Introduction to Structural Equation Modeling

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Outlines

- Introduction
  - SEM
  - Terms in SEM
  - Path diagram
- Relationships in SEM
  - Correlation
  - Causal
  - Mediation
  - Moderation

Expected outcomes

- Understand and apply the basic knowledge of SEM
- Specify SEM models involving correlation, causal, mediation & moderation, and interpret the results

Introduction

SEM

- Structural Equation Modeling (SEM) is a multivariate statistical modeling that aims to explain the structure of relationships among multiple variables (Hair, Black, Babin, and Anderson, 2010)
- Needs strong theoretical specification of the model ahead of the analysis → to verify our theory on the relationships

SEM

- Consists of TWO components (Bartholomew et al., 2008):
  1. measurement model (CFA): dealing with latent variables (factors) and the relationships between the items and the factors
  2. structural model (path analysis): dealing with how latent variables are related to each other

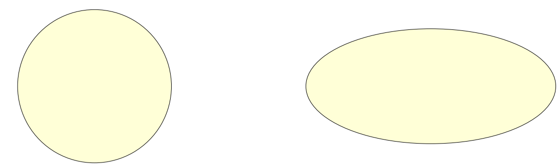
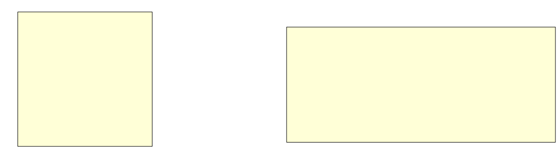
SEM

- Similar to CFA, how the variance-covariance matrix produced from the model fits the variance-covariance matrix of the observed data → Goodness of fit of model to the data

Terms in SEM

Term	Description
Exogenous variable	Independent, predictor variable. Could be observed (manifest) or unobserved (latent) variables
Endogenous variable	Dependent, outcome variable. Could be observed (manifest) or unobserved (latent) variables
Path diagram	A visual representation of the SEM model

Path Diagram

Concept	Diagram
Latent variable	
Observed variable	
Correlation, covariance	
Causal relationship	

Relationships in SEM

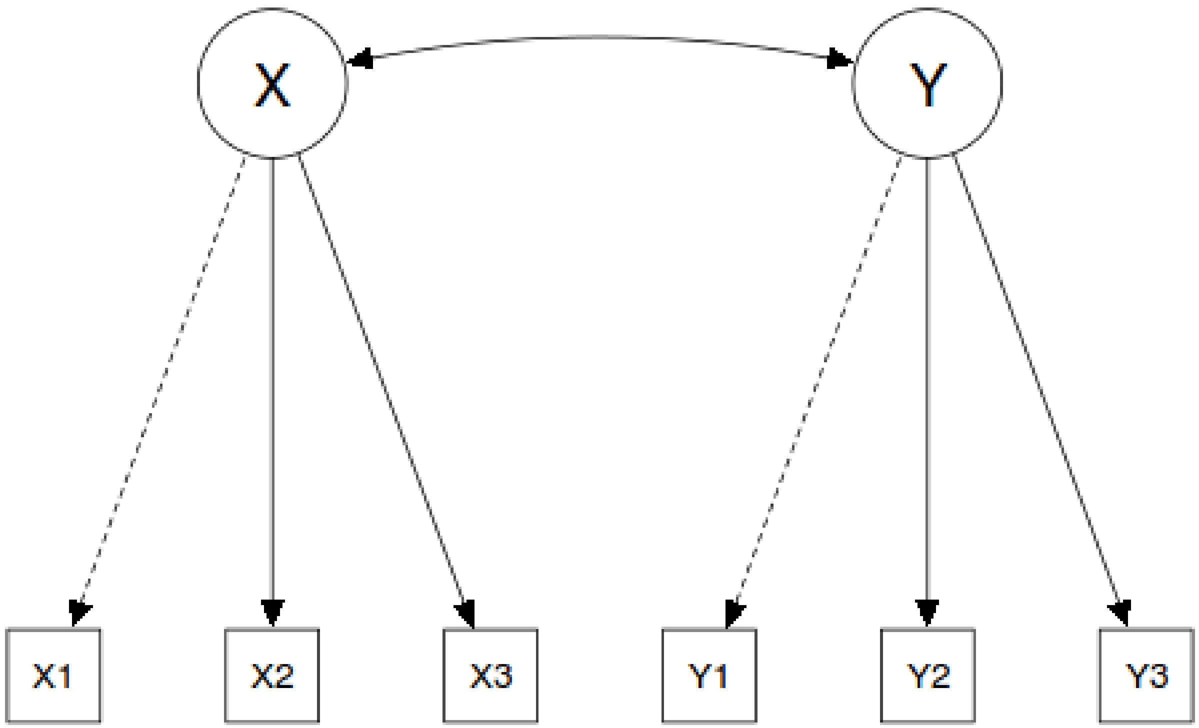
Correlation

- Bidirectional correlation/covariance between variables (observed/latent)

Correlation

Between observed variables

Correlation

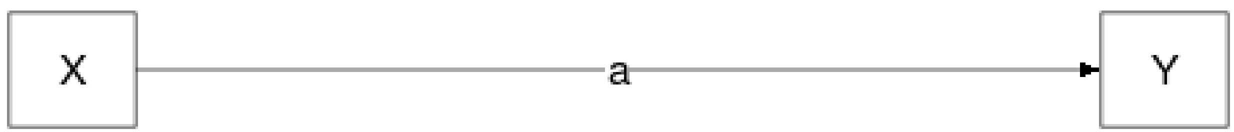


Between latent variables

Causal

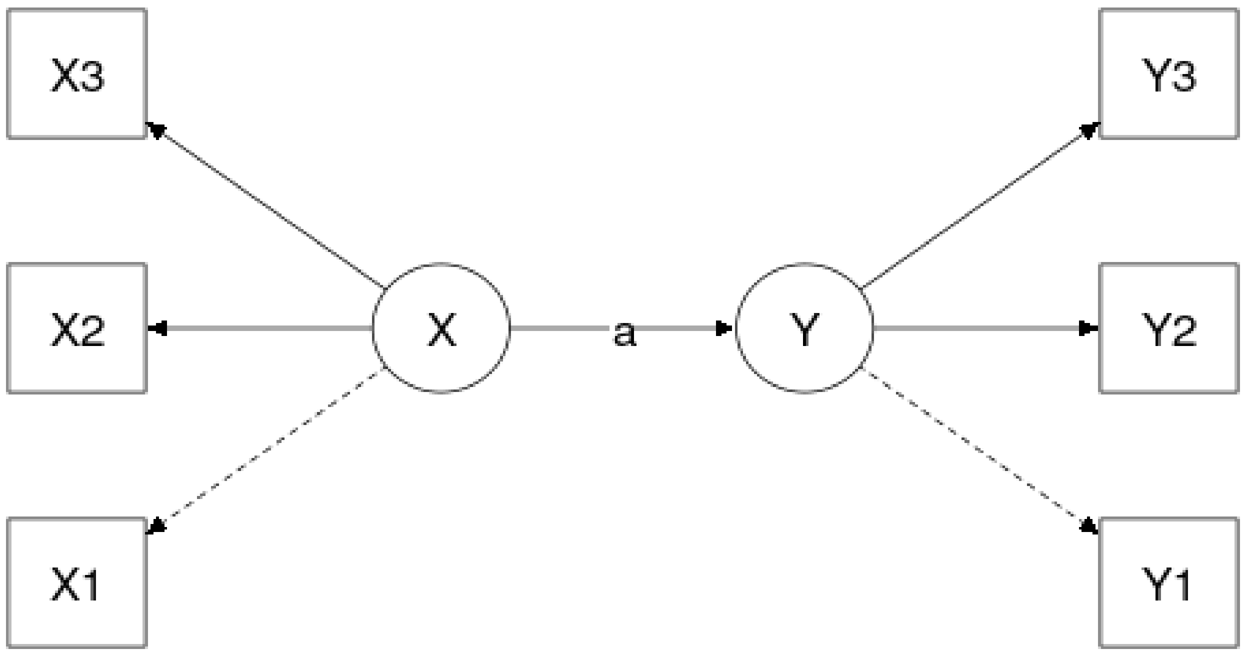
- Causal relationship between variables (observed/latent)
- Assign dependent and independent variables

Causal



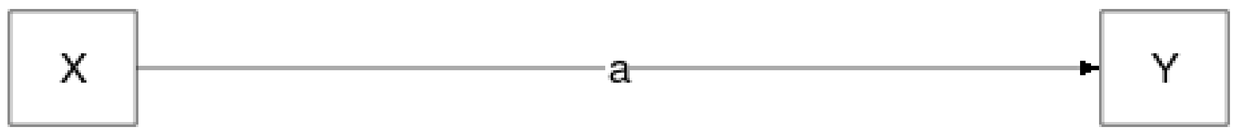
Endogenous/dependent Y caused by exogenous/independent X (observed)

Causal



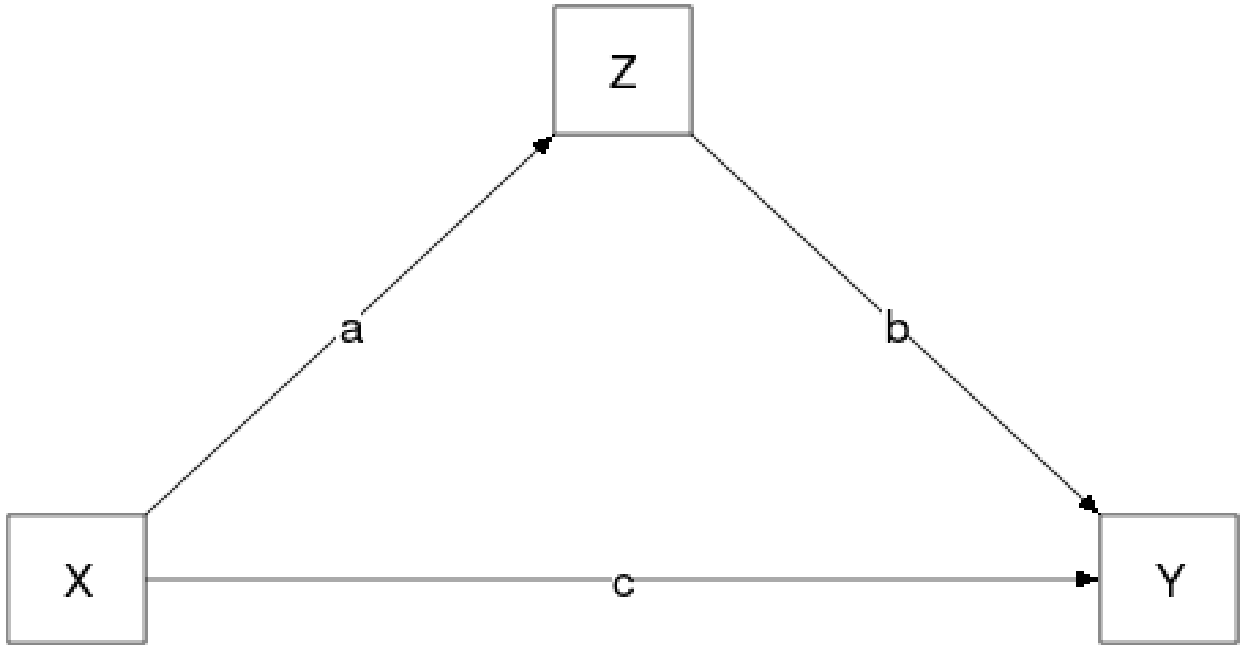
Endogenous/dependent Y caused by exogenous/independent X (latent)

Mediation



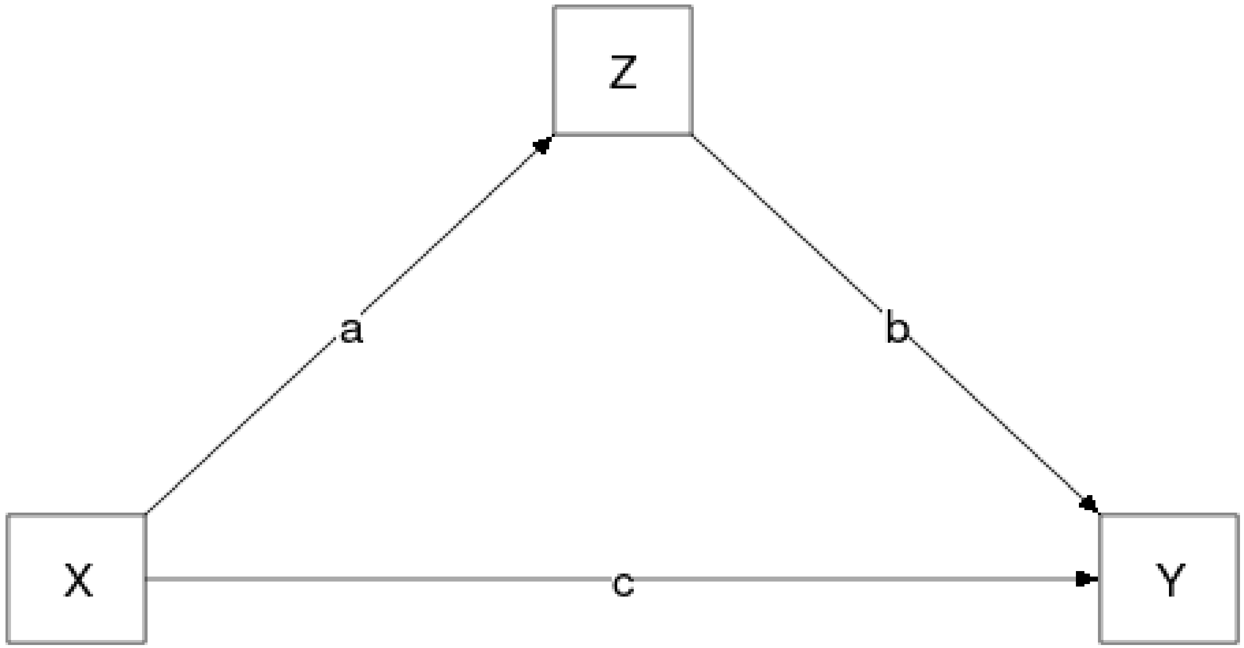
- Figure shows <u>direct causal effect</u> from independent X to dependent Y
- In SEM it is also possible to examine the effect of a mediating variable (mediator) Z on this established relationship

Mediation



- A mediator Z is a third variable that intervenes between two related variables (Hair et al., 2010)
- Two roles, as an DV in one equation and IV in another (Awang, 2012)
- Z <u>mediates</u> relationship of X to Y

Mediation

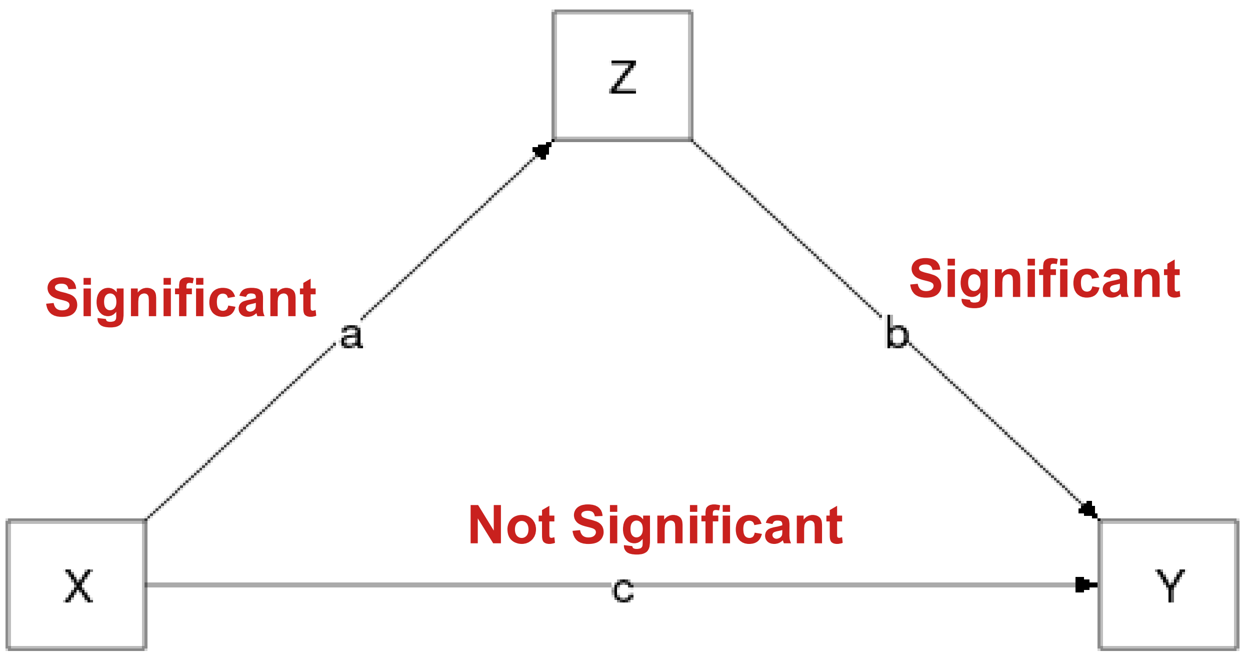


- If relationship between X and Y is mediated by Z, it indicates <u>indirect causal effect</u> of X to Y (X → Z → Y).
- <u>Total causal effect</u> is the <u>sum of direct and indirect effects</u> of X and Z on Y Kline (2016)

Mediation

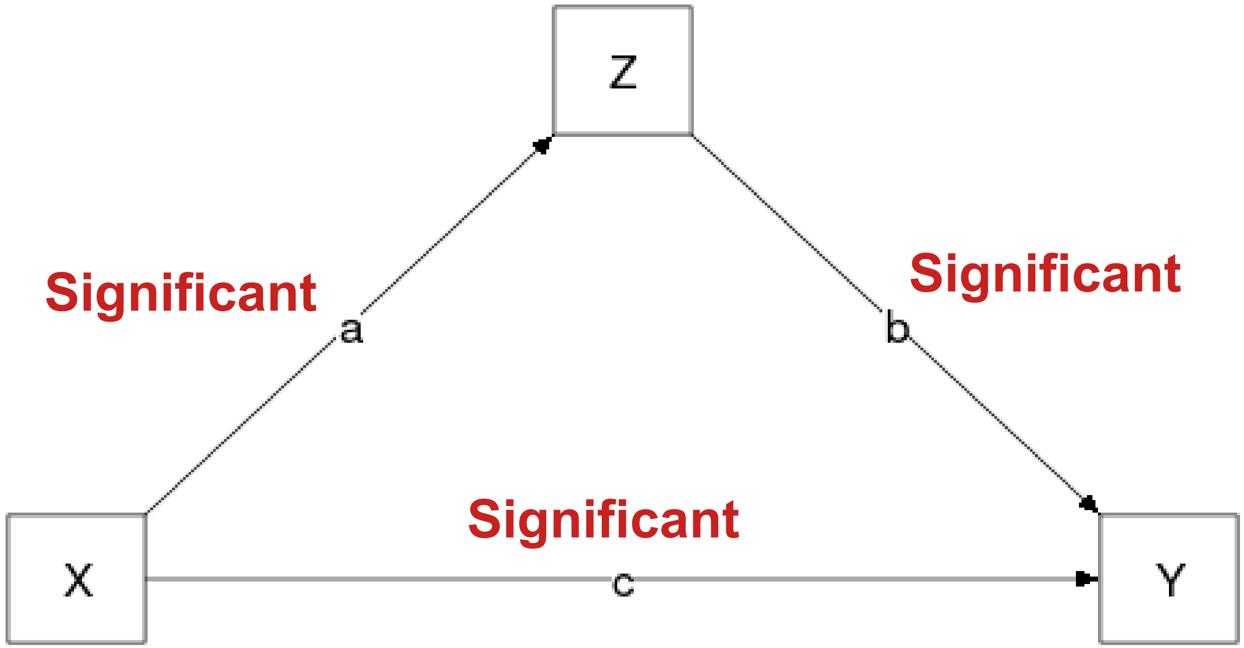
- Mediation effect can be classified into three outcomes (Awang, 2012):
  1. Complete mediation
  2. Partial mediation
  3. No mediation

Complete Mediation



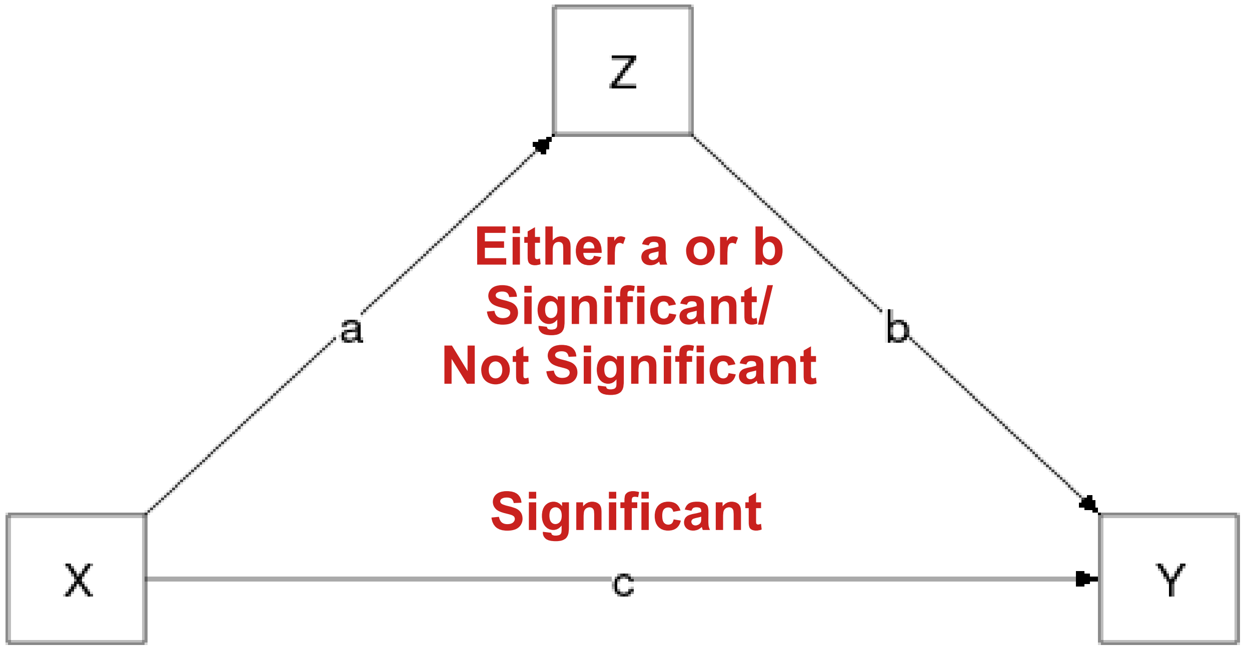
- Z completely mediates the effect of X on Y
- X indirectly causes Y

Partial Mediation



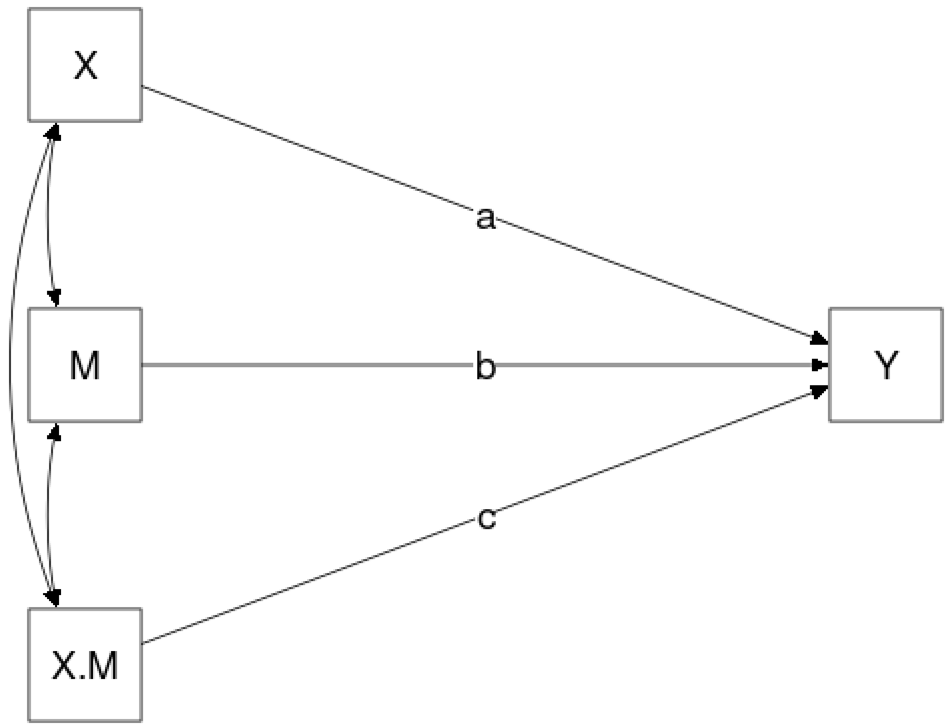
- Z partially mediates the effect of X on Y
- X directly and indirectly causes Y
- c (with Z) < c (without Z) (Hair et al., 2010)

No Mediation



- Z does not mediate the effect of X on Y
- X directly causes Y

Moderation

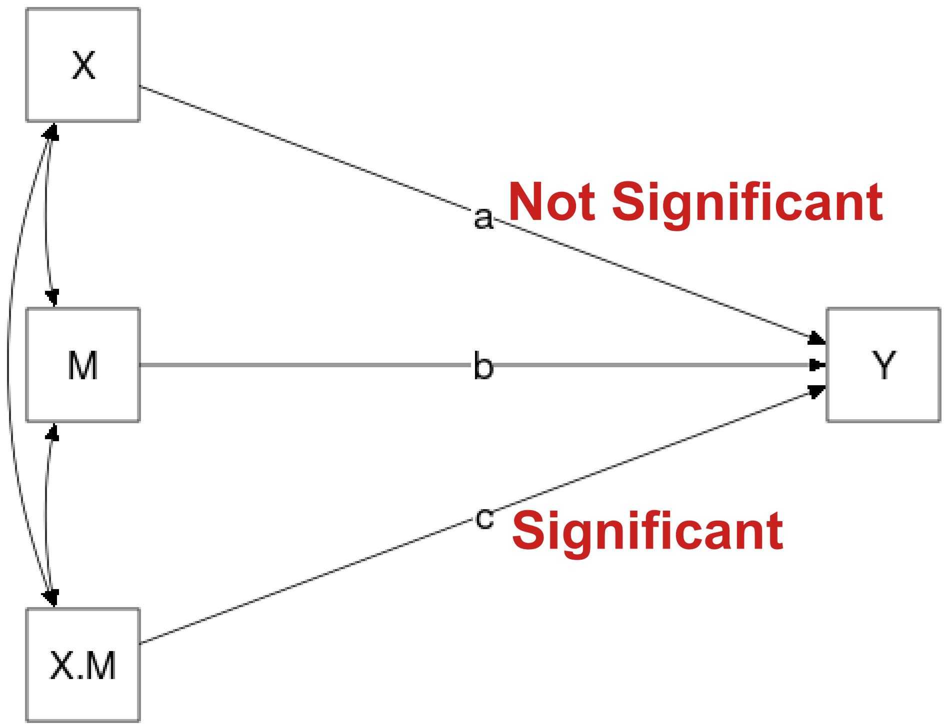


- A moderator M is a third variable that changes the relationship between two related variables X and Y (Hair et al., 2010)
- M moderates the causal effect that an IV has on a DV (Awang, 2012)
- Also commonly known as interaction

Moderation

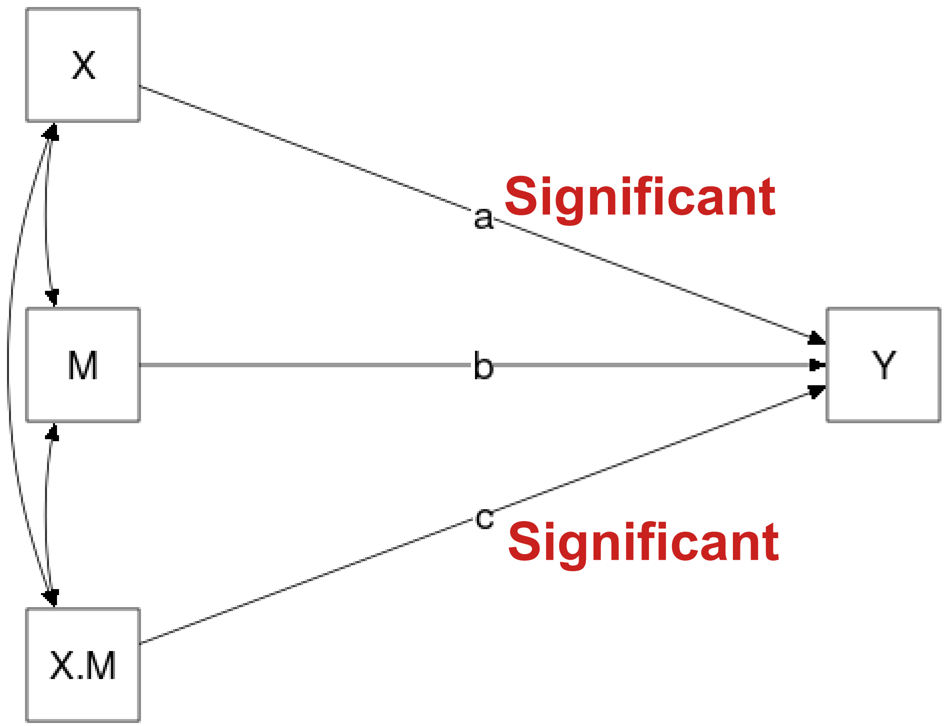
- Moderation effect can be classified into three outcomes (Awang, 2012):
  1. Complete moderation
  2. Partial moderation
  3. No moderation

Complete Moderation



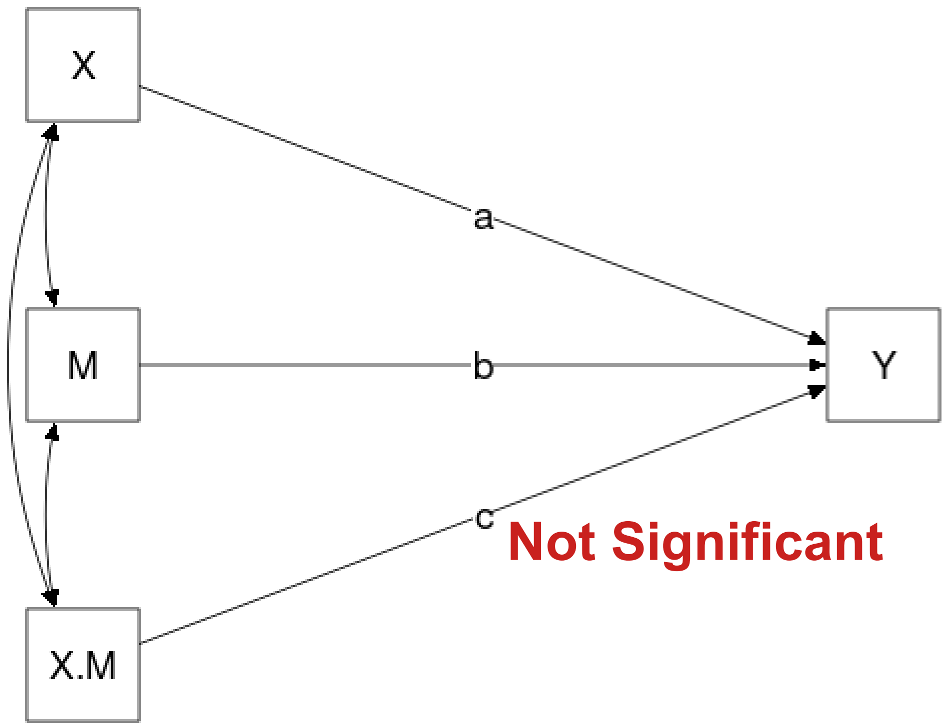
- M completely moderates the effect of X on Y
- M moderates the causal effect that an IV has on a DV (Awang, 2012)
- Also commonly known as interaction

Partial Moderation



- M partially moderates the effect of X on Y
- a (with X*M) < a (without X*M)

No Moderation



- M does not moderate the effect of X on Y
- a (with X*M) = a (without X*M)

Moderation

- Moderation effect is typically applied to observed variables only
- For latent variables, it is complicated and requires:
  - multi-group CFA for categorical moderator (Hair et al. 2010; Awang, 2012)
  - adding a latent variable consisting of interaction items (e.g. for items in latent X*M, items in latent X × items in latent M) in the model for numerical moderator (Hair et al., 2010)

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