Mediation Model, Moderation model and Moderated mediation model

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by

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Installation of PROCESS macro

1. Download software from https://www.processmacro.org/index.html

2. in SPSS

1) If use SPSS with other version before 24 follow this root

Extensions > utilities > install custom dialog (compatibility mode) and choose file process.spd from your specific folder

2) If use SPSS with other version 24 and newer follow this root

Extensions >utilities > Custom dialog Builder for Extensions > open choose file process.spd from our specific folder

Software use

1. PROCESS load from http://www.processmacro.org/index.html

It is an Add-in software for SPSS Regression, so you have to ins if the tall SPSS first. But

There are 74 PROCESS templates that can be downloaded from

http://dm.darden.virginia.edu/ResearchMethods/Templates.pdf

3. Edrawmax (trial version) can be downloaded from

https://www.edrawsoft.com/download-edrawmax.php

4. Smart PLS 3.3.3 This is a free one-month trial version that can be downloaded from https://www.smartpls.com/downloads

5. ADANCO (**AD**vanced **AN**alysis **CO**mposite) can be downloaded from

https://www.composite-modeling.com/get-adanco/ with cost of 3 USD for a 1-year trial version

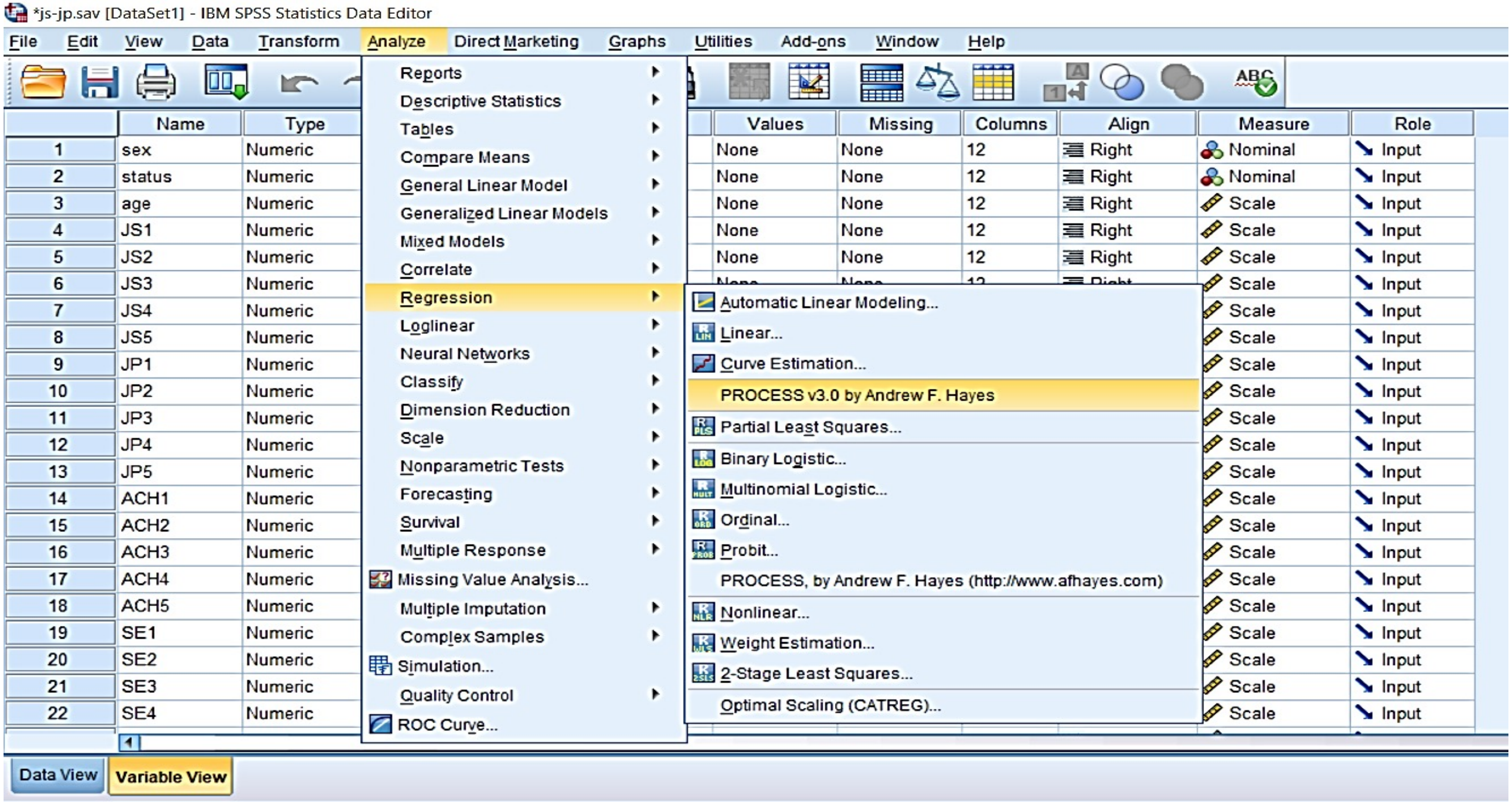
Software use

1. ADANCO, Smart PLS, RISREL, AMOS use for research tool (questionnaire) assessment and SEM analysis

2. Edrawmax or other drawing software use for drawing the research framework

3. PROCESS accompanying to SPSS uses for mediation analysis, moderation analysis, moderated moderation analysis and moderated mediation analysis under given PROCESS templates or customized model.

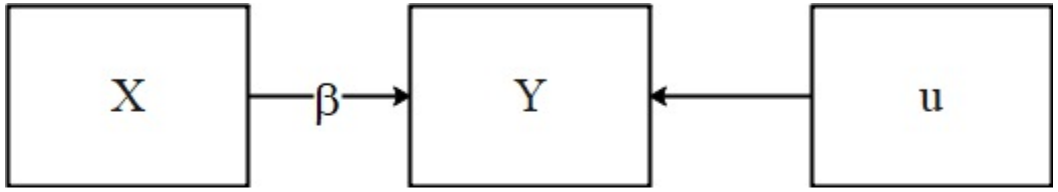
Dialog box of PROCESS after installation completed



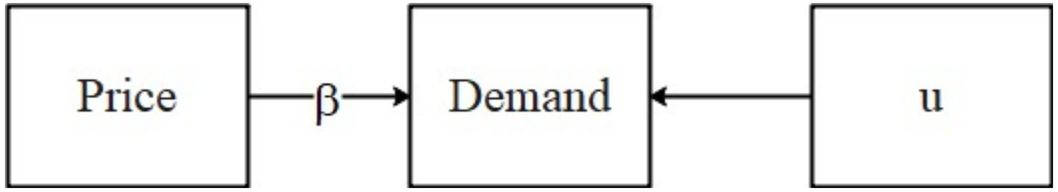
Relationship between SRA, MRA, PA และ SEM

Simple regression Analysis (SRA) can be modelled and presented in graphic as:

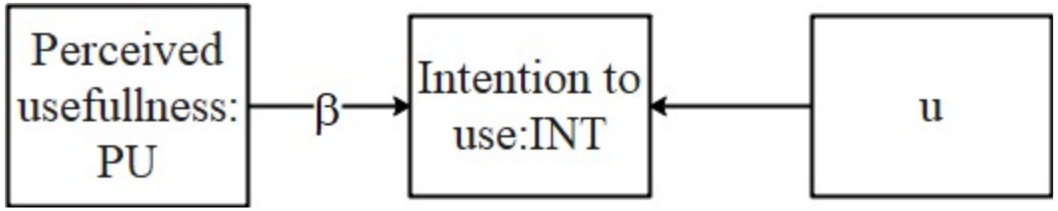
$Y = \alpha + \beta X + u$



For example, $Demand = \alpha + \beta\ Price + u$



$Perceived\ Usefullness = \alpha + \beta\ Perceived\ Usefullness + u$



Simple Regression Analysis (SRA)

Standardized regression equation is a SRA with observation (X, Y) has been standardized to z-score as (Z_1, Z_y), where

$$Z_1 = \frac{x_i - \bar{x}}{s_1} \text{ and } Z_y = \frac{Y_i - \bar{Y}}{s_y} \text{ and the SRA model is}$$

$$z_y = \rho_1 z_1 + z_u \; ; -1 \leq \rho_1 \leq 1$$

ρ_1 is a correlation between X and Y interpreted as if X increase by 1 SDx will cause Y increase (or decrease if negative) by 1 SDy* ρ_1

Multiple Regression Analysis (MRA)

regression model is

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k + u \,;\; -\infty \leq \beta_j \leq \infty$$

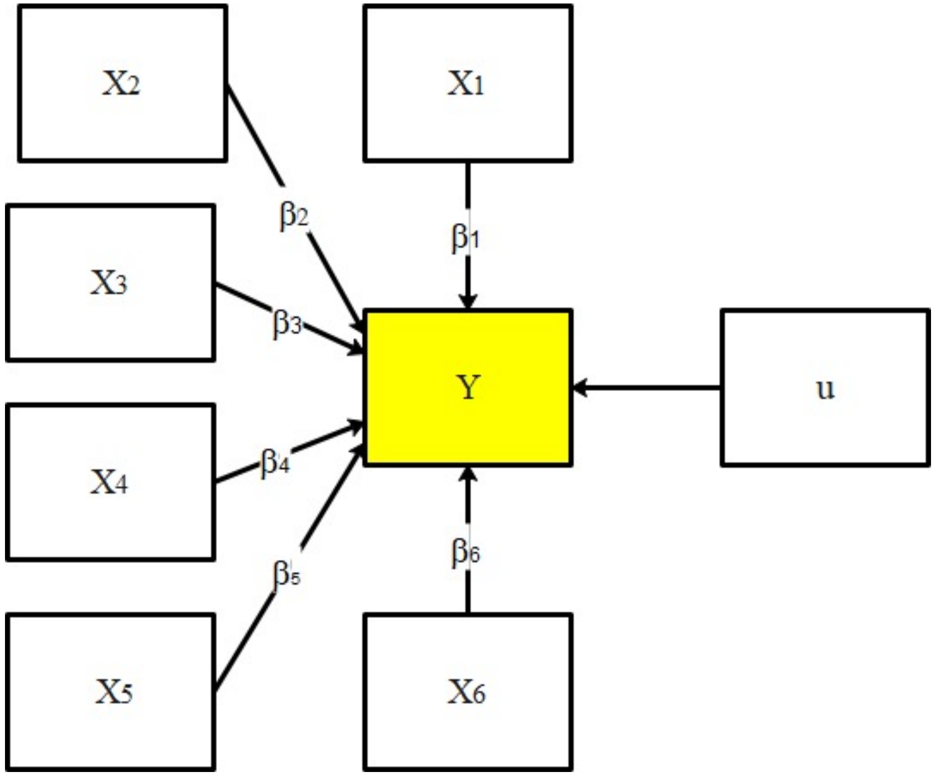
standardized model is

$$Z_y = \rho_1 Z_1 + \rho_2 Z_2 + \ldots + \rho_k Z_k + u \,;\; -1 \leq \rho_j \leq 1$$

Multiple Regression Analysis (MRA)

Model and graphic representation of MRA are:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_5 X_5 + u$$



Multiple Regression Analysis (MRA)

Regression coefficient can be interpreted as in SRA, i.e.,

$\beta_j = \frac{\Delta Y}{\Delta X_j}$ = rate of change in Y when X_j change by if the while other variables hold constant.

ρ_1 is a correlate between X_j and Y such that if X increase by 1 SDj will cause a change in Y increase (or decrease if negative) by 1 SDy* ρ_j

$\rho_i > \rho_j$ means X_i affects Y more than X_j

$R^2 = \frac{\sum_1^n \hat{y}_i^2}{\sum_1^n y_i^2}$ = % total variation of Y that can be explained by X's , $0 \leq R^2 \leq 1$

Multiple Regression Analysis (MRA)

MRA quality assessment

1. Sign of regression coefficient (+,-) must comply its theoretical and/or practical context. Plus sign means X and Y change in same direction. Negative sign means X and Y change in reciprocal direction.

2. Size of regression coefficient complies what that have been shown in literature. Higher standardized regression coefficient mean higher effect.

3. Significant comply literature perspectives or contemporary researches, i.e., H: $\rho_j \neq 0$ as in literature (p-value $\leq$ 0.10, 0.05,0.01 or $|t| \geq$ 1.65, 1.96, 2.58 where

$$t_j = \frac{\hat{\beta}_j}{se_j} \text{ (for testing of Ho: } \beta_j = 0 \text{ vs H1: } \beta_j \neq 0 \text{ (or } \rho_j \neq 0 \text{)}$$

4. No multicollinearity, no serial correlation, no heteroscedastic variance, no non-normality of residual or

Multicollinearity in MRA

Multicollinearity uses for measure independence of variable(s), it can be assessed by several ways, one of which is Variance Inflation Factor (VIF). VIF has a threshold as follows: R_j^2 calculated from equation

$$X_j = f(X_1, X_2, .., X_{j-1}, X_{j+1}, \dots, X_k)\ ;\ j = 1,2,3,\dots,\ k \text{ and } VIF_j = \frac{1}{1-R_j^2}$$

If $R_j^2 = 0.75$ to 0.85 then $VIF_j = \frac{1}{1-R_j^2}$ equals 4 to 6.67

$R_j^2 = .75$ means 75% of variation in X_j originated from other variables in model

$R_j^2 = .80$ means 80% of variation in X_j originated from other variables in model

$R_j^2 = .85$ means 85% of variation in X_j originated from other variables in model

In SEM if VIF (variance inflation factor) of any pair of indicator goes higher than these threshold the iteration for solution may not

Effect size in MRA

$R^2 = \frac{\sum_1^n \hat{y}_i^2}{\sum_1^n y_i^2}$ = % change of Y that can be explained by $X_1, X_2, \ldots, X_k; 0 \leq R^2 \leq 1$

Effect size $f_j^2 = \frac{R^2_{\text{include Xj}} - R^2_{\text{exclude Xj}}}{1 - R^2_{\text{include Xj}}} = \frac{R^2_{\text{change of Xj}}}{1 - R^2_{\text{include Xj}}}$

f_j^2 indicate impotance of X_j (Cohen, 1988). The thresholds are:

$f^2 \geq$ 0.020- 0.149 means small effect sizes i.e., least important

$f^2 \geq$ 0.150-0.349 means medium effect sizes i.e., medium important

$f^2 \geq$ 0.350, means large effect sizes i.e., most important

Path Analysis (PA) or Path Model (PM)

PA is a network of variables that are connected to each other by theoretical evidences or empirical investigations through MRA.

For example, Job performance (JP), job satisfaction (JS), organization commitment (OC) and Organization justice (OJ) connected to each other through these 3 regression models:

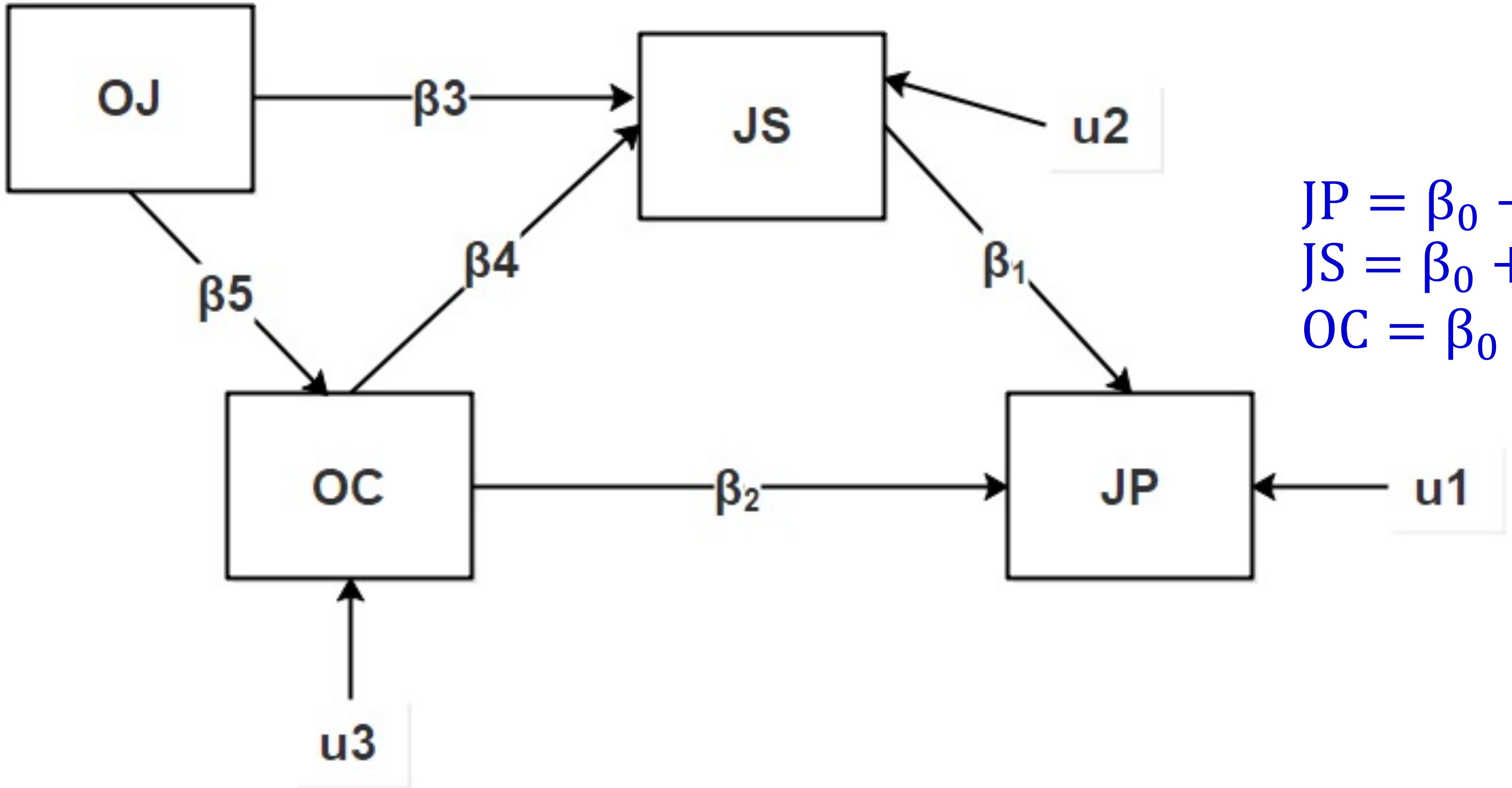
$$JP = \beta_0 + \beta_1 JS + \beta_2 OC + u_1$$

$$JS = \beta_0 + \beta_3 OJ + \beta_4 OC + u_2$$

$$OC = \beta_0 + \beta_5 OJ + u_3$$

Path Analysis (PA)

So, path model was drawn as:

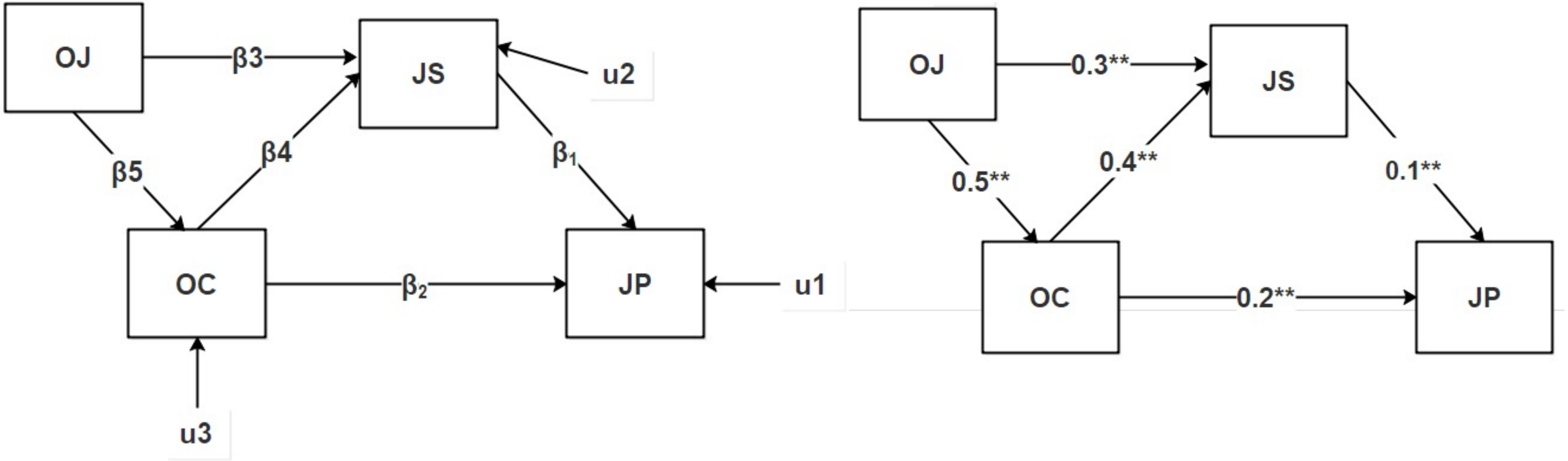


$$JP = \beta_0 + \beta_1 JS + \beta_2 OC + u_1$$
$$JS = \beta_0 + \beta_3 OJ + \beta_4 OC + u_2$$
$$OC = \beta_0 + \beta_5 OJ + u_3$$

Path Analysis (PA)

Suppose parameters from these 3 models were estimated to be

$\hat{\rho}_1 = 0.1$, $\hat{\rho}_2 = 0.2$, $\hat{\rho}_3 = 0.3, \hat{\rho}_4 = 0.4, \hat{\rho}_5 = 0.5$ and significant, we can place them on path coefficients $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5$ accompany with appropriated significant sign (either asterisk or p-value or t-value)



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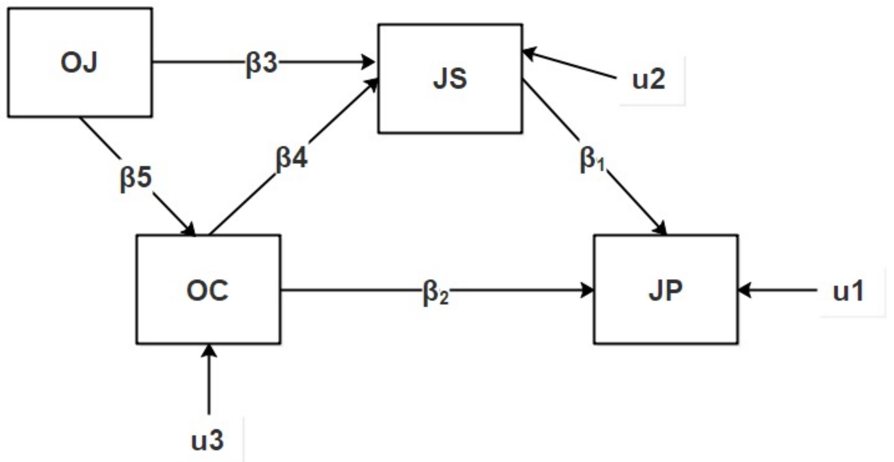
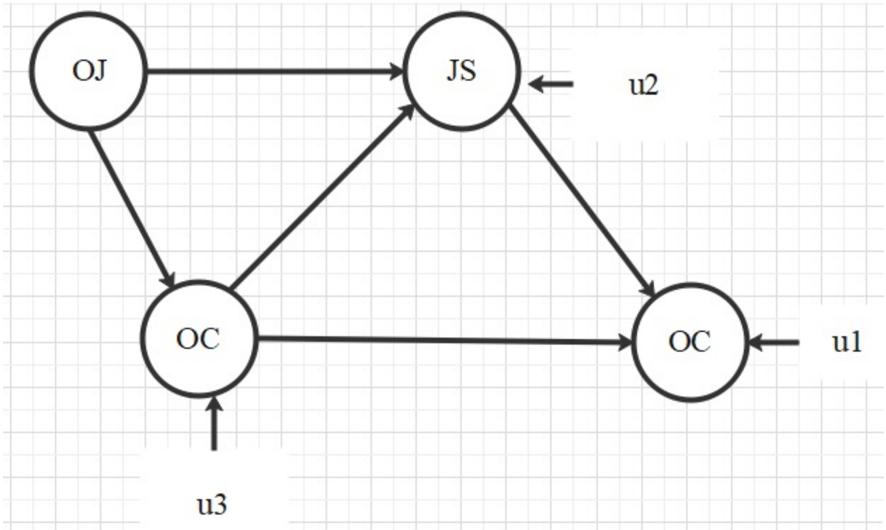
Path Analysis (PA) and Structural Equation Modeling (SEM)

1. If variables can be measure directly or measure indirectly through indicators and aggregated to be single variables (total score, z-score, factor score/construct score) we will employ Path analysis--PA/Path model--PM). Observe that variables are drawn in rectangular or square.



2. If variables are concepts (latent variable--LV, trait) that are usually indirectly measured through indicators (index, dummy, manifest variable) and the researchers also intend to present the measurement models, we will employ structural equation model--SEM. Observe that variables are drawn in oval or circle.

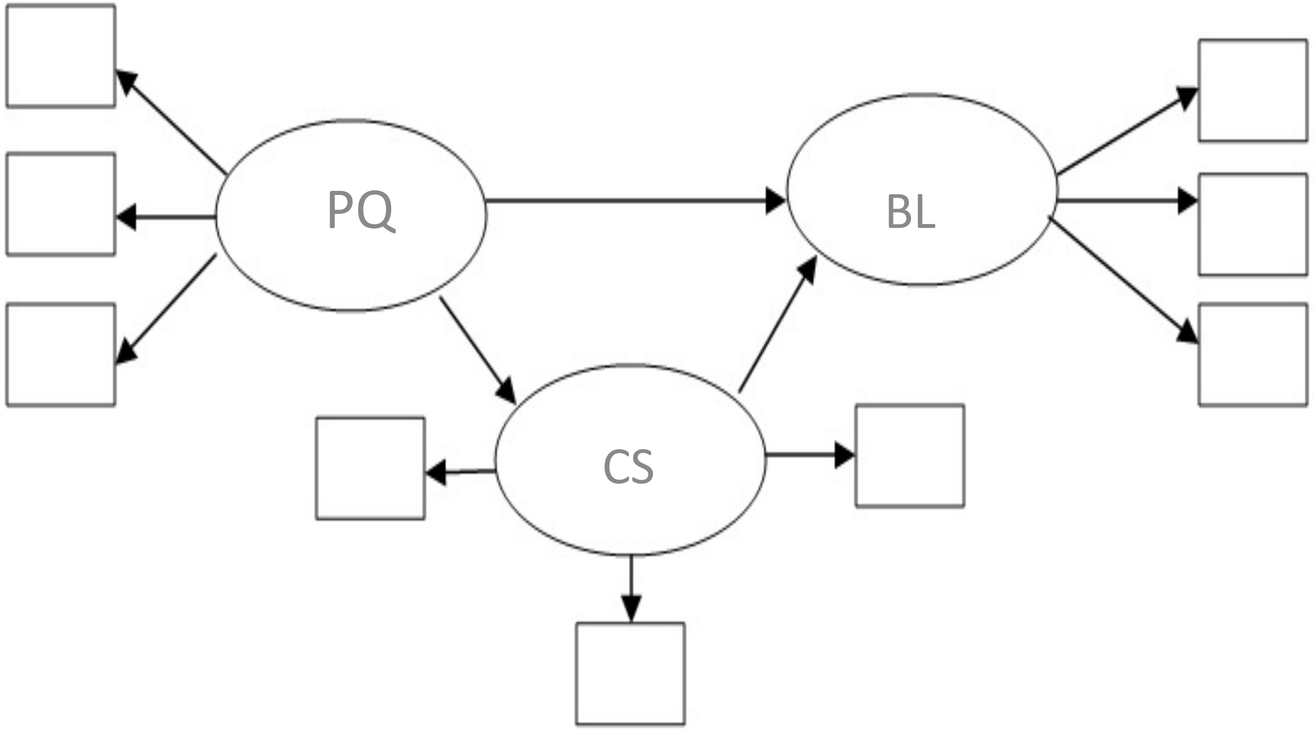


Research design for SEM

1. causality

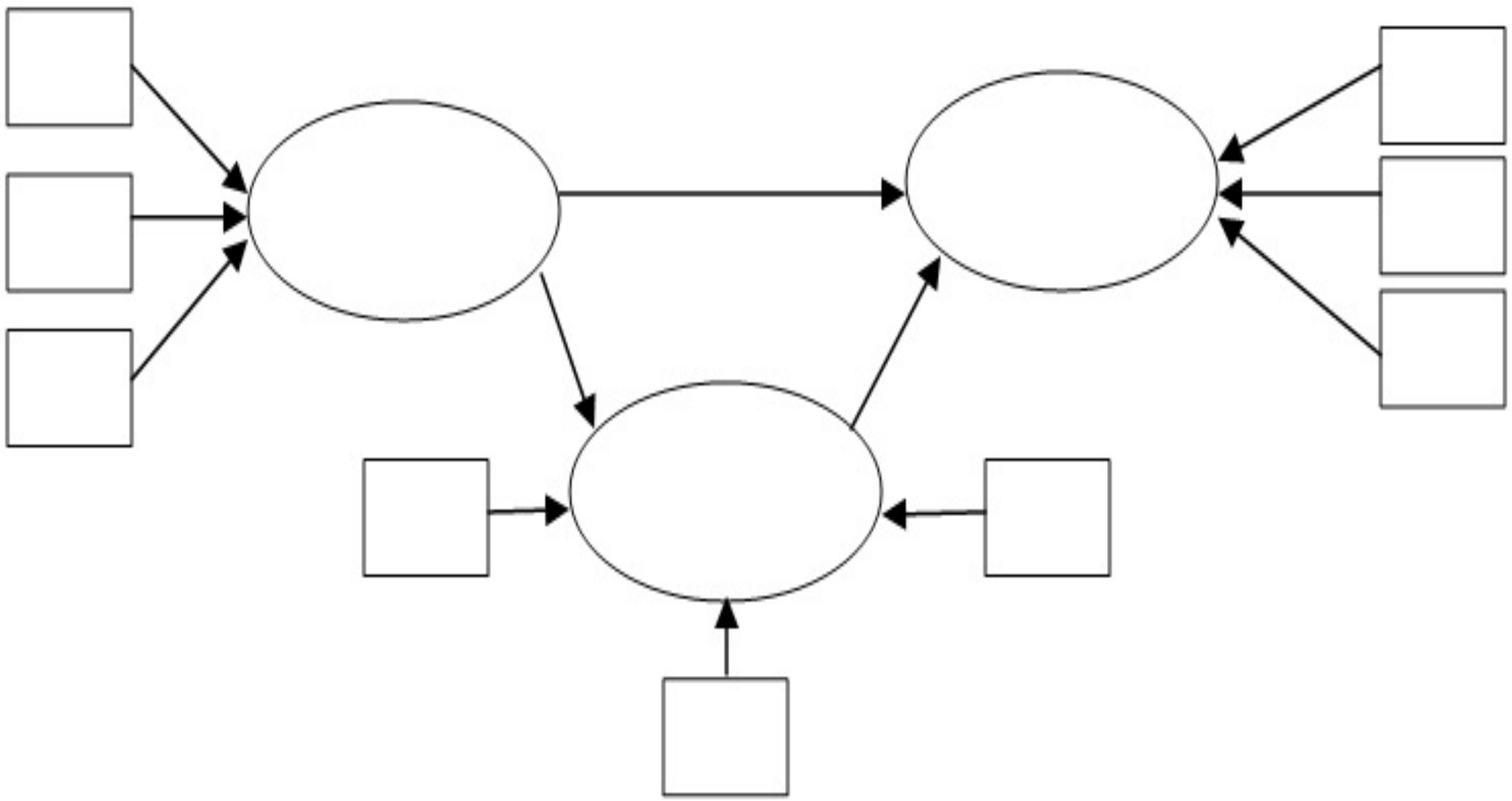
Causality or causation is a network of variables that are linked through theories or empirical investigation and we want to confirm these theories (paths) by data in our context (time, social, economy, politics, culture etc.)

1) Recursive structural model, reflective measurement model



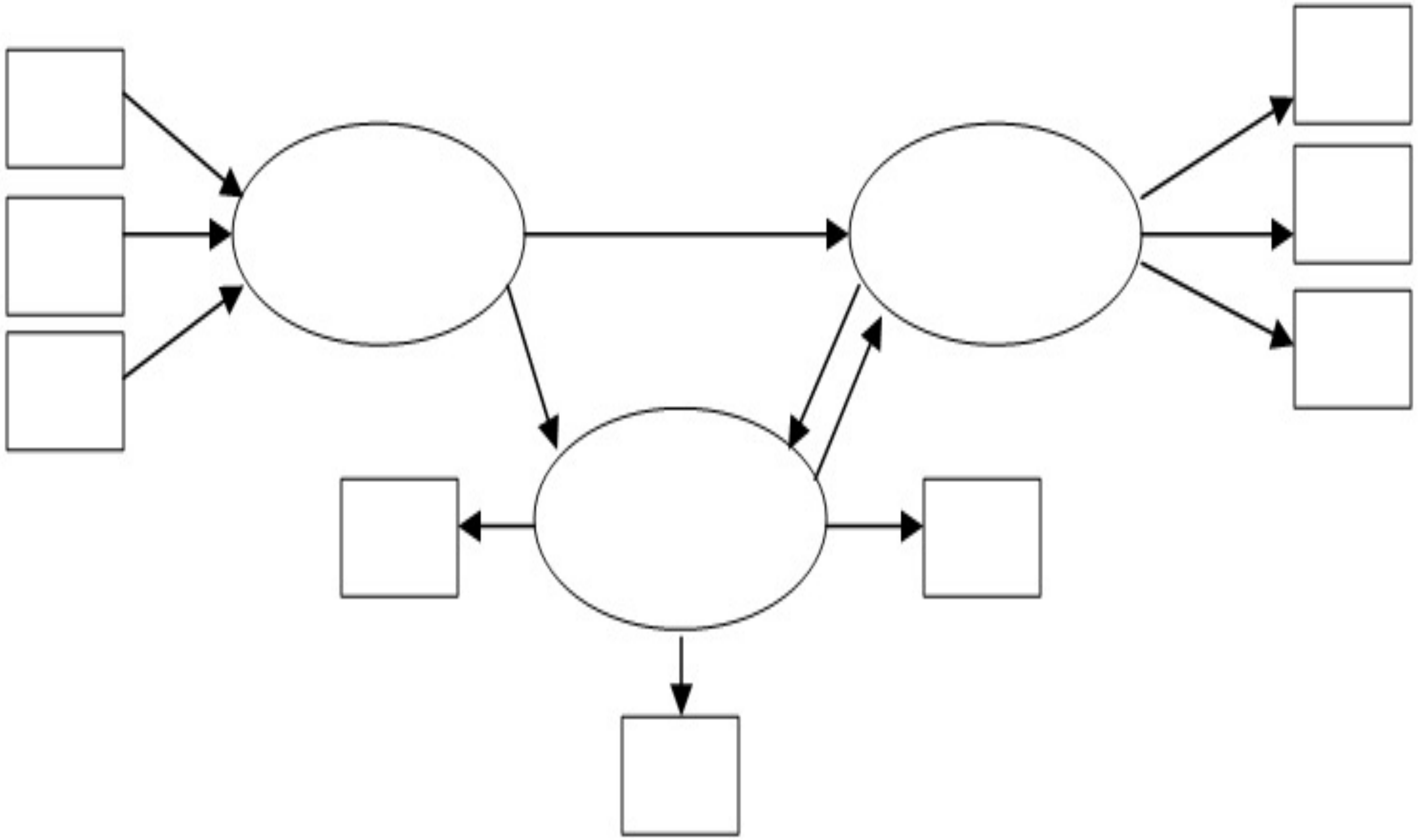
Research design for SEM

2) Recursive structural model, formative measurement model



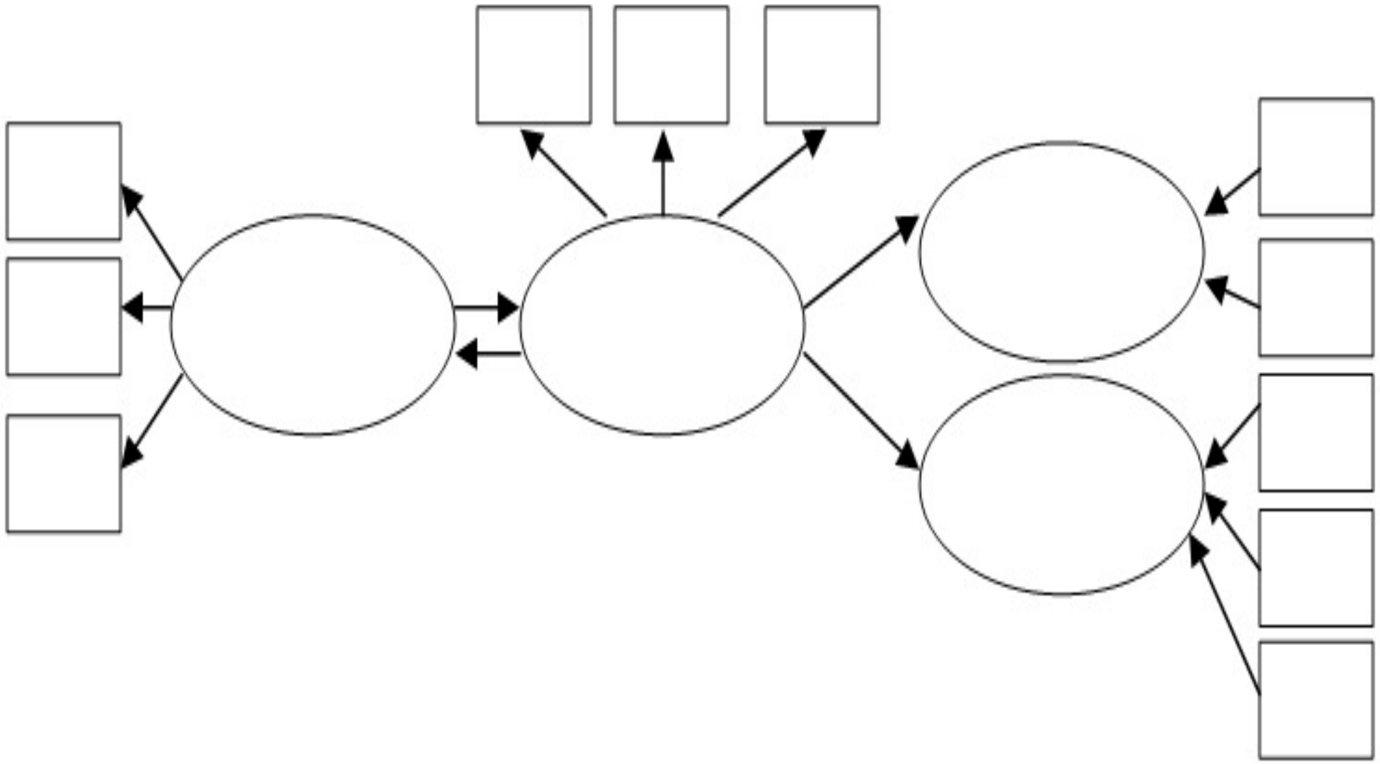
Research design for SEM

3.1) Non-recursive structural model, mixed measurement



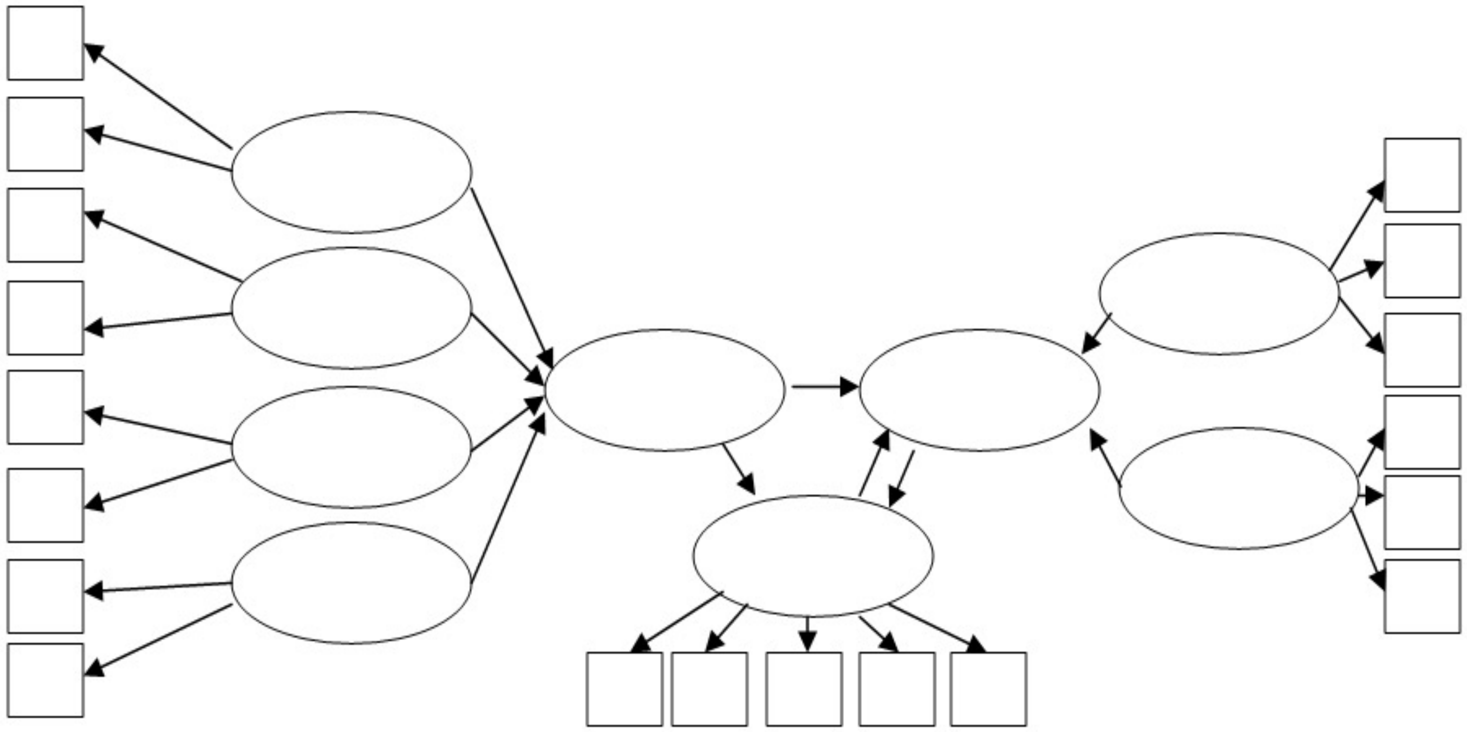
Research design for SEM

3.2) Non-recursive structural model, mixed measurement model

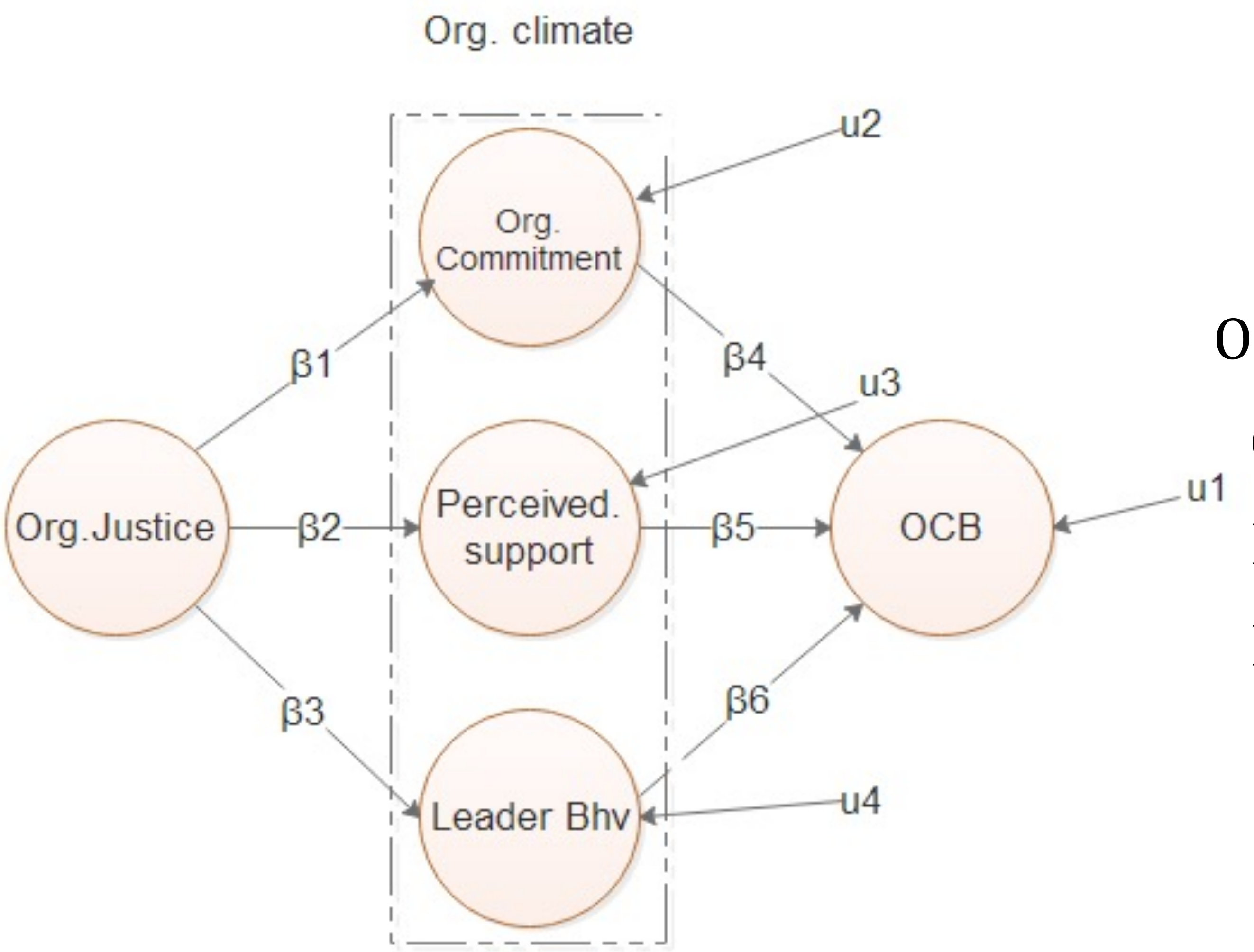


Research design for SEM

3.3) Second order formative feedback structural model, reflective measurement model (2nd order or 3rd order model is a multi-dimensional construct or multiple-facet construct where each sub-dimension reflects the following related dimension)



4. Mediation and multiple mediation model



$$OCB = \beta_0 + \beta_4 OC + \beta_5 PS + \beta_6 LB + u_1$$

$$OC = \beta_0 + \beta_1 OJ + u_2$$

$$PS = \beta_0 + \beta_2 OJ + u_3$$

$$LB = \beta_0 + \beta_3 OJ + u_4$$

Mediation model

Mediators are variables that transmit influence of antecedent to outcome variable(s) in secret. That is $X \rightarrow Y$ does not mean X affects Y but may be because

$X \rightarrow M_1 \rightarrow Y$ or

$X \rightarrow M_1 \rightarrow M_2 \rightarrow M_3 \rightarrow Y$ or

$X \rightarrow M_1 \rightarrow Y$,

$X \rightarrow M_2 \rightarrow Y$,

$X \rightarrow M_3 \rightarrow Y$.

Mediation analysis aims to find out HOW antecedent affects outcome variable(s), i.e., directly or indirectly or both. Called as underlying mechanism of $X \rightarrow Y$

5. Moderation model

Moderator aka. interaction or conditional variable is a hidden variable W that when interact with antecedent variable will help make change in outcome variable at values or at pick-a-point of W.

Moderation model aims to study effect of X*W WHEN viz.

1. If coefficient of X*W is positive and significant W will help increase in Y of the path X $\longrightarrow$ Y and help decrease in Y if negative.

2. If coefficient of X*W is non-significant W will help increase in Y of the path X $\longrightarrow$ Y and help decrease in Y if negative at pick-a-point.

Mediation Analysis

Mediation effect

Mediators are a hidden variables that transmit X to Y and cause a superfluous relationship. Indicators are:

1. If path coefficient ≥ 0.20 (Chin, 1998) then there should be an over-impact

2. From VAF (Variable Account For) $= \dfrac{\text{indirect effect}}{\text{direct effect+indirect effect}}$ (Hair et al., 2013, p.224)

   1) If VAF ≤ 0.20 no mediator is needed

   2) If $0.20 \leq$ VAF ≤ 0.80 is indicator of a partial mediation, i.e., more other mediators are hide

   3) If VAF > 0.80 is indicator of a full mediation, i.e., all possible indicators are included.

Method of single mediation analysis

1. Whether total effect (regression coefficient) from X⟶Y greater than 0.20

2. If there is a sign of over-impact insert W and check:

1) if indirect effect X ⟶ W ⟶ Y is significant then W is a mediator

2) if direct effect (DE) decline subjectively

(1) if decline to 0 or non-significant then W a mediator and no more mediator exist

(2) if decline to some near zero number but significant and VAP assume any value between 0.20 to 0.80 then there are some more other hidden variables to be tested.

Method of parallel mediation analysis

1. Check whether total effect of path X$\longrightarrow$Y is over-impact.

2. Insert mediators W1, W2,…,Wk and follow these steps:

1) if $(a_1b_1+a_2b_2+\ldots+a_kb_k)$ significant then W1, W2,…,Wk are mediators

(1) test all path X$\longrightarrow$Wi$\longrightarrow$Y; i=1,2,…, k

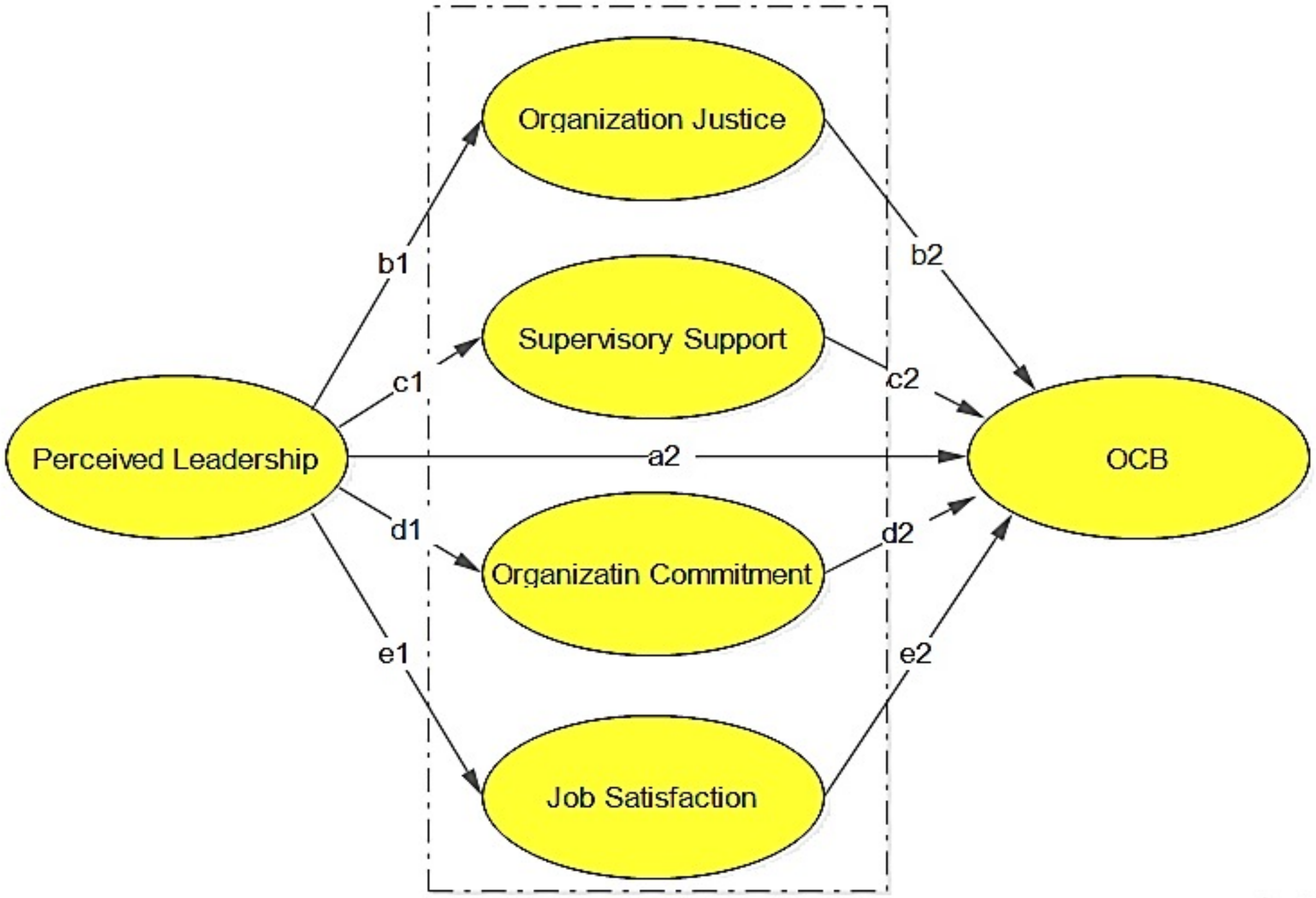
(2) sort IE by size, the more IE the more important of corresponding mediator

2) whether direct effect approach zero

(1) if decline to zero or near zero then W1, W2,…,Wk are mediators

(2)) if decline to some near zero number but significant and VAP assume any value between 0.20 to 0.80 then there are some more other hidden variables to be tested.

parallel mediation analysis



Research question is

HOW perceived leadership affect OCB, directly or must pass through OJ, OS, OC, JS? or

If OJ, OS, OC, JS are underlying conditions of the relationship PL⟶OCB?

parallel mediation analysis

Research hypotheses for parallel mediation analysis are:

1. Total mediation effect aka. total indirect effect คือ

$$H: b1*b2+c1*c2+d1*d2+e1*e2 \neq 0$$

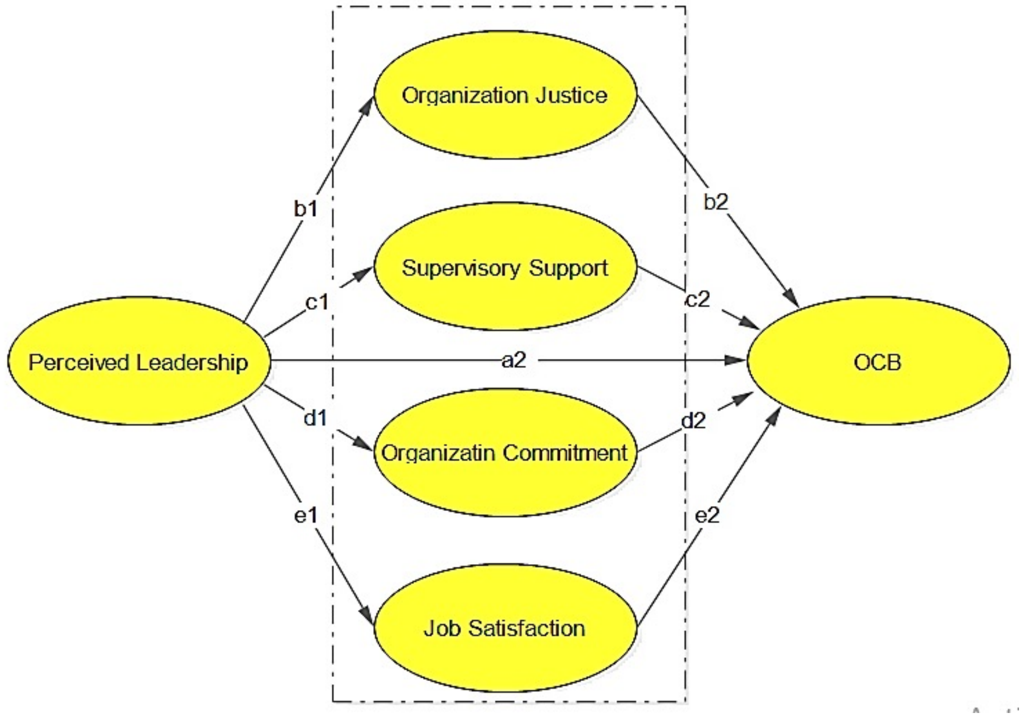
2. Specific indirect effects are:

$$H: b1*b2 \neq 0$$

$$H: c1*c2 \neq 0$$

$$H: d1*d2 \neq 0$$

$$H: e1*e2 \neq 0$$



Method of serial mediation analysis

1. Check whether total effect (TE) from path X⟶Y is over-impact.

2. Insert W1, W2,W3 (suppose there are 3 of them) and analyse

1) whether indirect effect (IE) $b_{1*}b_{2*}b_3$ significant

(1) if significant then W1, W2,W3 are mediators

(2) if non-significant then some of Ws may non-significant and some may not, we then check for available shortcuts

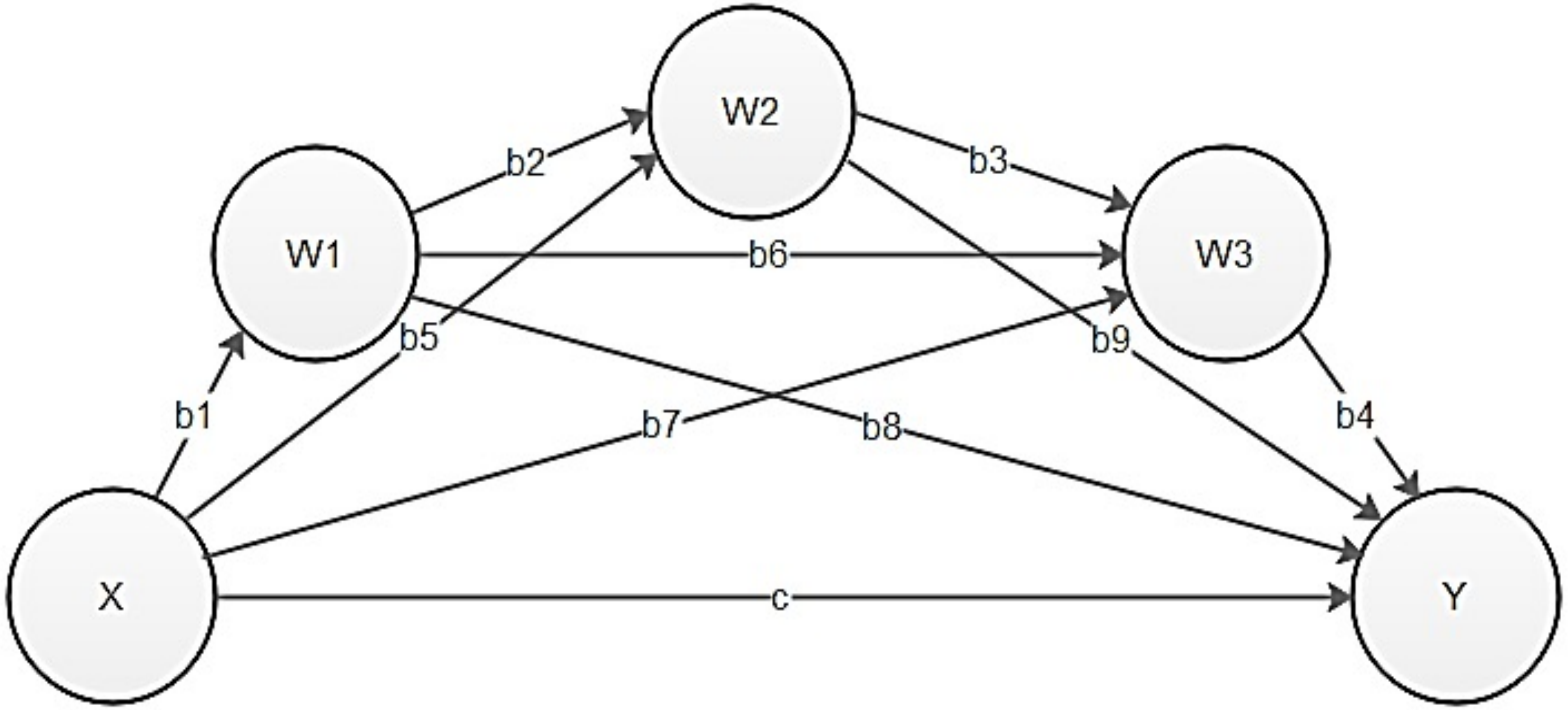
(3) sort IE by size, the more IE the more importance

2) whether DE decline to zero or near zero

(1) if decline to zero or non-significant then W1, W2,W3 are mediators

(2) if decline to some near zero number but significant and VAP assume any value between 0.20 to 0.80 then there are some more other hidden variables to be tested.

Serial mediation analysis



Research question is

How X impacts Y, directly or serially? What are optimal causal chains?

Test for serial mediation

Research hypotheses คือ:

H: b1*b2*b3*b4 $\neq$ 0

H: b1*b2*b9 $\neq$ 0

H: b1*b6*b4 $\neq$ 0

H: b1*b8 $\neq$ 0

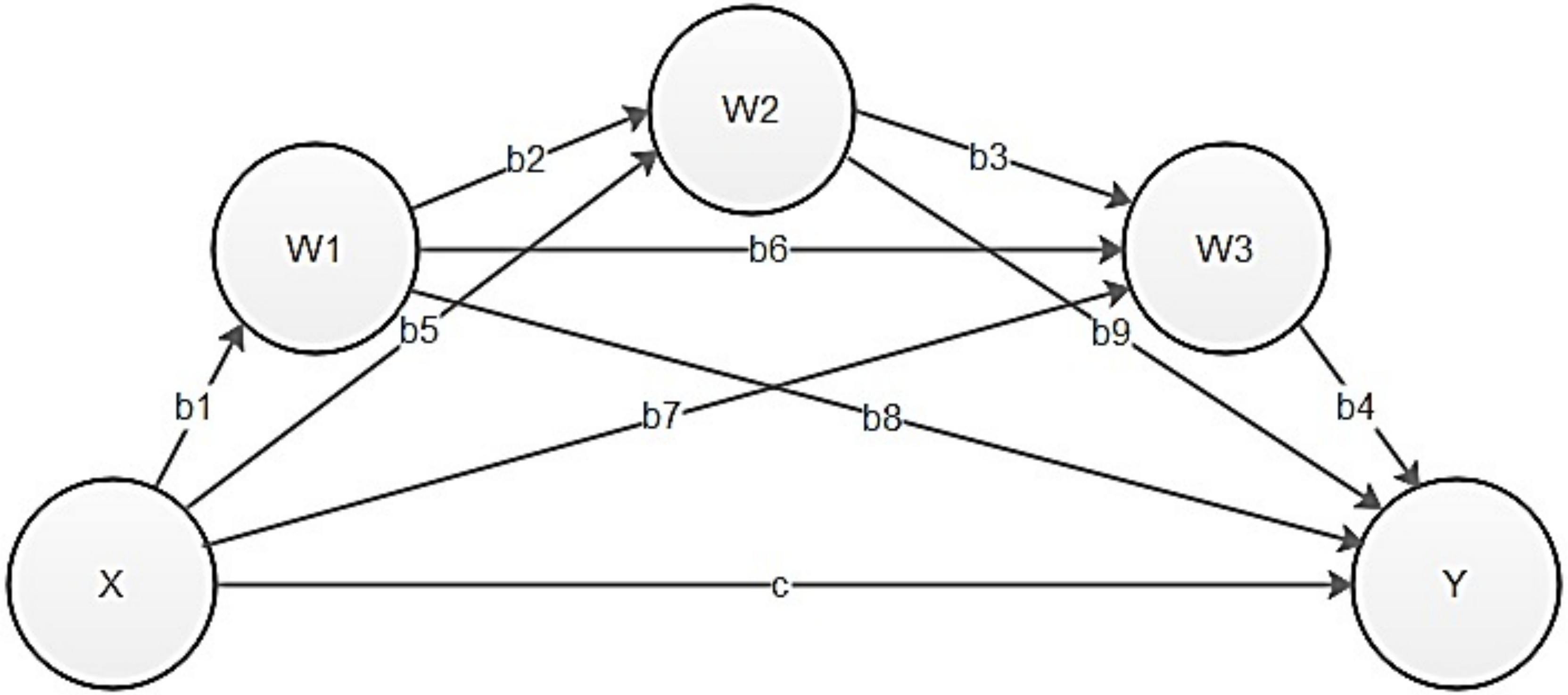
H: b1*b2*b3*b4 $\neq$ 0

H: b5*b3*b4 $\neq$ 0

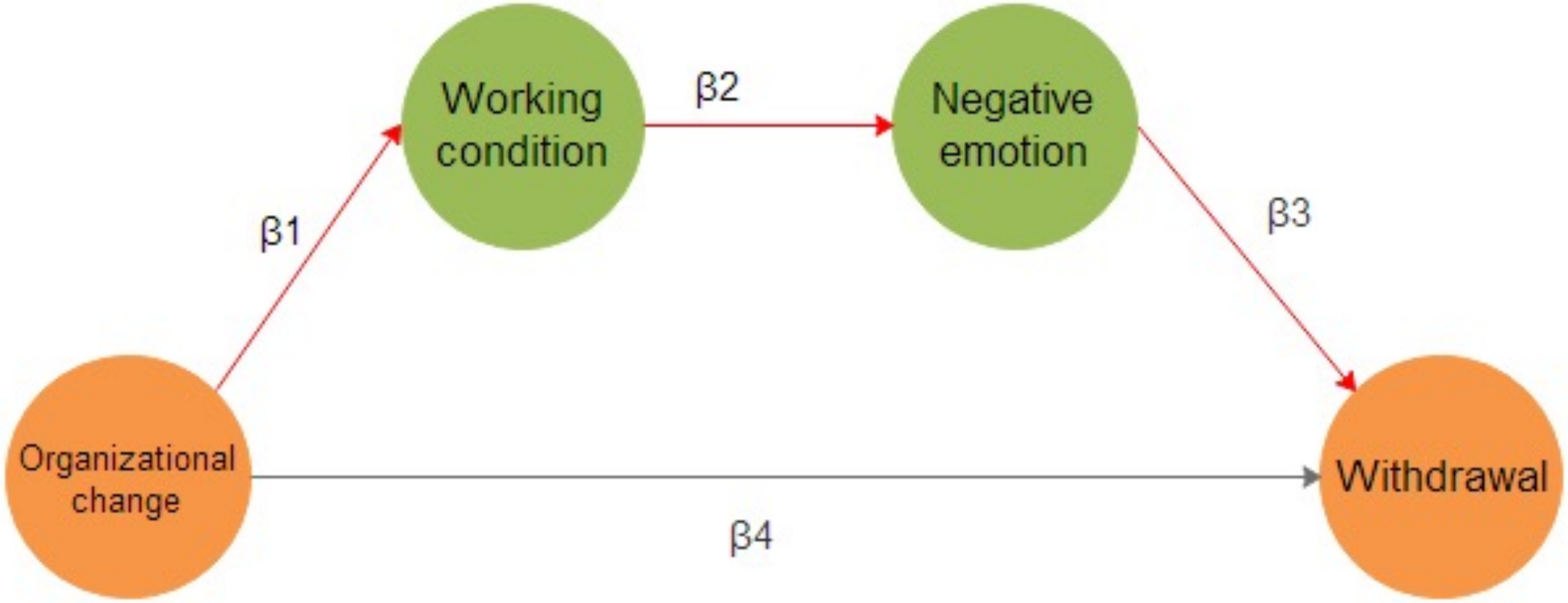
H: b5*b9 $\neq$ 0

H: b7*b4 $\neq$ 0

H: c $\neq$ 0



Example serial mediation model



Aaron B. Taylor David P. MacKinnon Jenn-Yun Tein (2007).Tests of the Three-Path Mediated Effect, Organizational Research Methods Online First, published on July 23, 2007 as doi: 10.1177/1094428107300344

ตัวอย่าง serial mediation model

AIDA model and its modifications

Basic AIDA Model: Awareness⟶ Interest⟶ Desire⟶ Action

(Priyanka, R., 2013)

Lavidge et al.'s Hierarchy of Effects: Awareness⟶ Knowledge⟶ Liking⟶ Preference⟶ Conviction⟶ Purchase

(Lavidge,R.J. and Steiner, G.A., 1961)

McGuire's model: Presentation ⟶ Attention ⟶ Comprehension ⟶ Yielding ⟶ Retention ⟶ Behavior.

(McGuire, W., 1978)

Modified AIDA Model: Awareness⟶ Interest⟶ Conviction ⟶Desire⟶ Action (purchase or consumption)

(Barry, T.E. and Howard, D.J., 1990)

AIDAS Model: Attention ⟶ Interest ⟶ Desire ⟶ Action ⟶ Satisfaction

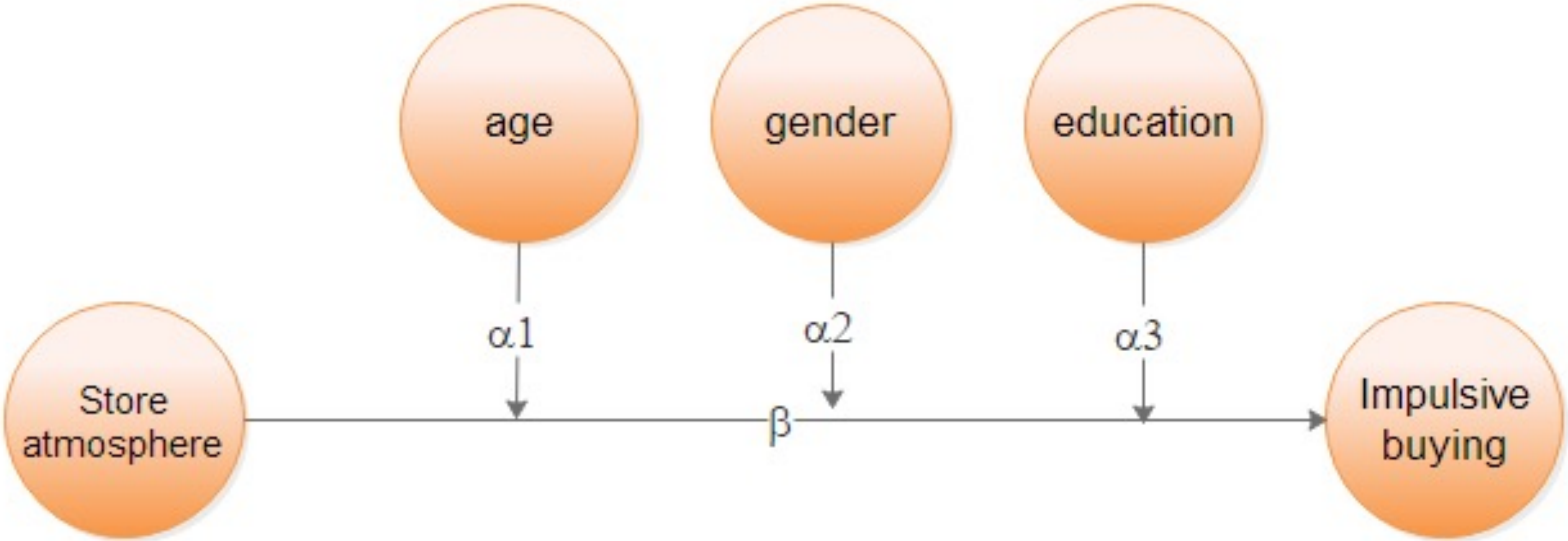
(Barry, T.E. and Howard, D.J., 1990)

AISDALSLove model: Awareness⟶ Interest⟶ Search ⟶Desire⟶ Action ⟶ Like/Dislike ⟶ Share ⟶ Love/ Hate

(Wijaya, Bambang Sukma, 2012)

Moderation Analysis

Example Moderation model



Akram, U., Hui, P., Khan, M. K., Hashim, M. and Rasheed, S. (2016). SERSC Impact of Store Atmosphere on Impulse Buying Behavior: Moderating Effect of Demographic Variables, International Journal of u- and e- Service, Science and Technology Vol.9, No. 7 (2016), pp.43-60

Process in Mediation analysis, Moderation analysis, Moderated mediation model, Moderated moderation analysis throush PROCESS

1. Assess the data file by using SEM software, e.g., Smart PLS, ADANCO, LISREL, AMOS (convergent validity, discriminant validity, item collinearity, EFA, CFA)

2. data cleaning (missing data imputation, unengaged case deletion, trimming, Winzorizing)

3. summate score by total score, construct score, z-score

4. Choose a template and run. If no template satisfy our model, customize it. If run by using SEM software we have to run another software for testing indirect effect or conditional direct/indirect effect such as Sobel's Z-test.

Test of 3-path causal chain

Methods of Testing the Three-Path Mediated Effect

Method	Test ($\alpha = .05$)
Joint significance	Reject Hypothesis$_0$ if $\lvert b_1\rvert/s_{b1} > t_{.975(n-2)}$ and $\lvert b_2\rvert/s_{b2} > t_{.975(n-3)}$ and $\lvert b_3\rvert/s_{b3}\ t_{.975(n-4)}$, where $t_{.975(df)}$ is the critical t value for a two-tailed test given the *df*. For example, $t_{.975(100)} = 1.98$.
Multivariate delta standard error	Reject Hypothesis$_0$ if 95% confidence interval $= b_1b_2b_3 \pm z_{.975}(s^2_{\text{multivariate delta}})^{1/2}$ does not include zero, where $s^2_{\text{multivariate delta}} = b_1^2b_2^2s_{b3}^2 + b_1^2b_3^2s_{b2}^2 + b_2^2b_3^2s_{b1}^2$ and $z_{.975} = 1.96$.
Unbiased standard error	Reject Hypothesis$_0$ if 95% confidence interval $= b_1b_2b_3 \pm z_{.975}(s^2_{\text{unbiased}})^{1/2}$ does not include zero, where $s^2_{\text{unbiased}} = b_1^2b_2^2s_{b3}^2 + b_1^2b_3^2s_{b2}^2 + b_2^2b_3^2s_{b1}^2 - b_1^2s_{b2}^2s_{b3}^2 - b_2^2s_{b1}^2s_{b3}^2 - b_3^2s_{b1}^2s_{b2}^2 + s_{b1}^2s_{b2}^2s_{b3}^2$.
Exact standard error	Reject Hypothesis$_0$ if 95% confidence interval $= b_1b_2b_3 \pm z_{.975}(s^2_{exact})^{1/2}$ does not include zero, where $s^2_{\text{exact}} = b_1^2b_2^2s_{b3}^2 + b_1^2b_3^2s_{b2}^2 + b_2^2b_3^2s_{b1}^2 + b_1^2s_{b2}^2s_{b3}^2 + b_2^2s_{b1}^2s_{b3}^2 + b_3^2s_{b1}^2s_{b2}^2 + {}^2_{b1}s_{b2}^2s_{b3}^2$.
Percentile bootstrap	Draw a large number of bootstrap samples and estimate $b_1b_2b_3$ in each to form bootstrap distribution. Endpoints of a 95% confidence interval are 2.5th and 97.5th percentiles of distribution. Reject Hypothesis$_0$ if confidence interval does not include zero.
Bias-corrected bootstrap	Form bootstrap distribution as above. Find p, proportion of the distribution greater than original sample $b_1b_2b_3$. Calculate $z_{\text{lower}} = -1.96 + 2z_0$ and $z_{\text{upper}} = 1.96 + 2z_0$, where z_0 is the z score corresponding to probability p. For example, for $p = .55$, $z_0 = 0.13$. End points of a 95% confidence interval are percentile ranks from the bootstrap distribution corresponding to normal percentiles for z_{lower} and z_{upper}. Reject Hypothesis$_0$ if confidence interval does not include zero.

Research tool assessment

Convergent validity

1. Measure of homogeneity, i.e., indicators in any specific block must covary

2. Loading ≥ .707 or at least 0.5 so that AVEq $\geq$ 0.50 where **AVEq** = $\frac{1}{P_q}\lambda^2_{\hat{\xi}_q \to x_{pq}} \geq 0.50$

3. Cronbach's alpha $\alpha_q = \frac{\sum_{p \neq p'}^{P_q} corr(x_{pq}, x_{p'q})}{P_q + \sum_{p \neq p'}^{P_q} corr(x_{pq}, x_{p'q})} * \frac{P_q}{P_q - 1} \geq 0.7$

4. Composite Reliability (CR), Dillon-Goldstein's ρ, Joreskog's ρ

$$\rho_q = \frac{\left(\sum_{p=1}^{P_q} \lambda_{pq}\right)^2}{\left(\sum_{p=1}^{P_q} \lambda_{pq}\right)^2 + \sum_{p=1}^{P_q}(1 - \lambda_{pq}^2)} \geq 0.6$$

5. No item multicollinearity

Research tool assessment

Discriminant validity

1. HTMT ratio < 1

$$\underbrace{\mathrm{HTMT}_{ij} = \frac{1}{K_i K_j}\sum_{g=1}^{K_i}\sum_{h=1}^{K_j} r_{ig,jh}}_{\text{average heterotrait–heteromethod}} \div \underbrace{\left(\frac{2}{K_i(K_i-1)}\cdot\sum_{g=1}^{K_i-1}\sum_{h=g+1}^{K_i} r_{ig,ih}\cdot\frac{2}{K_j(K_j-1)}\cdot\sum_{g=1}^{K_j-1}\sum_{h=g+1}^{K_j} r_{jg,jh}\right)^{\frac{1}{2}}}_{\substack{\textit{geometric mean of the average monotrait–heteromethod} \\ \textit{correlation of construct } \xi_i \textit{ and the average} \\ \textit{monotrait–heteromethod correlation of construct } \xi_j}}.$$

2. Cross loading

Jörg Henseler & Christian M. Ringle & Marko Sarstedt (2015),A new criterion for assessing discriminant validity in variance-based structural equation modeling J. of the Acad. Mark. Sci. (2015) 43:115–135

Model quality

When looking at any outcome variable that was affected by some antecedents, effect size of each antecedent will show how important they are. Effect size define as:

$$f_i^2 = \frac{R^2_{included} - R^2_{excluded}}{1 - R^2_{included}}, \; i = 1,2,3,\ldots,k$$

$f_i^2 = 0.02$ LV_i left least effect, i.e., least important

$f_i^2 = 0.15$ LV_i left medium effect, i.e., medium important

$f_i^2 = 0.35$ LV_i left high effect, i.e., high important

Lathan, H. and Ramli, N. A. (2013). The Results of Partial Least Squares-Structural Equation Modelling Analyses (PLS-SEM), Retrieved 1 June, 2018 from https://www.researchgate.net/profile/Hengky_Latan/publication/272304948_The_Results_of_Partial_Least_Squares-Structural_Equation_Modelling_Analyses_PLS-SEM/links/59e86340a6fdccfe7f8b49e9/The-Results-of-Partial-Least-Squares-Structural-Equation-Modelling-Analyses-PLS-SEM.pdf

Model quality

Communality is an average value of item reliability also present in Average Variance Extracted (AVE) use for explaining how LV reflect its characteristics to its indicators.

$$\mathrm{Com}_q = \frac{1}{P_q} \sum_{p}^{P_q} \mathrm{corr}^2(x_{pq}, \hat{\xi} q)$$

where Pq is number of indicator in q_{th} block.

R-square is a ratio of explained to total variation in Y

$R^2 = 0.02$ means antecedent LV left small effect to outcome LV

$R^2 = 0.13$ means antecedent LV left medium effect to outcome LV

$R^2 = 0.26$ means antecedent LV left high effect to outcome LV

Lathan, H. and Ramli, N. A. (2013). The Results of Partial Least Squares-Structural Equation Modelling Analyses (PLS-SEM), Retrieved 1 June, 2018 from https://www.researchgate.net/profile/Hengky_Latan/publication/272304948_The_Results_of_Partial_Least_Squares-Structural_Equation_Modelling_Analyses_PLS-SEM/links/59e86340a6fdccfe7f8b49e9/The-Results-of-Partial-Least-Squares-Structural-Equation-Modelling-Analyses-PLS-SEM.pdf

Model quality

Note

CB-SEM software and VB-SEM software assess model quality by different method

CB-SEM mostly use EFA and CFA by using root mean square error ≤ 0.05, $\frac{\chi^2}{df} < 2$ and fit index ≥ 0.9

Model quality note

Note

VB-SEM develop its algorithm by using OLS, i.e., minimize sum square residual $\frac{d}{d\hat{\beta}}\sum_{i=1}^{n} e_i^2 = 0.$ No normal assumption is needed, no multivariate normal assumption is assume, so, no covariance matrix is use then no chi-square test for good fit is employed. But VBSEM use

1. Convergent validity

loadings are positive, no item multicollinearity, significant, with value at least 0.707 or at least 0.5 but with AVE at least 0.5

2. Discriminant validity

HTMT< 1 or cross correlation are discriminated, CR $\geq$ 0.6

Mediation analysis

Mediation analysis aims to investigate how does antecedent affects outcome variable

1) directly influent (observe from significance of total effect and direct effect)

and/or

2) indirectly influent (observe from significance of indirect effect)

Importance of Mediation analysis

(1) The mediators help transmit in dark. They are unknown to discipline under investigation so that when found it is a novelty. Most often, these variables come from practical perspective rather than theoretical perspective.

(2) Mediators help force changing outcome variable because there are successive impact on causal chain from antecedent through mediator (s) to outcome variable. So, mediators are underlying condition of change in outcome variable.

Mediation analysis

Research question can be

How antecedent impacts outcome variable? Or

Whether mediator(s) help increase more impact of antecedents on outcome variable(s)

There are a lot of templates support mediation study mostly in an integration concept.

Templates

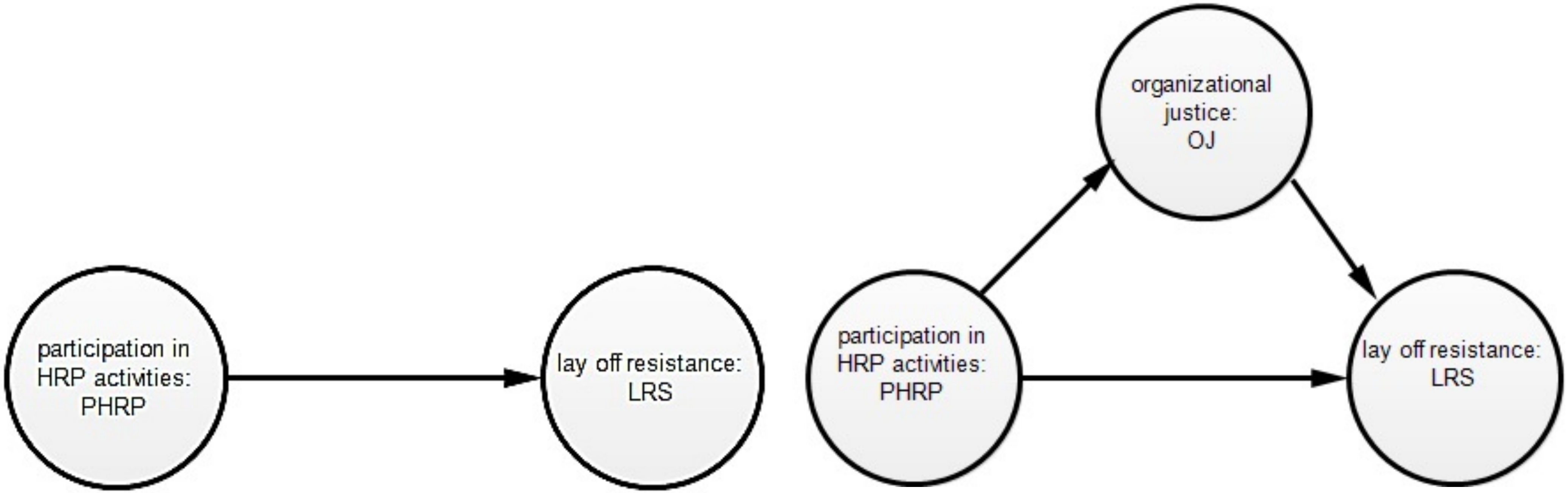
Mediation analysis example

Example 1

participation in HRP⟶lay off acceptance

In practice, if employees were laid off they always object, veto, obstruct, hate and prosecute the organization. But, however, if the lay off process was operated with the principle of organization justice we believe that objection, veto, obstruction, hostile and prosecute will be exiguous (Rockwood, J., 2017).

Mediation analysis

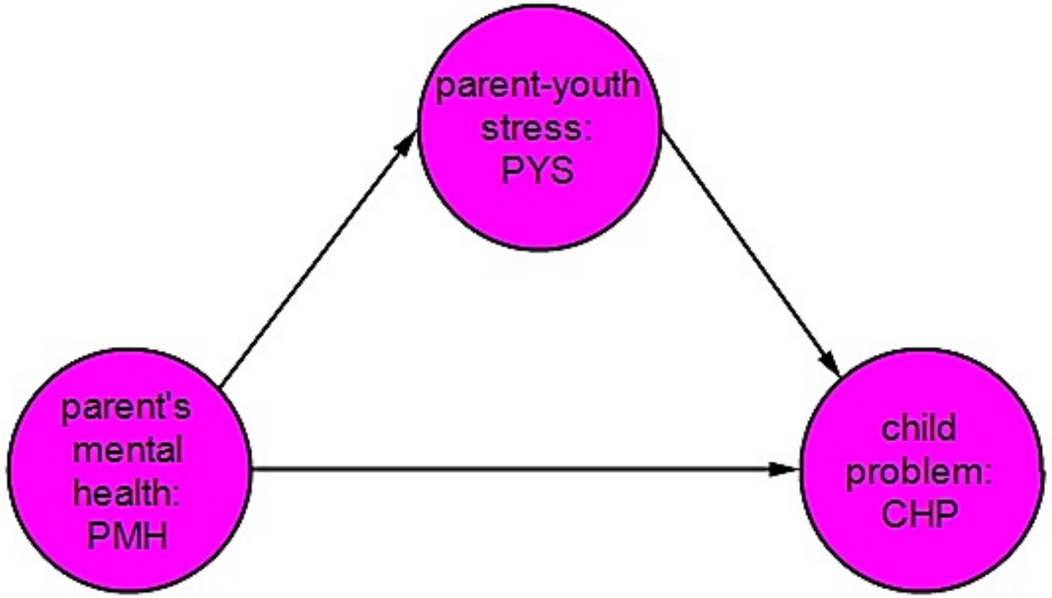


Mediation analysis

Example 2

parent mental health⟶child problem

Child problem originates from family living environment and relationship between family member. If some stress between parent and child more child problem follows. (Rockwood, J. 2017



Mediation analysis

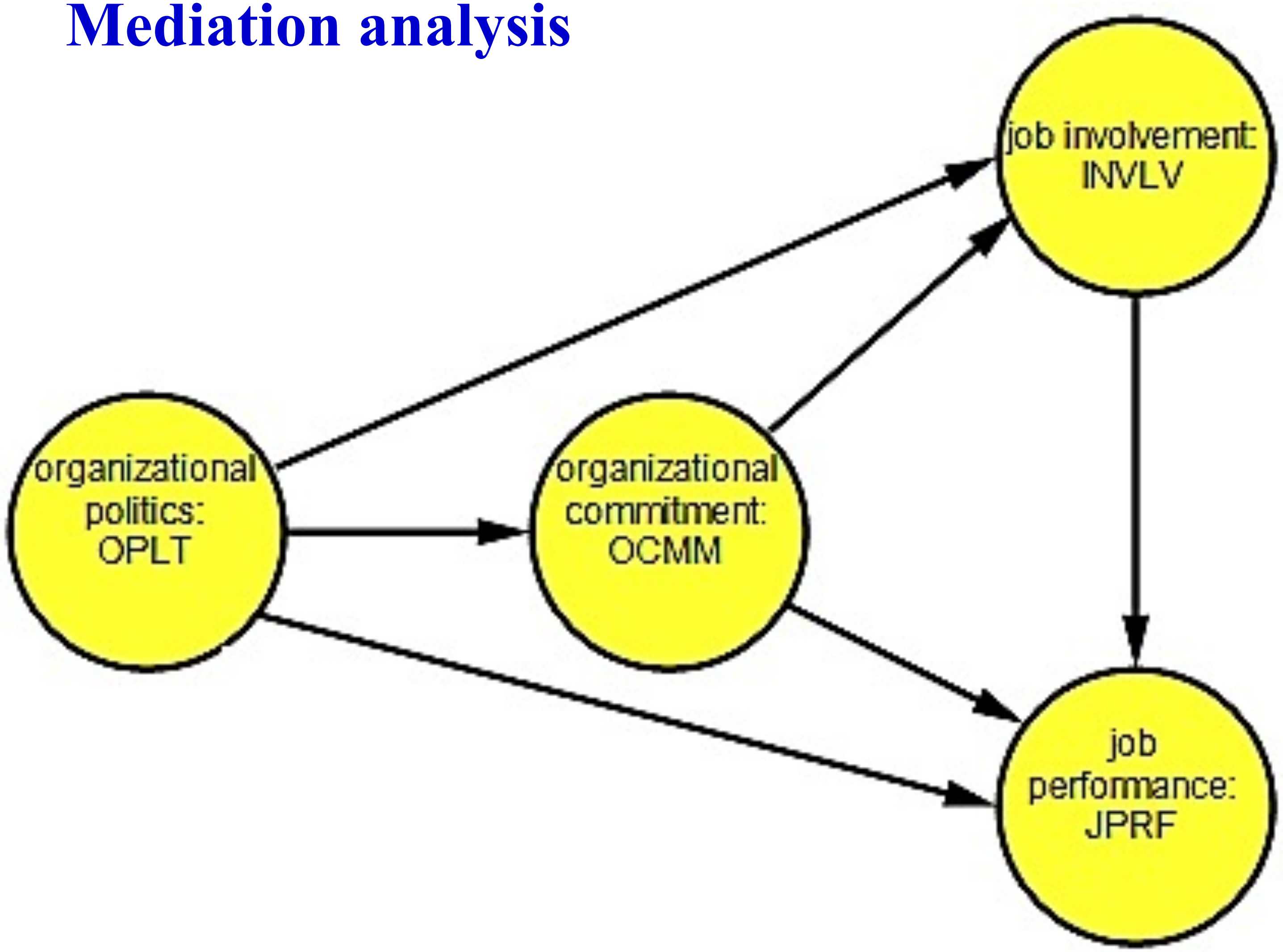
Example 3

organizational politics→job performance

organizational politics→job involvement

Generally, politics in organization leave a negative impact to lob involvement and job performance. If there is organization commitment especially affective commitment some negative effect may decline.

Mediation analysis



Awan, K. Z., Ibn-e-Waleed Qureshi, I., Akram, M. and Shahzad, K. (2014), Mediation Role of Organizational Commitment in the Relationships of Organizational Politics and Job Involvement and Employee Performance, International Journal of Academic Research in Economics and Management Sciences Nov 2014, Vol. 3, No. 6.

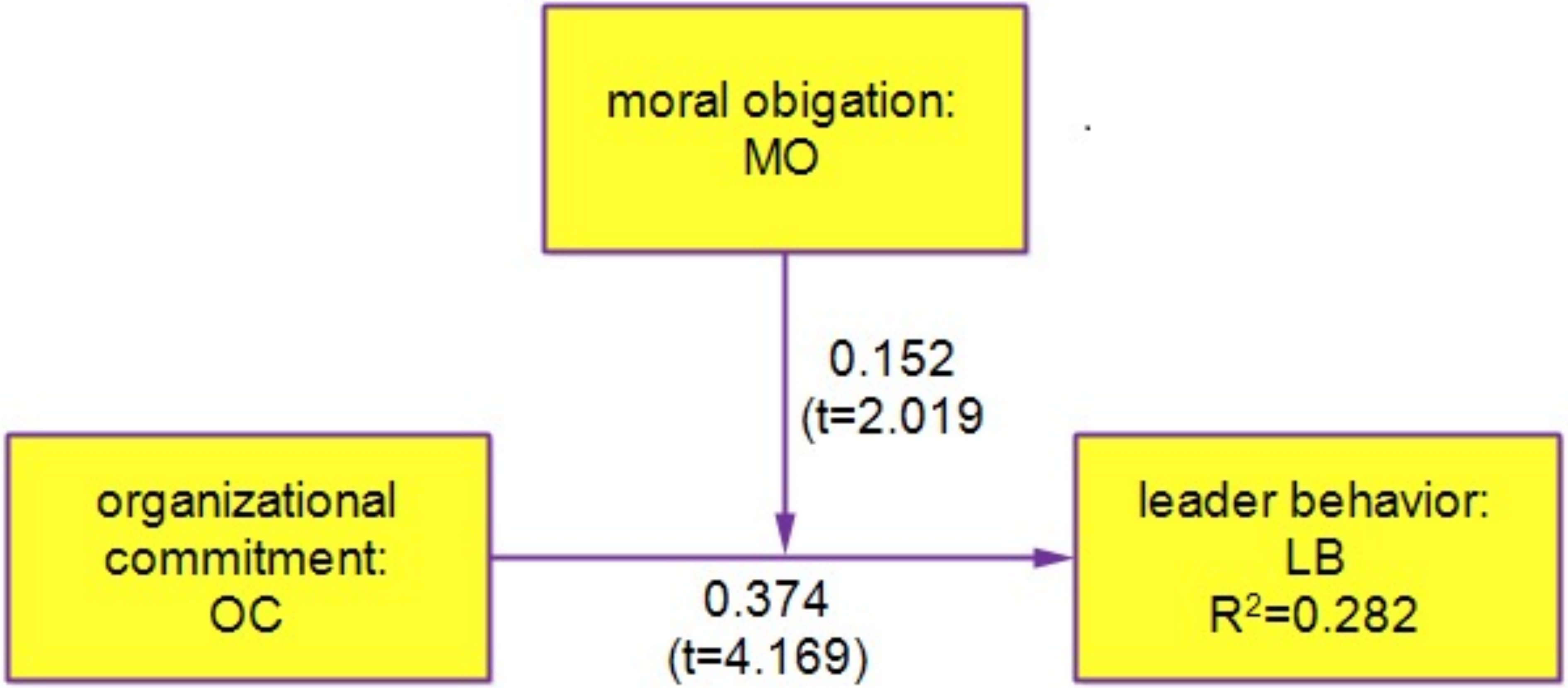
Moderation analysis

Moderation analysis aims to investigate at what values of moderators (W, Z) causes X leaves more (or less) effects on Y

Example

Conditional effects of moral obligation on the direct effect of organization commitment on leader behavior

moderation analysis (model 1)



Total effect = 0.489 t=6.954

Model 1,7

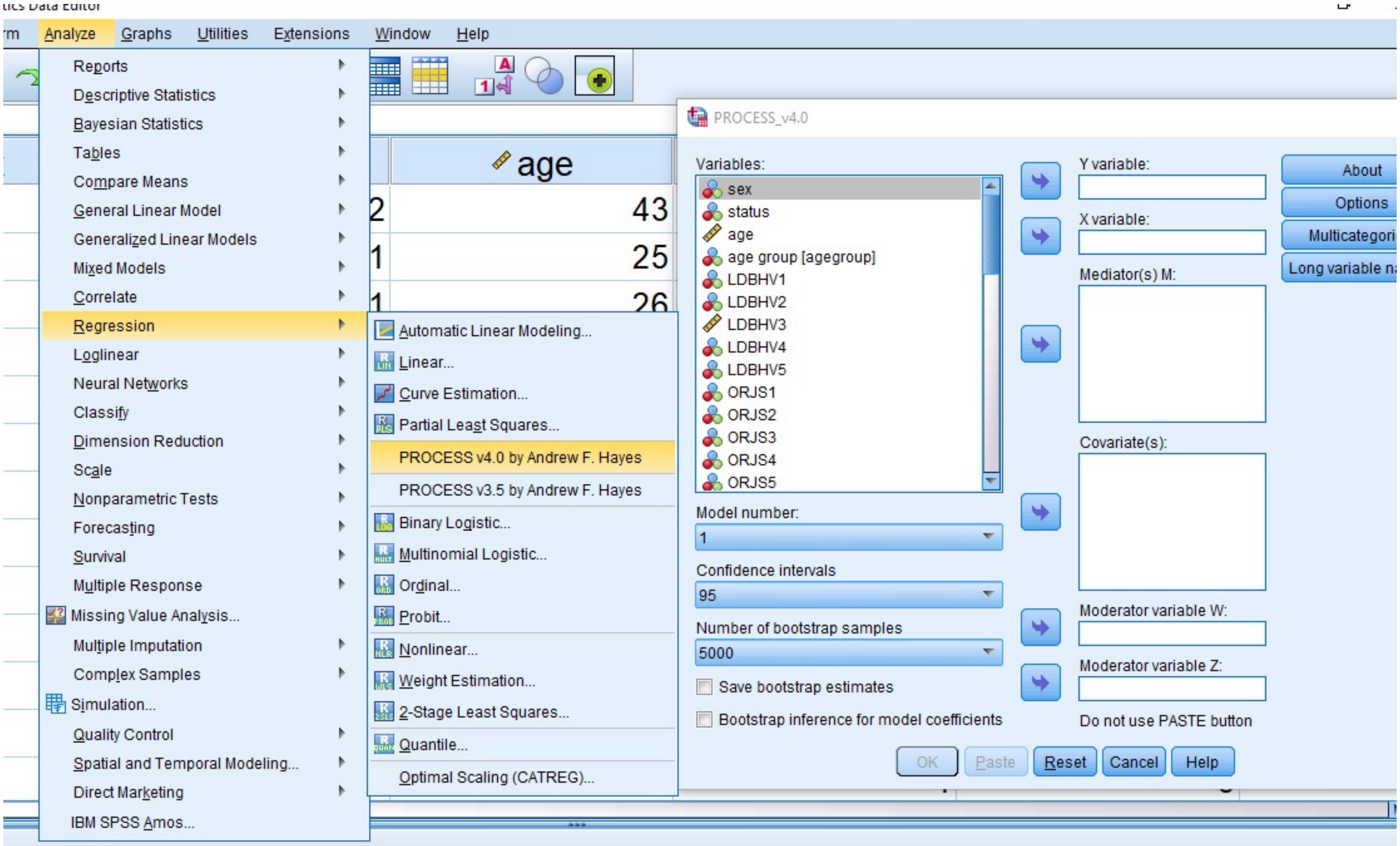
moderation analysis (model 1)

From model there is 1 equation as

$$LB = \beta_o + \beta_1 OC + \beta_2 MO + \beta_3 OC * MO + u$$

After rearrange, the conditional direct effect will be a function of MO as shown

$$LB = \beta_o + \beta_2 MO + \beta_1 OC + \beta_3 OC * MO + u$$
$$= \beta_o + \beta_2 MO + (\beta_1 + \beta_3 MO) OC + u$$


Analyze
Graphs
Utilities
Extensions
Window
Help
Reports
Descriptive Statistics
Bayesian Statistics
Tables
Compare Means
General Linear Model
Generalized Linear Models
Mixed Models
Correlate
Regression
Loglinear
Neural Networks
Classify
Dimension Reduction
Scale
Nonparametric Tests
Forecasting
Survival
Multiple Response
Missing Value Analysis...
Multiple Imputation
Complex Samples
Simulation...
Quality Control
Spatial and Temporal Modeling...
Direct Marketing
IBM SPSS Amos...
Automatic Linear Modeling...
Linear...
Curve Estimation...
Partial Least Squares...
PROCESS v4.0 by Andrew F. Hayes
PROCESS v3.5 by Andrew F. Hayes
Binary Logistic...
Multinomial Logistic...
Ordinal...
Probit...
Nonlinear...
Weight Estimation...
2-Stage Least Squares...
Quantile...
Optimal Scaling (CATREG)...
age
43
25
26
PROCESS_v4.0
Variables:
sex
status
age
age group [agegroup]
LDBHV1
LDBHV2
LDBHV3
LDBHV4
LDBHV5
ORJS1
ORJS2
ORJS3
ORJS4
ORJS5
Y variable:
X variable:
Mediator(s) M:
Covariate(s):
Moderator variable W:
Moderator variable Z:
Do not use PASTE button
Model number:
1
Confidence intervals
95
Number of bootstrap samples
5000
Save bootstrap estimates
Bootstrap inference for model coefficients
About
Options
OK
Paste
Reset
Cancel
Help

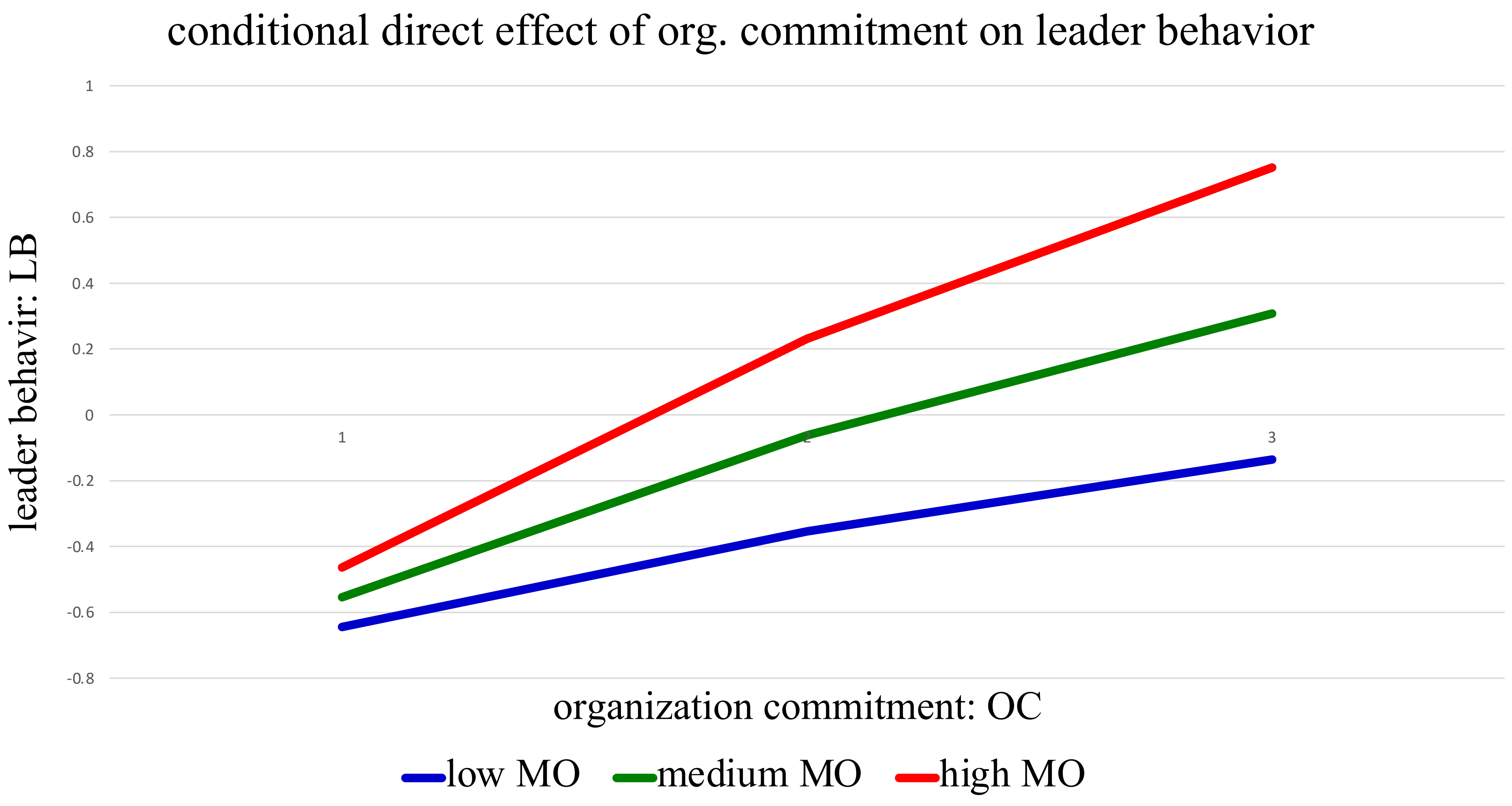
Interpretation

It was found that OC left a direct effect to LB and the effect decline somewhat after insertion of moderator, MO, between them (effect declined from 0.489**to 0.374**) which revealed that not only OC that affect LB. Insertion of MO comes from beliefs that interaction, i.e., OC*MO caused change in LB if employees practiced better MO.

Both conditional direct effect as displayed in pick-a-point manner and a Neyman-Johnson output indicated that as MO went higher (i.e., employees recognize better goodness) OC will cause leaders offer better practices and provide better offerings for there followers.

Conditional effects of the focal predictor at values of the moderator(s):

MO	Effect	se	t	p	LLCI	ULCI
-1.035	0.2182	0.1154	1.8905	0.0606	-0.01	0.4462
-0.026	0.3697	0.0895	4.1288	0.0001	0.1928	0.5466
0.983	0.5213	0.1183	4.4076	0.0000	0.2876	0.7549


conditional direct effect of org. commitment on leader behavior
leader behavir: LB
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
1
2
3
organization commitment: OC
low MO
medium MO
high MO

Conditional effect of focal predictor at values of the moderator (Johnson-Neyman output):

MO	Effect	se	t	p	LLCI	ULCI
-3.052	-0.085	0.2403	-0.353	0.7245	-0.5596	0.3899
-2.817	-0.05	0.2241	-0.221	0.8255	-0.4923	0.3933
-2.581	-0.014	0.2082	-0.068	0.9460	-0.4254	0.3972
-2.346	0.0212	0.1925	0.1102	0.9124	-0.3591	0.4016
-2.111	0.0566	0.1772	0.3193	0.7500	-0.2935	0.4067
-1.875	0.0919	0.1623	0.5663	0.572	-0.2288	0.4126
-1.64	0.1273	0.148	0.8599	0.3912	-0.1652	0.4198
-1.404	0.1626	0.1345	1.2092	0.2284	-0.1031	0.4284
-1.169	0.198	0.122	1.6231	0.1066	-0.0430	0.439ข
-0.994	0.2243	0.1135	1.9757	0.0500	0.0000	0.4486
-0.934	0.2334	0.1108	2.1054	0.0369	0.0144	0.4523
-0.698	0.2687	0.1015	2.6474	0.009ข	0.0682	0.4692
-0.463	0.3041	0.0945	3.2171	0.0016	0.1173	0.4908
-0.228	0.3394	0.0904	3.7533	0.0002	0.1608	0.5181
0.0078	0.3748	0.0896	4.1807	0.0000	0.1977	0.5519
0.2432	0.4101	0.0922	4.4464	0.0000	0.2279	0.5924
0.4786	0.4455	0.0979	4.5482	0.0000	0.252ข	0.639ข
0.714	0.4808	0.1063	4.5248	0.0000	0.2709	0.6908
0.9493	0.5162	0.1166	4.4255	0.0000	0.2857	0.7467
1.1847	0.5516	0.1286	4.2897	0.0000	0.2975	0.8056
1.4201	0.5869	0.1417	4.1427	0.0001	0.307ข	0.8668
1.6555	0.6223	0.1556	3.998	0.0001	0.3148	0.9298

Interpretation of moderation analysis

Moderation is interaction effect, i.e., effect of X*W on Y when other variables in model hold constant. Significant coefficient of X*W can be interpreted as:

1. If positive, X will leave more effect on Y if W assume larger value.

2. If negative, X will leave less effect on Y if W assume larger value.

Interpretation of moderation analysis

Line graph of X⟶ Y at different values of W will help explain the effects on different conditions, i.e., pick-a-point if coefficient of X*W non-significant and both pick-a-point and Johnson-Neyman output if significant. Conditioning values of W are all possible values in Johnson-Neyman output and low-medium-high in pick-a-point.

We label mean, mean-sd, mean+sd as medium value, low value and high value respectively.

Moderation analysis-how to calculate effects

From

$$Y = \beta_o + \beta_1 X + \beta_2 W + \beta_3 X * W + u$$

$$Y = \beta_o + \beta_2 W + \beta_1 X + \beta_3 X * W + u$$

$$= \beta_o + \beta_2 W + (\beta_1 + \beta_3 W) X + u$$

Term $\omega = (\beta_1 + \beta_3 W)$ indicates effect of X on Y. It is a condition direct effect which was a function of W. If we execute a 5,000 bootstrapping we will have 5,000 estimated values of $\beta_o, \beta_1, \beta_2, \beta_3$ and 3*5,000 = 15,000 value of ω and $\hat{Y}$

Moderated mediation analysis

Moderated mediation analysis is an integration of mediation analysis and moderation analysis. It aims to disclose both HOW and WHEN perceptions

Process for moderated mediation analysis

1. Investigate whether M_1, M_2, …, M_k are mediators. If they are mediators we can conclude that M_1, M_2, …, M_k help X more explain Y (observe at significance of indirect effects)

2. At the moderated path(s) if interaction is significant, X will leave direct effect on outcome variable(s) at values of W (observe from significant of X*W, pick-a-point and Johnson-Neyman output)

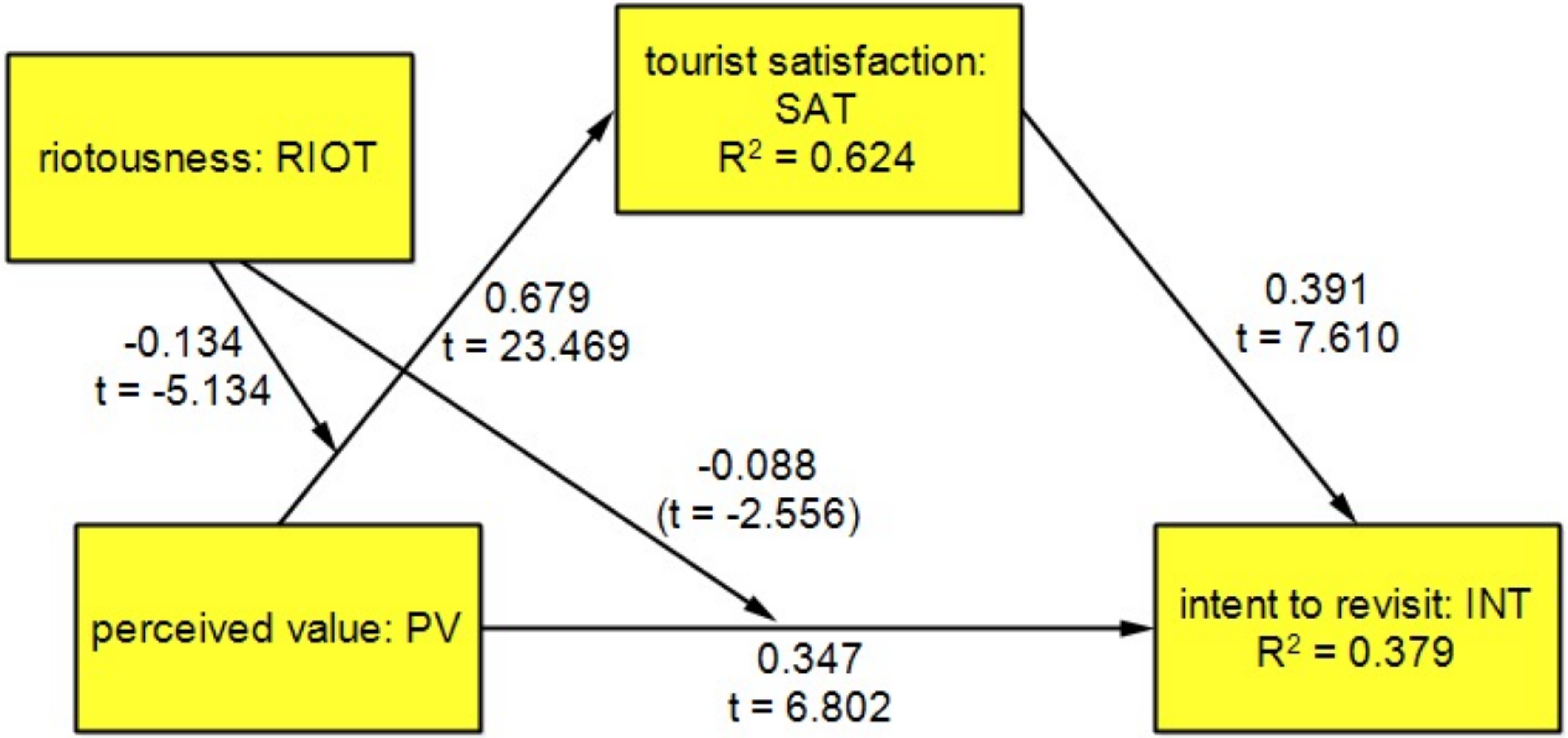
Moderated mediation analysis

3. How change in IE at values of W (observe from conditional indirect effect)

4. Whether, in overview, W causes change in IE (observe at index of moderated mediation and pairwise contrast between conditional indirect effect)

Moderation effect of riotousness on the effect of perceived value on intention to revisit through tourist satisfaction

Moderated mediation analysis (model 8)



total effect = 0.534, t = 15.809

Model 1,7

Moderated mediation analysis (model 8)

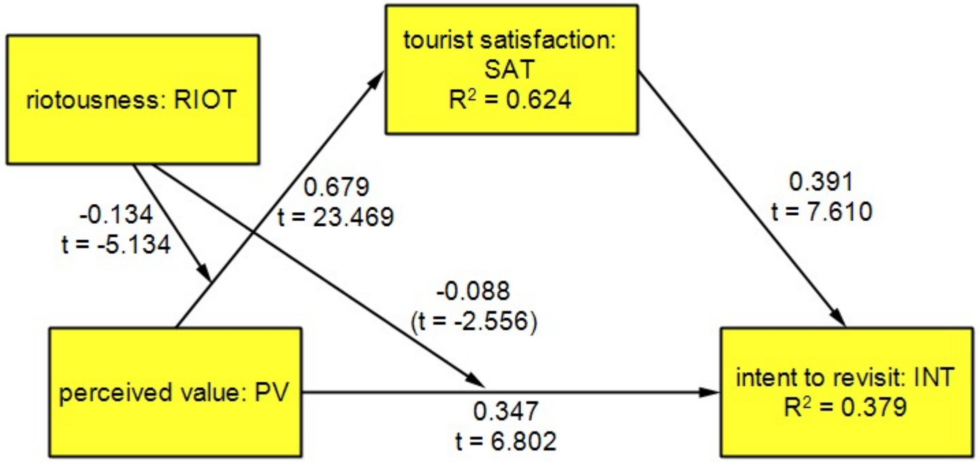
Two equations are

1. $\mathrm{SAT} = \beta_o + \beta_1\mathrm{PV} + \beta_2\mathrm{RIOT} + \beta_3\mathrm{PV} * \mathrm{RIOT} + u$

   $\mathrm{SAT} = \beta_o + \beta_2\mathrm{RIOT} + (\beta_1 + \beta_3\mathrm{RIOT})\mathrm{PV} + u$

2. $\mathrm{INT} = \beta_o + \beta_1\mathrm{PV} + \beta_2\mathrm{SAT} + \beta_3\mathrm{PV} * \mathrm{RIOT} + u$

   $\mathrm{INT} = \beta_o + \beta_2\mathrm{SAT} + (\beta_1+\beta_3\mathrm{RIOT})\mathrm{PV} + u$



Interpretation

From picture and tables, DI has declined by 35% after insertion of mediator (here is SAT) in to the model

(total effect = 0.534, t = 15.809, direct effect = 0.347, t = 6.802) and IE was high (IE = 0.326 resulted from model 4). It revealed that PV is very important cause of revisited intention and PV played a role of re-enforce so that PV affect Int much stronger.

Research claimed that RIOT will lower effect of PV on INT.

Analysis shown that RIOT*PV left negative effect on SAT and INT. So, If more RIOT tourists will have less SAT and less INT with no regard to values of PV.

From analysis of PV $\longrightarrow$ SAT $\longrightarrow$ INT, we found the IE was significant decrease at all increasing values of RIOT. And finally, RIOT cause change in mediating role of SAT.

Focal predict: PV (X) Mod var: RIOT (W) Dep var: SAT						
Conditional effects of the focal predictor at values of the moderator(s):						
RIOT	**Effect**	**se**	**t**	**p**	**LLCI**	**ULCI**
-0.9199	0.8028	0.0368	21.8428	0.0000	0.7306	0.8750
-0.2684	0.7154	0.0295	24.2797	0.0000	0.6575	0.7732
1.0347	0.5405	0.0405	13.3366	0.0000	0.4610	0.6201

Johnson-Neyman output

Conditional effect of focal predictor at values of the moderator:						
RIOT	Effect	se	t	p	LLCI	ULCI
-1.2456	0.8465	0.0425	19.8991	0.0000	0.763	0.93
-1.0285	0.8174	0.0386	21.1918	0.0000	0.7416	0.8931
-0.8113	0.7882	0.0351	22.4742	0.0000	0.7194	0.8571
-0.5941	0.7591	0.0322	23.5727	0.0000	0.6959	0.8223
-0.3769	0.73	0.0301	24.2202	0.0000	0.6708	0.7891
-0.1598	0.7008	0.0291	24.1218	0.0000	0.6438	0.7579
0.0574	0.6717	0.0291	23.1159	0.0000	0.6146	0.7287
0.2746	0.6425	0.0301	21.3121	0.0000	0.5833	0.7017
0.4917	0.6134	0.0322	19.0384	0.0000	0.5501	0.6767
0.7089	0.5843	0.0351	16.6482	0.0000	0.5153	0.6532
0.9261	0.5551	0.0386	14.383	0.0000	0.4793	0.6309
1.1432	0.526	0.0426	12.3562	0.0000	0.4424	0.6096
1.3604	0.4968	0.0469	10.5952	0.0000	0.4047	0.5889
1.5776	0.4677	0.0515	9.085	0.0000	0.3666	0.5688
1.7948	0.4386	0.0563	7.7942	0.0000	0.3281	0.5491
2.0119	0.4094	0.0612	6.6892	0.0000	0.2892	0.5296
2.2291	0.3803	0.0663	5.7389	0.0000	0.2502	0.5104
2.4463	0.3511	0.0714	4.9169	0.0000	0.2109	0.4914
2.6634	0.322	0.0766	4.2015	0.0000	0.1715	0.4725
2.8806	0.2929	0.0819	3.5748	0.0004	0.132	0.4537
3.0978	0.2637	0.0873	3.0223	0.0026	0.0924	0.4351
3.3149	0.2346	0.0926	2.5324	0.0116	0.0527	0.4165

Conditional direct effect(s) of X on Y:						
RIOT	Effect	se	t	p	LLCI	ULCI
-0.9199	0.4278	0.0627	6.8188	0.0000	0.3046	0.5511
-0.2684	0.3707	0.0528	7.0208	0.0000	0.267	0.4744
1.0347	0.2564	0.0591	4.3412	0.0000	0.1404	0.3724

INDIRECT EFFECT:				
PV $\longrightarrow$ SAT $\longrightarrow$ INT				
RIOT	Effect	BootSE	BootLLCI	BootULCI
-0.9199	0.3140	0.0416	0.2409	0.4068
-0.2684	0.2798	0.0373	0.2153	0.3627
1.0347	0.2114	0.0301	0.1608	0.2788

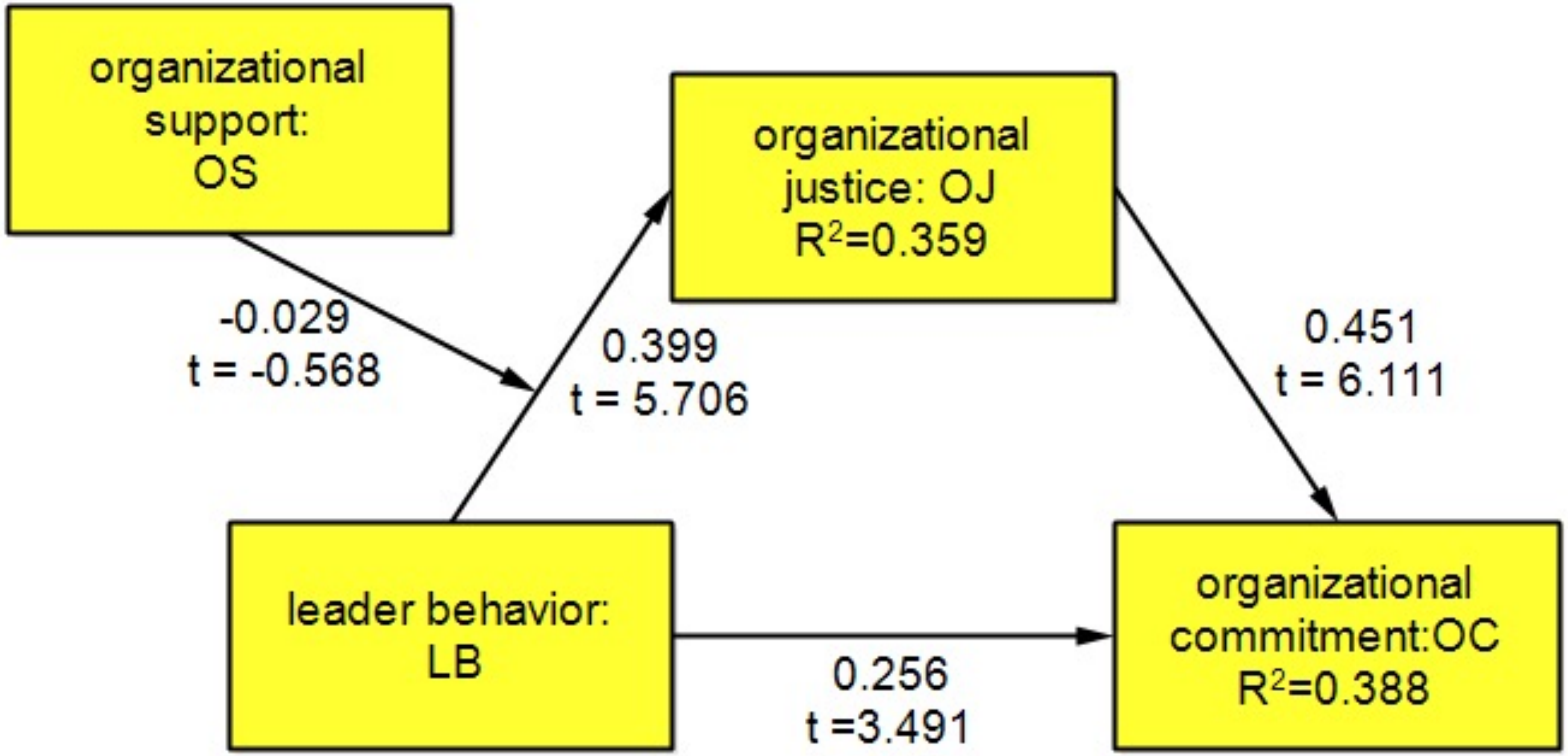
Index of moderated mediation:					
	Index	BootSE	BootLLCI	BootULCI	
RIOT	-0.0525	0.0089	-0.0707	-0.0365	

Pairwise contrasts between conditional indirect effects (Effect1 minus Effect2)

Effect1	Effect2	Contrast	BootSE	BootLLCI	BootULCI
0.2798	0.314	-0.0342	0.0058	-0.0461	-0.0238
0.2114	0.314	-0.1026	0.0175	-0.1382	-0.0713
0.2114	0.2798	-0.0684	0.0117	-0.0921	-0.0475

Example Conditional effects of Organization Support on the effect of Leader Behavior on Organizational Commitment through Organizational Justice

Moderated mediation analysis (model 7)



Total effect = 0.492, t = 7.06

[Model 1,7]

Moderated mediation analysis (model 7)

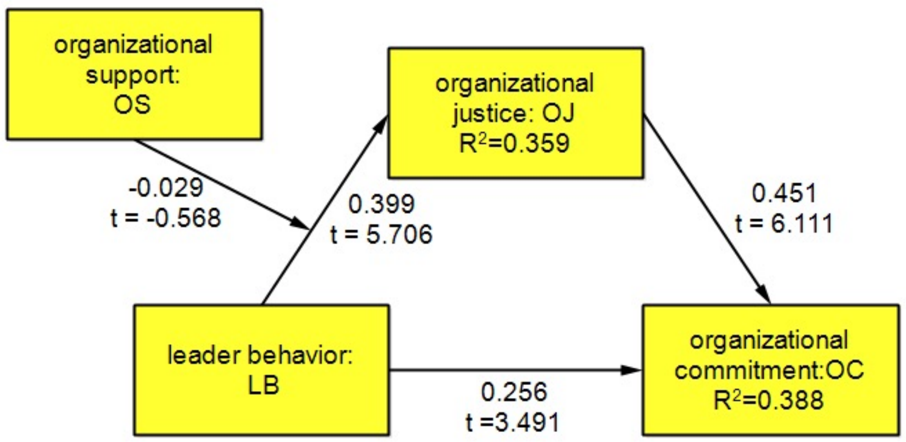
Two equations are

$$OJ = \beta_o + \beta_1 LB + \beta_2 OS + \beta_3 LB * OS + u$$

becomes $OJ = \beta_o + \beta_2 OS + (\beta_1 + \beta_3 OS) LB + u$

and $OC = \beta_o + \beta_1 LB + \beta_2 OJ + u$

Conditional indirect effect = $(\beta_1 + \beta_3 OS) * \beta_2$



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From picture and tables, TE of path LB→OC decrease by about 48% after insertion of OJ (total effect = 0.492, t =7.06, direct effect = 0.256, t = 3.491) and IE assumed high value of 0.210 (from model 4) revealed that OJ helps increase LB on OC.

Research claimed that with an introduction of OS as moderator role of LB on OC may change in preferable direction.

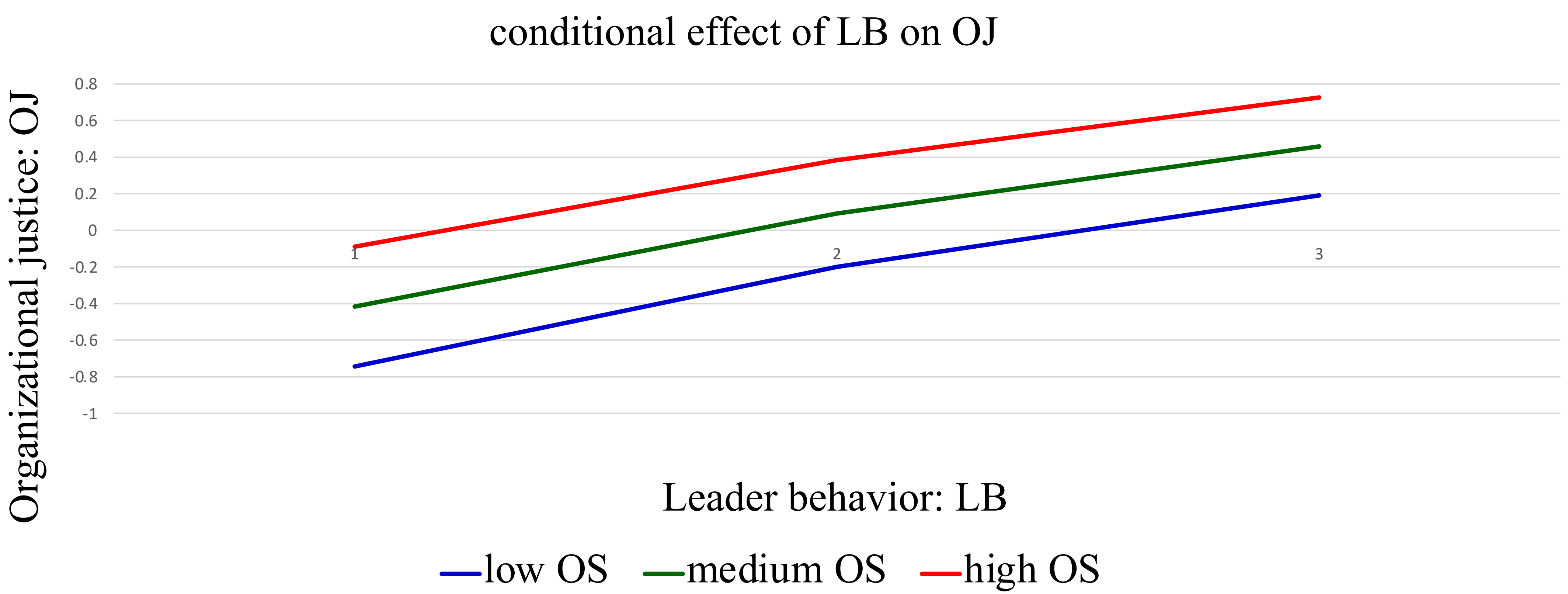
An analysis of moderated mediation analysis revealed that LB*OS assumed a negative quantity but non-significant indicated that OS cause no change, overall, in OJ . But at pick-a-point context we found that LB cause more change in OJ when OS went high.

OS not help change in IE of LB → OJ → OC.

Tendency of predicted OJ at conditional values of OS

LB	OS	OJ
-1.0648	-0.905	-0.7441
0.2149	-0.905	-0.2005
1.1363	-0.905	0.1909
-1.0648	0.0437	-0.4167
0.2149	0.0437	0.0921
1.1363	0.0437	0.4585
-1.0648	0.9923	-0.0893
0.2149	0.9923	0.3847
1.1363	0.9923	0.726

Tendency that LB causes change in LB at 3 different conditions of OS



Conditional indirect effect

OS	Effect	BootSE	BootLLCI	BootULCI
-0.905	0.1914	0.0549	0.0772	0.2874
0.0437	0.1792	0.0431	0.0982	0.2679
0.9923	0.1669	0.0516	0.0850	0.2904

Index of moderated mediation:

	Index	BootSE	BootLLCI	BootULCI
OS	-0.0129	0.033	-0.0521	0.0752

Pairwise contrasts between conditional indirect effects (Effect1 minus Effect2)

Effect1	Effect2	Contrast	BootSE	BootLLCI	BootULCI
0.1792	0.1914	-0.0123	0.0313	-0.0494	0.0713
0.1669	0.1914	-0.0245	0.0627	-0.0989	0.1426
0.1669	0.1792	-0.0123	0.0313	-0.0494	0.0713

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