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STATISTICAL MEDIATION ANALYSIS USING THE SOBEL TEST AND HAYES SPSS PROCESS MACRO

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ABSTRACT: *This paper aims to focus on the emerging practical application of mediational analysis in social science research practice. Objectives: The paper introduces simple mediation analysis to social science researchers discusses two statistical methods used to examine the effect of mediating variables on the relationship between the independent and dependent variables. These are the Sobel test and bootstrapping using Hayes Process Macro. The paper (1) defines and discusses the purpose of mediation, (2) discusses conditions for mediation, (3) presents research questions examined by mediation, (4) outlines assumptions of mediation analysis, (5) presents computer programs used in mediation analysis, and (6) presents a detailed practical example illustrating how to conduct mediating analysis, read the results output, and write the results. Implications: The paper concludes with a discussion on the implications of mediation research for social science research and practice.*

KEYWORDS: *mediation, Sobel test, bootstrap, process macro*

INTRODUCTION

Examination of causal relationships provides understanding of the degree to which variation in the independent variable (X) results in change in a dependent variable (Y). Practically, it offers insight as to whether an intervention or treatment was successful or showed a hypothesized effect. However, few causal explanations exist between two variables alone, as X causes Y, or the X-Y relationship may be reciprocal. Consequently, researchers may seek to examine the degree to which other variables contribute to the simple bivariate relationship between the independent and dependent variables, X and Y, respectively. These variables, sometimes called extraneous variables, intervening variables, covariates, or process variables, offer a more complex and deeper understanding of the relationship between X and Y.

Wegener and Fabrigar (2000) describe three types of intervening variables for causal hypotheses: (1) direct causal effect, (2) mediated causal effect, and (3) moderated causal effect. Mediators and moderators are often confused and used interchangeably

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(Baron and Kenny 1986; Wu and Zumbo 2008). However, as Baron and Kenny (1986) report, they are distinct conceptually, strategically, and statistically. While moderators strengthen the relationship between independent and dependent variables, mediators intervene between the independent and dependent variables. Mediators, labeled as “M”, create an indirect relationship by linking the two variables, X and Y, which helps to explain the process of the relationship. These variables essentially refine a causal relationship by explaining why and how a cause leads to an outcome (Baron and Kenny 1986; Frazier et al. 2004; Wu and Zumbo 2008).

This paper focuses on the emerging practical application of mediational analysis in social science research practice. First, the paper discusses mediating variables and their use, research questions examined by mediation analysis, and then presents two useful statistical methods for analyzing mediating relationships: Sobel test (Sobel 1982) and Hayes SPSS Process Macro (Hayes 2013). The paper also discusses the underlying assumptions for using these analyses. Lastly, a practical example is provided, which illustrates how to compute the analyses and how to interpret the output.

LITERATURE/THEORETICAL UNDERPINNING

The origins of mediation analysis date as far back as 1920 with Sewall Wright’s method of analysis by path coefficients in which he proposed indirect and direct causal relationships for the genetically-derived color variations in guinea pigs (Wright 1920). He described mediation as product of coefficients. Eight years later, R.S. Woodworth presented the Stimulus Organism Response (SOR) theory, which posits that different mediating mechanisms functioning within an organism intervene between the stimulus and the response (Woodworth 1928). As illustrated by these seminal works, mediating variables intervene between or mediate the relationship between the independent and dependent variables.

The value of mediating variables cannot be overstated. As noted, mediating variables are foundational for understanding mechanisms of effects. Additionally, mediating processes underpin many fields, including theory testing for intervention science, applied research related to prevention and treatment, and development of psychological theories, particularly behavioral psychology (MacKinnon, Fairchild, and Fritz 2007). This third application may be most relevant when discussing full or partial mediation. Specifically, the observation of partial mediation offers clear implications for empirically testing other indirect effects that are operating (Rucker et al. 2011). This naturally lends itself to further theoretical development. Furthermore, while mediators have proven useful for theory development in the field of psychology, as we later discuss, we submit for consideration that these unique variables have strong application in other social science fields, such as social work and sociology.

Vol.9, No.1, pp.42-61, 2021

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Mediation

Purpose of Mediators

Mediation is an extension of simple linear regression in that it adds one or more variables to the regression equation. Mediating variables describe the way in which an intervention yields its outcome. Simply defined, mediating variables are "mechanism through which X [independent variable] influences Y [dependent variable]" (Hayes 2013:7). In mediation analysis, researchers assume that the independent variable (X) affects the mediator (M), which in turn, affects the dependent variable (Y). In other words, the relationship between the independent and dependent variable is assumed to be indirect. Figure 1 is a simple mediation model illustrating the relationship between X, M, and Y.

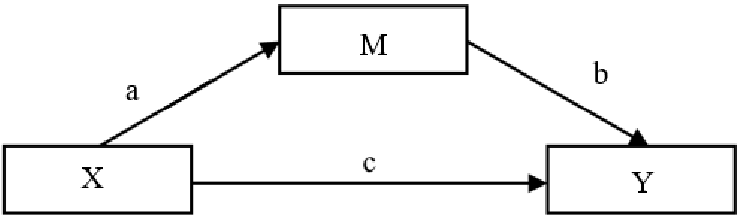

Figure 1: Simple Mediation Model

Effect of X on Y

The relationship between the independent (X) and dependent (Y) variables may be direct or indirect. Direct effect occurs when the relationship between X and Y cannot be influenced by a third (or fourth) variable. Indirect effect occurs when the relationship between X and Y is influenced by one or more variables, that is, mediated by other variables.

In figure 1, the paths "a", "b", and "c" represent the regression coefficients, the correlation between X and M, M and Y, and X and Y, respectively. The coefficient "c" conveys the *direct effect* of X on Y, whereas the coefficients "a" and "b" convey the *indirect effect* of X on Y. The *total effect* of X on Y in figure 1 is equal to "c + a*b" (Baron and Kenny 1986). Based on this figure, if either "a" or "b" is *zero*, then the relationship between X and Y is said to be direct and the total effect is equal to "c" (Total effect = c + a*b = c + 0 = c). The ratio of the indirect effect (a*b) and total effect (a*b + c) represents the proportion of the effect that is contributed to the mediator (formula 1) (Hayes 2013).

Formula 1: Ratio of Indirect Effect to Total Effect

$$P_M = \frac{a * b}{a * b + c}$$

Vol.9, No.1, pp.42-61, 2021

ISSN 2056-3620(Print)

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Conditions for Mediation

According to Baron and Kenny (1986), a variable can function as a mediator in the causal sequence if regression analyses reveal statistically significant relationships at the first three levels under the following conditions:

1. The independent variable is a statistically significant predictor of the dependent variable (X predicts Y).
2. The independent variable is a statistically significant predictor of the mediator (X predicts M). Here, the mediator serves as a dependent variable for the independent variable.
3. The mediator is a statistically significant predictor of the dependent variable while controlling for the effect of X (M predicts Y). Here, the mediator serves as an independent variable for the dependent variable. These three steps should show a direct effect. If any of these relationships is not statistically significant, then mediation cannot be assumed and is determined unlikely or impossible. Once a statistical significance has been established, we can proceed to the fourth step.
4. The observed effect of the mediator on the relationship between X and Y is examined as either full or partial mediation model.

A full mediation model occurs when X no longer statistically significantly affects Y, after controlling for M; that is, the correlation between X and Y is reduced and is no longer significant. Conversely, if the effect of X on Y is still statistically significant but reduced, partial mediation model is supported. In general, the smaller the coefficient "c" becomes, the greater is the effect of the mediator.

The causal step approach designed and popularized by Baron and Kenny (1986) has received some criticism for its first step, that X must cause Y for a mediational effect to exist. MacKinnon et al. (2007) suggested that a mediational effect could possibly exist despite there being no effect of X on Y. Similarly, Rucker et al. (2011) developed a simulation model to demonstrate that significant indirect effects could be found without a direct effect between X and Y. To develop a model that could include multiple mediators, Saunders and Blume (2018) contrasted a single step approach by handling mediators as covariates. This treatment of mediators starkly contrasts MacKinnon's handling of mediators, as MacKinnon (2018) notes that covariates, while related to X and Y, are not in the causal sequence between X and Y. As aforementioned, mediators are unique variables in that their role is to delineate a cause between X and Y, making the mediator the crux of the causal relationship between X and Y. Despite some criticism, and though Baron and Kenny's (1986) four-step approach for testing mediation remains the cornerstone approach, other approaches are often used as a supplement to their technique or as a replacement. These include the empirical M-test (Holbert and Stephenson 2003), bootstrapping (Stine 1989), and the Sobel test (Sobel 1982). Of particular interest for this paper are the latter two techniques.

Research Questions

Suppose a researcher was interested in examining the effect of a mediator variable on the relationship between the independent and dependent variables. The researcher may state the research questions as follow:

- Is there a statistically significant relationship between the independent (X) and dependent (Y) variables, and can this relationship be mediated by a third variable (M)?
- To what extent is the dependent variable (Y) related to the independent variable (X) and is this relationship mediated by a third variable (M)?

For examples, a health care settings administrator may want to examine if "there is a statistically significant relationship between hours of frontline work (X) in a hospital setting and fear levels (y) and whether this relationship is mediated by perception of community support (M)". Or a behavioral organizational researcher may want to examine "to what extent job satisfaction (Y) among social services employees is related to their satisfaction with their supervisions (X) and if this relationship is mediated by promotion opportunities (M)." Also, a mental health provider may want to examine if "there is a statistically significant relationship between immigrants' physical health (X) and their levels of depression (Y) and if this relationship is mediated by their levels of emotional balance (M)."

Types of Data and Assumptions

Because mediation analysis relies on a linear regression analysis, mediating variables follow same set of assumptions required by regression analysis. These assumptions include the following (Author 2016): Levels of Measurement: The independent variable (X) can be either a dummy variable (coded as 0 and 1) or a continuous variable that is measured at the interval level of measurement or higher. The mediating (M) and the dependent (Y) variables should be continuous data and measured at the interval level of measurement or higher.

Normality: The distributions of X, M, and Y should be normal. To evaluate normality, inspect Pearson's and Fisher's skewness coefficients, normality tests (Kolmogorov-Smirnov and Shapiro-Wilks), and both histogram and Q-Q plots for X, M, and Y.

Linearity: The relationship between X, M, and Y must be linear relationship. To evaluate linearity, inspect the results of the Pearson's correlation and the scatterplots for X and M, M and Y, and X and Y.

Homoscedasticity: For each level of the independent variable, the mediating and dependent variables should be normally distributed. To evaluate this assumption, inspect the scatter plot for the residuals (errors) against the predicted values. This plot is available through the SPSS regression menu.

Normality of errors: Errors, also called residuals, must be normally distributed. To evaluate this assumption, inspect the histogram and normality plots for the residuals. These plots are available through the SPSS regression menu.

Vol.9, No.1, pp.42-61, 2021

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ISSN 2056-3639(Online)

Statistical Computer Programs

As aforementioned, several statistical methods have been used to examine the effect of a third (fourth, etc.) variable on the relationship between the independent and dependent variables. These include multiple regression analysis (Author 2016), structural equation models (Byrne 2001; Kline 1998), Sobel test (Sobel 1983), and Hayes SPSS Process Macro (Hayes 2013). The last two methods are discussed here.

Sobel Test

This is a simple test statistic proposed by Sobel (1982). The Sobel test is utilized to examine the hypothesis in which the relationship between the independent (X) and dependent (Y) variables is mediated / affected by a third variable (Y); that is, X and Y have an indirect relationship. In other words, Sobel test examines whether the inclusion of a mediator (M) in the regression analysis considerably reduces the effect of the independent variable (X) on the dependent variable (Y) (Preacher 2020). The hypothesis is tested that there is no statistically significant difference between the total effect and the direct effect after accounting for the mediator; if a significant test statistic results, then total or partial mediation can be supported (Allen 2017). The Sobel test is simple to utilize. It requires three steps:

1. Run a simple linear regression analysis for the effect of the independent variable (X) on the mediator (M). This step computes both unstandardized regression coefficient (*a*) and the standard error of "a" (S_a).
2. Run a multiple linear regression analysis for the effect of the independent (X) and mediating (M) variables on the dependent variable (Y). This step computes both unstandardized regression coefficient (*b*) and the standard error of b (S_b).
3. Use a Sobel test computer calculator (e.g., http://quantpsy.org/sobel/sobel.htm) to calculate the test statistic, standard error, and the level of significance (p value).

You may also use formula 2 to compute the Sobel test statistic value, which is based on the Z score. This formula was proposed by Sobel (1982), which is the ratio of the product of "a" and "b" to the standard error.

Formula 2: Z value for Sobel Test

$$\boldsymbol{Z} = \frac{\boldsymbol{a} * \boldsymbol{b}}{\sqrt{(\boldsymbol{b}^2 * \boldsymbol{S}_a^2 + \boldsymbol{a}^2 * \boldsymbol{S}_b^2)}}$$

If formula 2 is utilized to compute the Sobel test statistic, use a "Z Scores" table to determine if the computed Z value falls outside the critical values (Author 2020). For example, the computed Z score will be statistically significant if it falls outside ±1.96 given a two-tailed alpha of .05 and outside ±2.58 given a two-tailed alpha of .01.

The Sobel test, however, has been criticized by various researchers in that it is based on the standard normal distribution (z scores), which requires a large sample size to conduct mediation analysis (Kenny et al. 1998; MacKinnon et al. 2002; Sobel 1982).

Vol.9, No.1, pp.42-61, 2021

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To overcome the problem of normality, some researchers (Hayes 2013; Preacher and Hayes 2004) recommend the use of a bootstrap method to examine mediation effect. Originated by B. Efron in 1979, bootstrapping methods are computer techniques that allow for resampling of a large number of small samples (e.g., 1000, 5000 samples, etc.) with replacement from the original sample to provide an estimate of the standard error and generate a confidence interval (Efron 1979; Hayes 2009). Bootstrapping requires fewer assumptions, yields the highest power, and diminishes the risk of type 1 error (Hayes 2009; 2013).

HAYES SPSS PROCESS MACRO

Process Macro is a bootstrapping statistical computer tool written by Andrew Hayes as an extension for both SPSS and SAS software (Hayes 2013). The program is used to examine the effect of one or more mediating or moderating variables on the relationship between the independent and dependent variables. The program computes the direct, indirect, and total effects of X on Y as well as unstandardized and standardized regression coefficients, standard errors, and other statistics including t and p values and R^2. Furthermore, unlike Sobel test, which assumes a continuous outcome (Y), Process Macro can be used with both continuous outcome (linear regression analysis) and dichotomous outcome (logistic regression analysis). Users of SPSS or SAS can download *Process Macro* from (http://www.processmacro.org/download.html).

Practical Example

This example is based on a self-administered survey data collected from 155 immigrant Muslims aged fifty and above (Author 2020). Among others, participants completed standardized measures on their physical health (PH), emotional balance (EB), and depressive symptoms (CESD). The SPSS data file used for this example, Mental Health, can be obtained from (https://global.oup.com/us/companion.websites/9780190615222/).

Research Question

To what extent are participants' depressive symptoms (Y) related to their physical health (X), and is this relationship mediated by participants' emotional balance (M)? Or, does participants' emotional balance affect the relationship between their physical health and depressive symptoms? Figure 2 illustrates this research question.

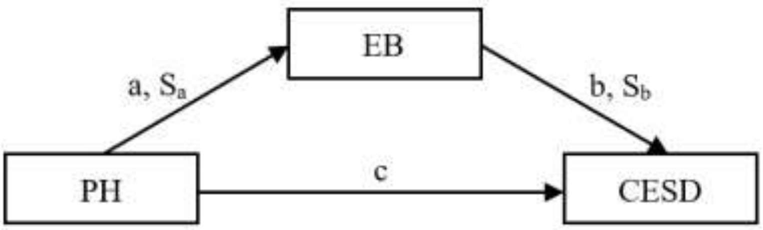

Figure 2: Simple Mediation Model - Physical Health and Depression by Emotional Balance

Hypotheses

H_o: Emotional balance does not significantly mediate the relationship between physical health and depressive symptoms.

H_a: Emotional balance significantly mediates the relationship between physical health and depressive symptoms.

Steps in Mediating Analysis

Step 1: Before proceeding with any regression and mediation analysis, it is essential to evaluate the data for normality of all variables under study and their residuals, linearity, and homoscedasticity. Because this process requires a number of SPSS calculations, tables and figures, and it is not the subject of this paper, it will not be discussed here although the variables discussed here have met these assumptions (Author 2016).

Step 2: Now, we should establish that there is a ground for mediation by confirming the following conditions (Baron and Kenny 1986):

The independent variable (physical health - PH) predicts the dependent variable (depressive symptoms - CESD); that is, "c" is statistically significant. The independent variable (PH) predicts the mediator (EB); that is, "a" is statistically significant. The mediator (EB) predicts the dependent variable (CESD) while controlling for the effect of the independent variable (PH); that is, "b" is statistically significant. To examine these three conditions, use SPSS, or any statistical program, and run three regression analyses as follow: (1) regress CESD on PH, (2) regress EB on PH, and (3) regress CESD on PH and EB (Author 2016).

Tables 1-3 display the SPSS regression output. These tables display the unstandardized and standardized regression coefficients, standard errors, the t and p values, and the 95% confidence interval for each analysis. Table 1 shows that the independent variable (PH) is a significant predictor of the dependent variable (CESD) ($t = -3.47$, $p < .01$). In other words, "c" (unstandardized coefficient = -.630) is a statistically significant.

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	95.0% Confidence Interval for B Lower Bound	Upper Bound
1	(Constant)	35.939	3.631		9.899	.000	28.764	43.115
	PH	***-.630***	***.181***	-.277	***-3.473***	***.001***	-.988	-.271

a. Dependent Variable: CESD

Table 1: Regression Analysis of Physical Health on Depression

Table 2 shows that the independent variable (PH) is also a significant predictor of the mediating variable (EB) ($t = 6.14$, $p < .001$). That is, "a" (unstandardized coefficient = .485) is a statistically significant.

ISSN 2056-3620(Print)
ISSN 2056-3639(Online)

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	95.0% Confidence Interval for B Lower Bound	Upper Bound
1	(Constant)	10.180	1.589		6.408	.000	7.041	13.320
	PH	***.485***	***.079***	.452	***6.136***	***.000***	.329	.641

a. Dependent Variable: EB

Table 2: Regression Analysis of Physical Health on Emotional Balance

Table 3 shows that while controlling for the independent variable (PH), the mediating variable (EB) is a significant predictor of the dependent variable variable (CESD) ($t = -4.96$, $p < .001$). That is, "b" (unstandardized coefficient = -.874) is a statistically significant.

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	95.0% Confidence Interval for B Lower Bound	Upper Bound
1	(Constant)	47.123	3.827		12.314	.000	39.558	54.688
	PH	-.306	.189	-.134	-1.621	.107	-.678	.067
	EB	***-.874***	***.176***	***-.409***	***-4.957***	***.000***	***-1.223***	***-.526***

a. Dependent Variable: CESD

Table 3: Regression Analysis of Physical Health and Emotional Balance on Depression

Step 3: Next, after confirming the three conditions for mediation are established, examine if the mediating variable (emotional balance) is a statistically significant using the Sobel test (using the Z formula) or Hayes Process Macro. For this article, we will illustrate these two methods.

Sobel Test

To utilize the Sobel test, follow these steps:

Determine both "a" and "b" unstandardized regression coefficients and their standard errors (S_a and S_b, respectively). These values are found in both tables 2 and 3, respectively, and are summarized in figure 3.

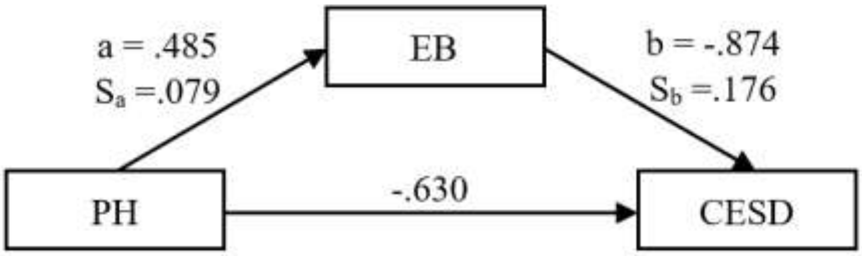

Figure 3: Unstandardized Regression Coefficients and Standard Errors

Vol.9, No.1, pp.42-61, 2021

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ISSN 2056-3639(Online)

Open the computer calculator program, found at http://quantpsy.org/sobel/sobel.htm, and insert the values for "a", "b", "S_a", and "S_b" in the "*Input*" boxes and click on "*Calculate*" as shown in Screen 1.

Input:			Test statistic:	Std. Error:	*p*-value:
a	.485	Sobel test:	-3.86094262	0.10978925	0.00011295
b	-.874	Aroian test:	-3.83034855	0.11066617	0.00012796
s_a	.079	Goodman test:	-3.89228169	0.10890527	0.00009931
s_b	.176	Reset all	Calculate		

Screen 1: Computer Calculator for Mediation

Screen 1 displays the results of the Sobel test as well as two additional tests: Aroian and Goodman tests. The latter two tests use slightly modified formulas of the Sobel test to compute the Z score (MacKinnon, Warsi, and Dwyer 1995). You may also compute the Sobel test statistic using formula 2 as follows:

$$Z = \frac{(.485)x(-.874)}{\sqrt{(-.874)^2 \times (.079)^2 + (.485)^2 \times (.176)^2}}$$

$$Z = \frac{-.424}{\sqrt{.005 + .007}}$$

$$Z = \frac{-.424}{.110} = -3.85$$

Because the computed z score (-3.85) falls outside the z critical values of ±2.58, it indicates a statistically significant result at alpha .01.

Writing the Results of the Sobel Test

Sobel test was utilized to examine if emotional balance mediated the relationship between physical health and depressive symptoms. First, results of simple linear regression show that physical health was a statistically significant predictor of depressive symptoms (b = -.63, beta = -.28, t = -3.47, p < .01). Next, when the mediator, emotional balance, was entered in the regression analysis, physical health was no longer a significant predictor of depressive symptoms (b = -.31, beta = -.13, t = -1.62, p > .05). On the other hand, the mediator, emotional balance, emerged as a

significant predictor of depressive symptoms (b = -.87, beta = -.41, t = -4.96, $p < .001$; 95% CI1 = “-1.22” to “-.53”).
To further investigate the mediator, the Sobel test was utilized to examine if emotional balance significantly mediated the relationship between physical health and depressive symptoms. The results confirmed that emotional balance significantly mediates the relationship between physical health and depressive symptoms (Z = -3.86, $p < .001$).

Hayes SPSS Process Macro Test
Next, we will utilize the SPSS Process Macro to examine the null hypothesis. Unlike Sobel test, Process Macro provides various coefficients and test statistics that explain the indirect, direct, and total effects as well total and partial effect sizes.
To utilize the SPSS Process Macro, follow these steps (make sure to download the Process Macro for your SPSS or SAS from http://www.processmacro.org/download.html):
In the SPSS main menu, click on Analyze, scroll down to Regression, and click on Process v3.5 by Andrew F. Hayes.
From the variables list, move the dependent variable (CESD) in the Y variable’s box, the independent variable (PH) in the X variable’s box, and the mediator (EB) in the Mediator(s) M’s box.
Click on the Model number dropdown arrow and select 4 (this is the model for a single mediator analysis. See Hayes, 2013 for other models) (see screen 2).
Click on Options and check the boxes of “Show total effect model”, “Effect size”, and “Standardized coefficients” (screen 3).
Click on “Continue” and then “Ok”.

[1] If “zero” falls within the 95% confidence interval, then don’t reject the null hypothesis; mediation cannot not be assumed.

Vol.9, No.1, pp.42-61, 2021

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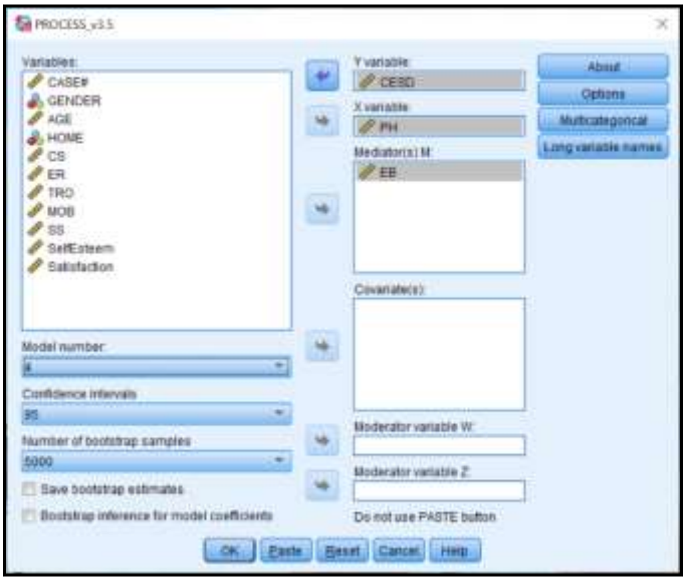
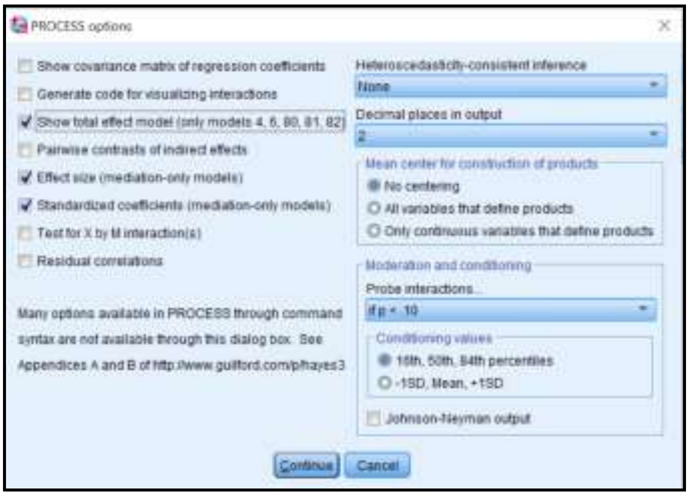
ISSN 2056-3639(Online)



Screen 2: SPSS Process Macro Main Dialog Box



Screen 3: SPSS Process Macro Options Dialog Box

Reading the SPSS Process Macro Output

As stated earlier, Hayes SPSS Process Macro produces various coefficients and test statistics. First, the program produces two regression analyses, one for X on M (table 4) and another for X and M on Y (table 5). These are similar to tables 2 and 3, respectively. Unlike tables 2 and 3, tables 4 and 5 also report the multiple correlation coefficient (R), R square, ANOVA test statistic, and the standardized coefficients for each analysis (these are also produced by the SPSS main regression analysis; see Author, 2016 for details).

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Vol.9, No.1, pp.42-61, 2021

ISSN 2056-3620(Print)

ISSN 2056-3639(Online)

OUTCOME VARIABLE: **(Authors' note: *Simple linear regression - X on M, path "a = .49"*)**
EB

Model Summary

R	R-sq	MSE	F	df1	df2	p
.46	.21	26.36	37.49	1.00	143.00	.00

Model

	coeff	se	t	p	LLCI	ULCI
constant	10.19	1.60	6.36	.00	7.02	13.35
PH	**.49**	.08	6.12	.00	.33	.64

Standardized coefficients

	coeff
PH	.46

Table 4: Regression Analysis of Physical Health on Emotional Balance

OUTCOME VARIABLE: **(Authors' note: *Multiple linear regression - X & M on Y, path "b = -.87"*)**
CESD

Model Summary

R	R-sq	MSE	F	df1	df2	p
.48	.23	117.26	21.78	2.00	142.00	.00

Model

	coeff	se	t	p	LLCI	ULCI
constant	47.12	3.83	12.31	.00	39.56	54.69
PH	-.31	.19	-1.62	.11	-.68	.07
EB	**-.87**	.18	-4.96	.00	-1.22	-.53

Standardized coefficients

	coeff
PH	-.13
EB	-.41

Table 5: Regression Analysis of Physical Health and Emotional Balance on Depression

Table 6 conveys the results of the mediation analysis. The table reports the direct, indirect, and the total effects of the independent variable on the dependent variable, as well as the 95% confidence interval using the Bootstrapping method.

Total effect of X on Y: (Authors' note: *Total effect is equal to Direct & Indirect effects*)

Effect	se	t	p	LLCI	ULCI	c_ps	c_cs
-.73	.18	**-4.04**	**.00**	-1.09	-.37	-.06	-.32

Direct effect of X on Y

Effect	se	t	p	LLCI	ULCI	c'_ps	c'_cs
-.31	.19	**-1.62**	**.11**	**-.68**	**.07**	-.02	-.13

Indirect effect(s) of X on Y: (Authors' note: *Indirect effet = a * b*)

	Effect	BootSE	BootLLCI	BootULCI
EB	**-.43**	.10	**-.62**	**-.25**

Table 6: Bootstrap Estimates of Direct, Indirect, and Total Effects of Physical Health on Depression

Direct Effect

This examines if the relationship between the independent and dependent variables is direct and not mediated by a third variable. The results in table 6 show that the direct effect was -.31 with a t value of -.162 and a p value of .11 ($p > .05$). Thus, we fail to reject the null hypothesis in which the relationship between physical health and

Vol.9, No.1, pp.42-61, 2021

ISSN 2056-3620(Print)

ISSN 2056-3639(Online)

depressive symptoms is not direct. Notice that "zero" falls within the 95% confidence interval (-.68 to .07). In other words, the "c" coefficient is not statistically significant ($p > .05$).

Indirect Effect

This part of the results examines the null hypothesis that the indirect relationship between the independent (X) and the dependent (Y) variables is equal to zero. The table shows that the indirect effect is equal to "-.43" with a 95% bootstrap confidence interval of -.62 (lower limit) to -.25 (upper limit). Because "zero" does not fall within the 95% confidence interval, we will reject the null hypothesis. In other words, we conclude that emotional balance mediates the relationship between physical health and depressive symptoms; that is, "a*b" is a statistically significant at alpha .05 ($p < .05$).

Total Effect

This is the total effect produced by the entire model, indirect and direct effect. It is the sum of indirect effect (a*b) and direct (c) effects. Table 6 shows that the total effect was -.73 with a "t" value of -4.04 and a p value of ".00", thus indicating a statistically significant effect ($p < .05$).

Writing the Results of Hayes Process Macro

A bootstrapping method was performed using SPSS Process Macro to examine if emotional balance mediated the relationship between physical health and depressive symptoms. First, the results of the regression analysis show that the physical health (independent variable) was a significant predictor of emotional balance ($b = .49$, $t = 6.12$, $p < .001$). Next, while controlling for emotional balance (mediator), the results of the second regression analysis show that physical health was not a significant predictor of depressive symptoms (dependent variable ($b = -.31$, $t = -1.62$, $p > .05$).
The results of the indirect effect based on 5000 bootstrap samples show a significant indirect negative relationship between physical health and depressive symptoms mediated by emotional balance ($a*b = -.43$, Bootstrap $CI_{95} = -.62$ and -.25). The mediator, emotional balance, accounted for approximately 59% of the total effect on depressive symptoms [$P_M = (-.43) / (-.73)$]. On the other hand, there was no statistically significant direct effect between physical health and depressive symptoms (b = -,31, $t = -1.62$, $p > .05$). Table 7 displays the results of the mediation analysis.

Variable / Effect	*b*	*SE*	*t*	*p*	*95% Confidence Interval*	
PH → CESD	-.31	.19	-1.62	> .05	-.68	.07
PH → EB	-.49	.08	6.12	< .001	.33	.64
PH → EB → CESD	-.87	.18	-4.96	< .001	-1.22	-.53
Effects						
Direct	-.31	.19	-1.62	> .05	-.68	.07
Indirect*	-.43	.10			-.62	-.25
Total	-.73	.18	-4.04	< .00	-1.09	-.37

Based on 5000 bootstrap samples
Table 7: Mediation Analysis

DISCUSSION AND IMPLICATIONS TO RESEARCH AND PRACTICE

The value of mediating variables in social science research is notable. Mediators enhance the complexity of relationships by providing explanations for how variables affect each other, which may lead to the development of novel theoretical models (MacKinnon, Fairchild, and Fritz 2007). Within the last four decades, there has been a substantial increase in interest in the effect that mediators have on bivariate relationships (Magill 2011). The empirical applications of mediational research to social science fields. Many of the clientele typically consists of people who present with varied, multi-layered problems. The very nature of these professions requires the use of multifarious interventions to help clients address these problems. Consistent with the depth of the problems and the interventions, evaluation techniques that offer a degree of complexity seem appropriate, and due to the multi-faceted layered problems, an analysis approach that can capture such nuances is necessary.

We offer for consideration that mediation analyses are quite compatible with social science practice. Previous mediation-based research spans an array of social science topics. Within the topic of mental health, Whitley, Kelley, and Lamis (2016) studied social support as a mediator between depression and mental health. Connecting the fields of mental health and physical health, Lee, Gottfried, and Bride (2018) investigated secondary traumatic stress as a mediator between exposure to client traumas and perceived health. From the bodies of knowledge regarding mental health and coping behaviors, O'Hare, Shen, and Sherrer (2007) mediated the relationship between reported distress from traumatic events and present PTSD symptoms with two mediators: distress from maladaptive coping behaviors and alcohol use. Additionally, Calvete, Corral, and Estevez (2008) researched disengaged coping as a mediator between psychological abuse and mental health symptoms. Employing character traits as a mediator, the impact of resilience as a mediator between depression and Internet addiction was studied by Jin, Author, and Lee (2019). Across bodies of knowledge pertaining to child welfare and mental health, Plant et al. (2017) studied maternal depression and offspring child maltreatment as mediators between maternal history of childhood maltreatment and offspring internalizing and externalizing difficulties. Within the employment body of knowledge employment,

Vol.9, No.1, pp.42-61, 2021

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Einarsen et al. (2016) investigated conflict management as a mediator between bullying and job engagement, while Quiñones, Van den Broeck and De Witte (2013) researched job resources as a mediator between work engagement and psychological empowerment. Additionally, perceived efficacy as a mediator between workload and job satisfaction in social workers was investigated by Cole, Panchanadeswaran, and Daining (2004). These studies provide a minor glimpse into the mediational research that has been conducted across social science fields.

Furthermore, mediational analyses also aid in theoretical development. The following are examples of mediational research for social science topics used for this purpose. Naimi et al. (2016) used mediation analysis to explain the relationship between breastfeeding prior to hospital discharge and racial disparity in infant mortality. Park and Ono (2017) theorized that perception of job insecurity explained the relationship between workplace bullying and health problems. A final example, Santini et al. (2020) used a longitudinal mediation analysis to explain the relationship between social disconnectedness and mental illness symptoms when mediated by social isolation. These examples and others provide vast implications for a plethora of social science mediation-based research, and in effect, highlight the potential for theoretical perspectives and interventions useful for addressing clients' multi-faceted problems.

Recommendations for Future Directions

This paper introduced mediational analysis for social scientists. As aforementioned, mediational analysis' degree of complexity is very compatible with social science practice due to the layered, multi-faceted problems that these clientele face. As such, directions for future methodological applications are vast. First, since the paper presented an introduction to these techniques, future research might employ more advanced methods, further examining the intricacies between variables when mediators are incorporated. Secondly, as an introduction, this paper focused on the incorporation of one mediating variable; however, consistent with the complexities of social science problems, multiple mediating factors often contribute to and exacerbate clients' presenting problems, so research addressing the use of mediational analysis where there are multiple mediators may prove beneficial. Lastly, while mediational analysis is compatible with social science research and practice, moderating variables also provide causal explanations between bivariate relationships, albeit in different capacity; research on these intervening variables could also offer a degree of complexity that is well-suited to explain the nuanced and intricate problems faced by clientele receiving services provided by social science professions.

CONCLUSION

While mediators have generated much interest, so have the techniques that are used to analyze these relationships. Spanning nearly 100 years (Baron and Kenny 1986; Preacher and Hayes 2008; Sobel 1982; Wright 1920), techniques have evolved tremendously, as emerging techniques have developed to lessen the burdens of complex mediational analyses and safeguard against sampling errors. Specifically, in this paper, we addressed the techniques of bootstrapping using Hayes Process Macro – which allows for re-sampling while requiring fewer assumptions, providing a higher study power, and lowering the risk of falsely rejecting the null hypothesis – and the Sobel test – which, assuming a normal distribution, determines the degree to which the mediator decreases the impact of the independent variable on the dependent variable. This paper sought to introduce these widely used techniques to social science researchers who seek to examine stimulating questions and develop newer theoretical models that help explain the pervasive complexities of social problems.

REFERENCES

Allen, Mike. 2017. Sobel Test. In the Sage Encyclopedia of Communication Research Methods. (Vol. 1-4). Thousand Oaks, CA: SAGE Publications, Inc.

Author. 2016. Advanced and Multivariate Statistical Methods for Social Science Research. New York, NY: Oxford University Press.

Author. 2020. Using Statistical Methods in Social Science Research with a Complete SPSS Guide (3rd. ed). New York, NY: Oxford University Press.

Baron, Reuben M. and David A. Kenny. 1986. “The Moderator–Mediator Variable Distinction in Social Psychological Research: Conceptual, Strategic, and Statistical Considerations.” Journal of Personality and Social Psychology, 51(6), 1173-1182.

Byrne, Barbara M. 2001. Structural Equation Modeling with AMOS. Mahwah, NJ: Lawrence Erlbaum Associates.

Calvete, Ester, Susana Corral, and Ana Estevez. 2008. “Coping as a Mediator and Moderator between Intimate Partner Violence and Symptoms of Anxiety and Depression.” Violence Against Women, 14(8), 886–902.

Cole, Danny, Subadra Panchanadeswaran, and Clara Daining. 2004. “Predictors of Job Satisfaction of Licensed Social Workers: Perceived Efficacy as a Mediator of the Relationship between Workload and Job Satisfaction.” Journal of Social Service Research, 31(1), 1–12.

Efron, Bradley. 1979. “Bootstrap Methods: Another Look at the Jackknife.” Annals of Statistics, 7(1), 1-26.

Einarsen, Ståle, Anders Skogstad, Erlend Rørvik, Åshild Bjørke Lande, and Morten Birkeland Nielsen. 2016. “Climate for Conflict Management, Exposure to Workplace Bullying and Work Engagement: A Moderated Mediation Analysis.” International Journal of Aging and Human Development, 29(3), 549-570.

Frazier, Patricia, Andrew Tix, and Kenneth Baron. 2004. “Testing Moderator and Mediator Effects in Counselling Psychology.” Journal of Counselling Psychology, 51(2), 115–134.

Hayes, Andrew F. 2009. “Beyond Baron and Kenny: Statistical Mediation Analysis in the New Millennium.” Communication Monographs, 76(4), 408–420.

Hayes, Andrew F. 2013. Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach. New York, NY: The Guilford Press.

Holbert, R. Lance and Michael T. Stephenson, M. 2003. “The Importance of Indirect Effects in Media Effects Research: Testing for Mediation in Structural Equation Modeling.” Journal of Broadcasting and Electronic Media, 47(4), 556-572.

Jin, Seok Won, Author, and Yeonggeul Lee. 2019. “Does Resilience Mediate the Link between Depression and Internet Addiction among African American University Students?” Journal of Negro Education, 88(2), 114-129.

Kenny, David A., Deborah A. Kashy, and Niall Bolger. 1998. Data Analysis in Social Psychology. In D. Gilbert, S. T. Fiske, and G. Lindzey (eds.). Handbook of Social Psychology (4th ed.) (pp. 233-265). New York, NY: McGraw-Hill.

Kline, Rex B. 1998. Principles and Practice of Structural Equation Modeling. New York, NY: The Guilford Press.

Lee, Jacqueline, Ruth Gottfried, and Brian E. Bride. 2018. “Exposure to Client Trauma, Secondary Traumatic Stress, and the Health of Clinical Social Workers: A Mediational Analysis.” Clinical Social Work Journal, 46, 228–235.

MacKinnon, David P., Amanda Fairchild, and Matt Fritz. 2007. “Mediation Analysis.” Annual Review of Psychology, 58(1), 593-614.

MacKinnon, David P. 2018. “Tutorial in Modern Mediation Analysis.” Retrieved from https://psychology.clas.asu.edu/sites/default/files/apatutorialfinaloneslide.pdf.

MacKinnon, David P., Chondra M. Lockwood, Jeanne M. Hoffman, Stephen G. West, and Virgil Sheets. 2002. “A Comparison of Methods of Test Mediation and Other Intervening Variable Effects.” Psychology Methods, 7(1), 83-104.

MacKinnon, David P., Ghulam Warsi, and James, H. Dwyer. 1995. “A Simulation Study of Mediated Effect Measures.” Multivariate Behavioral Research, 30(1), 41-62.

Magill, Molly. 2011. “Moderators and Mediators in Social Work Research: Toward a More Ecologically Valid Evidence Base for Practice.” Journal of Social Work (London), 11(4), 387–401.

Naimi, Ashley I., Mireille E. Schnitzer, Erica E. M. Moodie, and Lisa M. Bodnar. 2016. “Mediation Analysis for Health Disparities Research.” American Journal of Epidemiology, 184(4), 315–324.

O’Hare, Thomas, Shen, Ce, Sherrer, Margaret. 2007. “Validating the Posttraumatic Symptom Scale with Persons Who Have Severe Mental Illness.” Research on Social Work Practice, 17(6), 720–728.

Park, Joon Hyung and Masakatsu Ono. 2017. “Effects of Workplace Bullying on Work Engagement and Health: The Mediating Role of Job Insecurity.” International Journal of Aging and Human Development, 28(22), 3202-3225.

Plant, Dominic T., Fergal W. Jones, Carmine S. Pariante, and Susan Pawlby. 2017. “Association Between Maternal Childhood Trauma and Offspring Childhood

Psychopathology: Mediation Analysis from the ALSPAC Cohort." The British Journal of Psychiatry. 211(3), 144-150.

Preacher, Kristopher J. and Geoffrey Leonardelli. 2020. "Calculation for the Sobel Test: An Interactive Calculation Tool for Mediation Tests." Retrieved August 27, 2020 from http://quantpsy.org/sobel/sobel.htm.

Preacher, Kristopher J. and Andrew F. Hayes. 2004. "SPSS and SAS Procedures for Estimating Indirect Effects in Simple Mediation Models." Behavior Research Methods, Instruments, and Computers, 36, 717-731.

Quiñones, Marcela, Anja Van den Broeck, and Hans De Witte. 2013. "Do Job Resources Affect Work Engagement Via Psychological Empowerment? A Mediation Analysis." Revistade Psicologiadel Trabajoydelas Organizaciones, 29(3), 127-134.

Rucker, Derek, Kristopher J. Preacher, Zachary L. Tormala, and Richard E. Petty. 2011. "Mediation Analysis in Social Psychology: Current Practices and New Recommendations." Social and Personality Psychology Compass, 5(6), 359-371.

Santini, Ziggi I., Erin York Cornwell, Ai Koyanagi, Line Nielsen, Carsten Hinrichsen, Charlotte Meilstrup, Katrine R Madsen, and Vibeke Koushede. 2020. "Social Disconnectedness, Perceived Isolation, and Symptoms of Depression and Anxiety Among Older Americans (NSHAP): A Longitudinal Mediation Analysis." The Lancet Public Health, 5(1), e62-e70.

Saunders, Christina T. and Jeffrey Blume. 2018. "A Classical Regression Framework for Mediation Analysis: Fitting One Model to Estimate Mediation Effects." Biostatistics, 19(4), 514–528.

Sobel, Michael E. 1982. "Asymptotic Confidence Intervals for Indirect Effects in Structural Equation Models." Sociological Methodology, 13, 290–312.

Stine, Robert. 1989. "An Introduction to Bootstrap Methods." Sociological Methods and Research, 18(2-3), 243-291.

Wegener, Duane T. and Leandre R. Fabrigar. 2000. Analysis and Design for Nonexperimental Data: Addressing Causal and Noncausal Hypothesis. In H. T. Reis and C. M. Judd (Eds.), Handbook of research methods in social and personality psychology (pp. 412–450). Cambridge, England: Cambridge University Press.

Whitley, Deborah, Susan Kelley, Dorian Lamis. 2016. "Depression, Social Support, and Mental Health: A Longitudinal Mediation in African American Custodial Grandmothers." International Journal of Aging and Human Development, 82(2-3), 166-187.

Woodworth, Robert S. 1928. Dynamic Psychology. In C. Murchison (Ed.). Psychologies of 1925. Worchester, MA: Clark University Press.

Wright, Sewall. 1920. "The Relative Importance of Heredity and Environment in Determining the Piebald Pattern of Guinea Pigs." Proceedings of the National Academy of Sciences of the United States of America, 6, 320-332.

Wu, Amery D. and Bruno D. Zumbo. 2008. "Understanding and Using Mediators and Moderators." Social Indicators Research. 87(3), 367-392.

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