NIELS J. BLUNCH

INTRODUCTION TO STRUCTURAL EQUATION MODELLING

USING SPSS AND AMOS

Introduction to Structural Equation Modelling using SPSS and AMOS

Niels J. Blunch

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Introduction to Structural Equation Modelling using SPSS and AMOS

Contents

Preface

This book contains what I consider to be the essentials for a non-mathematical introductory course in structural equation modelling (SEM) for the social and behavioral sciences.

It builds on material that I have used during the years in a compulsory course in behavioral science methods for first year graduate students at Aarhus School of Business (Denmark).

The book should be well suited for introductory courses in SEM for last year undergraduate or first year graduate students who have had an introductory course in statistics up to and including multiple regression. The book contains an appendix on statistical prerequisites that could be used as a refresher. The appendix could be read as an introduction to the text or consulted when necessary during reading.

The examples in the book are real life examples taken from a wide range of disciplines—including psychology, political science, marketing and health—and the same goes for the exercises downloadable from the books homepage: they build on real data. The companion web page for this title, along with exercises, is available at: www.sagepub.co.uk/blunch.

A book on SEM could either illustrate the programming aspects by showing examples of how models are programmed in the various computer programs available (e.g. LISREL, EQS, AMOS, Mplus, Mx Graph)—or one could concentrate on one and only one computer program and use it all through the book.

I have chosen the last-mentioned method using SPSS and AMOS as the workhorses: SPSS is a statistics program used at most universities and it should be well-known to many students in the social and behavioral sciences. AMOS is now sold as an add-on to SPSS and it is very easy to use as it was originally developed with a view to its use in the classroom.

The book is divided into two sections, of which the first (containing three chapters) lays the basis for structural equation modelling. Among the subjects covered here are scale construction and the concepts of reliability and validity along the lines of classical test theory (Chapter 2) and component analysis and exploratory factor analysis (Chapter 3).

Then, in the second part AMOS is introduced and the reader is taken through five chapters, from the simplest SEM model, consisting of only manifest variables to more complicated ones involving latent variables, models that build on several samples from different populations and problems like incomplete and in other ways problematic data.

I would like to thank my two reviewers professor Dale R. Fuqua of Oklahoma State University (US) and research associate Elizabeth Ackerly of Lancaster University (UK) for helpful comments and suggestions. The same thanks go to professor Joachim Scholderer from Aarhus School of Business (Denmark), who has done careful reading of the first three chapters at an early stage of the project, and professor Carsten Stig Poulsen from Aalborg University (Denmark) who, despite a busy life, found time to work his way through the complete manuscript in its (nearly) final form.

I would also like to thank the many persons who have allowed me to use their data for examples and exercises—without them it would have been impossible to write the book. They are too many to mention here, but credits are given where the data are introduced.

Last—but not least—my thanks go to my wife Anne-Marie for her loving support during the long writing process.

Niels J. Blunch
02.11.07

Section I

Exploring your Data

CHAPTER

1

Introduction

As is the case with all scientific analysis, the techniques for analyzing causal structures based on non-experimental data presented in this book are based on models of the phenomena being studied. Therefore this first chapter begins with an intuitive introduction to *structural equation models* (SEM) by showing a few examples of such models.

Then I discuss two problems differentiating the social and behavioral sciences from the natural sciences. The first problem is that the ideal way of doing causal research, namely experimentation, is, more often than not, impossible to implement in the social and behavioral sciences. This being the case we face a series of problems of a practical as well as a philosophical nature. Another problem differentiating the social and behavioral sciences from the natural sciences is the vague nature of the concepts we are studying (intelligence, preference, social status, attitude, literacy and the like) for which no generally accepted measuring instruments exist.

You will also meet a short introduction to the matrices found in the output from AMOS (Analysis of Moment Structures)—the computer program used in this book.

I will not go deeply into the mathematical and statistical calculations, which are the basis for SEM-estimation, but a brief intuitive explanation of the principles is presented. A short outline of the history of SEM follows and an overview of the rest of the book ends the chapter.

A companion website with exercises is available at: www.sagepub.co.uk/blunch.

1. Theory and Model

This is a book about drawing conclusions based on non-experimental data about causal relationships (although, as pointed out below, the word 'causal' must be used with care in SEM) between non-measurable concepts—and about using

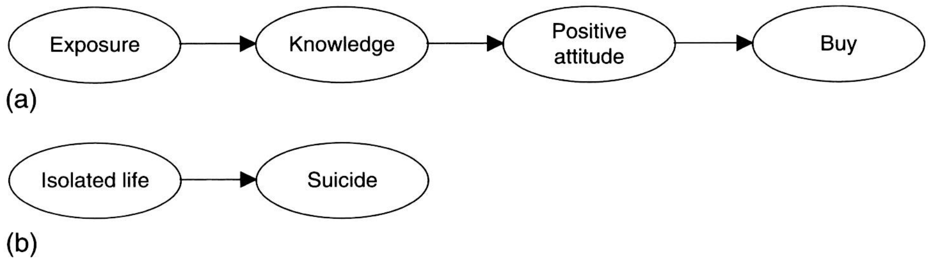

Figure 1.1 The hierarchy-of-effects model (a) and Durkheim's suicide model (b)

the computer program AMOS (Analysis of Moment Structures) to facilitate the analysis.

The first step is to form a graphical depiction—*a model*—showing how the various concepts fit together. An example of such a model is the well-known hierarchy-of-effects model depicting the various stages through which a receiver of an advertising message is supposed to move from awareness to (hopefully!) the final purchase (e.g. Lavidge and Steiner, 1961). See Figure 1.1a.

Another example is the pioneering French sociologist and philosopher Emile Durkheim's theory that living an isolated life increases the probability of suicide (Durkheim, 1897). This theory can be depicted as in Figure 1.1b.

We see that a scientific theory may be depicted in a graphical model in which the hypothesized causal connections among the concepts of the theory are shown as arrows.

In order to verify such a model (or theory) two conditions must be met:

1. We must make clear what we mean with the various concepts making up the model: The concepts must be defined *conceptually.*
2. We must construct instruments to measure the concepts: The concepts must be defined *operationally.*

Example 1

Taking Durkheim's theory as a point of departure, the concepts 'isolated life' and 'suicide' must be defined conceptually and operationally. Now, the definition of 'isolated life' seems to be the more problematic of the two. What is an 'isolated life'? Are there several forms of isolation? This latter question should probably be answered in the affirmative: You can be physically isolated because you spend a large part of your time alone or you can be psychologically isolated even if you are together with several people—just as you are not necessarily psychologically alone if you are only surrounded by few or no people.

You can also look at the various situations in which you are 'isolated' and e.g. distinguish between work and leisure.

In this way we can tentatively split our concept 'isolated life' into four dimensions, as shown in Table 1.1.

Table 1.1 Four dimensions of the concept 'isolated life'

	Physical isolation	*Psychological isolation*
At leisure	1	2
At work	3	4

Other/more dimensions could of course be mentioned—depending on the problem at hand—but these will do as an illustration.

Now, the question is: Are all four dimensions relevant for the present problem or only some of them? The relevant dimensions are now included in the model as shown in Figure 1.2a, and the next step is to define conceptually the four dimensions now making up the independent variables.

A characteristic of the four independent variables in the model in Figure 1.2a is that they are not directly measurable by a generally accepted measuring instrument, a characteristic they share with many of the concepts from the social and behavioral sciences: satisfaction; preference; intelligence; life style; social class and literacy; just to mention a few. Such non-measurable variables are called *latent variables*.

As latent variables cannot be measured directly, they are measured by *indicators*, usually questions in a questionnaire or some sort of test—these are the so-called *manifest variables*. If we add such indicators the model becomes 1.2b.

In accordance with general tradition, latent variables are depicted as circles or ellipses and manifest variables as squares or rectangles.

The model includes ten additional latent variables.

The nine ε-variables indicate that factors other than the latent variable affect the result of a measurement—ε (*error*) is the combined effect of all such 'disturbing' effects. In other words: ε is the measurement error of the indicator in question. The δ (*disturbance*) is the combined effect of all factors having an effect on the dependent variable, but not being explicitly included in the model.

As can be seen the model contains the hypothesized causal effects of the four 'isolation-variables' on suicide as well as the connections between the latent (non-measurable) variables and their manifest (measurable) indicators.

The model thus consists of two parts:

1. The *structural model* describing the causal connections among the latent variables. Mapping of these connections is the main purpose of the analysis.
2. The *measurement model* describing the connections between the latent variables and their manifest indicators. When—as is the case with suicide—a variable has only one indicator, the variance of the error is often taken to be 0.00, meaning that the measurement is without error—and the latent variable is in reality manifest.

While the arrows connecting the latent variables depict (possible) causal effects, the arrows connecting a latent variable with its manifest variables should be interpreted as follows.

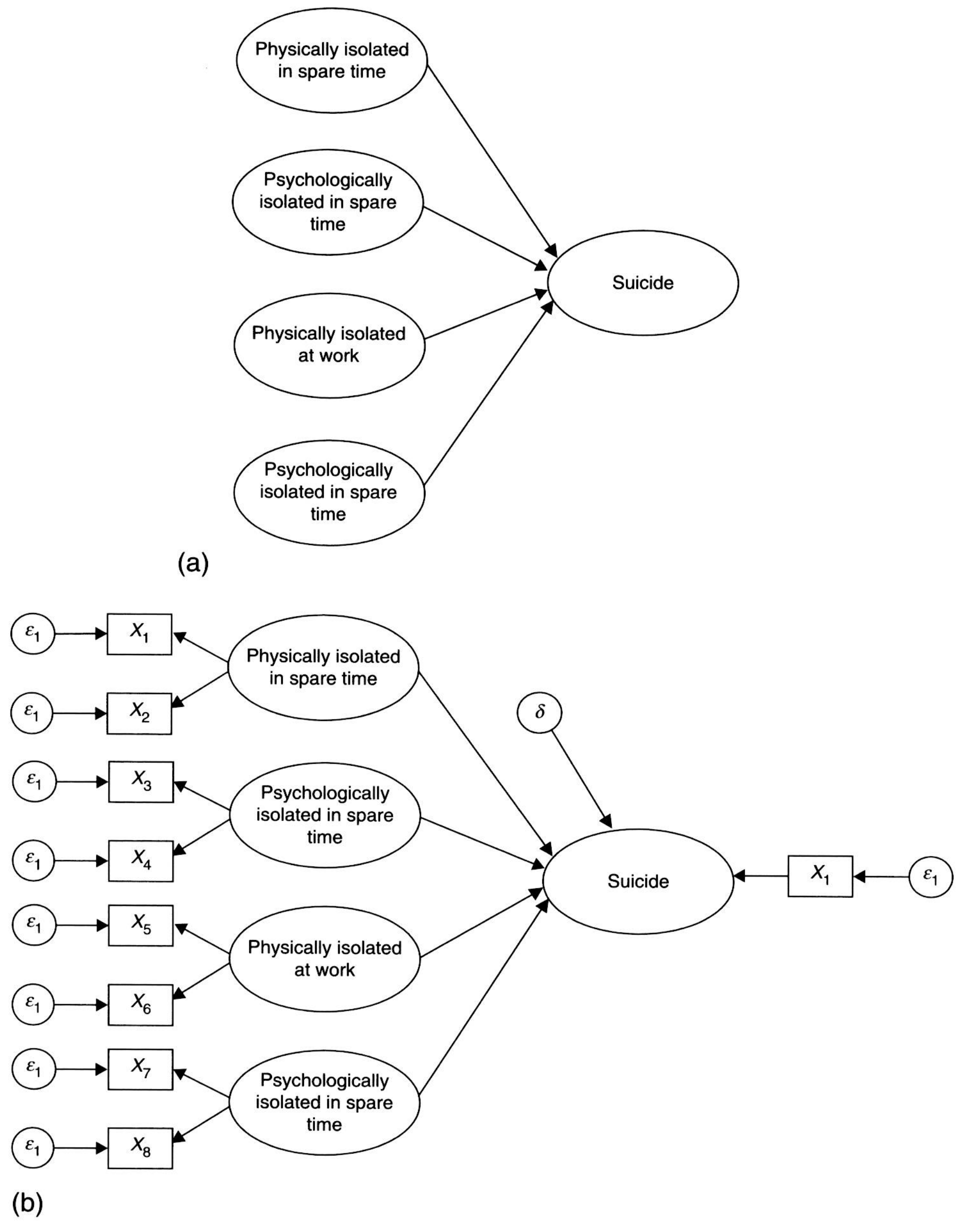

Figure 1.2 (a) The four dimensions of the concept 'isolated life,' (b) The final model with latent and manifest variables

If a latent variable were measurable on a continuous scale—which of course is not the case as a latent variable is not measurable on *any* scale—variations in a person's (or whatever the analytical unit may be) position on this scale would be mirrored in variations in its manifest variables. This is the reason why the arrows point *from* the latent variable *towards* its manifest indicators and not the other way round.

To sum up: A theory is a number of hypothesized connections among conceptually defined variables. These variables are usually latent, i.e. they are not directly measurable and must be operationalized in a series of manifest variables.

These manifest variables and their interrelations are all we have at our disposal to uncover the causal structure among the latent variables.

Let us have a look at an empirical example before we go deeper into the many problems of using structural equation modelling for causal analysis.

Example 2

106 salesmen in a large company were interviewed in order to map the factors influencing their performance (Bagozzi, 1976; Aaker and Bagozzi, 1979). One of the models used is shown in Figure 1.3.

The figures can be interpreted as standardized regression coefficients—so-called *Beta Coefficients* (see Appendix A), and the coefficients of the δ and ε terms are fixed at '1' in accordance with traditional regression analysis (see Appendix A).

The model has four latent variables: job tension; self-esteem; satisfaction and sales. $-sales for each individual salesman were taken from company records, which were considered error-free. Therefore the variance of ε_5 was not freely estimated, but set at 0.00, and the '1' on the arrow from F_3 (Factor 3) to ε_5 equalize the two variables—so in reality F_3 is not a latent variable. This has the effect that δ_3 and ε_5 are confounded. Most often ε is assumed to be negligible and the variable is considered measured without error. In this case such an assumption seems reasonable. As you may have guessed, it takes at least two indicators to separate δ_3 and ε_5, and if the assumption of negligible measurement error is not plausible, the problem must be solved in other ways (to which I will return in Chapter 7).

The (other) latent variables were measured by *summated scales* in a questionnaire. A summated scale is constructed by adding scores obtained by answering a series of questions. One of the most popular is the Likert scale: The respondents are asked to indicate their agreement with each of a series of statements by checking a scale from e.g. 1 (strongly disagree) to 5 (strongly agree) and the scores are then added to make up the scale—the scale values being in opposite direction for statements that are favorably worded versus unfavorably worded in regard to the concept being measured. Construction of summated scales is discussed in the next chapter.

In this case the following scales were used:

TEN 1: Eight 5-point scales indicating how frequently the salesman feels bothered with limits of authority, opportunities for advancement, supervisor

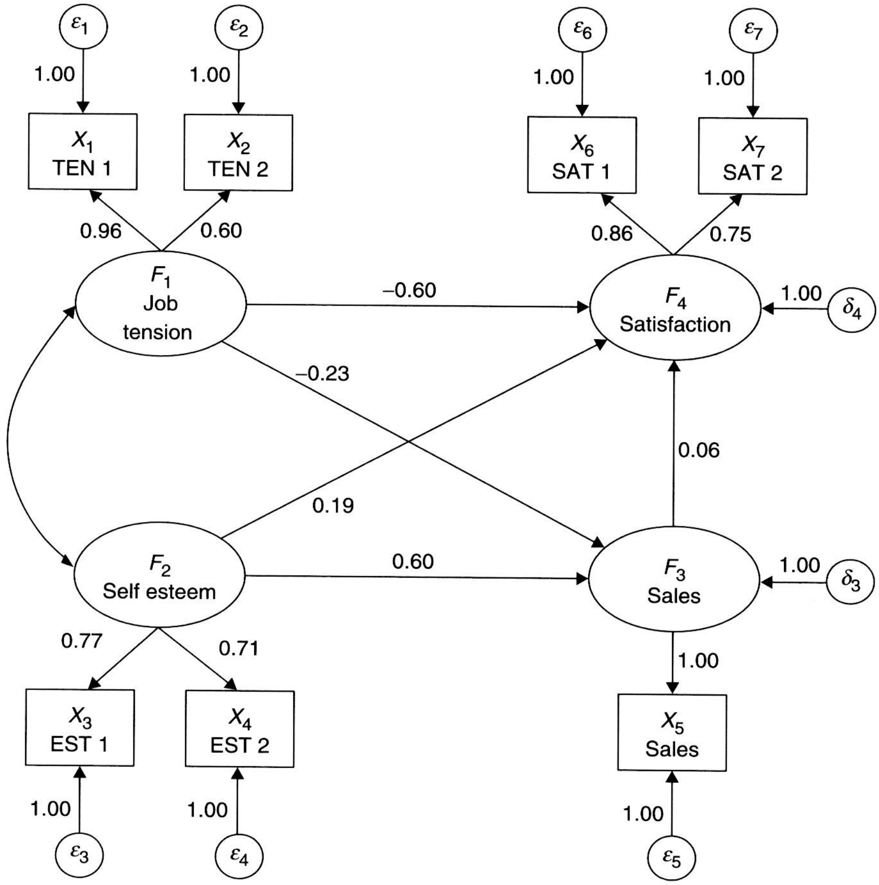

Figure 1.3 Example 2: Bagozzi's model (The figures can be interpreted as standardized regression coefficients—so-called *beta coefficients* (see Appendix A)

demands and decisions, how the amount of work interferes with its quality, and how work interferes with family life.

TEN 2: Seven 5-point scales indicating how frequently the salesperson feels bothered with the scope and responsibilities of the job, work load, the qualifications required for the job, difficulty of obtaining information necessary to perform the job, relations with co-workers, and decisions conflicting with one's values.

EST 1: Two 9-point and one 5-point scales measuring each salesperson's attributions (relative to other salespeople in the company) of the quantity of sales they achieve, the potential for achieving the top 10% sales in their company, and the quality of their performance with regard to planning and management of time and expenses.

EST 2: Three 9-point scales measuring each salesperson's ability to reach quota, feeling as to the quality of customer relations, and self-regard as to knowledge of own products and company, competitors' products and customers' need.

SAT 1: Four 6-point scales measuring degree of satisfaction with promotion, pay, and the overall work situation.

SAT 2: Four 6-point scales measuring satisfaction with opportunity to demonstrate ability and initiative, job security, belief that work is challenging and gives one a sense of accomplishment, and felt degree of control over aspects of job.

The two-headed arrow connecting F_1 and F_2 indicates that the possibility of a *correlation* (see Appendix A) between these two variables as a consequence of factors not included in the model is left open.

The model can also be depicted as a system of equations:

$$\begin{aligned}
F_3 &= -0.23F_1 + 0.60F_2 + \delta_3 \\
F_4 &= -0.60F_1 + 0.19F_2 + 0.06F_3 + \delta_4 \\
X_1 &= 0.96F_1 + \varepsilon_1 \\
X_2 &= 0.60F_1 + \varepsilon_2 \\
X_3 &= 0.77F_2 + \varepsilon_3 \\
X_4 &= 0.71F_2 + \varepsilon_4 \\
X_5 &= F_3 \\
X_6 &= 0.86F_4 + \varepsilon_6 \\
X_7 &= 0.75F_4 + \varepsilon_7
\end{aligned} \tag{1}$$

The first two equations describe the structural model and the last seven the measurement models.

We see that a hypothesized causal structure can be depicted in two ways:

1. As a graph with variables shown as circles (or ellipses) and squares (or rectangles), (possible) causal links shown as arrows and covariances not explained by the model shown as two-headed arrows.
2. As a system of equations.

Both ways of depicting causal models have their advantages. The graph has great communicative force, and the equations make it possible to use traditional algebraic manipulations. Usually during a causal study you sketch one or more models, and then translate the drawings into equations, which are used as input to calculations. Newer computer programs (such as AMOS) also make it possible to draw a graph of the model, which the program then translates into command statements and carries out the calculations necessary to estimate the parameters.

After the model has been estimated it is tested in various ways and if necessary revised in order to improve its fit and at the same time obtain parsimony. In this example it is tempting to remove the arrow from F_3 to F_4. A coefficient of 0.06 is hardly of any practical importance.

The Basic Problems

From the examples it should be clear that drawing causal conclusions from non-experimental data—a situation in which behavioral and social scientists often find themselves—calls for different statistical techniques than used in sciences where the possibilities for making experiments with well-defined variables are greater.

The problems facing the researcher stem from two conditions:

1. Basing causal conclusions on non-experimental data usually necessitates statistical models comprising several equations, as opposed to traditional regression analysis and analysis of variance, which serve us so well in the simpler situations we meet when we analyze experimental data. Besides, the statistical assumptions underlying the models used are more difficult to fulfill in non-experimental research and, last but not least, the concept of causality must be used with greater care in non-experimental research.
2. The variables with which the social researcher works are usually more diffuse than concepts such as weight, length and the like, for which well-defined and generally accepted measuring methods exist. Rather the social scientist works with concepts such as attitudes, literacy, alienation, social status, etc. Concepts, which are not directly measurable and therefore must be measured indirectly via indicators—be they questions in a questionnaire or some sort of test.

We will now look at these two complications in turn.

2. The Problem of Non-Experimental Data

As is well known, you are not able to observe causation—considered as a 'force' from cause to effect. What you *can* observe is:

1. *Co-variation*—the fact that two factors *A* and *B* co-vary is an indication for the possible existence of a causal relationship—in one direction or the other.
2. *The time sequence*—the fact that occurrence of *A* is generally followed by the occurrence of *B* is an indication for *A* being a cause of *B* (and not the other way round).

However—and this is the crucial requirement—

3. These observations must be made under conditions that rule out all other explanations of the observations than that of the hypothesized causation.

These three points could be used as building blocks in an operational definition of the concept of causation—even if this concept 'in the real world' is somewhat dim, and perhaps meaningless, except as a common experience facilitating communication between people (Hume, 1739).