SCALE CONSTRUCTION – STRUCTURE EQUATION MODELING

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SEMINAR REPORT

ON

Scale Construction – Structure Equation Modelling

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INDEX

SL. NO.	PARTICULARS	PAGE NO.
1.	Introduction	1-2
2.	Scale construction in behavioural science 2.1. Scale of Measurement in Research Methodology 2.2. Definition of Scaling 2.3. Process of Scaling 2.3.1. Gathering Related Variables 2.3.2. Shortlisting the Variables 2.3.3. Formation of Scale 2.4. Scale Construction Techniques 2.5. Criteria for good scale 2.6. Importance of scaling 2.7. General Methods of scale construction	2-11
3.	Structure Equation Modleing 3.1. Basic concepts 3.1.1 Latent versus observed variable 3.1.2. Exogenous versus endogenous latent variable 3.1.3. The factor analytic model 3.1.4. The full latent variable model 3.1.5. General purpose and process of statistical modelling 3.1.6. The general structural equation model 3.2. Using AMOS model 3.3. Model specification 3.4. Model Identification 3.5 Absolute fit indices 3.5.1. Model Chi – square 3.5.2. Root mean square error of approximation (RMSEA) 3.5.3. Goodness-of-fit statistic (GFI) 3.5.4. Root mean square residual (RMR) 3.6. Incremental fit indices Incremental fit indices 3.7. Parsimony fit indices 3.8. Reporting fit indices	11-34

	3.9. How to improve model fit	
4.	Advantages and challenges of structure equation model 4.1. Validity 4.2. Reliability / Measurement Error 4.3. Complex models 4.4. Confirmatory Approach 4.5. Challenges and Potential Problems	34-38
5.	Literature available / Research studies / Case studies	38- 40
6.	Conclusion	40 -42
7.	Bibliography	42
8.	Discussion	43-44
9.	Synopsis	45 - 46
10.	Enclosed Power point presentation slides	

1. Introduction

There are some tangible measures such as birth, age, marital status, number of children that quantify easily in Social Science but the pictures become fuzzy or difficult when once considered different characters related with human behavior like the intelligence, attitude, perception, awareness, opinion, values, beliefs, satisfaction etc. at individual or organization or both levels. Along with that, in the social science, it is often blurred whether the problem is the measures, the theory, or both. In social science concepts are huge in number, ambiguous, and do not bear a simple relationship with the other. Therefore, scaling comes in the picture to measure latent or behavioral characteristic of target audience. It developed in the early 1930s primarily to measure hidden ability and achievement; application of psychophysical work on sensation and perception to attitude, measurement of intelligence and value measurement using the method of paired comparisons. In the present context, for the measurement of social and psychological latent concepts scaling applications were increased. For the construction of scale, a questionnaire was design so that quantitative measurement of an abstract hypothetical/theoretical variable will be measured. In recent years, numerous measurement scales have been developed to assess attitudes, techniques, and interventions in a variety of scientific applications. Measurement is a fundamental activity of science, so that acquiring of knowledge about people, objects, events, and processes will be enables by the researchers. The phenomena that cannot be measured directly, by the use of measurement scales act as useful tools to attribute scores in numerical dimension. Scaling consists of sets of items revealing levels of theoretical variables otherwise unobservable by direct means. Empirical research in the social sciences requires both accurate and reliable tools for measures. Any measurement tool should consider main three criteria i.e., validity, reliability, and practicality one while evaluating. In the social sciences data are collected in many forms, including measurement of attitude, perceptions, cognitions, opinions, and other latent constructs that can't be measured directly.

A series of categories or items arranged in a progressive manner based on magnitude or value is called 'scale'. Different responses of individuals are quantitatively placed on such scales. Every scale includes a lowest point, a highest point and some intermediate points representing a particular activity or attitude. If the first point or item on the scale is of highest degree, the second point is higher in nature, than the third point is consequently, the third point is higher in nature than the fourth point and so on. The process of developing a continuum for placing the measured objects is called scaling. These measured objects may involve interests, opinions, attitude, and other responses of the individuals. Thus, the next operation involved in measurement is the scaling process. In this, different qualitative aspects are associated with quantitative components. Measurement is followed by scaling procedure in a research activity. Researchers always face the problem of how to measure or quantify abstract concepts and how to relate one individual's response to that with another response. Hence, the problem is two-fold. First is, how to quantify a response in absolute terms, and the second is, how to relate it with other responses. This problem is resolved by scaling process or assigning the numbers or values to responses and positioning them on a common scale. Hence, scaling is the process or procedure of quantifying and measuring abstract concepts like attitudes, opinions, emotions, etc. Scaling also quantitatively determines the position of an individual in a range of values. Techniques used in developing set of items or categories in a progressive manner (in a continuous spectrum) to measure an individual's preference towards given event or object, refers to scale construction techniques. Paired comparison, Equal appearing intervals, Successive intervals, Scalogram analysis and Summated rating scales are the popular approaches in scale construction. With the development of psychometrics with help of statistical development the advanced methods like Analytical hierarchy process, Perceptual mapping, Structure equation modeling are evolving and practiced by the large number of behavioral researchers in addressing their research question more appropriately. With this brief background, the current seminar has been conceptualized with the following objectives:

1. To understand the concept of scale construction in behavioral science
2. To understand the concept, procedure of Structure Equation Modeling (SEM) and its implications and challenges
3. To review the relevant literature available on SEM

2. Scale construction in behavioral science

2.1. Scale of Measurement in Research Methodology :

Measurement is followed by scaling procedure in a research activity. Researchers always face the problem of how to measure or quantify abstract concepts and how to relate one individual's response to that with another response. Hence, the problem is two-fold. First is, how to quantify a response in absolute terms, and the second is, how to relate it with other responses. This problem is resolved by scaling process, or assigning the numbers or values to responses and positioning them on a common scale. Scaling can then be defined as, "creating a continuum with two extreme limits and few immediate values between them". Hence, scaling is the process or procedure of quantifying and measuring abstract concepts like attitudes, opinions, emotions, etc. Scaling also quantitatively determines the position of an individual in a range of values.

2.2. Definition of Scaling

According to Edwards, scaling can be defined as, "Procedure for the assignment of numbers (or other symbols) to a property of objects in order to impart some of the characteristics of numbers to the properties in question" In a scale, the values are progressively placed according their value or magnitude in such a manner that moving forward in a scale will depict an item to be always higher than the immediate lower one.

2.3. Process of Scaling

Among all the commonly used direct techniques to measure attitudes, like word-association tests, sentence-completion tests, story-telling. performance of 'objective' tasks. physiological reactions, etc., the 'self-report method' is the most popular. In this method, the respondent is asked to give his opinion about a particular object freely. Described below is a step-by-step guide on how to construct a self-report:

2.3.1. Gathering Related Variables : Once the subject of inquiry has been decided, it is time to collect all possible variables and related statements, which are then examined to remove those that are imprecise and ambiguous, so that the questionnaire is easily comprehensible and accurately answerable. Utmost care should be taken to ensure the use of simple, easily understandable language,

2.3.2. Shortlisting the Variables : Once the pool of variables or questions has been finalized, it is time for scrutinizing the variables to ensure that the question or variable can be included in the scale. Some of the criteria for selecting the variables are as follows :

1. Relevant with the enquiry,
2. Indispensible,
3. Easily comprehensible,
4. Accurately answerable,
5. Covers all the possible dimensions and angles of the subject of enquiry.

Before finalizing, its efficacy is needed to be tested either through a sample tested on a dummy or by assigning the task to a group of experts.

2.3.3. Formation of Scale :

Once the variables have been finalized, the scale is then tested for its validity and reliability, before being put to use in a survey.

2.4. Scale Construction Techniques

Techniques used in developing set of items or categories in a progressive manner (in a continuous spectrum) so as to measure an individual's attitude towards given event or object, refers to scale construction techniques. Different scale construction techniques in research methodology used in scaling are as follows :

1) Arbitrary Scales : In this technique, large number of items or categories, which are able to represent the concept under study are collected and (then) measured in terms of same characteristic. Subjective selection of the researcher plays an important role here. Firstly, few related statements or items are selected by the researcher, and then these statements are filtered for being included in the measuring instrument. A list of filtered statements is presented to the respondents and they are required to tick the most suitable one.

2) Cumulative Scales : A series of statements is used in developing scale for the respondents in cumulative scales. These are also called 'Louis Guttman's scales. These scales require respondents to show their agreement or disagreement over the statements. These scales are called cumulative scales because a cumulative series is formed by different statements here. For example, the confirmation of an extreme position item should also lead to the confirmation of less extreme position items.

3) Consensus Scaling : This method of scaling was given by L.L. Thurstone. In this, a panel of judges uses different attributes like attitude. relevance and ambiguity factor so as to select items or categories. Generally, differential scales are created by this method, which focus on measuring attitudes of respondents concerning specific issues like religion, war, etc. These are the most suitable scales for recording only a single attitude of the given concept. A high level of cost and effort is needed to create such scales. Judges' own attitudes may affect their functioning of assigning values to different statements.

4) Item Analysis : In this type of scale construction technique, a group of respondents is given a test created by selecting different individual items. Following steps are involved in this technique :

- Firstly, large number of items expressing their positive or negative aspects is selected.
- Then, a group of respondents assigns scores to them.
- Then for each respondent, total scores for all items are calculated. Then using these scores, they are divided into four constructs. Two middle constructs are then eliminated from the calculation.
- Then average score is calculated separately for each item.
- T-test is then used to compare average of items of different groups to select Items with noteworthy t-values.

In this, different statements expressing the positive or negative attitude towards the selected object are used to create the scale and the respondents are asked to check the most suitable one. Thus, the agreement or disagreement of respondents over different statements is recorded. The most common example of item analysis is Likert scale. In this, several degrees of agreement or disagreement (generally five, but sometimes three or seven) are used by the respondents to respond to 'different statements. This type of scale is very easy to develop.

5) Factor Scales : Several different techniques are involved in constructing such scales. The purpose of using different scales is to study multi-dimensional items, to find the relations between different dimensions and to identify any other dimensions of the items. In the end, limited set of factors are available each having interrelated dimensions. Scales developed through this technique are as follows :

i) Q-Sort Technique : In this, the respondent is asked to sort the different given statements into prefixed categories.

ii) Semantic Differential (SD) : Factor analysis of assumed interval scales results in semantic differential scales.

iii) Stapel Scale : It is a non-verbal rating scale having even number of scales. Single adjectives are used in items or categories. It is necessary to measure both the dimensions consequently. There is no need of assuming the ratings or the interval equality.

iv) Mull-Dimensional Scaling : In multi dimensional scaling, a multi-dimensional space is assumed to be present. A set of techniques are developed to deal with such multi-dimensional space.

v) Standardized Instruments : In this, an available measuring instrument is selected for data collection. No new measuring instruments are developed. The opinion of expert is taken for selecting such standardized instruments.

2.5. Criteria for Good Scale

Any scale must satisfy the following criteria to prove its efficacy

1) Validity : Validity is the most critical aspect. It establishes or indicates the extent to which the scale does what it is supposed to do. Does it measure what it was intended to measure? In other words, whether or not the test has been useful or worthwhile.

2) Reliability : This indicates whether or not the findings of a measuring instrument can be relied upon. To know this, the researcher needs to answer some questions, such as, Are the outcomes accurate? Can they be replicated? Are the findings consistent?, etc. While reliability contributes to validity, it is not true the other way round. A reliable instrument may or may not be necessarily valid.

3) Practicality : Practicality refers to ease and economy, of constructing the measuring instrument as well as administration and interpretation of the test outcome. It measures the achievability, and practicality of an instrument. The benefits or results should justify the costs.

4) Sensitivity : This refers to how well the test is standardized. It tests how much an instrument is able to measure accurately. For example, a test which requires respondents to merely say 'yes' or 'no', may not be very sensitive. On the other hand, if the respondent is asked to rule on a '5' or "7"-point scale, the scale may be considered to be highly sensitive. It may however be noted that all scales need not be highly sensitive. It largely depends upon the requirement of the test.

5) Generalisability : This refers to whether or not one can generalize the findings, i.e., whether or not the findings can be applied to both similar and different situations. Whether or not the sample or respondents selected can be said to represent larger population. For example, exit polls can be said to have a high degree of generalisability.

6) Economy : This factor emphasizes on the aspect that whether the instrument, is economical to be constructed and conducted. Tests are expensive to develop and administer. Therefore, the results or benefits of the tests must justify or warrant the costs.

7) Convenience : A measuring instrument is convenient, if it is easy to conduct. The instruments that provide guidelines to use are much more convenient than those instruments that do not include this feature. Generally, it is considered that the requirement for convenience increases with the level of complexity of a measuring instrument.

2.6. Importance of Scaling: In business or management research, scaling is very crucial for the research process. It helps in measuring. and analyzing attitudes of different individuals. The exact behavior of an individual is reflected by such attitude analysis. Number of attitude measuring scales has been developed by researchers. For example, in order to measure the attitude of an individual about a particular tourist place, product or election candidate, i.e., if he visits, buys or votes, respectively, a suitable scale is developed. The different facts describing the importance of scaling are as follows :

1) Attitude Scoring :

Scaling is particularly used for altitude scoring of an individual. In scaling, with the help of an individual's responses a particular number or point is selected on given scale, which represents the attitude of that individual.

2) Broad Application : Different management research processes as well as scientific inventions use scaling as their crucial element. Data collection methods like interviews, observations, surveys, etc,, also use scaling for attitude measurement of respondents.

3) Hypothesis Testing : Scaling is also functional in hypothesis testing. Without effective measure of attitudes of different respondents, it is not easy to test hypothesis about the population.

4) Dimension Checking : Scaling is useful in determining the dimensional aspects of different quantitative concepts or items. It helps in checking whether a particular item is single dimensional or multi-dimensional.

5) Others :

- It is an essential element of the exploratory research.
- It is used to check whether a set of questions is measuring single aspect or multiple aspects.

2.7. General Methods of Scale construction

1. **Paired comparison technique:** The technique of paired comparison for scale construction has been developed by Louis Leon Thurstone on the basis of comparative judgement. The scale helps in ordering stimuli along a continuum. While formulating scale by using this method, the stimuli are compared with one another and hence this method of scale construction is known as 'Paired Comparison Technique'. By using this method researcher can also identify the estimates of distances between each of the stimulus.
2. **Equal appearing interval scale:** For measuring respondent's/ subject's attitude/ feeling as well as behaviour, Thurstone scale of 'Equal Appearing Interval Scale' is used. It is a type of onedimensional scale. Like other scales, 'Equal Appearing Interval Scale' tries to measure the attitude or positive (+ve) or negative (-ve) feeling of the respondent which indicate the respondent's favourable or unfavourable inclination towards some idea/ concept, topic or object etc. Respondents indicate their degree of agreements/ disagreements through responses towards the items or statements. Louis Leon Thurstone developed the 'Equal Appearing Interval Scale' construction technique in the year 1928. This scale construction method uses the fundamentals used in Likert scale. One of the major point in this type of scale is that it not only take in to

account the value of each items but also neutral values of any statement (item) is also taken in to account.

3. **Scalogram analysis:** Scalogram analysis is a method developed for evaluating statements or items in a measurement instrument to determine whether it forms a Guttman scale (Kishor, 2014). The approach known as Guttman scale represents the most common version of deterministic models and found applications in subjective measurements (Maggino, 2014). According to this approach, the nonsystematic variation is not explicitly definable and is completely attributed to cases' and items' position on the continuum representing the measured characteristic. Consequently, the probability to obtain a certain score for a certain item can be 0 or 1 at any point of the underlying continuum.
4. **Q sort methodology:** Q methodology was invented by the British physicist/psychologist William Stephenson in 1935, and introduced by him in a letter to the editor of the British scientific journal, Nature on 24 August 1935. Stephenson was the last assistant to Charles Spearman, a statistical theorist who first developed factor analysis. Stephenson was interested in a way to reveal the subjectivity involved in any situation, for instance, in aesthetic judgment, poetic interpretation and perceptions of organisational role. What makes Q methodology unique is that all perceptions, concepts, reports of events, music, literature, etc, can be transformed into operant factors which Q methodology develops. In other words, definitions of viewpoints are those of the participant's own subjective standpoint rather than intuitive or arbitrary .
5. **Likert summated rating scale:** The summated rating scale is one of the most frequently used tools in the social sciences. Its invention is attributed to Rensis Likert (1932), who described this technique for the assessment of attitudes. These scales are widely used across the social sciences to measure not only attitudes, but opinions, personalities, and descriptions of people's lives and environments as well. Scales presently exist that measure emotional states (e.g., anger, anxiety, and depression), personal needs (e.g., achievement, autonomy, and power), personality (e.g., locus of control and introversion), and description of jobs (e.g., role ambiguity and workload). These are but a few of the hundreds of variables for which scales have been developed. For many variables several scales exist, some of which were created for specialized purposes.t

Features :

- A scale must contain multiple items. The use of summated in the name implies that multiple items will be combined or summed
- Each individual item must measure something that has an underlying, quantitative measurement continuum. In other words, it measures a property of something that can vary quantitatively rather than qualitatively. An attitude, for example, can vary from being very favorable to very unfavorable.
- Each item has no "right" answer, which makes the summated rating scale different from a multiple-choice test. Thus summated rating scales cannot be used to test for knowledge or ability. Finally, each item in a scale is a statement, and respondents are asked to give ratings about each statement. This involves asking subjects to indicate which of several response choices.

6. **Perceptual Mapping:** A perceptual map can be defined as the visual representation of a respondent's perceptions of two or more dimensions or features (Hair et al., 1992). Perceptual maps fall into two broad categories: decompositional (attribute-free) and compositional (attribute-based). Decompositional maps are based on overall perceptions of similarity or dissimilarity. Compositional maps are based on respondents' ratings or associations of objects to a pre-determined set of attributes. The perceptual maps are constructed by way of techniques such as factor analysis, discriminant analysis and correspondence analysis and, more recently, brand-anchored conjoint analysis.
7. **Saatys Analytical Hierarchy process and fuzzy AHP:** Basic theory behind Analytic Hierarchy Process (AHP) is principle of pair-wise comparison, and it comes under psychophysical methods. Psychophysical methods are predominantly used in social science research to measure psychological constructs in social sciences. Ordering of objects in terms of their measured weights is said to be on a physical continuum and psychological continuum advocates ordering of objects on the basis of judgments. So, psychophysical method deals with relationship between physical and psychological continuums. Thurstone once developed law of comparative Judgment.

Statements in the law of comparative judgment can be ordered in a psychological continuum. The originator of the AHP is Thomas Saaty. “There are three principles which one can recognize in problem solving: 1. Decomposition, 2. Comparative Judgements and 3. Synthesis of priorities. The decomposition principle calls for structuring the hierarchy to capture the basic elements of the problem. The principle of comparative judgement calls for setting up a matrix to carry out pairwise comparisons of the relative importance of the elements in a level with respect to the elements in the level immediately above it. This matrix is used to generate a ratio scale. Finally, the principle of synthesis of priorities is used to generate the global or composite priority of the elements at the lowest level of the hierarchy.

8. **Structure equation modeling:** Structural equation modeling (SEM) is a statistical methodology that takes a confirmatory (i.e., hypothesis-testing) approach to the analysis of a structural theory bearing on some phenomenon. Typically, this theory represents “causal” processes that generate observations on multiple variables. The term structural equation modeling conveys two important aspects of the procedure: (a) that the causal processes under study are represented by a series of structural (i.e., regression) equations, and (b) that these structural relations can be modeled pictorially to enable a clearer conceptualization of the theory under study. The hypothesized model can then be tested statistically in a simultaneous analysis of the entire system of variables to determine the extent to which it is consistent with the data. If goodness-of-fit is adequate, the model argues for the plausibility of postulated relations among variables; if it is inadequate, the tenability of such relations is rejected.

3. Structure Equation Modeling

Structural equation models (SEM) are complex methods of data analysis. In the social sciences, they allow for analyses that would not be possible using other methods. Even in cases where alternative methods of analyses are available, structural equation modeling may offer more meaningful and more valid results. On the other hand, more effort is necessary until the greater complexity pays off. Assumptions on the data may be higher, and the process of interpreting the results is more complex compared to other methods of data analysis.

Several aspects of SEM set it apart from the older generation of multivariate procedures. First, as noted above, it takes a confirmatory rather than an exploratory approach to the data analysis (although aspects of the latter can be addressed). Furthermore, by demanding that the pattern of intervariable relations be specified a priori, SEM lends itself well to the analysis of data for inferential purposes. By contrast, most other multivariate procedures are essentially descriptive by nature (e.g., exploratory factor analysis), so that hypothesis testing is difficult, if not impossible. Second, whereas traditional multivariate procedures are incapable of either assessing or correcting for measurement error, SEM provides explicit estimates of these error variance parameters. Indeed, alternative methods (e.g., those rooted in regression, or the general linear model) assume that error(s) in the explanatory (i.e., independent) variables vanish(es). Thus, applying those methods when there is error in the explanatory variables is tantamount to ignoring error, which may lead, ultimately, to serious inaccuracies—especially when the errors are sizeable. Such mistakes are avoided when corresponding SEM analyses (in general terms) are used. Third, although data analyses using the former methods are based on observed measurements only, those using SEM procedures can incorporates both unobserved (i.e., latent) and observed variables. Finally, there are no widely and easily applied alternative methods for modeling multivariate relations, or for estimating point and/or interval indirect effects; these important features are available using SEM methodology. Given these highly desirable characteristics, SEM has become a popular methodology for nonexperimental research, where methods for testing theories are not well developed and ethical considerations make experimental design unfeasible. Structural equation modeling can be utilized very effectively to address numerous research problems involving nonexperimental research.

3.1. Basic Concepts

3.1.1. Latent versus observed variables: In the behavioral sciences, researchers are often interested in studying theoretical constructs that cannot be observed directly. These abstract phenomena are termed latent variables, or factors. Examples of latent variables in psychology are self-concept and motivation; in sociology, powerlessness and anomie; in education, verbal ability and teacher expectancy; and in economics, capitalism and social class. Because latent variables are not observed directly, it follows that they cannot be measured directly.

Thus, the researcher must operationally define the latent variable of interest in terms of behavior believed to represent it. As such, the unobserved variable is linked to one that is observable, thereby making its measurement possible. Assessment of the behavior, then, constitutes the direct measurement of an observed variable, albeit the indirect measurement of an unobserved variable (i.e., the underlying construct). It is important to note that the term behavior is used here in the very broadest sense to include scores on a particular measuring instrument. Thus, observation may include, for example, self-report responses to an attitudinal scale, scores on an achievement test, in vivo observation scores representing some physical task or activity, coded responses to interview questions, and the like. These measured scores (i.e., measurements) are termed observed or manifest variables; within the context of SEM methodology, they serve as indicators of the underlying construct which they are presumed to represent. Given this necessary bridging process between observed variables and unobserved latent variables, it should now be clear why methodologists urge researchers to be circumspect in their selection of assessment measures. Although the choice of psychometrically sound instruments bears importantly on the credibility of all study findings, such selection becomes even more critical when the observed measure is presumed to represent an underlying construct.

3.1.2. Exogenous versus endogenous latent variables: It is helpful in working with SEM models to distinguish between latent variables that are exogenous and those that are endogenous. Exogenous latent variables are synonymous with independent variables; they “cause” fluctuations in the values of other latent variables in the model. Changes in the values of exogenous variables are not explained by the model. Rather, they are considered to be influenced by other factors external to the model. Background variables such as gender, age, and socioeconomic status are examples of such external factors. Endogenous latent variables are synonymous with dependent variables and, as such, are influenced by the exogenous variables in the model, either directly or indirectly. Fluctuation in the values of endogenous variables is said to be explained by the model because all latent variables that influence them are included in the model specification.

3.1.3. The factor analytic model: The oldest and best-known statistical procedure for investigating relations between sets of observed and latent variables is that of factor analysis. In using this approach to data analyses, the researcher examines the covariation among a set of observed variables in order to gather information on their underlying latent constructs (i.e., factors). There are two basic types of factor analyses: exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). We turn now to a brief description of each. Exploratory factor analysis (EFA) is designed for the situation where links between the observed and latent variables are unknown or uncertain. The analysis thus proceeds in an exploratory mode to determine how, and to what extent, the observed variables are linked to their underlying factors. Typically, the researcher wishes to identify the minimal number of factors that underlie (or account for) covariation among the observed variables. For example, suppose a researcher develops a new instrument designed to measure five facets of physical self-concept (e.g., Health, Sport Competence, Physical Appearance, Coordination, and Body Strength). Following the formulation of questionnaire items designed to measure these five latent constructs, he or she would then conduct an EFA to determine the extent to which the item measurements (the observed variables).

were related to the five latent constructs. In factor analysis, these relations are represented by factor loadings. The researcher would hope that items designed to measure health, for example, exhibited high loadings on that factor, and low or negligible loadings on the other four factors. This factor analytic approach is considered to be exploratory in the sense that the researcher has no prior knowledge that the items do, indeed, measure the intended factors.

In contrast to EFA, confirmatory factor analysis (CFA) is appropriately used when the researcher has some knowledge of the underlying latent variable structure. Based on knowledge of the theory, empirical research, or both, he or she postulates relations between the observed measures and the underlying factors a priori and then tests this hypothesized structure statistically. For example, based on the example cited earlier, the researcher would argue for the loading of items designed to measure sport competence self-concept on that specific factor, and not on the health, physical appearance, coordination, or body strength self-concept dimensions. Accordingly, a priori specification of the CFA model would allow all sport competence self-concept items to be free to load on that factor, but restricted to have zero loadings on the remaining factors. The model would then be evaluated by statistical means to determine the adequacy of its goodness-of-fit to the sample data.

In summary, then, the factor analytic model (EFA or CFA) focuses solely on how, and the extent to which, the observed variables are linked to their underlying latent factors. More specifically, it is concerned with the extent to which the observed variables are generated by the underlying latent constructs and thus strength of the regression paths from the factors to the observed variables (the factor loadings) are of primary interest. Although interfactor relations are also of interest, any regression structure among them is not considered in the factor analytic model. Because the CFA model focuses solely on the link between factors and their measured variables, within the framework of SEM, it represents what has been termed a measurement model.

3.1.4. The full latent variable model: In contrast to the factor analytic model, the full latent variable (LV) model allows for the specification of regression structure among the latent variables. That is to say, the researcher can hypothesize the impact of one latent construct on another in the modeling of causal direction. This model is termed full (or complete) because it comprises both a measurement model and a structural model: the measurement model depicting the links between the latent variables and their observed measures (i.e., the CFA model), and the structural model depicting the links among the latent variables themselves.

A full LV model that specifies direction of cause from one direction only is termed a recursive model; one that allows for reciprocal or feedback effects is termed a no recursive model. Only applications of recursive models are considered in the present book.

3.1.5. General purpose and process of statistical modeling: Statistical models provide an efficient and convenient way of describing the latent structure underlying a set of observed variables. Expressed either diagrammatically or mathematically via a set of equations, such models explain how the observed and latent variables are related to one another.

Typically, a researcher postulates a statistical model based on his or her knowledge of the related theory, on empirical research in the area of study, or on some combination of both. Once the model is specified, the researcher then tests its plausibility based on sample data that comprise all observed variables in the model. The primary task in this model-testing procedure is to determine the goodness-of-fit between the hypothesized model and the sample data. As such, the researcher imposes the structure of the hypothesized model on the sample data, and then tests how well the observed data fit this restricted structure. Because it is highly unlikely that a perfect fit will exist between the observed data and the hypothesized model, there will necessarily be a differential between the two; this differential is termed the residual. The model-fitting process can therefore be summarized as follows:

Data = Model + Residual

Where,

Data represent score measurements related to the observed variables as derived from persons comprising the sample.

Model represents the hypothesized structure linking the observed variables to the latent variables and, in some models, linking particular latent variables to one another.

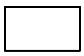
Residual represents the discrepancy between the hypothesized model and the observed data.

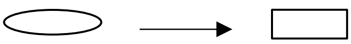
In summarizing the general strategic framework for testing structural equation models, Jöreskog (1993) distinguished among three scenarios which he termed strictly confirmatory (SC), alternative models (AM), and model generating (MG). In the strictly confirmatory scenario, the researcher postulates a single model based on theory, collects the appropriate data, and then tests the fit of the hypothesized model to the sample data. From the results of this test, the researcher either rejects or fails to reject the model; no further modifications to the model are made. In the alternative models case, the researcher proposes several alternative (i.e., competing) models, all of which are grounded in theory. Following analysis of a single set of empirical data, he or she selects one model as most appropriate in representing the sample data. Finally, the model-generating scenario represents the case where the researcher, having postulated and rejected a theoretically derived model on the basis of its poor fit to the sample data, proceeds in an exploratory (rather than confirmatory) fashion to modify and estimate the model. The primary focus, in this instance, is to locate the source of misfit in the model and to determine a model that better describes the sample data. Jöreskog (1993) noted that, although re specification may be either theory or data driven, the ultimate objective is to find a model that is both substantively meaningful and statistically well fitting. He further posited that despite the fact that “a model is tested in each round, the whole approach is model generating, rather than model testing” (Jöreskog, 1993).

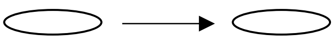
Of course, even a cursory review of the empirical literature will clearly show the MG situation to be the most common of the three scenarios, and for good reason. Given the many costs associated with the collection of data, it would be a rare researcher indeed who could afford to terminate his or her research on the basis of a rejected hypothesized model! As a consequence, the SC case is not commonly found in practice. Although the AM approach to modeling has also been a relatively uncommon practice, at least two important papers on the topic. Statistical theory related to these model-fitting processes can be found (a) in texts devoted to the topic of SEM (e.g., Bollen, 1989a; Kline, 2005; Loehlin, 1992; Long, 1983b; Raykov & Marcoulides, 2000; Saris & Stronkhurst, 1984; Schumacker & Lomax, 2004), (b) in edited books devoted to the topic (e.g., Bollen & Long, 1993; Cudeck, du Toit, & Sörbom, 2001; Hoyle, 1995b; Marcoulides & Schumacker, 1996), and (c) in methodologically oriented journals such as British Journal of Mathematical and Statistical Psychology, Journal of Educational and Behavioral Statistics, Multivariate Behavioral Research, Psychological Methods, Psychometrika, Sociological Methodology, Sociological Methods & Research, and Structural Equation Modeling.

3.1.6. The general structural equation model

3.1.6.1. Symbol notation

Structural equation models are schematically portrayed using particular configurations of four geometric symbols—a circle (or ellipse), a square (or rectangle), a single-headed arrow, and a double-headed arrow. By convention, circles (or  ellipses;) represent unobserved latent factors, squares (or rectangles; ) represent observed variables, single-headed arrows (→) represent the impact of one variable on another, and double-headed arrows (↔) represent covariances or correlations between pairs of variables. In building a model of a particular structure under study, researchers use these symbols within the framework of four basic configurations, each of which represents an important component in the analytic process. These configurations, each accompanied by a brief description, are as follows:

•  Path coefficient for regression of an observed variable onto an unobserved latent variable (or factor)

•  Path coefficient for regression of one factor onto another factor

- Measurement error associated with an observed variable
- Residual error in the prediction of an unobserved factor

3.1.6.2. The path diagram

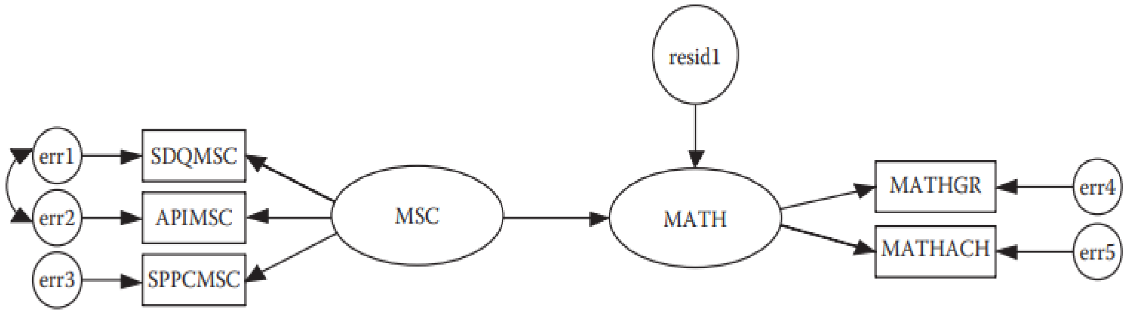


Fig 1. A general structure equation modeling

Schematic representations of models are termed path diagrams because they provide a visual portrayal of relations which are assumed to hold among the variables under study. Essentially, as you will see later, a path diagram depicting a particular SEM model is actually the graphical equivalent of its mathematical representation whereby a set of equations relates dependent variables to their explanatory variables. As a means of illustrating how the above four symbol configurations may represent a particular causal process, let me now walk you through the simple model shown in Figure.

In reviewing the model shown in Figure, we see that there are two unobserved latent factors, math self-concept (MSC) and math achievement (MATH), and five observed variables—three are considered to measure MSC (SDQMSC; APIMSC; SPPCMSC), and two to measure MATH (MATHGR; MATHACH). These five observed variables function as indicators of their respective underlying latent factors.

Associated with each observed variable is an error term (err1–err5), and with the factor being predicted (MATH), a residual term (resid1); 2 there is an important distinction between the two. Error associated with observed variables represents measurement error, which reflects on their adequacy in measuring the related underlying factors (MSC; MATH). Measurement error derives from two sources: random measurement error (in the psychometric sense) and error uniqueness, a term used to describe error variance arising from some characteristic that is considered to be specific (or unique) to a particular indicator variable. Such error often represents nonrandom (or systematic) measurement error. Residual terms represent error in the prediction of endogenous factors from exogenous factors. For example, the residual term shown in Figure represents error in the prediction of MATH (the endogenous factor) from MSC (the exogenous factor). It is worth noting that both measurement and residual error terms, in essence, represent unobserved variables. Thus, it seems perfectly reasonable that, consistent with the representation of factors, they too should be enclosed in circles. For this reason, then, AMOS path diagrams, unlike those associated with most other SEM programs, model these error variables as circled enclosures by default.

In addition to symbols that represent variables, certain others are used in path diagrams to denote hypothesized processes involving the entire system of variables. In particular, one-way arrows represent structural regression coefficients and thus indicate the impact of one variable on another. In Figure 1, for example, the unidirectional arrow pointing toward the endogenous factor, MATH, implies that the exogenous factor MSC (math self-concept) “causes” math achievement (MATH). 4 Likewise, the three unidirectional arrows leading from MSC to each of the three observed variables (SDQMSC, APIMSC, and SPPCMSC), and those leading from MATH to each of its indicators, MATHGR and MATHACH, suggest that these score values are each influenced by their respective underlying factors. As such, these path coefficients represent the magnitude of expected change in the observed variables for every change in the related latent variable (or factor). It is important to note that these observed variables typically represent subscale scores, item scores, item pairs, and /or carefully formulated item parcels. The one-way arrows pointing from the enclosed error terms (err1–err5) indicate the impact of measurement error (random and unique) on the observed variables, and from the residual (resid1), the impact of error in the prediction of MATH. Finally, as noted earlier, curved two way arrows represent covariances or correlations between pairs of variables. Thus, the bidirectional arrow linking err1 and err2, as shown in Figure 1, implies that measurement error associated with SDQMSC is correlated with that associated with APIMSC.

3.1.6.3. Structural equations

As noted in the initial paragraph of this chapter, in addition to lending themselves to pictorial description via a schematic presentation of the causal processes under study, structural equation models can also be represented by a series of regression (i.e., structural) equations. Because (a) regression equations represent the influence of one or more variables on another, and (b) this influence, conventionally in SEM, is symbolized by a single-headed arrow pointing from the variable of influence to the variable of interest, we can think of each equation as summarizing the impact of all relevant variables in the model (observed and unobserved) on one specific variable (observed or unobserved). Thus, one relatively simple approach to formulating these equations is to note each variable that has one or more arrows pointing toward it, and then record the summation of all such influences for each of these dependent variables.

To illustrate this translation of regression processes into structural equations, let's turn again to Figure 1.1. We can see that there are six variables with arrows pointing toward them; five represent observed variables (SDQMSC, APIMSC, SPPCMSC, MATHGR, and MATHACH), and one represents an unobserved variable (or factor; MATH). Thus, we know that the regression functions symbolized in the model shown in Figure 1. can be summarized in terms of six separate equation-like representations of linear dependencies as follows:

- MATH = MSC + resid1
- SDQMSC = MSC + err1
- APIMSC = MSC + err2
- SPPCMSC = MSC + err3
- MATHGR = MATH + err4
- MATHACH = MATH + err5

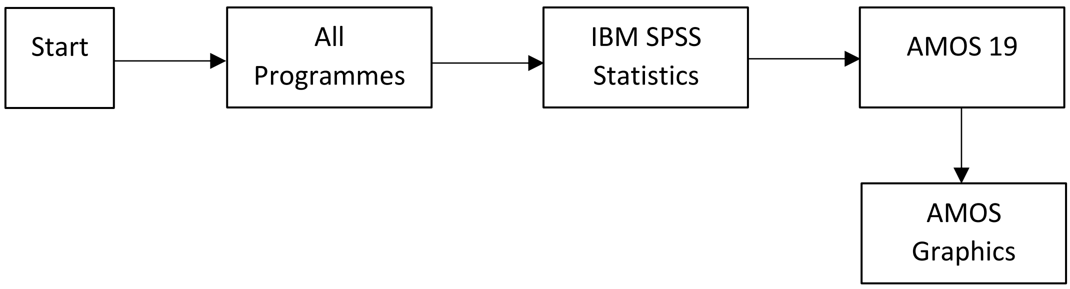
3.1.6.3. Nonvisible components of a model

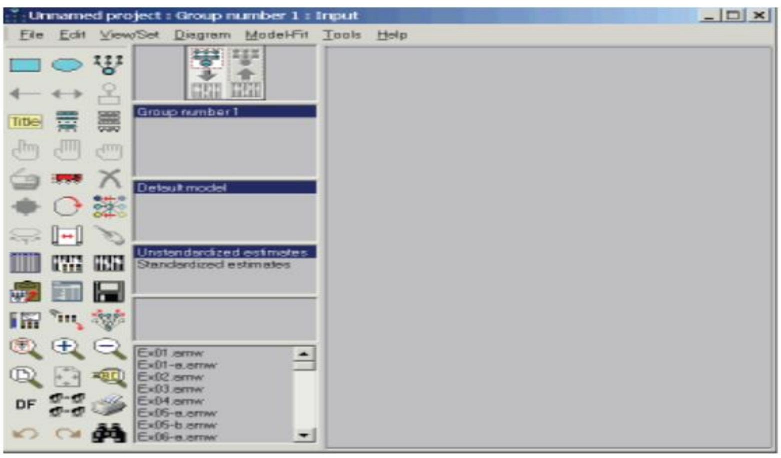
Although, in principle, there is a one-to-one correspondence between the schematic presentation of a model and its translation into a set of structural equations, it is important to note that neither one of these model representations tells the whole story; some parameters critical to the estimation of the model are not explicitly shown and thus may not be obvious to the novice structural equation modeler. For example, in both the path diagram and the equations just shown, there is no indication that the variances of the exogenous variables are parameters in the model; indeed, such parameters are essential to all structural equation models. Although researchers must be mindful of this inadequacy of path diagrams in building model input files related to other SEM programs, AMOS facilitates the specification process by automatically incorporating the estimation of variances by default for all independent factors.

3.2. Using the AMOS program

The name, AMOS, is actually an acronym for analysis of moment structures or, in other words, the analysis of mean and covariance structures. An interesting aspect of AMOS is that, although developed within the Microsoft Windows interface, the program allows you to choose from three different modes of model specification. Using the one approach, AMOS Graphics, you work directly from a path diagram; using the others, AMOS VB.NET and AMOS C#, you work directly from equation statements. The choice of which AMOS method to use is purely arbitrary and bears solely on how comfortable you feel in working within either a graphical interface or a more traditional programming interface. In the second edition of this book, I focus only on the graphical approach. For information related to the other two interfaces, readers are referred to the user’s guide.

To start AMOS graphics, it is needed to follow the usual steps as follows:

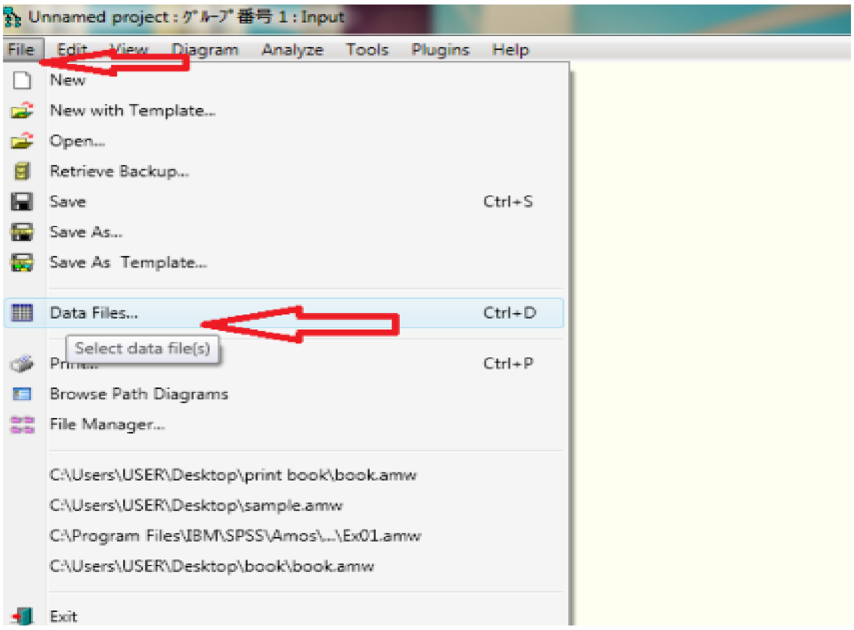




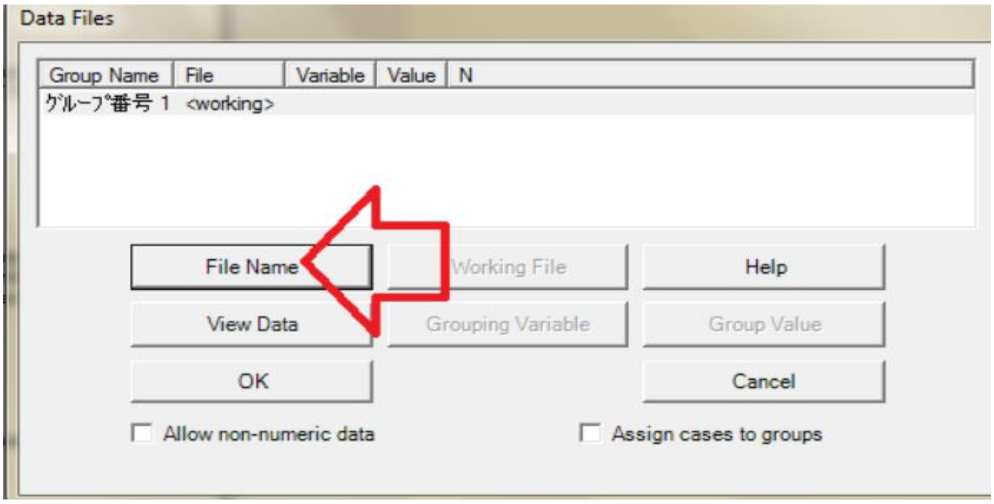
(Fig 2 AMOS Graphics Scene)

Once you finish these steps, you can see the AMOS graphic screen given in Figure. You can use the tools in the screen to draw the path diagram in the empty space of the screen.

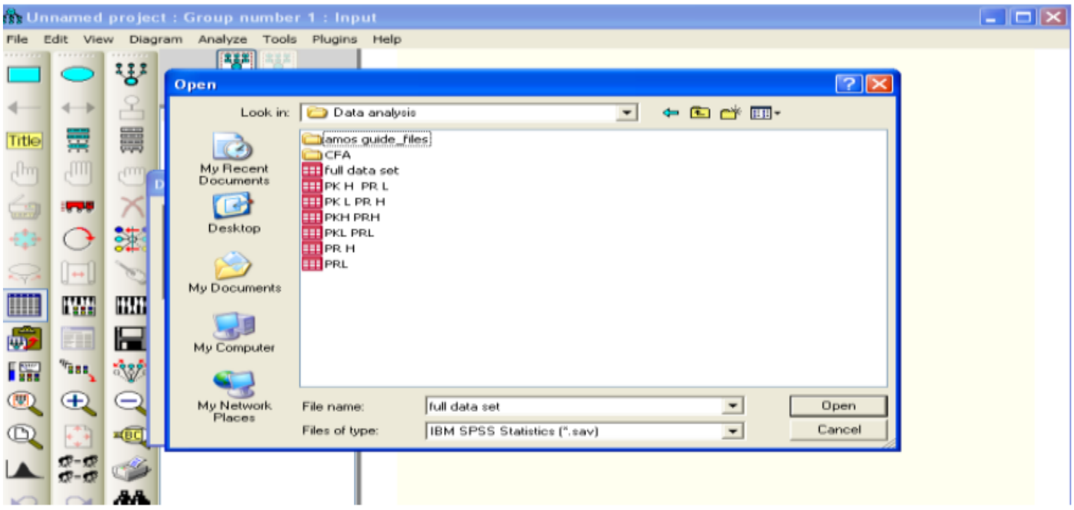
STEP 2: In order to start the drawing, first of all it is needed to select the data file. The Data Files dialog allows you to specify the database file (or files) to be analyzed. To select the database file click on "File" shown at the top of the graphic screen and then select "Data Files".



STEP 3: Then click on "File Name" and select the relevant database file and click on "OK".

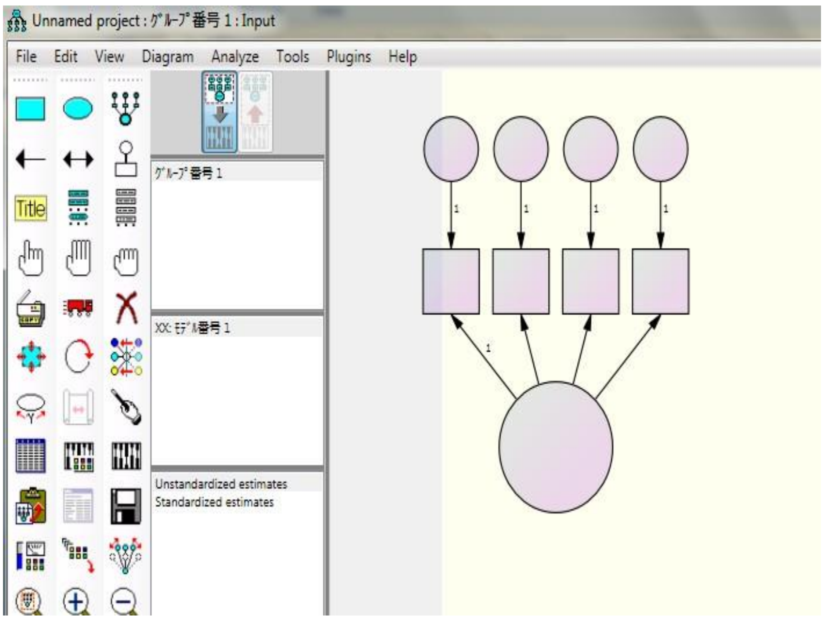


STEP 4: The SPSS saved files are indicated, but data files in other programs also can be accessed. By clicking the "view data" in the AMOS dialogue box given in Figure, it is possible to see the data file selected.



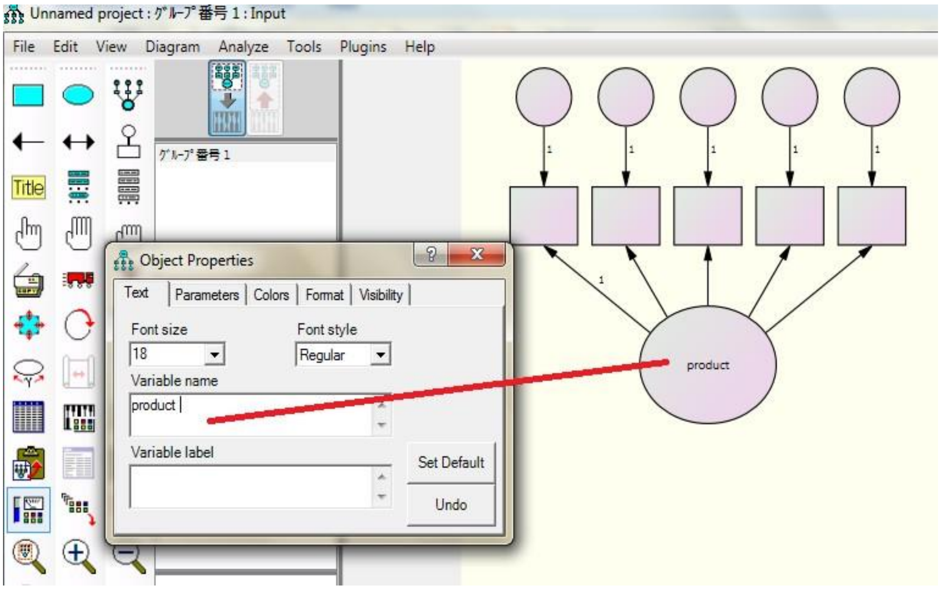
STEP 5: Drawing path diagram

Now you can start the drawing of your path diagram. You can use the drawing tools at the left side of the screen to draw the path diagram. You are required to click the relevant tool to activate it. Then click in the blank drawing space while holding down the left mouse button and dragging it slightly, you will be able to create the relevant picture. You can use either the tools of rectangle , ellipse , arrows to draw the diagram or the tool to draw a latent variable or add an indicator to a latent variable.



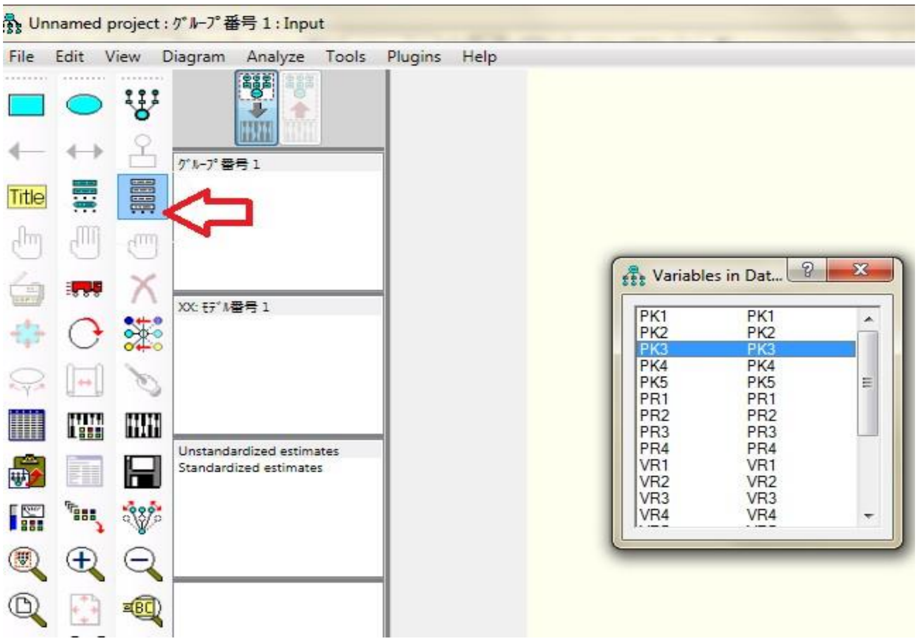
STEP 6: Naming the Variable

In order to name the variables, right click the rectangle/ellipse and choose "object properties" from the pop up menu. Then, type the variable name and close the pop up menu. The same method should be applied to name the other variables and error terms.

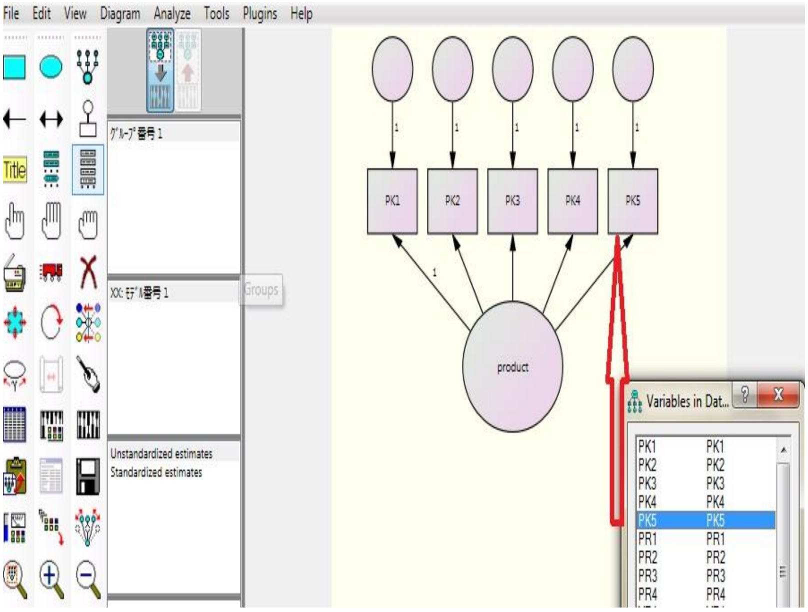


STEP 7: Naming the observed variable directly

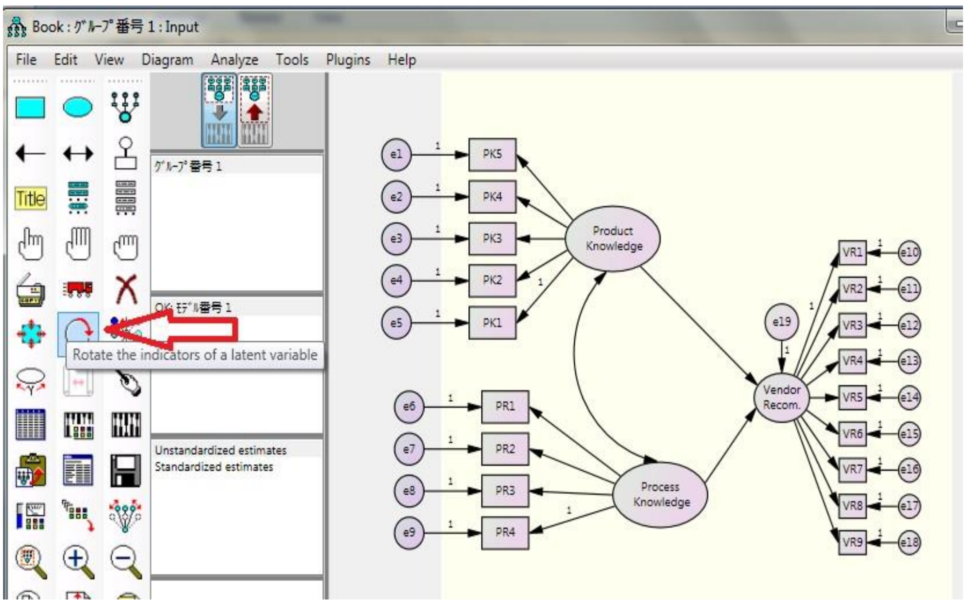
Observed variables can be directly taken from your data set easily without naming them as discussed above. Use the "List Variables in Dataset" button on the left-hand side to see the variables in your dataset.



STEP 8: Drag and drop the observed variables that you want to include in your model onto the gray workspace as shown in Figure



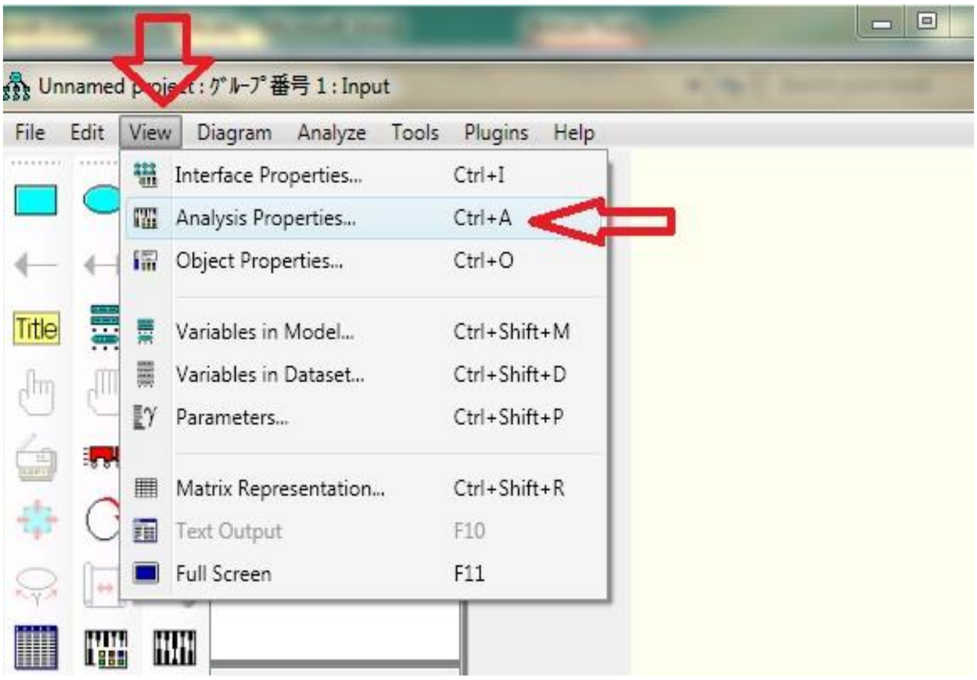
STEP 9: Similarly the path diagram can be rotate using the rotate button in the left hand side



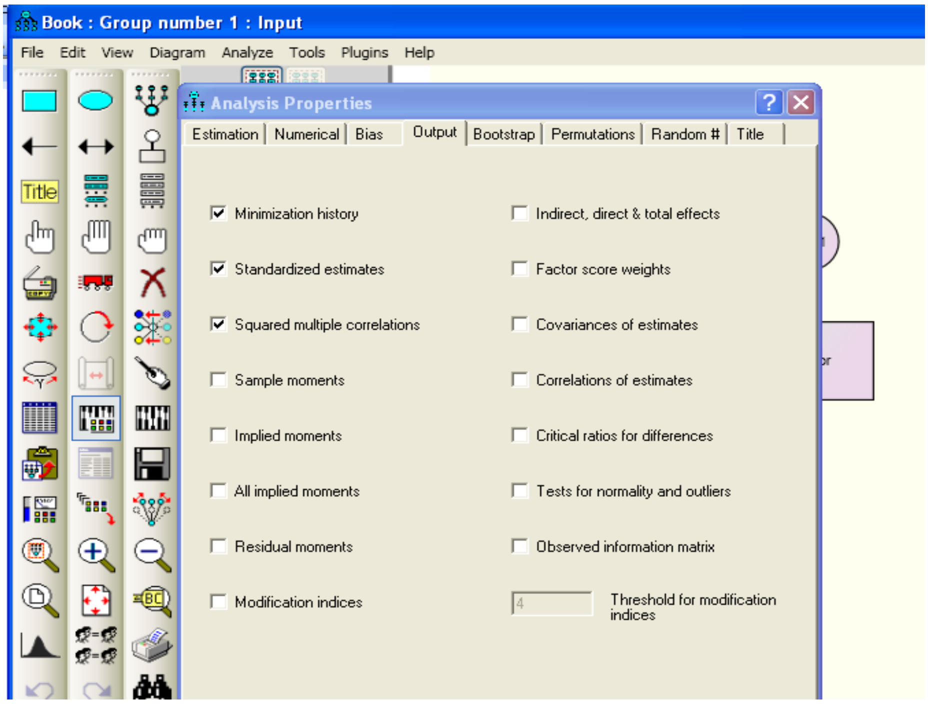
In the above Figure 2.9, there are two latent exogenous variables, product knowledge and process knowledge. In addition to that, there is a latent endogenous variable; vendor recommendations. Single headed arrows pointing towards endogenous variable (vendor recommendations), predicted as a linear combination of the other two exogenous variables, product knowledge and process knowledge. Error is an unobserved variable and therefore, used an ellipse to draw the variable. Double headed arrow shows the correlation between product and process knowledge. In other words, effects are represented by single-headed arrows in the path diagram while correlations and covariance are represented by bidirectional arrows, which represent relationships without an explicitly defined causal direction. In the above diagram there is an association or relationship between product knowledge and process knowledge. But, a claim cannot be made about product knowledge affect process knowledge or vice versa. Since effects are represented by single-headed arrows in the path diagrams, in the above path diagram, we can claim that product knowledge affect the scores observed on the measured variables p1 and p2 etc.

STEP 10: Saving the file: After the model is drawn, be sure to save it by choosing the File menu, and then selecting Save As. When you save the model, AMOS automatically creates two back-up model files in the same directory in which you have your original diagram. The back-up files will have the extensions .bk1 and .bk2, respectively.

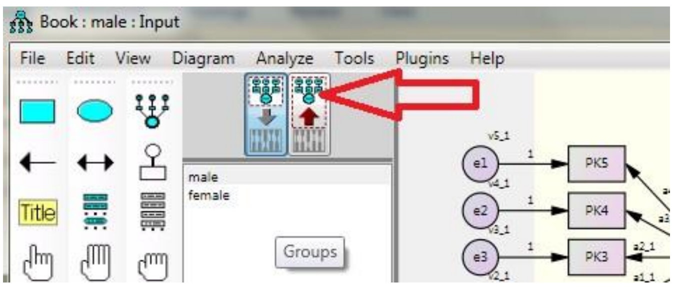
STEP 11: AMOS Output: In AMOS, it is not required to do different test at different times since AMOS provide all the required output by conducting analysis of the properties once. The output required to show after the analysis is optional in Amos. In other words, we can decide the output required at the end of the analysis. With the aim of selecting output options, select “view” at the top of the window and then choose “Analysis Properties” as shown in the Figure below.



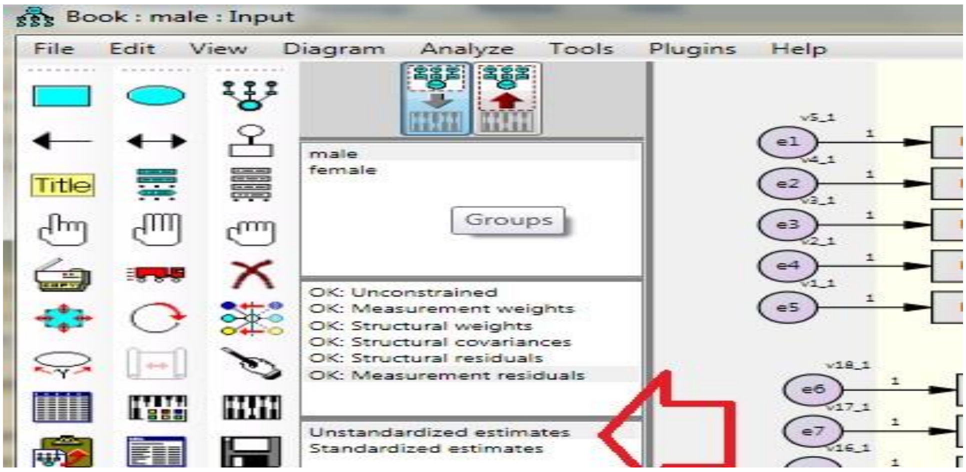
STEP 12 : Then, select the output in the analysis properties dialog box. The following dialog box will appear to select the outputs you required. For this example, Minimization history, Standardized estimates, and Squared multiple correlations are checked.



STEP 13: Next, examine the Estimation tab. This tab provides a check box that allows you to estimate means and intercepts if your database has any cases with incomplete data. AMOS will require you to estimate means and intercepts, if your database has any missing data on observed variables included in your model. Because this model‟s database does not contain any missing data and we are not interested in means at present, we leave the Estimation tab settings at their default values. Before you run the model, be sure to save it by choosing Save As from the File menu and saving a copy of the model file to an appropriate location on your computer‟s disk drive. To run the model, close the Analysis Properties window and click on the Calculate Estimates tool icon. It resembles an abacus:



STEP 14: Standardized vs. Un-standardized coefficients The standardized coefficients are sample specific and not stable across different samples. The un-standardized coefficients permit an examination of change across different samples. The coefficient values can be taken by clicking the required type of coefficient as shown in Figure.



Under standardized and un-standardized estimates the researcher is highly interested in to see the correlation coefficients and regression coefficients between variables.

3.3. Model specification: In model specification, researcher specifies the model determining every relationship among variables relevant to the researcher‟s interest. For this purpose researcher should conduct an extensive literature review. Otherwise, there may be a difference between true model and the implied model either having irrelevant variables in the model or not including important variables into the model.

3.4. Model Identification: SEM programs require an adequate number of known correlations or covariances as inputs in order to generate a sensible set of results. Identification refers to the idea that there is at least one unique solution for each parameter estimate in a SEM model. Models in which there is only one possible solution for each parameter estimate are said to be just identified. Models for which there are an infinite number of possible parameters estimate values are said to be under identified. Finally, models that have more than one possible solution (but one best or optimal solution) for each parameter estimate are considered overidentified. Model is considered as identified if the model is either just- or overidentified. If a model is identified only, the parameter estimates can be trusted. If the model is unidentified, the degrees of freedom for the model are zero or negative. However, such a model may become identified if additional constraints are imposed, that is, the degrees of freedom equal 1 or greater.

3.5. Absolute fit indices

Absolute fit indices determine how well an a priori model fits the sample data (McDonald and Ho, 2002) and demonstrates which proposed model has the most superior fit. These measures provide the most fundamental indication of how well the proposed theory fits the data. Unlike incremental fit indices, their calculation does not rely on comparison with a baseline model but is instead a measure of how well the model fits in comparison to no model at all (Jöreskog and Sörbom, 1993). Included in this category are the Chi-Squared test, RMSEA, GFI, AGFI, the RMR and the SRMR.

3.5.1. Model chi-square ($\chi 2$): The Chi-Square value is the traditional measure for evaluating overall model fit and, 'assesses the magnitude of discrepancy between the sample and fitted covariances matrices'. A good model fit would provide an insignificant result at a 0.05 threshold , thus the Chi-Square statistic is often referred to as either a 'badness of fit' or a 'lack of fit' measure. While the Chi-Squared test retains its popularity as a fit statistic, there exist a number of severe limitations in its use. Firstly, this test assumes multivariate normality and severe deviations from normality may result in model rejections even when the model is properly specified. Secondly, because the Chi-Square statistic is in essence a statistical significance test it is sensitive to sample size which means that the Chi-Square statistic nearly always rejects the model when large samples are. On the other hand, where small samples are used, the Chi-Square statistic lacks power and because of this may not discriminate between good fitting models and poor fitting models. Due to the restrictiveness of the Model Chi-Square, researchers have sought alternative indices to assess model fit. One example of a statistic that minimises the impact of sample size on the Model Chi-Square is relative/normed chi-square ($\chi 2/df$). Although there is no consensus regarding an acceptable ratio for this statistic, recommendations range from as high as 5.0 to as low as 2.0.

3.5.2. Root mean square error of approximation (RMSEA): The RMSEA is the second fit statistic reported in the LISREL program and was first developed by Steiger and Lind. The RMSEA tells us how well the model, with unknown but optimally chosen parameter estimates would fit the populations covariance matrix (Byrne, 1998). In recent years it has become regarded as ‘one of the most informative fit indices’ (Diamantopoulos and Siguaw, 2000: 85) due to its sensitivity to the number of estimated parameters in the model. In other words, the RMSEA favours parsimony in that it will choose the model with the lesser number of parameters. Recommendations for RMSEA cut-off points have been reduced considerably in the last fifteen years. Up until the early nineties, an RMSEA in the range of 0.05 to 0.10 was considered an indication of fair fit and values above 0.10 indicated poor fit (MacCallum et al, 1996). It was then thought that an RMSEA of between 0.08 to 0.10 provides a mediocre fit and below 0.08 shows a good fit (MacCallum et al, 1996). However, more recently, a cut-off value close to .06 (Hu and Bentler, 1999) or a stringent upper limit of 0.07 (Steiger, 2007) seems to be the general consensus amongst authorities in this area. One of the greatest advantages of the RMSEA is its ability for a confidence interval to be calculated around its value (MacCallum et al, 1996). This is possible due to the known distribution values of the statistic and subsequently allows for the null hypothesis (poor fit) to be tested more precisely (McQuitty, 2004). It is generally reported in conjunction with the RMSEA and in a well-fitting model the lower limit is close to 0 while the upper limit should be less than 0.08.

3.5.3. Goodness-of-fit statistic (GFI): The adjusted goodness-of-fit statistic (AGFI) The Goodness-of-Fit statistic (GFI) was created by as an alternative to the Chi-Square test and calculates the proportion of variance that is accounted for by the estimated population covariance. By looking at the variances and covariances accounted for by the model it shows how closely the model comes to replicating the observed covariance matrix. This statistic ranges from 0 to 1 with larger samples increasing its value. When there are a large number of degrees of freedom in comparison to sample size, the GFI has a downward bias. In addition, it has also been found that the GFI increases as the number of parameters increases and also has an upward bias with large samples. Traditionally an omnibus cut-off point of 0.90 has been recommended for the GFI however, simulation studies have shown that when factor loadings and sample sizes are low a higher cut-off of 0.95 is more appropriate. Given the sensitivity of this index, it has become less popular in recent years and it has even been recommended that this index should not be used. Related to the GFI is the AGFI which adjusts the GFI based upon degrees of freedom, with more saturated models reducing fit. Thus, more parsimonious models are preferred while penalised for complicated models. In addition to this, AGFI tends to increase with sample size. As with the GFI, values for the AGFI also range between 0 and 1 and it is generally accepted that values of 0.90 or greater indicate well fitting models. Given the often detrimental effect of sample size on these two fit indices they are not relied upon as a stand alone index, however given their historical importance they are often reported in covariance structure analyses.

3.5.4. Root mean square residual (RMR): Standardised root mean square residual (SRMR) The RMR and the SRMR are the square root of the difference between the residuals of the sample covariance matrix and the hypothesised covariance model. The range of the RMR is calculated based upon the scales of each indicator, therefore, if a questionnaire contains items with varying levels (some items may range from 1 – 5 while others range from 1 – 7) the RMR becomes difficult to interpret. The standardised RMR (SRMR) resolves this problem and is therefore much more meaningful to interpret. Values for the SRMR range from zero to 1.0 with well fitting models obtaining values less than .05, however values as high as 0.08 are deemed acceptable. An SRMR of 0 indicates perfect fit but it must be noted that SRMR will be lower when there is a high number of parameters in the model and in models based on large sample sizes.

3.6. Incremental fit indices Incremental fit indices: It is also known as comparative or relative fit indices, are a group of indices that do not use the chi-square in its raw form but compare the chi square value to a baseline model. For these models the null hypothesis is that all variables are uncorrelated.

3.6.1. Normed-fit index (NFI): The first of these indices to appear in LISREL output is the Normed Fit Index . This statistic assesses the model by comparing the $\chi 2$ value of the model to the $\chi 2$ of the null model. The null/independence model is the worst case scenario as it specifies that all measured variables are uncorrelated. Values for this statistic range between 0 and 1 with recommending values greater than 0.90 indicating a good fit. More recent suggestions state that the cut-off criteria should be NFI $\geq$ .95. A major drawback to this index is that it is sensitive to sample size, underestimating fit for samples less than 200 and is thus not recommended to be solely relied on this problem was rectified by the Non-Normed Fit Index (NNFI, also known as the Tucker-Lewis index), an index that prefers simpler models. However in situations were small samples are used, the value of the NNFI can indicate poor fit despite other statistics pointing towards good fit. A final problem with the NNFI is that due to its non-normed nature, values can go above 1.0 and can thus be difficult to interpret . Recommendations as low as 0.80 as a cutoff have been proferred however have suggested NNFI ≥ 0.95 as the threshold.

3.6.2. CFI (Comparative fit index): The Comparative Fit Index is a revised form of the NFI which takes into account sample size that performs well even when sample size is small . This index was first introduced by Bentler (1990) and subsequently included as part of the fit indices in his EQS program. Like the NFI, this statistic assumes that all latent variables are uncorrelated (null/independence model) and compares the sample covariance matrix with this null model. As with the NFI, values for this statistic range between 0.0 and 1.0 with values closer to 1.0 indicating good fit. A cut-off criterion of CFI ≥ 0.90 was initially advanced however, recent studies have shown that a value greater than 0.90 is needed in order to ensure that mis specified models are not accepted. From this, a value of CFI ≥ 0.95 is presently recognized as indicative of good fit . Today this index is included in all SEM programs and is one of the most popularly reported fit indices due to being one of the measures least effected by sample size.

3.7. Parsimony fit indices: Having a nearly saturated, complex model means that the estimation process is dependent on the sample data. This results in a less rigourous theoretical model that paradoxically produces better fit indices. To overcome this problem, Mulaik et al (1989) have developed two parsimony of fit indices; the Parsimony Goodness-of-Fit Index (PGFI) and the Parsimonious Normed Fit Index (PNFI). The PGFI is based upon the GFI by adjusting for loss of degrees of freedom. The PNFI also adjusts for degrees of freedom however it is based on the NFI (Mulaik et al 1989). Both of these indices seriously penalise for model complexity which results in parsimony fit index values that are considerably lower than other goodness of fit indices. While no threshold levels have been recommended for these indices, Mulaik et al (1989) do note that it is possible to obtain parsimony fit indices within the .50 region while other goodness of fit indices achieve values over .90 (Mulaik et al 1989). The authors strongly recommend the use of parsimony fit indices in tandem with other measures of goodness-of-fit however, because no threshold levels for these statistics have been recommended it has made them more difficult to interpret.

A second form of parsimony fit index are those that are also known as 'information criteria' indices. Probably the best known of these indices is the Akaike Information Criterion (AIC) or the Consistent Version of AIC (CAIC) which adjusts for sample size. These statistics are generally used when comparing non-nested or non-hierarchical models estimated with the same data and indicates to the researcher which of the models is the most parsimonious. Smaller values suggest a good fitting, parsimonious model however because these indices are not normed to a 0-1 scale it is difficult to suggest a cut-off other than that the model that produces the lowest value is the most superior. It is also worth noting that these statistics need a sample size of 200 to make their use reliable.

3.8. Reporting fit indices With regards to which indices should be reported, it is not necessary or realistic to include every index included in the program's output as it will burden both a reader and a reviewer. Given the plethora of fit indices, it becomes a temptation to choose those fit indices that indicate the best fit. This should be avoided at all costs as it is essentially sweeping important information under the carpet. When deciding what indices to report, going by what is most frequently used is not necessarily good practice as some of these statistics are often relied on purely for historical reasons, rather than for their sophistication. While there are no golden rules for assessment of model fit, reporting a variety of indices is necessary because different indices reflect a different aspect of model fit. Although the Model Chi-Square has many problems associated with it, it is still essential that this statistic, along with its degrees of freedom and associated p value, should at all times reported. and its associated confidence interval, the SRMR, the CFI and one parsimony fit index such as the PNFI. These indices have been chosen over other indices as they have been found to be the most insensitive to sample size, model misspecification and parameter estimates.

3.9. How to improve model fit Given the complexity of structural equation modelling, it is not uncommon to find that the fit of a proposed model is poor. Allowing modification indices to drive the process is a dangerous game, however, some modifications can be made locally that can substantially improve results. It is good practice to assess the fit of each construct and its items individually to determine whether there are any items that are particularly weak. Items with low multiple r2 (less than .20) should be removed from the analysis as this is an indication of very high levels of error. Following this, each construct should be modelled in conjunction with every other construct in the model to determine whether discriminant validity has been achieved. The Phi (φ) value between two constructs is akin to their covariance, therefore a Phi of 1.0 indicates that the two constructs are measuring the same thing. One test which is useful to determine whether constructs are significantly different is discriminant validity test. The formula for this is: parameter estimate (phi value) ±1.96 * standard error. If the value is greater than 1.0 discriminant validity has not been achieved and further inspections of item cross-loadings need to be made. Items with high Lambda-Y modification indices are possible candidates for deletion and are likely to be causing the discriminant validity problem. By deleting in discriminant items fit is likely to improve and is advantageous in that it is unlikely to have any major theoretical repercussions. A further way in which fit can be improved is through the correlation of error terms. This practice is generally frowned upon as it means that there is some other issue that is not specified within the model that is causing the covariation. If a researcher decides to correlate error terms there needs to be strong theoretical justification behind such a move. Correlating within-factor error is easier to justify than across latent variable correlations, however it is essential that the statistical and substantive impact are clearly discussed. If a researcher feels they can substantiate this decision, correlated error terms is acceptable, however it is a step that should be taken with caution.

4. Advantages of Structure Equation Model: Practical advantages of using structural equation modeling for data analysis include.

4.1. Validity: Theories in the social sciences frequently refer to variables that can not directly be observed (constructs), but that can only be inferred from observable variables (indicator variables). To operationalize these constructs, often many different variables come into consideration, and none of them may provide an optimal operationalization on its own. Structural equation modeling allows to make use of several indicator variables per construct simultaneously, which leads to more valid conclusions on the construct level. Using other methods of analysis would often result in less clear conclusions, and/or would require several separate analyses.

4.2. Reliability/Measurement Error: Data in the social sciences frequently contain a non-neglible amount of measurement error. Structural equation modeling can take measurement error into account by explicitly including measurement error variables that correspond to the measurement error portions of observed variables. Therefore, conclusions about relationships between constructs are not biased by measurement error, and are equivalent to relationships between variables of perfect reliability.

4.3.Complex Models: Theories in the social sciences frequently involve complex patterns of relationships or differences between a multitude of variables, conditions or groups. Structural equation modeling allows to model and test complex patterns of relationships, including a multitude of hypotheses simultaneously as a whole (including mean structures and group comparisons). Using other methods of analysis, this would frequently require several separate analyses.

4.4. Confirmatory Approach: For hypotheses testing, simple statistical procedures usually provide tests on the basis of explained variance in single criterion variables. This is inappropriate for evaluating complex models containing a multitude of variables and relationships. In contrast, structural equation modeling allows to test complex models for their compatibility with the data in their entirety, and allows to test specific assumptions about parameters (e. g., that they equal zero, or that they are identical to each other) for their compatibility with the data. In doing so, the variances and covariances of all the observed variables are factored in systematically: The empirical relationships between all observed variables (empirical covariance matrix) are compared to the relationships implied by the structure of the theoretical model (model-implied covariance matrix). This allows for:

– Global assessment: The model fits the data well or not so well.

– Local assessment: The model is or is not able to correctly reproduce relationships between particular variables. This can point to specific areas/parts where the model may be deficient.

– Exploratory suggestions for potential model improvements (modification indices): These suggestions can then be evaluated for interpretability and compatibility with an underlying theory.

4.5. Challenges and Potential Problems The complexity of structural equation modeling comes with statistical and interpretational challenges and potential problem

4.5.1. Model Identification/Parameter Identification: In structural equation models, a multitude of parameters (path coefficients, factor loadings, variances, etc.) corresponding to various hypotheses are estimated simultaneously (so that the empirical relationships between the observed variables can be reproduced by the model as good as possible). This only works if the empirical data provide enough information to estimate all these parameters. Most often, structural equation modeling is not based on raw data as input information, but on the empirical covariances of all indicator variables. Therefore, it is not possible to estimate more model parameters than there are (distinct) entries in the empirical covariance matrix. Given k indicator variables, a maximum of $k(k + 1)/2$ parameters can be estimated (then, the model would be just identified). Hypotheses testing is only possible as long as there are less parameters to be estimated than there are distinct empirical covariances, i. e. less than $k(k + 1)/2$ (the model would then be overidentified). This global condition for model identification is necessary, but not sufficient. It can happen that, despite a satisfied global condition, certain parts of the model are not identified (e. g., when empirical relationships between variables are particularly weak). Possible remedies or workarounds include reformulating the model, incorporating additional variables, or testing identified model parts separately.

4.5.2. Estimation Methods and Estimation Problems: Simultaneously including a multitude of relationships is computationally intensive and is being done by iterative algorithms, i. e. by trying to gradually approach an optimal solution (in terms of reproducing the empirical relationships). This can lead to estimation problems: 1. The algorithm may not converge, i. e. no optimal solution can be found. 2. The algorithm may converge and result in a supposedly optimal solution, but the parameter estimates do not make sense (so-called Heywood cases). For example, negative estimates of variances may occur, despite the fact that empirical variances can not be negative. This tends to happen mostly in situations where assuptions of the respective method of estimation are violated (see below), and/or in cases where the model analyzed is based on wrong assumptions or hypotheses (misspecified model). Possible remedies or workarounds include the use of a different estimation method (e. g., one with less strict assumptions), simplifying the model, separate analyses of parts of the model, and/or a larger sample size.

4.5.3. Assumptions—Sample Size and Distributions: Most often, parameter estimation in structural equation models is done by maximum likelihood, which is based on certain assumptions:

1. Multivariate normal distribution of the indicator variables

2. Large sample size In practice, data are rarely ever multivariate normal, and often they are univariate non-normal already.

In addition, especially in psychology, samples frequently consist of a few hundred cases at best, while the mathematical foundation of maximum likelihood estimation is based on asymptotically large sample sizes (going to infinity). In particular, combining small sample sizes, nonnormal data, and weak empirical relationships between variables can lead to estimation problems and unreliable results. Potential remedies include certain correction factors (e. g., for standard error estimates in cases of nonnormal data), or the use of a different estimation method (e. g. Unweighted Least Squares; explained in more detail on the handout on estimation methods and distributional assumptions.

Interpretation of Results: Properly assessing the quality of a structural equation model is usually not the matter of a single test of significance or a single measure of explained variance, but regularly comprises several steps and several coefficients or tests.

- ✓ Examining the parameter estimates for plausibility (to rule out Heywood cases which would call any further interpretation into question)
- ✓ Assessing the global "model fit", i. e. the global match between the empirical covariance matrix of all indicator variables, and the covariance matrix reproduced by the model: For this purpose, there is a χ 2 test for significant differences between model and data, and a multitude of descriptive goodness-of-fit indices as measures of either the degree of congruence between model and data, or discrepancies between model and data.

- ✓ Assessing particular aspects of model fit, especially by checking the (standardized) residuals (differences between empirical and model-implied covariances), which provide evidence whether the empirical covariances between specific variables can or cannot be correctly reproduced by the model
- ✓ If model fit is satisfactory: Interpreting the parameter estimates, testing parameters for significance, assessing the predictive accuracy of the model.

5. Literature available / Research studies / Case studies

1. Using structural equation modeling to predict Indian people's attitudes and intentions towards COVID-19 vaccination – *Hilal et al* (2021)

Introduction: Understanding people's attitudes towards Covid-19 vaccination is crucial to the successful implementation of a vaccination program. Hence this research study seeks to identify critical factors influencing Indian people's attitudes and intentions to take up Covid-19 vaccinations.

Methods: An online questionnaire was administered to a sample (n ¼ 254) drawn from Indian population, to assess the impact of perceived benefits, risk perceptions, social media exposure, social norms, and trust associated with Covid-19 vaccines on people's attitudes towards Covid-19 vaccines and their intentions to take up the Covid-19 vaccinations.

Results: The findings showed in table 1 that the perceived benefits, social norms, and trust correlated significantly with people's attitudes towards Covid-19 vaccinations. In contrast, risk perceptions and social media exposure showed an insignificant influence on people's attitudes towards Covid-19 vaccinations. Social norms, trust, and people's attitudes towards the Covid-19 vaccinations are significantly correlated with their intentions to take up Covid-19 vaccinations. On the contrary, social media exposure was found to have an insignificant influence on people's intentions to take up Covid-19 vaccinations.

Table1. Hypothesis testing of models

	Estimates	SE	CR	P	Decision
PB -> ATT	0.344	0.071	4.878	***	Supported
RP -> ATT	0.054	0.037	1.462	0.144	Not Supported
SN -> ATT	0.115	0.047	2.441	*	Supported

ME -> ATT	0.083	0.053	1.570	0.116	Not Supported
TR -> ATT	0.202	0.055	3.641	***	Supported
SN -> INT	0.157	0.054	2.916	**	Supported
ME-> INT	0.066	0.060	1.107	0.269	Not Supported
TR -> INT	0.286	0.066	4.301	***	Supported
ATT -> INT	0.526	0.088	5.977	***	Supported
PB = Perceived benefits, RP= Risk perception, ME= Media exposure , Social norms					

Conclusion: Participants' intentions to take up Covid-19 vaccinations was influenced mainly by their attitudes and perceptions of Covid-19 vaccines in general, which strongly confirms the importance of various dimensions (perceived benefits, trust, social norms) of Covid-19 vaccines in cultivating Covid-19 vaccination acceptance among participants'.

2. Understanding Farmers' Intention to Use a Sustainability Standard: The Role of Economic Rewards, Knowledge, and Ease of Use – ***Veronica and Jhonnes (2021)***

Introduction: Voluntary approaches to improving sustainability in agriculture can contribute significantly to reduce the sector's negative environmental impacts and provide a foundation for sustainable land use and farmers' incomes. The investigation focus on what motivates farmers to implement comprehensive sustainability management on their farms.

Methodology: For this purpose, we use a structural equation model (SEM) to evaluate the individual factors influencing the decision-making process within the technology acceptance model (TAM). Our empirical data from 363 farmers fit the theoretical model very well.

Results: The model confirms a positive influence of expected economic rewards and subjective norms on the perceived usefulness of such an innovation. However, ease of use is most important, as it is related directly to the stated intention to use a standard.

Latent construct	Path[1]	Loading[2]	SE[3]	Hypothesis	R^2
SN (Subjective Norm)	-> PU ®	0.646***	0.0528	H4	0.417

PR (personal reward)	<- SN (f) -> PU (r)	0.399*** 0.524***	0.0573 0.121	H5 H3	0.705
ER I(Economic reward – process optimization)	-> PU (r)	0.833***	0.0312	H1	0.694
ER II(Improved technology)	-> PU (r)	0.824***	0.0368	H2	0.679
PU (Perceived usefulness)	<- Know (f) <- PEU (f)	0.233*** 0.305***	0.0656 0.103	H6 H9	0.146
INT (Intension to use)	<- PU (f) <- PEU (f) <- Know (f) <-RT (f)	0.195** 0.663*** 0.427*** -0.040	0.0868 0.0716 0.0530 0.0472	H8 H10 H7 H12	0.777
PEU (Ease of use)	<- RP (f)	0.537***	0.0775	H11	0.288
Paths: f= Formative measurement, r= reflective measurement. SE= Standard error, Significance level * 10%, ** 5%, *** 1 %.					

In addition, the data indicate a high, significant, and direct effect of prior knowledge of on-farm sustainability management on stated intent to use a standard. These findings can serve as a starting point to improve not only existing sustainability management systems, but also emerging farm management information systems (FMISs), or agri-environmental schemes with the aim to make their use more attractive.

6. Conclusion

Structural Equation Modeling (SEM) is a statistical technique that has become increasingly popular in social science research. SEM provides a powerful tool for testing complex theories and models that involve both observed and latent variables. SEM allows researchers to estimate both direct and indirect effects of variables on one another, which offers a comprehensive approach to testing complex relationships between variables. One of the primary benefits of SEM is its ability to account for measurement error, which is an important aspect of social science research. Measurement error can cause inaccuracies in statistical analysis and can lead to false conclusions. SEM provides a way to estimate and control for measurement error in a model, which improves the accuracy of the model's predictions. This makes SEM a valuable tool for researchers who want to gain a deeper understanding of the relationships between variables in complex social systems. Another advantage of SEM is its ability to test alternative models, which is particularly useful when working with complex theoretical frameworks. By testing multiple models, researchers can determine the best theoretical model to explain the relationships between variables, which can aid in theory development and testing. This is especially important in social science research, where theories are often complex and multifaceted.

However, there are some limitations to SEM that researchers must consider when applying this technique. One limitation is that SEM requires a large sample size to achieve reliable estimates, particularly when testing complex models. Another limitation is that SEM requires the researcher to specify the model's parameters beforehand, which can be challenging when dealing with complex theoretical frameworks. Careful attention must be paid to the model's assumptions and the data's adequacy, as failing to meet these conditions can lead to unreliable results.

Despite these limitations, SEM remains an essential tool for social science research. SEM has been used in a variety of fields, including psychology, sociology, education, and economics, to name a few. By providing a way to test complex theories and models, SEM offers researchers the ability to gain a deeper understanding of the complex relationships between variables in social systems. Moreover, SEM can be used for a variety of purposes, such as hypothesis testing, model fitting, and theory development. It can also be used to evaluate the effectiveness of interventions and programs, as well as to explore the impact of policy changes. SEM provides a flexible and adaptable approach to statistical analysis, which makes it an essential tool for social science researchers working in diverse fields.

In conclusion, Structural Equation Modeling is a powerful statistical technique that has become increasingly popular in social science research. It provides a comprehensive approach to testing complex relationships between variables and offers a way to estimate both direct and indirect effects of variables on one another. SEM has many advantages over traditional statistical techniques, such as regression analysis, including its ability to account for measurement error and to test alternative models. Despite its limitations, SEM remains an essential tool for social science researchers working in diverse fields, providing a valuable way to gain a deeper understanding of complex social systems. With continued refinement and development of SEM techniques, social science researchers will continue to benefit from the insights that SEM provides.

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8. Discussion

1. We tried SEM in masters, but results are very poor?

Ans: The SEM results always depends on the sample and number of statements. The more the statements the more should be the sample for analysis. The factor loading score will be dependent on the sample size, which is most important in factor analysis. The greater the sample size the factor score can be kept low.

2. Can we use SEM in your research?

Ans: SEM is the very lengthy and time-consuming process. This SEM generally used for development of models which have high validity as result of good theoretical orientation. The scale construction under SEM is most evolving and rapidly adopting concept in extension and other behavioral research. The using SEM scale construction alone can become one full thesis. This SEM I can apply at last instead of in scale construction to identify the observed variable inter relationships can be observed.

3. How did they measured mass media in Covid research study?

Ans: The researcher used mass media as dimension and used the items related to only social media in the item analysis. The operational definition of mass media was not written any where in the study. They used 3 items related to social media for measuring the construct mass media.

4. How norms are related with vaccine?

Ans: Social norms are found supported to the model in adoption of covid 19 vaccine. The models were measured by family recommendation, friends' recommendation and people who are important found to supported to model.

5. What are under social norms?

Ans: The construct social norms is measured by three latent constructs i.e. My family recommended take me vaccine, People who are important to me influence my decision and my friends and colleagues influenced.

6. Library utilisation example in presentation and mass media what we measuring should be sufficient?

Ans: I agree. The statements measuring the mass media usage should be modified and need to using mass media for agriculture information instead of just usage of mass media utilisation behaviour.

7. Weather Undecided is required in continuum?

Ans: It is recommended that the continuum Undecided can be eliminated if your sample is intellectual and master of subject. It is strongly recommended farmer sample as some items may be undecided point that need to be documented for measurement.

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Class	:	III Ph.D.	Time	:	10:30 am
ID. No.	:	PAMB 0028	Date	:	31-12-2022

Seminar-III

Scale Construction – Structure Equation Modeling (SEM)

A series of categories or items arranged in a progressive manner based on magnitude or value is called 'scale'. Different responses of individuals are quantitatively placed on such scales. Every scale includes a lowest point, a highest point and some intermediate points representing a particular activity or attitude. If the first point or item on the scale is of highest degree, the second point is higher in nature, than the third point is consequently, the third point is higher in nature than the fourth point and so on. The process of developing a continuum for placing the measured objects is called scaling. These measured objects may involve interests, opinions, attitude, and other responses of the individuals. Thus, the next operation involved in measurement is the scaling process. In this, different qualitative aspects are associated with quantitative components. Measurement is followed by scaling procedure in a research activity. Researchers always face the problem of how to measure or quantify abstract concepts and how to relate one individual's response to that with another response. Hence, the problem is two-fold. First is, how to quantify a response in absolute terms, and the second is, how to relate it with other responses. This problem is resolved by scaling process or assigning the numbers or values to responses and positioning them on a common scale. Hence, scaling is the process or procedure of quantifying and measuring abstract concepts like attitudes, opinions, emotions, etc. Scaling also quantitatively determines the position of an individual in a range of values. Techniques used in developing set of items or categories in a progressive manner (in a continuous spectrum) to measure an individual's preference towards given event or object, refers to scale construction techniques. With the development of psychometrics with help of statistical development the advanced methods like Analytical hierarchy process, Perceptual mapping, Structure equation modeling are evolving and practiced by the large number of behavioral researchers in addressing their research question more appropriately. With this brief background, the current seminar has been conceptualized with the following objectives:

1. To understand the concept of scale construction in behavioral science
2. To understand the concept, procedure of Structure Equation Modeling (SEM) and its implications and challenges
3. To review the relevant literature available on SEM

SEM is a second-generation multivariate data analysis method that is often used in marketing research because it can test theoretically supported linear and additive causal models. With SEM, researchers can visually examine the relationships that exist among variables of interest to prioritize resources to better utilization and adoption. The fact that unobservable, hard-to-measure latent variables can be used in SEM makes it ideal for tackling research problems. There are two sub models in a structural equation model; the inner model specifies the relationships between the independent and dependent latent variables, whereas the outer model specifies the relationships between the latent variables and their observed indicators. In SEM, a variable is either exogenous or endogenous. An exogenous variable has path arrows pointing outwards and none leading to it. Meanwhile, an endogenous variable has at least one path leading to it and represents the effects of other variable(s). The whole process of development of SEM model includes various steps like problem identification, Theory selection, Construct development, data collection, factor analysis, exploratory factor analysis etc. Validity, Reliability explanation of complex model relationships and confirmatory approach are the major advantages of SEM. Model identification, Parameters identification, Model estimation and estimation problems, Sample size, Interpretation are the challenges and potential problems in adopting SEM.

Research studies

Hilal *et al* (2021) that the perceived benefits, social norms, and trust correlated significantly with people's attitudes towards Covid-19 vaccinations. In contrast, risk perceptions and social media exposure showed an insignificant influence on people's attitudes towards Covid-19 vaccinations. Social norms, trust, and people's attitudes towards the Covid-19 vaccinations are significantly correlated with their intentions to take up Covid-19 vaccinations. On the contrary, social media exposure was found to have an insignificant influence on people's intentions to take up Covid-19 vaccinations.

Veronika and Johannes (2021) reported that ease of use is most important, as it is related directly to the stated intention to use a standard. In addition, the data indicate a high, significant, and direct effect of prior knowledge of on-farm sustainability management on stated intent to use a standard by using SEM model approach.

Conclusion

Quantifying the behaviour is the one of the challenging things in behavioral sciences. It is fact that in many of the abstract construct variables i.e., latent variables cant be directly observed and measured through dimensions and indicators. The reason to prefer SEM over other multivariate techniques are SEMs utilize multiple indicator variables to measure the latent variables and one or more predictor variables are unreliable this may cause wrong coefficients or wrong signs.

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