The Strengths and Limitations of the Statistical Modeling of Complex Social Phenomenon: Focusing on SEM, Path Analysis, or Multiple Regression Models

Jihye Jeon

Abstract—This paper analyzes the conceptual framework of three statistical methods, multiple regression, path analysis, and structural equation models. When establishing research model of the statistical modeling of complex social phenomenon, it is important to know the strengths and limitations of three statistical models. This study explored the character, strength, and limitation of each modeling and suggested some strategies for accurate explaining or predicting the causal relationships among variables. Especially, on the studying of depression or mental health, the common mistakes of research modeling were discussed.

Keywords—Multiple regression, path analysis, structural equation models, statistical modeling, social and psychological phenomenon.

I. INTRODUCTION

RESEARCHERS use statistical methods for investigating relationships among variables. In recent years, there have been a large number of publications using SEM, path analysis, or multiple regression models, which contribute to the growth of quantitative researches. However, each of the methods has still limitations and strengths and researchers should consider them when using a statistical model of complex social phenomenon in their researches. Sometimes, the limitations of statistical modeling are not discussed or ignored by researchers [1]. When establishing a research model, researchers should consider the purpose of research, the availability and characters of given data, the time, cost, and ability of researcher and so on. It is important to use a statistical model carefully with respects to limitations and strengths for an accurate explaining or predicting the causal relationships among variables. The correct understanding on statistical modeling and appropriate using of methods will lead to the correct interpretation of results, the better application to policy change and the contribution to academic field. Therefore, in this paper, the conceptual framework of three statistical methods: multiple regression, path analysis, and structural equation models will be reviewed and the advantages and disadvantages of each approach will be discussed.

II. REGRESSION ANALYSIS

Regression analysis is a statistical method to investigate relationships between more than one independent variables and only one dependent variable. If the independent variable is one,

J. Jeon is with the Division of Policy Development and Research, Korea Disabled People's Development Institute, Seoul, 150-917,Republic of Korea (phone: 82-2-3433-0658; fax: 82-2-412-0463; e-mail: ikwwjh@koddi.or.kr).

it is simple regression. But, in social science, it is rare that having only one independent variable (predictor) to predict a social phenomenon. So, most researchers use multiple regression analysis. In past tens of years, researchers have used this multiple regression analysis as a powerful tool because it allows to model statistically the relationship between dependent variable and a set of independent variable. Linear regression is used with continuous dependent variables, while logistic regression is used with dichotomous variables.

Both regressions allow for the assessment of whether independent variables such as age, gender, education, attitude, behavior are associated with dependent variables (outcome/criterion) while controlling for the outcomes overlapping associations with other variables.

A. Common Purposes of Regression Analysis

The purposes of regression analysis are identified by following: (1) figuring out independent variable influencing on dependent variable, (2) providing relationship between independent variable and dependent variable (in other words, when one unit of independent variables change, a researcher can know the amount of changes in dependent variable), (3) estimating the dependent variables according to the changes of a set of independent variables. In sum, when the goal is to understand (including predicting and explaining) the causal influence on a population outcome, regression analysis can be a powerful tool.

B. Prediction and Explanation

Prediction and explanation are central concept of scientific research. Pedhazur (1997) stated that the potential power and added complexity of regression analysis are best reserved for either predicting outcomes or explaining relationships. Prediction only requires a correlation but explanation require more [2]. In predictive research, practical application is main emphasis, while in explanatory research, understanding phenomena is the main emphasis. Therefore, to distinguish them is important to the use of regression analysis and to the prediction of results.

For example, if perceived discrimination of ethnical minority were highly correlated with the depression level, the perceived racial discrimination would be a valid means of predicting depression. However, in the analysis of data, it is not simple to report the prediction. For example, if having a religion were highly correlated with the depression level, it would be valid to treat such index as a useful predictor of depression level. Then,

is it possible to consider religion as a cause of depression? Or as a policy suggestion in discussion, should it be stated that government force people to have religion for the improvement of mental health of national population? Maybe, the answer is No. Therefore, we have to be careful to optimize prediction of criteria and should be careful when interpreting and discussing about research findings.

C. Role of Theory

Multiple regression analysis is used for two different aims of research: prediction and explanation. Explanation is inconceivable without theory because it is in order to understand the process leading to criterion. Also, in prediction, theory is the best guide for selecting criteria and predictors as well as for developing measures of such variables. Predictors should be selected as a result of theoretical consideration [2]. It is not possible to decide whether and how to control for a variable without formulating a causal model about the process by which the independent variable affect the dependent variable. Here, the model reflects theory about the relations among the variables being studied.

D. Consideration in Regression Analysis: Limitations and Solutions

1) Analysis of Variance

In the regression analysis, we can see the report of analysis of variance, showing the approximate percentage of predictor's account for criterion (dependent variable). For example, the predictors account for 60% of the variance of criterion variable (when R^2 is .60). More predictors are inputted, higher R^2 are presented. Even, when adding statistically non-significant variables into equation, the R^2 may increase. So, a researcher cannot tell the importance of an independent variable by only using the increment of R^2. Pedhazar (1997) stated that such an increment would not be viewed as trivial [2]. This problem can be reduced by choosing appropriate selection method for their researches. This issue will be discussed in details later.

2) Statistical Significance

From the output of parameter estimates, a researcher can figure out if the hypothesis is accepted or rejected. Using alpha = .05, if the probability is smaller than .05, usually it means that the predictor variable is statistically significant. In result, the regression equation can be also reported as following: Y= A + B*X1 + C*X2 + D*X3 (X1, X2, and X3 are independent variables, Y is dependent variable).

Here, because some of dependent variables are correlated each other, it is possible that the variable that was shown to be a statistically non-significant can turn out to be a statistically significant when another variable(s) are deleted from the equation. So, making a set of independent variables in model is very important. Through deleting or adding variables, the total regression equation can change. This problem also can be reduced by choosing appropriate selection method for their researches.

3) Predictor Selection

Because many of the variables are inter-correlated, predictor selection is most important process in regression analysis. Practical considerations in the selection of specific predictors may be various, depending on the circumstance of the research, research interest or aims, resources, and frame of reference etc. There are various selection procedures for yielding the best regression equation; all possible regressions, forward selection, backward elimination, stepwise selection, and block-wise selection.

(3-1) All Possible Regression

Best subset of predictors may proceed by calculating all possible regression equations. The limitation of this method is that a researcher should examine very large number of equations: 2^K. When deciding on which is the best equation among 2^K equations, meaningfulness should be primary consideration rather than a statistically significant increment in R^2. For example, if there were two equations, the equation 1 composed of predictor A and B with 0.58 (R^2) and equation 2 composed of predictors A, B, and C with .62 (R^2). The difference of 4% as the increment in R^2 should be considered carefully. The choice of best equation to predict a criterion depends on the meaningfulness of the variable and test result of statistical significance corresponding to alpha value.

(3-2) Forward Selection

The predictor that has the highest correlation with criterion is entered first into the equation. The next predictor is the one that has highest partial correlation with criterion after partialing out the predictor that is already in the equation. Also, at that time, Sig T for the predictors is examined if the probability is less than .05 (default PIN, probability of F-to-enter). The third predictor to enter is the one that has highest partial correlation with criterion after partialing out the first two predictors. When the all values of Sig T report exceed the default PIN, the analysis is terminated. Here, researcher can control the level of default PIN. If the PIN=.10, more predictors are included into the regression equation. The limitation of Forward Selection is that predictors are locked in the order in which they were introduced into the equation. So, the predictor already in equation cannot be deleted at later stage although there is a change in selected predictor's correlation with criterion by the combined contribution of predictors introduced at later stage.

(3-3) Stepwise Selection

In forward selection, although the predictors in equation at early stage lose its usefulness upon introduction of additional predictor, the predictors are included in equation at later stage. However, in stepwise selection, such predictors are deleted at later stage. So, the subsets of significant variables are different in each step: a predictor that was shown as the best can turn out to be worst when the other predictors are in the equation. Then, a researcher should consider R^2 changes in each equation, co-linearity (because it is possible that of two equal predictors, one may be selected and the other may not be selected due to a slight difference in R^2), and Sig. value at .05 level. But a research has to still decide whether it is worthwhile to retain it in the equation. The final decision depends on researcher's responsibility to estimate the usefulness of a predictor.

(3-4) Backward Elimination:

This method starts with the squared multiple correlation of the criterion with all predictors. Then, predictors are scrutinized one at a time. Step by step, in the opposite way of forward selection, deleting a predictor from equation is conducted. The analysis is terminated when the deletion is judged to produce a meaningful reduction in R^2.

(3-5) Block-Wise Selection:

Predictors are grouped in blocks, based on theoretical considerations. Beginning with the first block, a Stepwise selection is applied and predictors of first block compete for entry into equation. Then, Stepwise Selection is applied to the predictors in second block, with the restriction that predictors selected at first stage remain in the equation. So, if there is a predictor of second block which has co-linearity problem with a predictor of first block that is already in the equation, the predictor will not be selected. The procedure is repeated until predictors from last block are considered. It is clear that whether a predictor enters into the equation or not depends on the order of entry assigned to the block. Variables belonging to a block assigned earlier order of entry have a better chance to be selected.

In Block-wise Selection, Forward Selection may be applied to each block, instead of Stepwise Selection. Here, no selection is applied to the predictors within a block. This combination of forcing some blocks into the equation and doing Block-wise Selection is useful in social and psychological science. For example, when being interested in depression as a criterion, the block-wise selection follows: 1) force into the equation the demographic information 2) force into the equation disability-related characters 3) do a Stepwise Selection to the various stressors (e.g. life time discrimination experience, everyday discrimination experiences and so on). Such a scheme is reasonable and useful because researcher can note whether the stressor variables increase the predictive power. One thing important is that it is designed to provide information for predictive, not explanatory purpose. For example, that discrimination experience does not increase the level of depression does not mean that discrimination experience is not an important determiner of depression.

In sum, the selected predictors in equation may be different, depending on the selection method used. Although predictors A and B are selected in equation by all possible regression method, predicter A and C are selected in equation by forward selection method. What is best regression equation depends on the selection method used in analysis. Also, the order of enter into equation is crucial in regression analysis. The "correct" order may be the one that meets the specific needs of the researcher. However, a researcher needs to distinguish between explanation and prediction and should be careful to interpret the results. Pedhazur (1997) stated "there is nothing wrong with any ordering of independent variables as long as the researcher does not use the results for explanatory purpose [2]."

4) Variance Partitioning

Variance partitioning is one of various methods in the pursuit of explanations. Variance partitioning means the attempts to partition R^2 into portions attributable to different independent variables or to different sets of independent variables. The problem is that the proportion of variance incremented by a given variables depends on its order of entry into equation, except when the independent variables are not intercorrlated. This situation occurred when the predictors are intercorrelated and the notion of independent contribution to variance has no meaning [2]-[4]. Goldberger (1991) asserted that high R^2 is not evidence in favor of the model and criticized empirical research reports expressing "I have high R^2 so my theory is good[5]." Lewis-Beck and Skalaban (1991) stated that in order to see the effect of X on a criterion, a research should consult the relevant slope estimate (b) instead of R^2. However, many researchers did not consider this problem deeply and used variance partitioning in social sciences for determining the relative importance of independent variables [6].

Incremental partitioning of variance was popularized by Cohen and Cohen (1983) and commonly called as hierarchical regression analysis: the proportion of variance accounted by all the independent variables are partitioned incrementally [7]. The incremented proportion at each step is expressed. By the way, the order of entry into regression analysis is crucial here. For example, whatever the correlation between A and B, if A is entered first into the analysis, the variance in criterion will include the explanatory power it has by virtue of its correlation with B. In order words, the shared explanatory power of A and B is allocated exclusively to A when it is entered into regression analysis. Therefore, such an analysis should not be intended to providing information about relative importance of variables, but rather about the effect of a variable after having controlled for another variable.

(4-1) Lessons from Inappropriate use of Variance Partitioning

Incremental partitioning of variance is used frequently in various researches, often inappropriately [2].

The knowledge about the proportion of variance incremented by blocks of variables entered in a given sequence sheds no light on the specific causal model because several other possible models of causation are more tenable. Sometimes, the combination of variables in a block is additional difficulties. For example, it is not easy to decide if the variable of 'economic activity' belongs to the block of personal elements or the block of social elements.

Determination of the order of entry into the regression analysis should be based on theoretical considerations. In the absence of a model about the relations among the variables, no meaningful decision about the order of entry of variables into the analysis can be made. There is an example of wrong expression: *"Two hierarchical multiple regressions were performed to investigate this question. In the first regression, the block of the four social competency variables was entered in the first step, followed in the second step by the block of four parental bond variables. In the second regression, this order of entry was reversed, with parental bonds entered first and social competencies entered second" [8].* Pedhazur (1997) criticized

that this analysis is not consistent with theory stated earlier that parental bonds affect social competencies [2]. Therefore, only second analysis should have been carried out and its results interpreted.

When a block occurred at the end of the block-wise regression analysis, its variances are relatively small. Therefore, incremental partitioning of variance is not valid to determine the independent variables' relative effects on a dependent variable. There is a common wrong expression : *"The data are presented in the form of a usefulness analysis which examines the relative abilities of procedural and distributive justice to explain the variance in the criterion variables depending on which predictor is entered first into the regression equation"* [9].

5) Does Regression Analysis Guarantee the Causal Relationship between Variables?

Regression analyses reveal relationships among variables, but do not imply that the relationship to be causal. A strong relationship between variables could stem from many other causes including the influence of other unmeasured variables. For example, if people with disabilities are found to be depressed by disability discrimination experiences, one may ask whether this is due to the discrimination itself or instead to a preexisting oppression (e.g. internalized oppression). This is one of the fundamental limitations of regression analysis, which refer to fail for distinguishing between characteristics that were merely associated with and occurred before the discrimination experience (preexisting element which may influence on the relationship between discrimination experience and depression) and those for which evidence of causality had been (risk factor such as discrimination experience). There is another example. Perceived discrimination experiences might result in loss of control, lower sense of control might result in perception of more discrimination, or there could be a circularrelation between these variables. In order words, the result of regression analysis does not guarantee the causal relationship between independent and dependent variables. Just the regression analysis can provide evidences which help readers to draw causal implications.

In this situation, researchers used to choose one of following two strategies: one is to use language carefully to avoid claim for causation and the other is to take refuge in the claim that they are studying only association and not causation. According to Rutter (2007), researchers can avoid causal claims employing correlational terms such as association, predictors, risk, or correlation. Researchers may count on readers to draw causal implications on their own [10].

In addition, for protecting effecting from preexisting elements, a researchers can make a control groups which involves random assignment of units to intervention or non-intervention (control group) conditions. Also, having validity is a important, as the same design may contribute to more or less valid inferences under different circumstances. When building validity of research inference involves ruling out alternative explanations or rival hypotheses.

Also, Theory-based regression analysis strategies also can help develop causal evidence from correlational data. Without theory, researcher cannot choose one meaningful model from tend of model which have good model fit. Whatever the model is, SEM, mediating model, or path analysis model, all research models should be based on theory. All these activities may contribute to the appropriate use of regression analysis.

6) Measurement Error

Because the dependent variable is one in regression analysis, measurement error occurs. Usually, a researcher makes dependent variable by using of MEAN of a set of variables. Especially, when estimating abstract concepts such as self-concept, depression levels, or self-esteem, measurement error occurs and influence on the predicting power of regression equations. When using SEM, the problem of measurement error can be reduced.

7) Assumptions of Regression Analysis

There are 4 assumptions: 1) linearity of the phenomenon measured 2) constant variance of the error terms 3) independence of the error terms 4) normality of the error term distribution All assumptions should be tested by checking partial regression plot, or by comparing null plot and residual plot. A researcher can identify outlier from the plots too. However, these assumptions are not satisfied, the results will provide wrong explanation and prediction.

8) Co-linearity or Multi-co-linearity

This means high relation between independent variables and may drive into reducing the predicting power of each independent variable and increasing the predicting power of shared portion of independent variables to variance. Therefore, a researcher should estimate the level of co-linearity or multi-co-linearity, and see if it is problematic or not. There are a couple of solutions: 1) deleting one variable if the correlation is very high 2) If highly correlated two variables are important in model, a researcher cannot tell the relative importance among two, and should report the result only for the purpose of predicting, not explaining. 3) Correlation analysis is necessary to see the relationship between each independent variable and dependent variable.

9) Sample Size

The degree of overestimation of R is affected by the ratio of the number of predictors to the sample size. Some researchers recommend the ratio1:30 [2]. However, to determine sample size, statistical power analysis is preferable. If the sample size is small, there is a problem in generalizing the results.

III. PATH ANALYSIS

Path analysis is a method for studying direct and indirect effects. Path analysis is intended not to discover causes but to shed light on the tenability of the causal model formulated by a researcher. So, the aim of path analysis is an explanation, not a prediction. Of course, the researcher should consider the theory or knowledge related to what s/he wants to study. Path analysis can be considered as one of SEMs which is composed of all

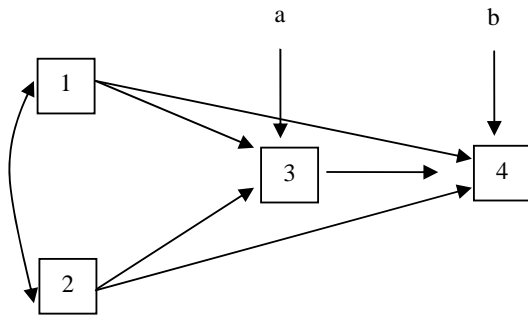observed variables, not using latent variables.

Fig. 1 An example of path analysis

Fig. 1 is an example of path analysis. The correlation between exogenous variables is depicted by a curved arrow, indicating that the researcher does not conceive of one variable being a cause of the other. The relation between exogenous variables remains unanalyzed. Variable 1 and 2 is taken as a cause of 3. Variable 3 is taken as a dependent on variable 1 and 2 and as one of the independent variables with respect to variable 4. Because it is almost never possible to account for total variance of variables, residuals expressed as 'a' and 'b' are introduced to represent effects of variables not included in the model.

A. The Advantage of Path Analysis

1) Simultaneous Analysis of Complex Model

Path analysis allows analyzing the relationship between dependent variables as well as between independent variables and dependent variables from one time analysis. In path analysis, path coefficient is calculated. It indicates the direct effect of a variable hypothesized as a cause of a variable taken as an effect. For example, P32 means the direct effect of variable 2 on variable 3. Actually, the path coefficient is the standardized regression coefficients (beta) obtained in multiple regression analysis. In the multiple regression analysis, dependent variable is regressed in a single analysis on all independent variables. However, in path analysis, more than one regression analysis may be called for. In the path analysis of Fig. 1, two path analyses are called for: from path analysis1, P31 and P32 are obtained by regressing variable 3 on 1, and 2, and from path analysis2, P41 P42 and P43 are obtained by regressing variable 4 on 1, 2and 3.

2) Decomposition of Correlations

Another advantage of path analysis is that it affords the decomposition of correlations among variables, thereby enhancing the interpretation of relations as well as the pattern of the effects of one variable on another. From the path analysis, researcher can show the total effect, the direct effect and indirect effect via mediation. In the analysis of causal models, a distinction is made between the direct and indirect effects of independent variables on dependent variables. A direct effect is defined as the part of its effect that is not mediated, or transmitted, by other variables. An indirect effect, on the other

hand, is the part of the effect of the independent variable that is mediated or transmitted by another variable. And the total effect is defined as the sum of direct and indirect effects. Depending on the causal model, a variable may or may not have a direct effect on another variable.
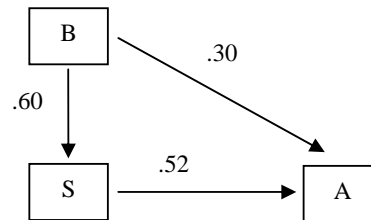

Fig. 2 Direct effect and indirect effect

Also, a variable may have more than on indirect effect on another variable. The use of path coefficients produces the correlation matrix and plays an important role in assessing the validity of a given causal model. Fig. 2 shows the direct effect and indirect effect. The direct effect of B on A is .30 and the indirect effect of B on A via S is .31(=.52*.60). So, the total effect is .61(=.30+.31).

Sometimes, it has been often suggested that path coefficients can be calculated by carrying out repeated multiple regression analyses on appropriate subsets of variables [11]. It is partly true but, if independent variables are not correlated at all, this model cannot be analyzed by multiple regressions and needs to define the correct correlation matrix by path analysis.

B. The Disadvantages of Path Analysis

Although path analysis is useful tool for analyzing multiple causalities, there are still several problems. Such problems as the requirements of linearity and homogeneity of variances or the use of predictor variables that are measured with errors are commonly cited. The following shorting comings are rarely discussed in the use of path analysis [12].

1) Limitation on Assumptions

The path analysis has the following assumptions. 1) Relations among variables in the model are linear, additive, and causal. 2) Each residual is not correlated with variables that precede it in the model. 3) There is one way causal flow. That is reciprocal causation between variables is ruled out. 4) The variables are measured on an interval scale. 5) The variables are measured without error. All these assumptions are hard to be satisfied in social science. Therefore, the assumptions itself are limitations. This issue will be discussed in next SEM section.

2) Co-linearity Issue

This is common problem in path analysis as well as regression analysis. Co-linearity occurs when independent variables are correlated highly, and influence on the estimation of path coefficients to be less accurate and make errors. When co-linearity increase, the ability to detect a significant effect is reduced and path coefficient becomes less accurate. Myers (1990) suggested that all VIF (Variance Inflation Factor) should be less than 10 [13]. Also, it is suggested that all

R-squire should be smaller than the R-square of the complete model [12].

3) Meaning of Model fit

Finding a significant fit of a path model to a data set does not demonstrate that relationships among variables are causal, because causation may be made by external elements to the statistical process of path analysis. Also, researchers may slip into a posteriori approach to path analysis by adding or dropping variables until a fit that maximizes the proportion of variance explained is found.

4) Sample Size and Categorical Variables

Use of categorical variables, non-random sampling, and small sample size prevents the variance-covariance structure of the sample from matching the variance-covariance structure of the population. Sample size should be at least to 20 times larger than the number of estimated paths to ensure reliable results. Using categorical variables with fixed treatment levels generally inflates the estimates of path coefficients. So, continuous variables are preferred [12].

IV. STRUCTURAL EQUATION MODEL (SEM)

Path analysis is based on a set of restrictive assumptions, some of which are the 1) variables are measured without error, 2) residuals are not correlated and 3) causal flow is unidirectional (recursive model). However, usually, it is very hard t measure without error. Classical approaches treated errors as being random, but, many sources of errors are nonrandom (systematic), affecting validity of measurement. Also, often, it is unreasonable to assume that residuals from different equations are not correlated. For example, in longitudinal research when subjects are measured at several points on the same variables, such assumption is untenable. Finally, the third assumption about recursive model is unrealistic in many researches which show reciprocal causation.
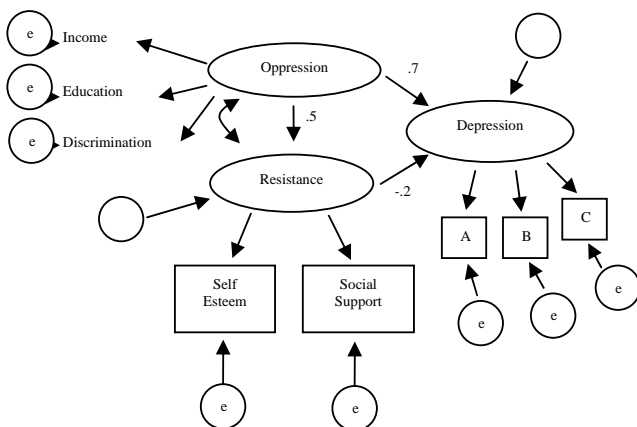

Fig. 3 An example of structural equation model

Structural equation model (SEM) with latent variable considers the above limitation of path analysis. SEM is composed of two major components; measurement equations (by confirmatory factor analysis) and structural equations (by path analysis). Confirmatory factor analysis models (CFA), a special case of SEM, are widely used in measurement applications for a variety of purpose. Designs for construct validation and scale refinement, measurement invariance can be evaluated through testing of CFA. In each component, measurement error and structural error is included in analysis. Compared that path analysis has only structural error, SEM includes both errors in analysis.

A. Advantages of SEM

1) Measurement Variables and Latent Variable

Measurement equations refer to capturing latent variables. The representative character of SEM is the use of 'latent variable' which are not applied at any other analysis method. Latent variable refer to constructs so that it is not observable. For example, mental ability, motivation, self-concept, attitude are latent variables. It is unrealistic to expect single indicators to capture validly and reliably such complex constructs. Instead, multiple indicators are necessary to capture the essence of such variables. To capture the constructs, measurement errors should be presented in the model. The measurement error refers to error term of indicators of latent variable and occurs when a researcher input wrong data, when respondents do not understand survey questions, and when respondents have difficulties to provide real information such as income or weight.

Identifying measurement error makes the causal equation model between latent variables more clear, compared path analysis or regression. For example, the measurement errors are neglected in multiple regression analysis. In the process of multiple regression analysis, one or more independent variables are allowed, but only one dependent variable is allowed. So, when producing one dependent variable, a researcher needs to combine several variables, which require reliability estimation (e.g. test-retest, internal consistency). Usually Cronbach's alpha is checked, the sum or mean of them is used in analysis after deleting the variable that has alpha value of smaller than .7 (or .6). In that process, measurement error is not considered. (e.g. the use of scale). If the reliability of a scale is equal to 1, it means there is no measurement error. But it is impossible that the value of reliability is 1 in social science. On the other hand, SEM considers the latent variable with measurement error which cannot be explained by latent variable. So, in SEM, a researcher can produce more accurate causal relationship between constructs. Although a researcher use same set of data, the standardized coefficient are different in each analysis method (SEM may show .67 and regression analysis may show .60) Because SEM consider the observed variables and measurement error, it is possible to inference causal relationship between pure constructs (latent variables).

A major advantage of using multiple indicators in SEM is that they afford the study of relations among latent variables uncontaminated by errors of measurement in the indicators. Here, structural error should be included in model. This is similar as the part unexplained by proportion of variance in multiple regression analysis. This is called as residual,

disturbance, equation error, or prediction error. Because endogenous latent variable are not influenced only by exogenous latent variables introduced in model, structural error occurs.

2) Simultaneous Estimation

The various statistical methods such as t-test, ANOVA, MANOVA, multiple regression analysis, canonical correlation analysis have a common limitation. Most of methods can show the single relation between independent variable and dependent variable. In regression analysis, one or more independent variables are included in analysis, but dependent variable should be one. In canonical correlation analysis and MANOVA, more than one independent variables and dependent variables are considered, but the analysis is restricted because it can only show the relationship between independent variable and dependent variable. On the other hand, SEM can show the relationship among dependent variables. In SEM, more than one of exogenous variables and endogenous variables are estimated simultaneously. Also, the causal relationship between endogenous variables can be estimated. For example, when a researcher wants to see the relationship, A-> B -> C-> D, total 4 analyses should be conducted in multiple regression analysis. On the other hand, through SEM, the simultaneous estimation is possible.

3) Direct Effect, Indirect Effect, and Total Effect

In SEM, a researcher can show the direct effect, indirect effect, and total effect because of more than one of exogenous variables and endogenous variables are estimated simultaneously. For example, see Fig. 3. The direct effect of oppression on depression is .7. The indirect effect of oppression on depression via resistance is -.1 (=-0.2*0.5). Total effect is .6 (=0.7-.01).

4) Applying Multiple Statistical Method in One Model

SEM is composed of measurement equations (by confirmatory factor analysis) and structural equations (by path analysis). Also the correlations between exogenous variable are considered in one model and presented as curved line. Moreover, structural errors in endogenous variable are considered. Therefore, confirmatory factor analysis, correlation analysis, and regression analysis can be conducted at one time in a model.

5) Reciprocal Causal Relationship

SEM can show reciprocal causal relationship between latent variable.

6) Easily Accessible

Software program, AMOS allows researchers to analyze data conveniently. For example, multi-sample modeling, wherein a model is fit simultaneously to sample data from different populations, is possible. This approach involves the testing of invariance of critical parameters across groups (e.g. comparing male and female to investigate predictors of emotional well-being).

B. The Disadvantages of SEM

SEM has various advantages as I mentioned above, but has been criticized by famous scholars such as Cox, Freedman, Rogosa, Rubin, Speed, Wermuth and so on [14]. The limitations of SEM are following.

1) Inappropriate Interpretation

Some researchers used to analyze model inappropriately or to interpret the result incorrectly. These problems are caused by poor understanding on regression analysis, factor analysis, or correlation analysis. Researchers should have knowledge about SEM related methods. Without understanding basic concept of them, to apply SEM results in the poor and inappropriate interpretation and the wrong application of SEM.

2) Various Modified Models

In SPSS, if different researchers use same data and apply same statistical method, their results are same. However, SEM provides various tools to researchers. So, when given same data and same research models, various models can be made by different researchers. For example, by using observed variables without latent variables, path analysis model can be made instead of SEM. Also, by putting in or getting out latent variables in model, or by adding or deleting paths, various modified model can be made. In a discussion of tests of SEM, Joreskog and Sorbom (1993) distinguished among the following research situation: SC, AM, and MG [15].

First, SC (Strictly Confirmatory) situation means that the researcher has formulated one single model and has obtained empirical data to test it in a strictly confirmatory situation. The model should be accepted or rejected. Second, AM (Alternative Models) situation means that the researcher has specified several alternative models or competing models and on the basis of a single set of empirical data, one of the models should be selected. Third, MG (Model Generating) situation means that the researcher has specified a tentative initial model. If the initial model does not fit the given data, the model should be modified and tested again using the same data. The goal is to find a model which not only fits the data well, but also has the property that every parameter of the model can be given a substantively meaningful interpretation. The specification of each model may be theory-driven or data-driven. Although the model may be tested in each round, the actual whole approach is model generating, not model testing.

Among them, MG situation is most common. The researchers may keep on making adjustments by adding new variables and dropping significant ones until the most preferred model is generated. So, SEM is criticized as probably poor tool in explanatory situations with many variables and weak or non-existing substantive theory [15].

3) Errors from the Use of Multiple Statistical Methods

In SEM, multiple statistical methods such as confirmatory factor analysis, path analysis, and correlation analysis are applied in one model and estimated simultaneously. This is an advantage and disadvantage of SEM at the same time because errors may occur in results. For example, the positive relationship between two variables in correlation analysis may

be shown as negative relationship in the result of SEM analysis. Or, path coefficient is shown as over 1 in the result of SEM analysis, which is not make sense in regression analysis because standardized coefficient cannot be over 1. These strange and difficult situations may happen in SEM analysis. By modifying model or by deleting a variable, researchers can solve the problems, but beginners who are not familiar with SEM may interpret the result inappropriately.

4) Generalization

There is a problem of generalization of findings from SEM because results from SEM are subject to sampling or selection effects with respect to at least three aspects: individuals, measures, and occasions [1]. First, there is sampling effect with respect to individuals in most researches, which cause the limitation in generalizing the results. By the use of cross-validation index, it is possible to provide an indication of which model yields a solution with greatest generalizability when sample size is not large. Cross-validation index is computed from a single sample, as an index of how well a solution obtained in one sample is likely to fit an independent sample. This index is useful for comparison of alternative models. Second, selection effects are in the choice of measured variables in a given study. Especially, in SEM, this issue is prominent with regard to the choice of indicators to compose of latent variables. The nature of the latent variables depends on the choice of indicators, which may influence results and interpretation. Valid results and interpretation rely on having appropriate latent variables. Third, selection effects involves occasions of measurement. In any study where one investigates effects that operate over time, these effects may vary with the length of the time interval.

5) Confirmation Bias

It is easy to accept an explanation that fits data well, and that researchers are not motivated to consider alternative models. Especially, with the existence of equivalent models, which are alternative models that fit any data to the same degree, researchers are almost unaware of this phenomenon, or they choose to ignore it. Ruling out their existence may strengthen the support of a favored model. MacCallum et al (2000) stated that equivalent models occur routinely in practice, often in large numbers and researchers need to generate the substantive meaningfulness of equivalent models [1].

6) When Single Indicator for Latent Variable Is Available

A full latent variables (LV) model specifies relationships of the indicators to the LVs as well as relationships of the LVs to each other. Sometimes, only one single indicator is available for each LV. This is similar as path analysis. In this case, it is a problem that the single variable is not enough to represent LV. If the single variable is composed of multi items scale (e.g. CESD, depression scale), it can be a solution to construct parcels. A parcel is simply a sum of a subset of items from the scale. Multiple parcels can be defined by aggregating distinct subset items and parcels serve as indicators of LVs. A researcher can get advantage of full LVs models and avoid

some difficulties associated with measured variables path analysis model.

7) Issue of Time

Directional effects in SEM can be considered as causal effects wherein a change in one variable results in a change in another variable, and there are three properties of such effects [1]: (a) these effects take some finite amount of time to operate (b) a variable may be influenced by the same variable at an earlier point in time (autoregressive effect) (c) the magnitude of an effect may vary as a function of the time lag [1]. Especially, a researcher should mention about these problems for cross-sectional models that include directional influences. Also, they should provide autoregressive effect for longitudinal designs. Unfortunately, however, many studies show inadequate consideration of time issue in design.

8) Sample Size

The model than can be best supported may depend on sample size. Simpler models are favored when sample size is small [1].

9) Issue of Time

In application of SEM, researcher must decide whether to fit a model to a covariance matrix, S or a correlation matrix, R. Currently, researchers seem unaware that fitting a model to R versus S introduce potential problem and about 50% of the published applications fit models to correlational matrix [1]. Actually, there are interpretational advantages to using R. So, MacCallum and Austin urged researchers fitting models to correlation matrix to be certain that their SEM software treats such matrix correctly. Otherwise, it would be preferable to fit model to covariance matrix.

10) Interpretation of Result

A finding of good fit does not imply that the model is correct or not, but only plausible. In addition, good model fit does not mean that effects hypothesized in the model are strong. The actual relationship may be very weak, even zero, because the relationship can be made by residual variance fro endogenous variables. Good model fit does not imply at all that such residual variances are small. Therefore, such information should be discussed and reported for full understanding of the magnitude of effects.

Application of SEM should provide at least the following information: a clear models and variables, including clear indicators of each LV, a clear statement of the type of data, with presentation of the sample correlation or covariance matrix; specification of the software and method of estimation; and complete results including model fit index such as RMSEA, NNFI, and GFI.

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Jihye Jeon received B.A. and M.A. in Social Welfare from Yonsei University in Seoul, South Korea in 2000 and 2002 respectively. She received another M.A. in Social Policy and Planning from London School of Economics and Political Sciences, UK in 2004 and received Ph.D. in Disability Study from University of Illinois at Chicago, USA in 2014. She is currently senior researcher in Korea Disabled People's Development Institute under Ministry of Health and Welfare.