000</td><td>4.3198</td><td>0.109</td><td>-0.4198</td><td>0.382</td><td>-1.100</td><td>| **| |</td><td>0.017</td></tr>
<tr><td>5</td><td>6.8000</td><td>6.4187</td><td>0.141</td><td>0.3813</td><td>0.371</td><td>1.027</td><td>| |** |</td><td>0.025</td></tr>
<tr><td>6</td><td>4.4000</td><td>4.4330</td><td>0.088</td><td>-0.0330</td><td>0.387</td><td>-0.085</td><td>| | |</td><td>0.000</td></tr>
<tr><td>7</td><td>5.8000</td><td>5.8006</td><td>0.121</td><td>-0.00057</td><td>0.378</td><td>-0.002</td><td>| | |</td><td>0.000</td></tr>
<tr><td>8</td><td>4.3000</td><td>4.0225</td><td>0.095</td><td>0.2775</td><td>0.386</td><td>0.720</td><td>| |* |</td><td>0.005</td></tr>
<tr><td>9</td><td>5.4000</td><td>5.3759</td><td>0.091</td><td>0.0241</td><td>0.387</td><td>0.062</td><td>| | |</td><td>0.000</td></tr>
<tr><td>10</td><td>5.4000</td><td>4.9584</td><td>0.075</td><td>0.4416</td><td>0.390</td><td>1.133</td><td>| |** |</td><td>0.008</td></tr>
<tr><td>11</td><td>4.3000</td><td>4.3080</td><td>0.081</td><td>-0.00800</td><td>0.389</td><td>-0.021</td><td>| | |</td><td>0.000</td></tr>
<tr><td>12</td><td>5.0000</td><td>4.9628</td><td>0.060</td><td>0.0372</td><td>0.393</td><td>0.095</td><td>| | |</td><td>0.000</td></tr>
<tr><td>13</td><td>4.4000</td><td>4.0547</td><td>0.082</td><td>0.3453</td><td>0.388</td><td>0.889</td><td>| |* |</td><td>0.006</td></tr>
<tr><td>14</td><td>5.0000</td><td>4.8830</td><td>0.083</td><td>0.1170</td><td>0.388</td><td>0.301</td><td>| | |</td><td>0.001</td></tr>
<tr><td>15</td><td>5.9000</td><td>6.1422</td><td>0.122</td><td>-0.2422</td><td>0.378</td><td>-0.641</td><td>| *| |</td><td>0.007</td></tr>
<tr><td>16</td><td>4.7000</td><td>5.1610</td><td>0.097</td><td>-0.4610</td><td>0.385</td><td>-1.197</td><td>| **| |</td><td>0.015</td></tr>
<tr><td>17</td><td>4.4000</td><td>4.2799</td><td>0.095</td><td>0.1201</td><td>0.386</td><td>0.311</td><td>| | |</td><td>0.001</td></tr>
<tr><td>18</td><td>5.6000</td><td>4.9096</td><td>0.095</td><td>0.6904</td><td>0.385</td><td>1.791</td><td>| |*** |</td><td>0.033</td></tr>
<tr><td>19</td><td>5.9000</td><td>5.7601</td><td>0.101</td><td>0.1399</td><td>0.384</td><td>0.364</td><td>| | |</td><td>0.002</td></tr>
<tr><td>20</td><td>6.0000</td><td>6.1422</td><td>0.122</td><td>-0.1422</td><td>0.378</td><td>-0.377</td><td>| | |</td><td>0.002</td></tr>
<tr><td>21</td><td>4.5000</td><td>4.2565</td><td>0.073</td><td>0.2435</td><td>0.390</td><td>0.624</td><td>| |* |</td><td>0.002</td></tr>
<tr><td>22</td><td>3.3000</td><td>3.1836</td><td>0.144</td><td>0.1164</td><td>0.370</td><td>0.315</td><td>| | |</td><td>0.003</td></tr>
<tr><td>23</td><td>5.2000</td><td>5.9471</td><td>0.116</td><td>-0.7471</td><td>0.380</td><td>-1.967</td><td>| ***| |</td><td>0.060</td></tr>
<tr><td>24</td><td>3.7000</td><td>3.7118</td><td>0.077</td><td>-0.0118</td><td>0.389</td><td>-0.030</td><td>| | |</td><td>0.000</td></tr>
<tr><td>25</td><td>4.9000</td><td>5.1660</td><td>0.066</td><td>-0.2660</td><td>0.391</td><td>-0.679</td><td>| *| |</td><td>0.002</td></tr>
<tr><td>26</td><td>5.9000</td><td>5.3004</td><td>0.059</td><td>0.5996</td><td>0.393</td><td>1.527</td><td>| |*** |</td><td>0.009</td></tr>
<tr><td>27</td><td>3.7000</td><td>3.6825</td><td>0.079</td><td>0.0175</td><td>0.389</td><td>0.045</td><td>| | |</td><td>0.000</td></tr>
<tr><td>28</td><td>5.8000</td><td>5.7065</td><td>0.101</td><td>0.0935</td><td>0.384</td><td>0.244</td><td>| | |</td><td>0.001</td></tr>
<tr><td>29</td><td>5.4000</td><td>4.8989</td><td>0.110</td><td>0.5011</td><td>0.382</td><td>1.313</td><td>| |** |</td><td>0.024</td></tr>
<tr><td>30</td><td>5.1000</td><td>4.7106</td><td>0.096</td><td>0.3894</td><td>0.385</td><td>1.011</td><td>| |** |</td><td>0.011</td></tr>
<tr><td>31</td><td>3.3000</td><td>4.1948</td><td>0.076</td><td>-0.8948</td><td>0.390</td><td>-2.296</td><td>| ****| |</td><td>0.034</td></tr>
<tr><td>32</td><td>5.0000</td><td>5.7382</td><td>0.109</td><td>-0.7382</td><td>0.382</td><td>-1.933</td><td>| ***| |</td><td>0.051</td></tr>
<tr><td>33</td><td>6.1000</td><td>6.0263</td><td>0.092</td><td>0.0737</td><td>0.386</td><td>0.191</td><td>| | |</td><td>0.000</td></tr>
<tr><td>34</td><td>3.8000</td><td>4.6127</td><td>0.082</td><td>-0.8127</td><td>0.389</td><td>-2.091</td><td>| ****| |</td><td>0.032</td></tr>
<tr><td>35</td><td>4.1000</td><td>3.6164</td><td>0.102</td><td>0.4836</td><td>0.384</td><td>1.260</td><td>| |** |</td><td>0.019</td></tr>
<tr><td>36</td><td>3.6000</td><td>4.0346</td><td>0.077</td><td>-0.4346</td><td>0.389</td><td>-1.116</td><td>| **| |</td><td>0.008</td></tr>
<tr><td>37</td><td>4.8000</td><td>4.7698</td><td>0.092</td><td>0.0302</td><td>0.386</td><td>0.078</td><td>| | |</td><td>0.000</td></tr>
<tr><td>38</td><td>5.1000</td><td>5.0304</td><td>0.070</td><td>0.0696</td><td>0.391</td><td>0.178</td><td>| | |</td><td>0.000</td></tr>
<tr><td>39</td><td>3.9000</td><td>3.4020</td><td>0.124</td><td>0.4980</td><td>0.377</td><td>1.321</td><td>| |** |</td><td>0.032</td></tr>
<tr><td>40</td><td>3.3000</td><td>3.6454</td><td>0.076</td><td>-0.3454</td><td>0.390</td><td>-0.886</td><td>| *| |</td><td>0.005</td></tr>
<tr><td>41</td><td>3.7000</td><td>4.1391</td><td>0.077</td><td>-0.4391</td><td>0.390</td><td>-1.127</td><td>| **| |</td><td>0.008</td></tr>
<tr><td>42</td><td>6.7000</td><td>6.4080</td><td>0.138</td><td>0.2920</td><td>0.372</td><td>0.785</td><td>| |* |</td><td>0.014</td></tr>
<tr><td>43</td><td>5.9000</td><td>5.5883</td><td>0.113</td><td>0.3117</td><td>0.381</td><td>0.819</td><td>| |* |</td><td>0.010</td></tr>
</table>

44	4.8000	5.0185	0.067	-0.2185	0.391	-0.558	*|	0.002
45	3.2000	3.5275	0.086	-0.3275	0.388	-0.845	*|	0.006
46	6.0000	5.6928	0.112	0.3072	0.381	0.806	|*	0.009
47	4.9000	4.7843	0.119	0.1157	0.379	0.305	|	0.002
48	4.7000	4.6039	0.097	0.0961	0.385	0.250	|	0.001
49	4.9000	5.0556	0.099	-0.1556	0.385	-0.405	|	0.002
50	3.8000	4.6978	0.121	-0.8978	0.378	-2.374	****|	0.096
51	5.0000	4.8782	0.101	0.1218	0.384	0.317	|	0.001
52	5.2000	4.9870	0.104	0.2130	0.383	0.556	|*	0.004
53	5.5000	5.1285	0.105	0.3715	0.383	0.970	|*	0.012
54	3.7000	4.0340	0.060	-0.3340	0.393	-0.851	*|	0.003
55	3.7000	3.6015	0.131	0.0985	0.375	0.263	|	0.001
56	4.2000	5.1431	0.079	-0.9431	0.389	-2.423	****|	0.040
57	6.2000	5.9190	0.111	0.2810	0.381	0.737	|*	0.008
58	6.0000	5.9743	0.084	0.0257	0.388	0.066	|	0.000
59	5.6000	4.9450	0.058	0.6550	0.393	1.668	|***	0.010
60	5.0000	4.7028	0.098	0.2972	0.385	0.772	|*	0.006
61	4.8000	4.7754	0.111	0.0246	0.381	0.064	|	0.000
62	6.1000	5.9218	0.091	0.1782	0.387	0.461	|	0.002
63	5.3000	5.1642	0.070	0.1358	0.391	0.348	|	0.001
64	4.2000	4.0914	0.092	0.1086	0.386	0.281	|	0.001
65	3.4000	3.4061	0.115	-0.00611	0.380	-0.016	|	0.000
66	4.9000	4.7390	0.057	0.1610	0.393	0.410	|	0.001
67	6.0000	5.5387	0.089	0.4613	0.387	1.192	|**	0.012
68	4.5000	4.2217	0.088	0.2783	0.387	0.719	|*	0.004
69	4.3000	4.8961	0.092	-0.5961	0.386	-1.543	***|	0.022
70	4.8000	4.8509	0.087	-0.0509	0.387	-0.131	|	0.000
71	5.4000	5.2294	0.118	0.1706	0.379	0.450	|	0.003
72	3.9000	4.8648	0.124	-0.9648	0.377	-2.557	*****|	0.118
73	4.9000	5.3280	0.094	-0.4280	0.386	-1.110	**|	0.012
74	5.1000	5.1475	0.078	-0.0475	0.389	-0.122	|	0.000
75	4.1000	4.6756	0.104	-0.5756	0.383	-1.502	***|	0.028
76	5.2000	5.2535	0.065	-0.0535	0.392	-0.137	|	0.000
77	5.1000	4.9827	0.098	0.1173	0.385	0.305	|	0.001
78	5.1000	4.6900	0.109	0.4100	0.382	1.073	|**	0.016
79	3.3000	3.2597	0.119	0.0403	0.379	0.106	|	0.000
80	5.1000	5.0341	0.059	0.0659	0.393	0.168	|	0.000
81	4.5000	5.0201	0.094	-0.5201	0.386	-1.348	**|	0.018
82	5.6000	5.4092	0.131	0.1908	0.375	0.509	|*	0.005
83	4.1000	4.0293	0.099	0.0707	0.384	0.184	|	0.000
84	4.4000	4.5215	0.071	-0.1215	0.391	-0.311	|	0.001
85	5.6000	5.0889	0.076	0.5111	0.390	1.312	|**	0.011
86	3.7000	4.0068	0.070	-0.3068	0.391	-0.785	*|	0.003
87	5.5000	4.9738	0.078	0.5262	0.389	1.352	|**	0.012
88	4.3000	4.3125	0.071	-0.0125	0.391	-0.032	|	0.000
89	4.0000	4.5287	0.100	-0.5287	0.384	-1.376	**|	0.021
90	6.1000	5.6432	0.095	0.4568	0.386	1.185	|**	0.014
91	4.4000	5.2702	0.081	-0.8702	0.389	-2.239	****|	0.037
92	5.5000	4.8052	0.098	0.6948	0.385	1.806	|***	0.036
93	5.2000	5.0019	0.123	0.1981	0.377	0.525	|*	0.005
94	3.6000	3.3322	0.101	0.2678	0.384	0.697	|*	0.006
95	4.0000	3.9668	0.106	0.0332	0.383	0.087	|	0.000
96	3.4000	3.0817	0.135	0.3183	0.373	0.853	|*	0.016
97	5.2000	5.3779	0.100	-0.1779	0.384	-0.463	|	0.002

98	3.7000	3.4886	0.094	0.2114	0.386	0.548			*			0.003
99	4.3000	4.8446	0.098	-0.5446	0.385	-1.415			**				0.021
100	4.4000	4.5063	0.084	-0.1063	0.388	-0.274							0.001

Sum of Residuals	0
Sum of Squared Residuals	14.8220
Predicted Resid SS (Press)	16.8038

Table 2: Covariance Matrix For the Initial ANC Model

	EDLEVWO	COMHOS	PART	CURACTWO	USEPRC	KNOWWEL	LIVIST	CURACTMA
EDLEVWO	1.2245	-0.6157	0.2734	0.2449	0.1396	-0.3360	0.0466	-0.1142
COMHOS	-0.6157	2.8425	-0.0051	-0.5036	-0.1404	0.6859	0.0179	0.0755
PART	0.2734	-0.0051	1.4795	-0.0839	0.1189	-0.0759	0.0021	0.0105
CURACTWO	0.2449	-0.5036	-0.0839	0.5845	0.0122	-0.4593	-0.1153	0.0068
USEPRC	0.1396	-0.1404	0.1189	0.0122	0.3984	-0.0750	0.0202	-0.0936
KNOWWEL	-0.3360	0.6859	-0.0759	-0.4593	-0.0750	0.8596	0.1933	0.0360
LIVIST	0.0466	0.0179	0.0021	-0.1153	0.0202	0.1933	0.2283	-0.0112
CURACTMA	-0.1142	0.0755	0.0105	0.0068	-0.0936	0.0360	-0.0112	0.9300
PLOR	-0.0605	0.0099	-0.0160	0.0459	-0.0063	0.0150	0.0078	0.0112
PLCHIL	1.3584	-2.9669	-0.6037	1.2074	-0.0472	-1.5987	-0.1123	-0.2557
YARRWO	-1.8923	4.5902	0.7218	-3.4992	0.6100	4.8096	1.5342	0.0185
COMPLY	1.3626	-0.5030	0.0017	0.9827	0.1440	-1.5388	-0.2930	-0.6455
AGE	-1.4602	2.4205	0.5847	0.1640	-0.5793	-0.7570	-1.3421	0.3451
NUBO	-0.3415	0.2386	0.1627	0.0080	-0.1092	-0.0761	-0.1682	0.0341
NUGI	-0.2858	0.3076	-0.0750	-0.0862	-0.2249	0.0649	-0.1423	0.2468
NUMISC	-0.0820	0.1084	-0.0384	0.0213	-0.1431	0.0146	-0.0272	-0.0805
NULOS	-0.0942	0.1745	-0.0244	-0.0485	-0.0314	0.0196	-0.0721	0.0006
HAPPRE	0.3417	0.5249	0.0441	0.2034	0.3269	-0.2412	0.0413	-0.1686

	PLOR	PLCHIL	YARRWO	COMPLY	AGE	NUBO	NUGI	NUMISC	NULOS	HAPPRE
EDLEVWO	-0.0605	1.3584	-1.8923	1.3626	-1.4602	-0.3415	-0.2858	-0.0820	-0.0942	0.3417
COMHOS	0.0099	-2.9669	4.5902	-0.5030	2.4205	0.2386	0.3076	0.1084	0.1745	0.5249
PART	-0.0160	-0.6037	0.7218	0.0017	0.5847	0.1627	-0.0750	-0.0384	-0.0244	0.0441
CURACTWO	0.0459	1.2074	-3.4992	0.9827	0.1640	0.0080	-0.0862	0.0213	-0.0485	0.2034
USEPRC	-0.0063	-0.0472	0.6100	0.1440	-0.5793	-0.1092	-0.2249	-0.1431	-0.0314	0.3269
KNOWWEL	0.0150	-1.5987	4.8096	-1.5388	-0.7570	-0.0761	0.0649	0.0146	0.0196	-0.2412
LIVIST	0.0078	-0.1123	1.5342	-0.2930	-1.3421	-0.1682	-0.1423	-0.0272	-0.0721	0.0413
CURACTMA	0.0112	-0.2557	0.0185	-0.6455	0.3451	0.0341	0.2468	-0.0805	0.0006	-0.1686
PLOR	0.2283	-0.0127	0.1880	-0.5403	-0.2274	-0.0401	0.0590	-0.0561	-0.0807	-0.1663
PLCHIL	-0.0127	11.3318	-16.3016	4.0584	-2.4098	-0.4928	-0.7962	0.2646	-0.2165	-0.3246
YARRWO	0.1880	-16.3016	49.4079	-10.5301	-12.2055	-1.9391	-1.0158	-0.9673	-0.7546	-0.1376
COMPLY	-0.5403	4.0584	-10.5301	16.0103	5.3691	0.5455	-1.2970	0.6583	0.7150	2.3760
AGE	-0.2274	-2.4098	-12.2055	5.3691	28.1914	-3.0369	-2.0067	1.3855	1.1271	0.6689
NUBO	-0.0401	-0.4928	-1.9391	0.5455	3.0369	1.0004	-0.0755	0.2047	0.1882	-0.0763
NUGI	0.0590	-0.7962	-1.0158	-1.2970	2.0067	-0.0755	1.2641	0.0578	0.1143	-0.4182
NUMISC	-0.0561	0.2646	-0.9673	0.6583	1.3855	0.2047	0.0578	0.5274	0.1083	0.0928
NULOS	-0.0807	-0.2165	-0.7546	0.7150	1.1271	0.1882	0.1143	0.1083	0.4855	0.1963
HAPPRE	-0.1663	-0.3246	-0.1376	2.3760	0.6689	-0.0763	-0.4182	0.0928	0.1963	2.2344

Determinant = 2.722 (Ln = 1.001)

Table 3: Normalized Residual Matrix for the Initial ANC Model

	EDLEVWO	COMHOS	PART	CURACTWO	USEPRC	KNOWWEL	LIVIST	CURACTMA
EDLEVWO	0.0000	-2.8002	1.9188	0.3989	1.9473	0.0049	1.7924	-0.7677
COMHOS	-2.8002	0.0000	-0.0213	-3.3154	0.4104	3.7233	0.1884	0.3942
PART	1.9188	-0.0213	0.0000	-0.2982	1.1445	-1.0970	-0.2966	0.0737
CURACTWO	0.3989	-3.3154	-0.2982	0.0000	1.1247	0.0177	-0.1462	0.2732
USEPRC	1.9473	0.4104	1.1445	1.1247	0.0373	-1.4689	-0.3675	-1.2093
KNOWWEL	0.0049	3.7233	-1.0970	0.0177	-1.4689	0.0000	0.8032	-0.0361
LIVIST	1.7924	0.1884	-0.2966	-0.1462	-0.3675	0.8032	0.0000	-0.2173
CURACTMA	-0.7677	0.3942	0.0737	-0.2732	-1.2093	-0.0361	-0.2173	0.0000
PLOR	-0.8414	0.1042	-0.2734	1.3731	-0.2920	-0.0613	0.0733	0.2054
PLCHIL	1.4722	-4.4358	-0.7559	0.1558	1.2107	-0.0353	1.9832	-0.6524
YARRWO	0.2421	3.2866	0.0001	0.0004	-0.8593	0.0126	0.0017	-0.0001
COMPLY	0.0811	-1.1761	0.2350	0.3908	0.7502	-0.3837	-0.0700	-1.2942
AGE	-2.1089	0.0000	0.7682	0.3428	-1.1385	-1.3049	-4.4887	0.5719
NUBO	-2.6183	0.0000	1.1346	0.0887	-1.0098	-0.6964	-2.9862	0.2996
NUGI	-1.9490	0.0000	-0.4651	-0.8508	-1.5802	0.5281	-2.2478	1.9312
NUMISC	-0.8658	0.0000	-0.3692	0.3257	-2.7229	0.1846	-0.6653	-0.9751
NULOS	-1.0364	0.0000	-0.2438	-0.7728	-0.8545	0.2574	-1.8377	0.0072
HAPPRE	1.7529	0.0000	0.2060	1.5102	0.3634	-1.4771	0.4905	-0.9923

	PLOR	PLCHIL	YARRWO	COMPLY	AGE	NUBO	NUGI	NUMISC	NULOS	HAPPRE
EDLEVWO	-0.8414	1.4722	0.2421	0.0811	2.1089	-2.6183	-1.9490	-0.8658	-1.0364	1.7529
COMHOS	0.1042	-4.4358	3.2866	-1.1761	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
PART	-0.2734	-0.7559	0.0001	0.2350	-0.7682	1.1346	-0.4651	-0.3692	-0.2438	0.206
CURACTWO	1.3731	0.1558	0.0004	0.3908	-0.3428	0.0887	-0.8508	0.3257	-0.7728	1.5102
USEPRC	-0.2920	1.2107	-0.8593	0.7502	1.1385	-1.0098	-1.5802	-2.7229	-0.8545	0.3634
KNOWWEL	-0.0613	-0.0353	0.0126	-0.3837	1.3049	-0.6964	0.5281	0.1846	0.2574	-1.4771
LIVIST	0.0733	1.9832	0.0017	-0.0700	4.4887	-2.9862	-2.2478	-0.6653	-1.8377	0.4905
CURACTMA	0.2054	-0.6524	-0.0001	-1.2942	-0.5719	0.2996	1.9312	-0.9751	0.0072	-0.9923
PLOR	0.0000	0.2593	0.0010	-2.2908	0.7604	-0.7128	0.9316	-1.3725	-2.0559	-1.9755
PLCHIL	0.2593	0.0000	-0.0009	0.6961	1.1440	-1.2419	-1.7851	0.9186	-0.7832	-0.5473
YARRWO	0.0010	-0.0009	0.0000	-0.4690	2.7750	-2.3404	-1.0906	-1.6079	-1.3072	-0.1111
COMPLY	-2.2908	0.6961	-0.4690	0.2352	-0.1240	-0.1601	-0.3868	0.0401	-0.1661	1.7664
AGE	-0.7604	-1.1440	-2.7750	0.1240	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
NUBO	-0.7128	-1.2419	-2.3404	-0.1601	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
NUGI	0.9316	-1.7851	-1.0906	-0.3868	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
NUMISC	-1.3725	0.9186	-1.6079	0.0401	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
NULOS	-2.0559	-0.7832	-1.3072	-0.1661	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
HAPPRE	-1.9755	-0.5473	-0.1111	1.7664	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Average Normalized Residual = 0.7373
Average Off-diagonal Normalized Residual = 0.8223

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