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# A STUDY ON MEDIATION, MODERATION AND STRUCTURAL EQUATION MODELING

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**ABSTRACT**

Mediation analysis is a statistical tool used to study how the effect of an independent variable on an ending is transmitted through a mediator. A moderator is a variable that transform the sign or strength of the effect of an independent variable on a dependent variable. To test single mediator model Structural Equation Modeling is used and also to estimate the rapport between multiple mediator, outcome and the moderator. This article gives an idea of meditation and the review is based on the book of statistical mediation and authors perceptive. This study proposes that Structural Equation Modeling has widespread to single mediator as well as multiple mediator models.



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## INTRODUCTION

Statistical mediation analysis is generally said to have been instigated by determining 1986 paper by Baron & Kenny. As will be verified in this discussion, one of the main aids of statistical mediation analysis is to translate the intuitive concepts. For instance, Pasteur's "mediating factors" into statements expressed as statistical models using mathematical rule. Another important contribution, which will also be thoroughly discussed in this review, is the casual pathways in the mediation. A hypothesized causal chain of mediation in which one variable affects a second variable that, in turn, affects a third variable. The intervening variable, M, is the mediator. It intervene the relationship between a forecaster and an effect. In a single mediation, the variables X M Y a b can be portrayed in the following way. Paths a and b are called direct effects. The mediational effect, in which X leads to Y through M, is called the indirect effect. The indirect effect signifies the portion of the relationship between X and Y that is mediated by M. In mediation, we consider a transitional variable, called the mediator that helps to explain how or why an independent variable controls an outcome.

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In the context of a behavioral study, it is often of immense concern to recognize and revise the mechanisms by which an intervention achieves its effect. By examining mediational processes that clarify how the treatments accomplish the study outcome, further for our understanding of the pathology of the syndrome and the mechanisms of treatment, however we possibly will also be able to make out unusual, more efficient, intercession strategies. A moderator variable is one in which the relation between the independent variable and dependent variable transforms crosswise levels of the moderator. Although often confused with mediation, a moderator is not transitional in the causal sequence from the independent variable to the dependent variable. Moderators are included in statistical models as an interface term. For the review of moderation effects, the relation between the independent and dependent variable must be diverse at different levels of a third variable. When the third variable is a faction variable, then the relation between the independent and dependent variable is simply different between the two groups. If the third variable is continuous Manne, Ostroff, & Winkel, 2007, then the relation between the independent and dependent variable may differ across the values of the third variable. More on moderator variables can be found in Aiken and West (1991).Path Analysis can test the implication of mediator variable in connecting with independent variables to dependent variable or simply called as mediation test. It can decide the endurance of direct and indirect effect of independent variable towards dependent variable. The conventional regression needs to be analyzed separately in order to determine the mediating effect.

## Mediation

The problem of how and why two variables are associated. These inquests are addressed by bearing in mind that variables explain how or why two things are associated. These variables are called mediating variables or mediators (David P. Mackinnon, 1957). Mediation analysis is a statistical technique that impends used to examine how the cause of an independent variable on an outcome is transmitted through an intervening variable (mediator) M. This variable represents asymmetric relation among variables. In Last's (1988) medical thesaurus, a mediator is defined as "casual pathway of a variable takes place from an independent variable to a dependent variable. Some mediation tests require that there is a significant relation between the independent and the dependent variable for mediation to exist. In a mediational process the effects are infrequent yet overall significant relation is possible between independent and dependent variable. If there is not a significant relation of an independent variable with a dependent variable and the indirect effect is statistically significant, Holmbeck (1997) concludes that there is an indirect effect but not a mediated effect. The idea is that if there is not a significant relation between two variables then it does not make sense to talk about mediation, but it does make sense to talk about indirect effects. As described in Holmbeck (1997, p. 603), the results imply that there will not be significantly account for the predictor criterion as there is no significance between the predictor and the criterion in the former position. Even if there is not a significant relation between the independent variable and the dependent variable, mediation can exist. Mediating variables are commonly called intervening or intermediate variables to clearly indicate their role as coming between an independent and a dependent variable. Mediating variables have also been called process variables (Judd & Kenny, 1981b) referring to their function as variables that describe the process by which an independent variable affects the dependent variable. In the medical literature, mediating variables are sometimes called surrogate or intermediate endpoints because these variables represent proximal measures of a distal outcome (Prentice, 1989). The two main appliances of mediation in research studies are once a relation between an independent and dependent variable is established, researchers often try to explain why or how the two variables are related. In this context, the purpose of mediation analysis is to investigate the processes underlying the observed relation between an independent variable and dependent variable. There are many examples of this purpose of mediation analysis, which is most common in psychology, sociology, and related fields.

## MODERATION

Moderators are variables that interact such that the relation between X and Y is different at different levels of the moderator variable. A moderator is a variable that changes the sign or potency of the outcome of an independent variable on a dependent variable. Moderator variables have also been called effect modifiers or effect measure modifiers given that the effect is modified by the levels of the third variable (Rothman & Greenland, 1998). The relative priority of investigating moderators versus mediators depends on the research question of interest. Generally, mediators are more appealing because they tackle the mechanisms by which an effect takes place, whereas moderators provide information on when effects are present. Mediation analysis is often used to explain the source of the effect when the moderator effect is originated. In addition to the Baron and Kenny (1986) landmark article, interesting discussions of the distinction between mediating and moderating variables have been described for nursing (Bennett, 2000), industrial and organizational psychology (James & Brett, 1984), child psychotherapy (Kazdin & Nock, 2003), clinical psychology (Holmbeck, 1997), psychoneuro immunology (Stone, 1992), and programs for children Petrosino, 2000). For example, Kraemer, Stice, Kazdin, Offord, and Kupfer (2001) specified mediators as variables that change over time after an intervention and moderators as variables that are measured before an intervention. For the most part, the relative priority of investigating moderators versus mediators depends on the research question of interest.

**Wright's path analysis:** Modern approaches to quantifying mediating mechanisms began with Sewall Wright's (Wolfle, 1999; Wright, 1920, 1921) methods for the path analysis of systems of relations among variables that included mediating processes as an important component. Wright used this system of equations for the relations among variables to quantify the hereditary and environmental influences on the color patterns of piebald guinea pigs. Wright's method, called path analysis, defined a model in terms of mathematical equations and displayed the model visually in a path diagram, in which variables were represented with symbols and causal relations between variables with arrows to indicate the direction of the relation. Path analysis provided a way to specify the causal relations among many variables and generated coefficients reflecting the size of the relation between variables. Path analysis generated quantitative estimates of the coefficients including mediated effects based on observed correlations among variables. Wright showed that the path coefficient for a mediating process was the product of all the path coefficients in a chain of mediation. As with number of new statistical methods, path analysis was widen to extract the maximum amount of information from data. Niles (1922, 1923) provided an important censure of Wright's path analysis. The criticisms by Niles are the same criticisms of path analysis and mediation methods that are voiced today. Niles assesses Wright on numerous accounts, of which three are most significant here. First, Niles stated that correlation and causation are the same thing so it was senseless to contrast them, an idea popularized by Pearson in his classic book, The Grammar of Science (Pearson, 1911). Pearson (1911) argued that correlation was a broad category with causation at its limit (Pearl, 2000) because all things are associated. The difficulty was the assessment of how closely things are associated, for which Pearson proposed the correlation coefficient. Niles' next second condemnation was that it is not possible to specify a correct system of the action of causes. In Wright's most important response to Niles' criticisms, Wright (1923, p. 240) stated an argument used to defend path analysis approaches to this day, "the combination of knowledge of correlations with knowledge of causal relations, to obtain certain results, is an unusual thing from the deduction of causal relations from correlations implied by Niles' statement. In summary, Wright argued that path analysis was not a method to infer causation; it was a method to quantify already supposed causal relations. Path Analysis can test the impact of mediator variable in between independent variables to dependent variable called mediation test. It can find out the existence of direct and indirect effect of independent variable towards dependent variable. Usually in SPSS/ANOVA, the conventional regression needs to be analyzed separately in order to determine the mediating effect. On the other hand in AMOS, the regression equations can be run at the same time. In general, mediation is explained in three modes:

- Complete mediation: once the independent variable connects towards dependent variable merely through mediator variable and there is no direct effect of independent variable towards dependent variable complete mediation takes place.
- Partial mediation: when independent variable relates towards the dependent variable through mediator variable and there is also a direct effect of independent variable towards dependent variable.
- No mediation: when independent variable does not connect to the dependent variable through mediator variable but has a direct effect towards dependent variable.

**Illustration:** Mediation analysis begins with in any case of three variables. Every unidirectional arrow that appears represents a hypothesized causal connection and must correspond to a plausible theoretical mechanism.

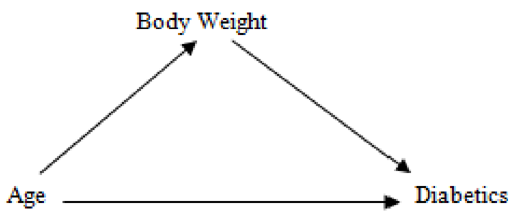


**Fig a. Mediated model of Age Vs Diabetics with single mediator variable.**

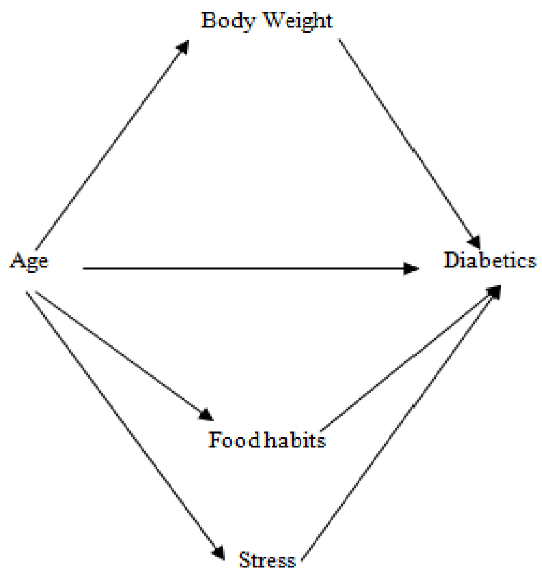


**Fig. b. Mediated model of Age Vs Diabetics with two mediator variable**

The above diagram represents a simple mediational model makes clear that an age of a person is one of the reasons for diabetics. Here, body weight is the mediator which influences the diabetics seems reasonable; processes that occur with advancing age, such as slowing metabolic rate, can lead to weight gain, and weight gain increases the demands on the cardiovascular system, which can cause an increase in sugar level. Similarly, for the multiple mediation model with the body weight, diet, exercise as the mediators. The above diagram reveals that an age of a person is a cause for diabetics with the direct effect. The mediators are body weight, food habits and stress can be relevantly maintained and can be followed to sustain the diabetic level. However, it would be drivel to propose a model of the following form: diabetics' → body weight → age, for example; there is no reasonable mechanism through which diabetics could persuade body weight, and weight cannot manipulate age in years.

**Structural equation models (sem):** The next important events in the quantification of mediating processes occurred when sociologists and economists developed models for sets of causal relations (Blalock, 1971; Duncan, 1966; Goldberger, 1972; Simon, 1954). Simon (1954) clarified the assumptions for the relations in three variable models. Structural Equation Modeling is also known as SEM has gained popularity among researchers, academicians and students nowadays. It is due to its litheness and simplification besides can produce an exact and specific estimation in building prediction. SEM analysis goes through the steps of model design, data collection, model estimation, model valuation and also model alteration. SEM is a distinctive method for the reason that the researcher can amend the structural model in order to enhance the model suitability. The path analysis multiple equation tradition, started by Wright and extended to sociology and economics, was combined with the psychometrics tradition with its focus on measurement. In an observed measures, a combined measurement structure from factor analysis of an analytical path frame by unobserved, erect with separating exact and error variance (Mulaik, 1972.

The estimation of each of the mediated effects in structural equation and path analysis models is called effect decomposition to identify the fact that there is a severance in terms of direct effects and mediated effects (Alwin & Hauser, 1975). There has been consistent development of statistical methods for covariance structure modeling such as methods for non-normal data (Browne, 1984), ordinal or limited variables (Muthén, 1984), alternative specifications of the model (Bentler & Weeks, 1982; McArdle & McDonald, 1984), and growth curve models (Rogosa, 1988). Statistical software, such as EQS (Bentler, 1997), Mx (Neale, Boker, Xie, & Maes, 2002), & LISREL (Jöreskog & Sörbom, 2001), Mplus (Muthén & Muthén, 2004), AMOS (Arbuckle & Wothke, 1999), and CALIS (SAS, 1989) has simplified the estimation of these models. Recent developments include the description and comparison of different tests of mediation (MacKinnon, Lockwood, Hoffman, West, & Sheets, 2002) and the estimation of mediated effects for continuous and categorical outcomes using single sample and re-sampling methods (Bollen & Stine, 1990). The single mediator model is used as a didactic device to describe the basic conception in mediation model that provides the values foSr direct and indirect effects. Also, in case of multiple mediation analysis and outcomes using SEM. A researcher can expand the single mediator model to find the bonding between the multiple mediators and to the outcome variables, moderators and covariates. The benefit of using SEM is the ability to measure the error in mediator and outcome variables. The guesstimate of the direct and indirect effects will be eased when the mediation and outcome variable of measurement error are not taken into account. In general, the error calculation of an indirect effect is to use of multivariate delta method (sobel, 1982). The next method to calculate the standard error is suggested by Craig 1936.Previous method used is Mplus and the recently used package is RMediation (Tofighi & Mackninnon, 2011).

## DISCUSSION

Mediation and Moderation are practiced in various areas. Most of the reviews are concerned with the significant relations between the mediating variables. Mediation does not subsist unless there is significant relation between the independent and dependent variables. But on the same way indirect effect can be discussed. Meanwhile moderators afford information when the effect exists. Ones the moderator effect originate the mediation can be worn to locate the source of effect. The present study highlights that SEM is used to test for single mediated data as well as multiple mediation and moderation. Also, to find the calculation of standard error of an indirect effect of a multivariate data.

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