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A Step-By-Step Tutorial for Performing a Moderated Mediation Analysis using PROCESS

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Abstract ■ Interest in moderation and mediation models have gained momentum since the 1980s and have become widespread in numerous fields of research including clinical, social, and health psychology in addition to behavioral, educational, and organizational research. There are resources available to help the user understand an analysis of a moderated mediation using the PROCESS macro and its resultant output, however, many are in video format (e.g., YouTube) or lack detailed instructions based on real world examples. To our knowledge, there are no resources that provide a thorough yet accessible step-by-step explanation of the procedure involved in using PROCESS v4.1 to analyze and interpret a moderated mediation model using real data in SPSS v28. The aim of this guide is to address this knowledge gap. An overview of mediation, moderation, and moderated mediation models is presented followed by instructions for verifying that assumptions are respected. Finally, a procedure to analyze data using PROCESS v4.1 is presented along with an interpretation of the resultant output.

Keywords ■ moderation, mediation, moderated mediation, tutorial, data analysis, data interpretation, statistical analysis. **Tools** ■ PROCESS, SPSS.

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Introduction

In the field of psychology, researchers are often interested in understanding whether different aspects of the human experience (e.g., emotions, cognition, behaviours) are associated. However, to go beyond the exploration of such associations, it is important to explore *how* they occur (i.e., mediation), and *when* they occur (i.e., moderation). Going one step further, understanding *when* one variable has an effect on *how* an association between two other variables occurs (i.e., moderated mediation) can shed greater light on the nature of a link between variables. Exploring such complexities in associations between diverse constructs adds to our understanding of important phenomena (e.g., depression, relationship satisfaction, memory), and in turn, can increase our knowledge of how to manage said phenomena.

Researchers are sometimes faced with a lack of resources or skills to test meaningful conceptual models of associations between various phenomena. The purpose of this tutorial is to demonstrate how to conduct a moderated mediation analysis using Hayes' PROCESS macro for SPSS (Hayes, 2013, 2018). PROCESS is based on path analysis and uses ordinary least squares (OLS) regression for continuous outcomes and is an easy-to-use tool for analyzing models of moderated mediation. There are resources available to assist users in performing an analysis of a moderated mediation model using the PROCESS macro with SPSS and its resultant output (e.g., YouTube). However, this tutorial uses real data to provide a detailed yet simple, step-by-step set of instructions for analyzing and interpreting a moderated mediation model using PROCESS that is accessible to anyone with at least a beginner knowledge of SPSS. We begin with an explanation of simple mediation, moderation, and moderated mediation followed by a step-by-step tutorial that includes instructions for verifying the assumptions of a moderated mediation analysis, as well as a procedure to analyze and interpret data using PROCESS v4.1.

Simple Mediation Model

Exploring whether an association exists between variables involves the use of correlational analysis, such as bivariate correlation. In this type of analysis, understanding whether an independent variable influences a dependent variable, such as in the case of prediction, is not of interest. However, when it is important to understand which variable is influencing the other (i.e., prediction), linear regression analysis is often used. To perform a linear regression analysis, a researcher must choose an explanatory variable (the independent variable, (IV or X)) and one or more response variables (DV or Y). It is important to note that simply performing a regression analysis does not provide conclusive evidence on the influence of an IV on a DV. In the case of a correlational research design, the choice of an IV and DV to use for a regression analysis is based on a theoretical framework. For instance, among couples who have experienced a transgression in their relationship, encouraging the restoration of trust in the transgressor can help the partner who has been hurt to forgive the transgressor (Hammer & Hargrave, 2016). In this scenario, the IV is trust in the transgressor, and the DV is forgiveness. However, exploring the ways in which (i.e., how) trust in the transgressor can help the partner who has been hurt to forgive the transgressor may provide a deeper insight into areas to target in couples' therapy that could encourage trust and thereby forgiveness. Performing an analysis of a simple mediation model can shed light on such areas to target.

Similar to performing a linear regression involving an IV and a DV, analysis of a simple mediation model involves performing a regression-based analysis (Hayes, 2018). In this model, the IV has an effect on an additional or third variable termed a mediator variable (M), which in turn has an effect on the DV when the IV is held constant (Caron & Valois, 2018; Gunzler, Chen, Wu, & Zhang, 2013). In other words, the IV is associated with the DV *through* M. This relationship is the *indirect effect*, which is the mediation relationship. As an example, research shows that trust in a romantic partner is associated with compassion for that partner (Salazar, 2015), and compassion is also one of the strongest predictors of forgiveness (Davis, 2017). Therefore, it could be hypothesized that trust is associated with forgiveness through compassion for a romantic partner. Specifically, a mediational model could be tested wherein trust in a romantic partner influences compassion for that partner (a), and compassion for the partner influences forgiveness of that partner (b), which would be the indirect effect of trust in a romantic partner on forgiveness through compassion for the romantic partner (ab). Should an analysis of this model suggest that the indirect effect is significant, it could be concluded statistically that compassion mediates the association between trust in a romantic partner and forgiveness. If the indirect effect is not significant, then there is no mediation, and it *cannot* be concluded that compassion plays a role in the association between trust in a romantic partner and forgiveness.

In addition to the indirect effect, a mediational model also examines the *direct effect* of the IV on the DV. Continuing with the scenario above, this would involve examining whether trust in a romantic partner is associated with forgiveness of that partner when compassion is held constant. The *direct effect* (c') and the *indirect effect* (ab) combined are the *total effect* (c) of the mediation model as shown in Figure 1A. Specifically, the indirect effect is the product of the a path and the b path ($a \times b$) while the total effect is the sum of the indirect effect and the direct effect ($c = c' + a \times b$). For a detailed explanation of the mathematical representation of a simple mediation relationship, as well as how to test a mediation model using PROCESS, please refer to Kane and Ashbaugh (2017) and Hayes (2018).

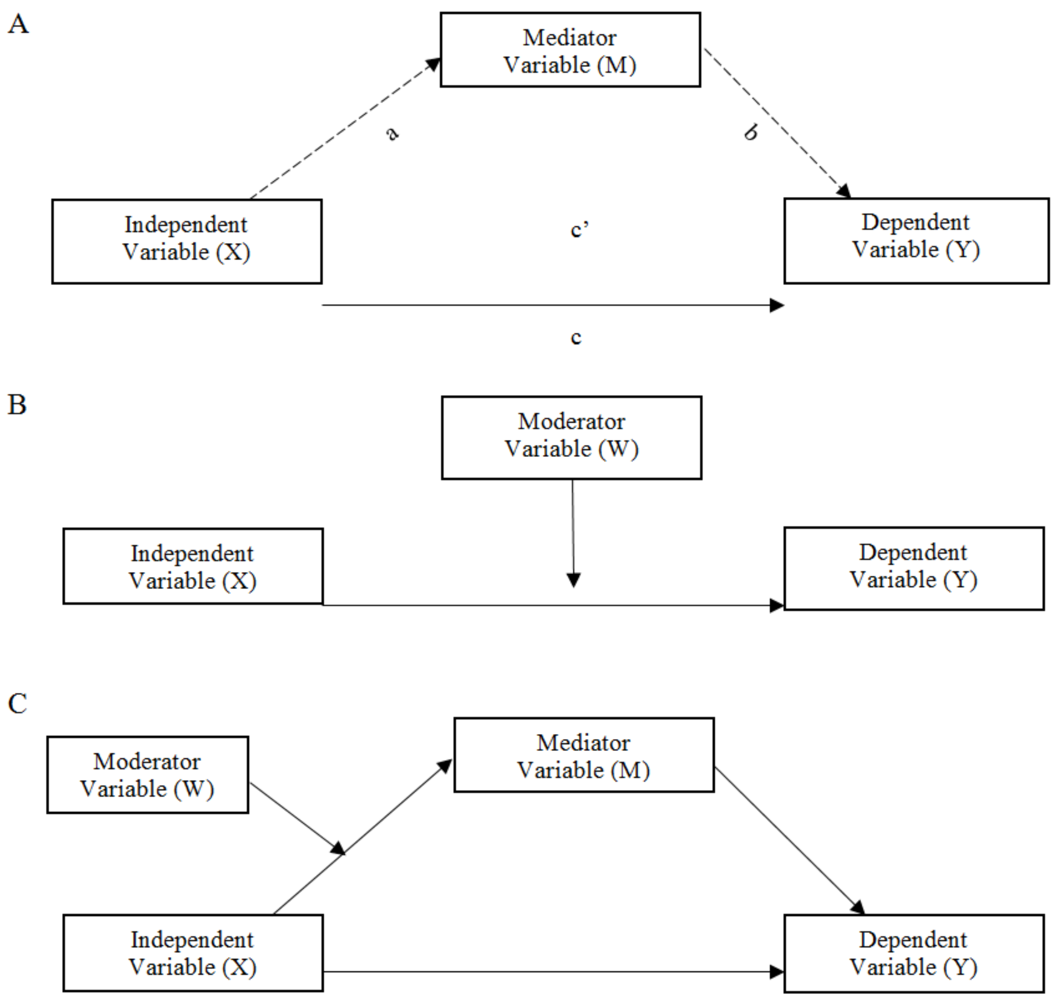
According to Meule (2019), there is a debate in the literature regarding the use of terms such as "complete mediation" (i.e., significant indirect effect and nonsignificant direct effect), and "partial mediation" (i.e., significant indirect and direct effects). Meule (2019) also contends that there is a debate in the literature regarding historical approaches (i.e., Baron & Kenny, 1986) causal steps approach and contemporary approaches to deciding whether a significant direct effect must be present for a significant indirect effect to be important. Moreover, Meule (2019) describes Hayes' PROCESS macro as a contemporary and simple way of analyzing a simple mediation model as it involves two linear regressions. The first regresses M on the IV (a), and the second regresses the DV on the IV (c') and M (b). Whether an indirect effect (or a mediation) exists is determined using bootstrap confidence intervals (CI), wherein a confidence interval of the ab path that does not include zero is considered suggestive of the presence of a significant indirect effect.

Thus, analyzing a simple mediation model could help to understand how compassion for a romantic partner is associated with trust in a romantic partner and forgiveness. Equally important to examine is *when* trust in a romantic partner is related to compassion for the partner, which involves examining a moderation model.

Moderation Model

As in the case of a mediation model, regression-based analysis can be used to analyze a moderation model (Hayes, 2018). Here we are interested in determining whether a third variable, or a moderator variable (W), influences the

Figure 1 ■ Panel A: Simple Mediation; panel B: Moderation; and panel C: Moderation Mediation Models. In panel A, the dashed lines denote the indirect path (ab) while the solid line denotes the direct path (c').



strength or direction of the association between the IV and the DV. Specifically: "Identifying a moderator of an effect helps to establish the boundary conditions of that effect or the circumstances, stimuli, or type of people for which the effect is large versus small, present versus absent, positive versus negative, and so forth" (Hayes, 2018, p. 220).

From a statistical standpoint, testing a moderation model is similar to testing the *interaction* between factors in an analysis of variance (ANOVA; Frazier, Tix, & Barron, 2004). An *interaction effect* is present when the effect of the IV on the DV is *conditional* upon W (Hayes, 2018). In other words, we are interested in whether the association between an IV and DV varies at different levels of W. Figure 1B demonstrates a conceptual diagram of a moderation model. For a detailed explanation of the mathematical representation of a moderation relationship, consult Caron, Valois, and Gellen-Kamel (2020) and Lorah (2020, 2022). For the procedure for analyzing a moderation model using PROCESS, consult Hayes (2018).

Returning to the example of trust, compassion, and forgiveness, researchers might be interested in understanding when trust influences compassion. In the pursuit of understanding healthy social behavior, humility has been identified as important in the cultivation of compassion (Worthington & Allison, 2018). Indeed, research has shown that viewing a romantic partner as humble is associated with also viewing them as compassionate (e.g., McDonald, Olson, Goddard, & Marshall, 2018). Moreover, research has shown an association between trust and humility (e.g., Wang, Edwards, & Hill, 2017). A moderation model could be hypothesized wherein the association between trust and compassion for a romantic partner is conditional upon viewing the romantic partner as humble.

Moderated Mediation Model

Moderated mediation, a concept put forth by James and Brett (1984), involves examining whether W influences the magnitude of an indirect effect (Preacher, Rucker, & Hayes, 2007). Specifically, a moderated mediation relationship is said to occur when a mediation relationship is dependent upon the level of a moderator (Preacher et al., 2007). Figure 1C presents a conceptual model of moderated mediation. Turning to our scenario involving trust, humility, compassion, and forgiveness, a model of moderated mediation could be hypothesized wherein trust in a romantic partner (X) is associated with forgiveness (Y) through compassion for that partner (M), and this association is strengthened by viewing that partner as humble (W).

Moderated Mediation Example

For this tutorial, we will be using data from a study that examined the association between dyadic trust, compassion for the injuring partner, perception of the injuring partner as humble, and forgiveness among individuals who experienced an attachment injury in their romantic relationship. Attachment injuries are defined as a perceived violation of trust or abandonment that occurs during a critical moment of need for the support and caring of a romantic partner (Johnson, Makinen, & Millikin, 2001). In the study discussed herein, dyadic trust refers to the degree of honesty and goodwill the injured partner perceives the injuring partner has toward them (Larzelere & Huston, 1980). Integral to the resolution of attachment injuries and the restoration of trust in a romantic relationship is forgiveness, which was defined in the study as when the injured partner has high levels of benevolence motivations (e.g., goodwill) and low levels of motivations to avoid or seek revenge toward the injuring partner.

Participants

The sample used for this tutorial consisted of 138 individuals who reported experiencing an attachment injury in their current romantic relationship for which they had forgiven their partner. Participants were between the ages of 18 and 62 ($M = 22.59$, $SD = 7.68$), and predominantly identified as female (84.1%) while the remainder identified as male (13.8%) and gender variant or nonconforming (2.2%). The majority of participants identified as White (58.0%) while the remainder identified as Asian (20.3%), Black (10.9%), Arab (7.2%), First Nations, Métis, or Inuit (2.2%), and Latinx or Hispanic (2.2%). Regarding sexual orientation, participants identified as heterosexual (75.4%), bisexual (14.5%), lesbian (3.6%), queer (3.6%), or other (2.9%). Participants' relationship duration ranged from one month to 32 years ($M = 2.96$ years, $SD = 5.17$ years) and the majority of participants reported being in a dating relationship (81.2%) and reported not currently living with their romantic partner (74.6%).

To be eligible to participate in the study, participants had to be at least 18 years of age, able to read and write in English, have experienced an attachment injury as defined by Johnson et al. (2001) in their current relationship, and have reported forgiving their romantic partner for the attachment injury. They also had to have been in the relationship for at least three months, which was considered a minimum level of relationship stability. Participants consisted of a combination of individuals living in the community and undergraduate students from a university in Eastern Ontario.

Procedure

Once participants provided informed consent, they completed self-report questionnaires online via `Qualtrics`. Participants completed a sociodemographic questionnaire and were asked to briefly describe the attachment injury and indicate whether or not they had forgiven their romantic partner for the attachment injury (yes/no). Dyadic trust was measured using the Dyadic Trust Scale (DTS; Larzelere & Huston, 1980), which consists of eight items rated using a scale ranging from 1 (*very strongly agree*) to 7 (*very strongly disagree*). Compassion for a romantic partner was measured using the Compassion Scale (CS; Pommier, Neff, & Tóth-Király, 2020), which was modified to be specific to the injured partner's level of compassion toward the injuring partner (e.g., "When my partner feels sadness, I try to comfort him/her"). The CS consists of 16 items rated using a scale ranging from 1 (*almost never*) to 5 (*almost always*). To measure whether the injured partner viewed the injuring partner as humble, the Relational Humility Scale (RHS; Davis et al., 2011) was modified with instructions that were specific to how the injured partner viewed the injuring partner (i.e., "For the following questions, please indicate your current thoughts and feelings about the person who hurt you; that is, we want to know how you feel about that person right now. Next to each item, chose the response that best describes your current thoughts and feelings."). The RHS consists of 16 items rated from 1 (*strongly disagree*) to 5 (*strongly agree*). The injured partner's forgiveness of the injuring partner was rated using the Transgressions-related Interpersonal Motivations Inventory (TRIM; McCullough et al., 1998; McCullough, Fincham, & Tsang, 2003). The TRIM consists of three subscales that measure an individual's motivation to avoid the person who hurt them, motivation to seek revenge against the person who hurt them, or motivation to appease and see goodwill come to the person who hurt them. Participants rated the 18 items using a scale that ranges from 1 (*strongly disagree*) to 5 (*strongly agree*). Using the framework of the TRIM-18, forgiveness was defined as low levels of motivation to avoid the injuring partner and seek revenge toward him/her, and high levels of benevolence motivations toward the injuring partner. For the purposes of this tutorial, the example presented only includes the benevolence subscale of the TRIM-18.

Steps for Performing a Moderated Mediation Analysis

Step 1: Material. The software required for this tutorial includes version 28 of SPSS (IBM Corp., 2021) and the PROCESS macro for SPSS (Hayes, 2013). This tutorial assumes the reader has beginner-level knowledge of how to use SPSS v28. To download the PROCESS macro for SPSS, and for instructions on how to install it, visit processmacro.org. The dataset used in this tutorial can be found on the journal's website.

Step 2: Assumptions. As mentioned above, the moderated mediation analysis we are presenting in this tutorial involves regression analyses, which requires that the assumptions necessary for performing regression analyses, specifically multiple regression, are met. These assumptions involve ensuring the independence of observations, linearity of relationships among the variables, error values are homoscedastic, multicollinearity does not exist among the IVs, and error values are normally distributed. A brief description of each assumption is provided below. For a detailed explanation of the different assumptions, see Hayes (2018). To verify that these assumptions are respected, we will perform a one-step procedure in SPSS v.28 that will provide all the output necessary to determine if we can proceed with the moderated mediation analysis.

Begin by selecting `Analyze > Regression > Linear` and move `TRIM_Ben` into the DV box, and move `DTST`, `CS_TOT`, and `RHSTOT` into the IV box. In the method box, ensure `Enter` is selected. Next, click the `Statistics` button and ensure `Estimates` and `Confidence intervals (95%)` are selected in the Regression Coefficients section on the left panel. On the right, ensure `Model fit`, `Descriptives`, `Part and partial correlations`, and `Collinearity diagnostics` are selected. In the Residuals section below, ensure `Durbin-Watson`, `Casewise diagnostics`, and `Outliers outside: 3 standard deviations` are selected, and then click on `Continue`. Next, select the `Plots` button on the Linear Regression dialogue box and ensure Histogram, Normal probability plot, and Produce all partial plots are selected and once again, select `Continue`. Next, click Save in the Linear Regression dialogue box. In the Predicted Values section on the left of the Linear Regression Save dialog box, ensure Unstandardized is selected. In the Residuals section on the right, ensure Studentized and Studentized deleted are selected. Click `Continue`, and then Ok to generate the predicted values and residuals. Three new variables will be created and added to the dataset, namely, `PRE_1` (unstandardized predicted value), `SRE_1` (studentized residual), and `SDR_1` (studentized deleted residual).

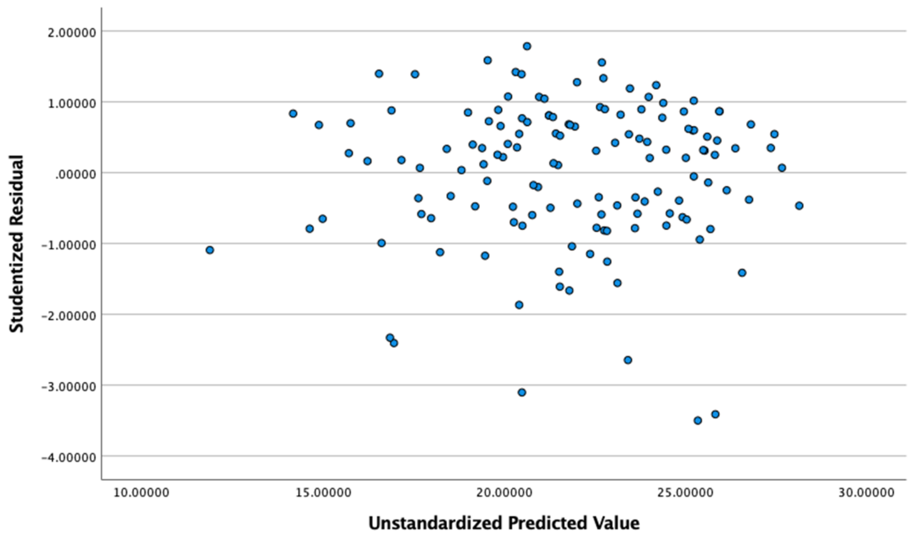
Independence

For the independence assumption to be met in regression, the residuals in the model must be independent. This means that information about one participant cannot influence information about another participant (Hayes, 2018). In our example, this would mean that the error in estimation of one participant's benevolence score does not influence the error in estimation of another participant's benevolence score. To test this assumption, we will use the Durbin-Watson statistic, which tests for the presence of autocorrelation in error terms (Uyanto, 2020). The Durbin-Watson statistic can vary between 0 and 4 ("Durbin–Watson Test," 2008) with values in the range of 1.5 to 2.5 indicative that the assumption of independence is met (Glen, 2022). To locate the Durbin-Watson statistic, first locate and expand the Output and then the Regression Dialogue on the left side of the SPSS output. Within the Regression dialogue, you will find the Model Summary dialogue which contains the Durbin-Watson values. In our example, the Durbin-Watson statistic is 2.035, which suggests the assumption of independence of residuals is met. We can now proceed to verifying the next assumption, which is the assumption of linearity.

Linearity

A core assumption of regression is IVs are related to the DV in a linear fashion such that as the IVs increase, the values of the DV either increase or decrease. This assumption can be tested by plotting the IVs and DV together or by using partial plots to verify the linear relationship between each IV and the DV. We will outline how to verify if the assumption of linearity is met by plotting all variables together. However, the output generated provides the partial plots for each IV, should the reader wish to verify the assumption of normality for each IV independently. To verify the assumption of linearity with the IVs and DV collectively, we will generate a scatter plot using the `SRE_1` (studentized residual) and `PRE_1` (unstandardized predicted value) values. First, click on `Graphs > Legacy Dialogs > Scatter/Dot > Simple Scatter >`

Figure 2 ■ Scatter diagram representing a linear relationship among all variables in the model.



`Define`. Move `PRE_1` to the X-Axis box, and `SRE_1` to the Y-axis box, and click Ok. A new figure will be generated in the SPSS output. Figure 2 shows the scatterplot generated using the data provided with this tutorial. Through visual inspection, the data appear to be horizontal in nature, which suggests the relationships between all variables in the model are linear.

Homoscedasticity

The assumption of homoscedasticity involves ensuring that the error that is present in the association between the IVs and the DV is consistent across the scores of the IVs. When the homoscedasticity assumption is violated, heteroscedasticity is present, which means that the error (the variability in the scores of the DV not attributable to the IVs) differs in size across the different scores of the DV (Osborne & Waters, 2002). To verify whether this assumption is satisfied, we can refer to the same scatter plot demonstrated in Figure 2. Recall that this is a plot of the residuals in the model and using the same visual inspection of the scatter plot performed above, we conclude that the residuals fit a rectangular shape. Thus, the error is scattered randomly across the different values of the DV, and the assumption of homoscedasticity is met. We can now proceed to verifying whether the assumption of multicollinearity is met.

Multicollinearity

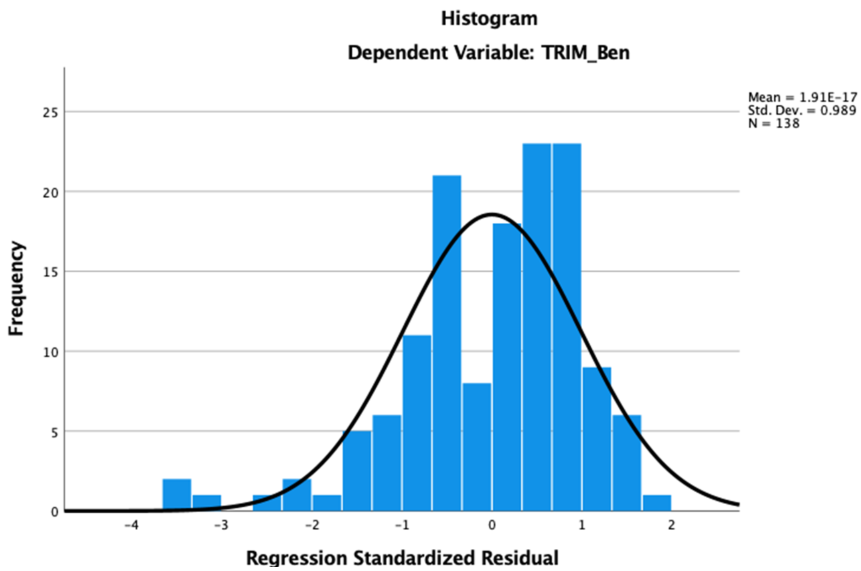
When two or more IVs are correlated with each other, multicollinearity may exist, which suggests that the scores of one or more IVs are determined by the other IVs in the model (Kim, 2019). To test whether multicollinearity exists, we will verify the values of either the variance inflation factor (VIF) or tolerance statistic generated in the SPSS output. The VIF and tolerance statistics are reciprocals of one another, so it is not necessary to check both values. The rules of thumb for each are such that tolerance should not be below 0.1 and VIF should not be above 10 (Miles, 2005). In our example, the tolerance values for the IVs range between 0.631 and 0.918, therefore multicollinearity does not exist in our model. The tolerance values can be found in the output view in SPSS by locating the Tolerance values in the Collinearity Statistics table which is found in Output / Regression / Coefficients. We now proceed to testing the assumption of normality.

Normality

The assumption of normality involves ensuring that the residuals, or the errors in estimation, are normally distributed (Hayes, 2018). We will verify whether this assumption has been met using plots that were generated in our output at the beginning of Step 2. We first perform a visual inspection of the histogram with a superimposed normality curve in Figure 3 which suggests that our data are somewhat negatively skewed.

Next, we visually inspect the P-P plot in Figure 4, which shows that the points are not perfectly aligned along the diagonal line and therefore the data is not normal. However, regression is robust against non-severe violations of normality (Hayes, 2018), thus the data will not be transformed,

Figure 3 ■ Histogram with normality curve.



and the moderated-mediation analysis will proceed.

Step 3: PROCESS Model 7 Moderated-Mediation Analysis. Since the data does not severely violate the assumptions of multiple regression analysis, we can proceed with the moderated-mediation analysis. For this example, Y is the total scores of benevolence motivations (`TRIM_Ben`), X is the total dyadic trust scores (`DTST`), M is the total compassion for the injuring partner scores (`CS_TOT`), and W is the total perception of the injuring partner as humble scores (`RHSTOT`). To perform a moderated mediation analysis using PROCESS, select `Analyze > Regression > PROCESS v4.1 by Andrew F. Hayes`. In the `PROCESS_v4.1` dialogue box, drag the `TRIM_Ben` into the Y variable window, `DTST` into the X variable box, `CS_TOT` into the Mediators(s) M box, and `RHSTOT` into the Moderator variable W box. In the Model Number drop-down box, select number 7 and in the remaining drop-down menus, select a confidence interval of 95%, and 5000 bootstraps (or more, but the analyses will take longer). The bootstrap value may be increased depending on the level of precision the user would like to obtain in the estimation of the limits of a confidence interval. As the number of bootstrap samples increases, the variability in the estimation of the limits of a confidence interval decreases (Hayes, 2018).

The types of analysis to conduct in PROCESS can be programmed by following the subsequent steps. First, click `Options` and then select `Generate code for visualizing interactions` to generate graphs of the interactions between the variables, `Pairwise contrasts of indirect effects` to compare the indirect effects of the moderator on the mediator, and the DV and IV. Under the `Heteroscedasticity-consistent inference` drop-down menu select `HC4 (Cribari-Neto)` to measure the standard error. In the `Conditional values` section in the bottom right, select `-1SD, Mean, +1SD` to view the results of the moderator at 1 standard deviation below and above the mean, and select `Continue`. In the `PROCESS_v4.1` dialogue box, click Ok to generate the output which can be found under Output > Matrix in the SPSS output window. This output has also been included in this tutorial, see Appendix 1.

Moderated-Mediation Data Interpretation

Step 4: Data Interpretation. The PROCESS output provides a comprehensive analysis of the data categorized into moderation, mediation, and moderated mediation output (Appendix 1). Before starting the analysis, confirm that the model was correctly generated by reviewing the IV, DV, W, and M variables as well as the sample size (lines 6 to 11). Also, ensure that there are no error messages that appear between lines 100 and 104. If variables were correctly analyzed and no error messages appear, then proceed with the subsequent steps.

Moderation Analysis

To determine if a moderation relationship exists between the IV and M, we need to interpret the model summary

Figure 4 ■ Normal P-P plot.

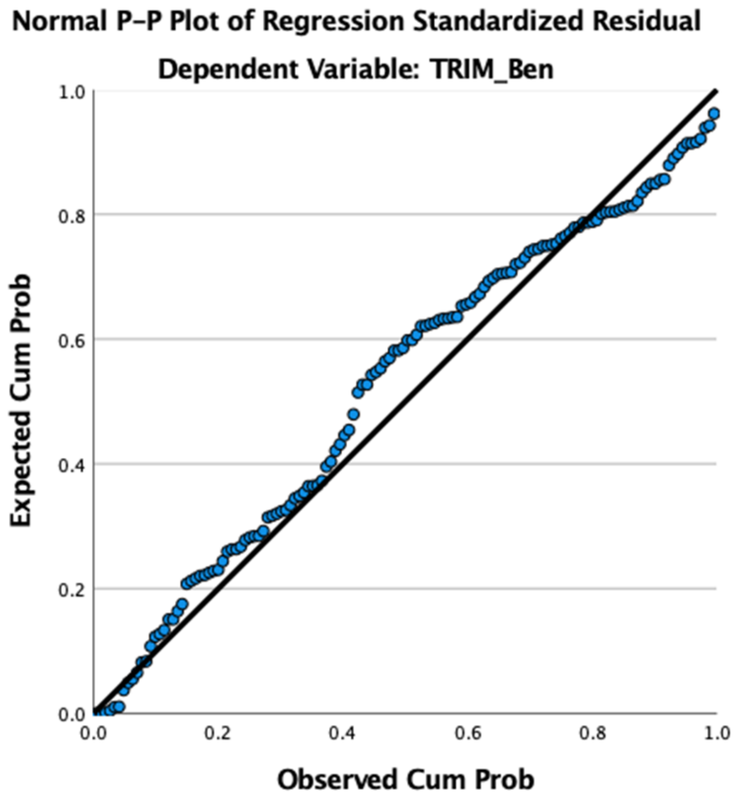
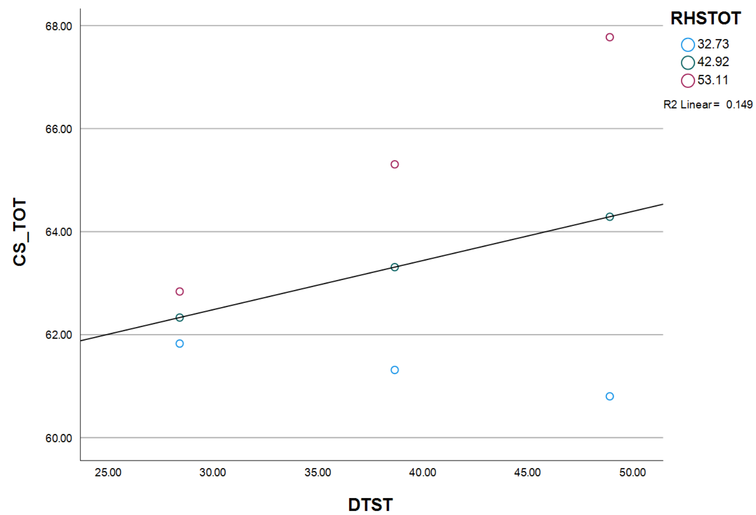


table for the Outcome Variable `CS_TOT` (compassion for injuring partner). This table is found from lines 13 to 21 of the SPSS PROCESS Output in Appendix 1. Within this table, there is a `Model Summary` section that provides the output necessary for determining if there are main effects of `RHSTOT` (W; perception of injuring partner as humble) and `DTST` (X; dyadic trust) as well as an interaction of these two variables on `CS_TOT` (M; lines 13 to 16). This can be determined by reviewing the p-value on line 16. As shown in the example, this model is significant ($p = .0008$) suggesting that there is a main effect and/or an interaction of `RHSTOT` (W) on the relationship between `DTST` (X) and `CS_TOT` (M). As this model is significant, it is important to determine which of the X and W variables contribute to the significant effect in this model. For this, determine if the p-value is below or above .05 and if the null of 0 falls between the confidence intervals for X and W. In this example, there were no main effects of dyadic trust ($b = -.517$, $t = -1.8519$, $p = .0662$; line 19) or the perception of the injuring partner as humble ($b = -.3549$, $t = -1.47$, $p = .1439$; line 20). However, there was a significant interaction (a path: $b = .0143$, $t = 2.3107$, $p = .0224$, line 21) which was also observed as the null of 0 does not fall between the confidence interval [0.0021, 0.0265]. The *Test(s) of highest order unconditional interaction(s)* table from lines 29 to 31 provides the r2 change reflecting the variance that the interaction explains. In this case, the RSTOT (W) explains 3.5% of the variance in the interaction between the `DTST` (X) and `CS_TOT` (M). Returning to our example, this suggests that the association between dyadic trust (X) and compassion for the injuring partner (M) is moderated by the perception of the injuring partner as humble (W).

As this interaction is significant, we can review the simple slopes to visualize this interaction between X on different levels of W, specifically at 1 SD below and above the mean, and at the mean. To visualize the interactions, select and copy all the lines of code from the PROCESS output (lines 43 to 56) and then paste these lines in a new syntax in SPSS by selecting `File > New > Syntax`. You are now ready to select `Execute` to generate a figure of the simple slopes of the interaction of `RHSTOT` (W) on the association between `DTST` (X) and `CS_TOT` (Y). The figure generated will not contain a fit line thereby making

Figure 5 ■ Simple slopes demonstrating the interaction of the moderation analysis.



it difficult to visualize the slopes. Therefore, to add this fit line, double-click on the figure that was created in the previous step and then select `Elements > Fit Line at Subgroups`. The fit line should now appear in your figure. The significance level at each of the three levels of `RHSTOT` is found in the `Conditional effects of the focal predictor at the values of the moderator(s)` table from lines 36 to 40. For the example used in this tutorial, compassion for the injuring partner (M) and dyadic trust (X) varies according to the extent to which the injured partner perceives the injuring partner as humble. Specifically, there is no significant association when the injured partner barely and moderately perceive the injuring partner as humble ($p = .2571$ and $p = .6368$; lines 39 and 38, respectively). In contrast, there is a significant effect of dyadic trust (X) and compassion for the injuring partner (M) when the injured partner perceives the injuring partner as highly humble (W, $p = .0222$; line 40). In Figure 5 below, the lower, average, and higher levels of `RHSTOT` are denoted by 32.73, 42.92, and 53.11, respectively.

Mediation Analysis

Now, we need to determine if there is a direct association between X and Y. To do this, we interpret the model summary in the Outcome Variable section for outcome variable `TRIM_Ben` (lines 59 to 67). According to the Outcome Variable – `TRIM_Ben` table found on lines 60 to 62, this model is significant ($p < .0001$; line 62). When looking at the R-squared value of the model summary, we can establish the variance explained by the predictors (X and M) on Y (line 62). In this case, the two predictors (e.g., `DTST` and `CS_TOT`) account for 31.8% of the variance of forgiveness (Y). Specifically, there is a significant direct effect [c' path: $t(135) = 3.6509$, $p = .0004$] as well as a significant indirect effect [ab path: $t(135) = 5.9916$, $p = .0000$] of X on Y. The c' and ab paths can be established by reviewing lines 67 and 66, respectively. The `Direct effect of X on Y` and `Conditional Indirect Effects of X on Y` are tables from lines 77-79 and 80-86, respectively. In this example, the null of 0 does not fall between the lower and upper limit of the 95% confidence interval for the IV [.0678, .2281; line 79] and at each level of M [.1954, .3880; line 67]. Therefore, there is a statistically significant effect of the level of dyadic trust on having compassion for the injuring partner, and of having compassion for the injuring partner on forgiveness.

Moderated Mediation Analysis

The `Index of moderated mediation` table provides information to determine if there is a significant moderated mediation following bootstrapping (lines 87 to 89). As seen in the output for this tutorial, the perception of the injuring partner as humble significantly moderates the indirect effect of dyadic trust (X) on forgiveness (Y) through compassion for the injuring partner (M), [CI = .0001 – .0077, line 89]. Therefore, there is evidence of a moderated mediation with this data.

Finally, the `Bootstrap results for the regression model parameters` table provide the confidence intervals for the a, b, and c' paths (lines 95 to 106). For this example, the interaction of `RHSTOT` on the association between DTST and CS_TOT is significant [CI = .0005, .0252, line 101]. The direct and indirect effects of DTST and CS_TOT on TRIM_Ben were also significant [CI = .0584, .2288 and .1920, .3885; lines 105 and 106 respectively]. We now turn to an example of how we would report the results of our moderation mediation analysis.

Step 5: Reporting results. Using the scenario for this tutorial to report the statistical findings, we conclude that there is a significant moderation effect of the perception of the injuring partner as humble (W) on the association between dyadic trust (X) and forgiveness (Y) through compassion for the injuring partner (M) [a path; $t(134) = 2.3107$, $p = .0224$]. Additionally, compassion for the injuring partner (M) has a significant effect on forgiveness (Y) [b path; $t(135) = 5.9916$, $p < .0001$]; however, dyadic trust (X) does not have a significant direct effect on forgiveness (Y) [c' path; $t(135) = 3.6509$, $p = .0678$]. Overall, this model indicates a statistically significant moderated mediation. This suggests that the perception of the injuring partner as humble significantly moderates the indirect effect of dyadic trust on forgiveness through compassion for the injuring partner [CI = .0001, .0077]. These findings are demonstrated in Figure 6.

Discussion

This tutorial provided step-by-step instructions for examining a moderated mediation model using PROCESS v4.1 for SPSS v28, and for analyzing the resultant output. A moderated mediation allows researchers to examine whether a mediation functions in a similar manner, or altogether differently, across varying groups of individuals (Jose, 2013). Although SEM is the most well-known statistical analysis for moderated mediation models (Hayes, Montoya, & Rockwood, 2017), other less complicated statistical analyses exist such as Hayes (2018) PROCESS macro for SPSS. While it can be seen from this tutorial that PROCESS is a simple, user-friendly statistical tool, it does have limitations that should be considered before it is incorporated into a statistical analysis strategy.

As mentioned above, PROCESS is not designed to be used with latent variables and Hayes (2020) suggests using Mplus to analyze models involving such variables. While specializing in models involving observed variables can be an advantage, it also has limitations including the potential for measurement error in the predictor variables, outcomes, and linear models (Hayes, 2012). With respect to moderated mediation models involving more than one mediator, PROCESS does not offer a model that combines moderation with serial multiple mediations (Hayes, 2012). Despite these limitations, PROCESS can be used to analyze several models of conditional processes beyond what this tutorial has demonstrated.

Conclusion

This tutorial presented instructions for using PROCESS with respect to a basic model of a moderated mediation (i.e., Model 7; Hayes, 2018) which serves as a useful starting point for understanding how to perform more complex models. We encourage the user to refer to Hayes (2018) for examples of complex conditional process models (e.g., double moderated mediation models). We hope that this tutorial inspires the development of more user-friendly methods for performing conditional process analyses along with easy-to-understand instructions for their use.

Authors' note

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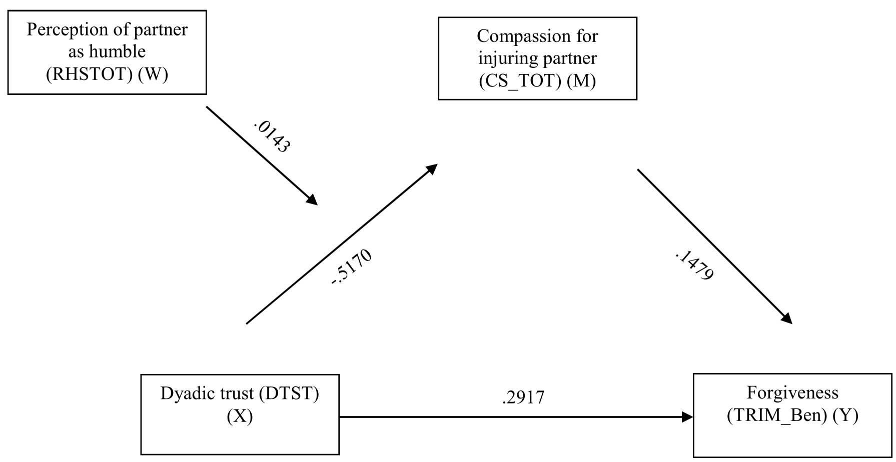
Figure 6 ■ Conceptualization of model 7 moderated mediation for fictional example.



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Appendix 1: PROCESS Output in SPSS

```
Run MATRIX procedure:
***************** PROCESS Procedure for SPSS Version 4.1 *****************
Written by Andrew F. Hayes, Ph.D.       www.afhayes.com    Documentation available in Hayes (2022). www.
    guilford.com/p/hayes3
**************************************************************************
Model  : 7
Y   : TRIM_Ben
X   : DTST
M   : CS_TOT
W   : RHSTOT
SampleSize:  138
**************************************************************************
OUTCOME VARIABLE: CS_TOT
Model Summary
R            R-sq        MSE          F        df1        df2          p
.3426        .1174    65.6657     5.9386     3.0000   134.0000      .0008
Model        coeff         se          t          p       LLCI       ULCI
constant   74.8582     9.9030     7.5591      .0000    55.2718    94.4447
DTST         -.5170      .2792    -1.8519      .0662    -1.0691      .0352
RHSTOT       -.3549      .2414    -1.4700      .1439     -.8323      .1226
Int_1         .0143      .0062     2.3107      .0224      .0021      .0265
Product terms key: Int_1      :        DTST       x        RHSTOT
Covariance matrix of regression parameter estimates:
           constant       DTST     RHSTOT      Int_1
constant    98.0696    -2.5880    -2.2642      .0579
DTST        -2.5880      .0779      .0560     -.0016
RHSTOT      -2.2642      .0560      .0583     -.0014
Int_1         .0579     -.0016     -.0014      .0000
Test(s) of highest order unconditional interaction(s):
  R2-chng      F          df1        df2             p
X*W      .0352      5.3392     1.0000   134.0000       .0224

```

```
Focal predict: DTST     (X)
Mod var: RHSTOT   (W)

Conditional effects of the focal predictor at values of the moderator(s):
RHSTOT      Effect        se         t          p        LLCI       ULCI
32.7287     -.0500      .1056     -.4733      .6368     -.2588      .1589
42.9203      .0955      .0839     1.1381      .2571     -.0704      .2613
53.1119      .2409      .1041     2.3135      .0222      .0349      .4468
Data for visualizing the conditional effect of the focal predictor: Paste the text below into a SPSS
    syntax window and execute to produce plot.
DATA LIST FREE/   DTST       RHSTOT     CS_TOT     .
BEGIN DATA.
28.3443    32.7287    61.8276
38.5942    32.7287    61.3154
48.8441    32.7287    60.8032
28.3443    42.9203    62.3331
38.5942    42.9203    63.3114
48.8441    42.9203    64.2898
28.3443    53.1119    62.8385
38.5942    53.1119    65.3074
48.8441    53.1119    67.7764
END DATA.
GRAPH/SCATTERPLOT=
DTST     WITH     CS_TOT   BY       RHSTOT

**************************************************************************
OUTCOME VARIABLE: TRIM_Ben
Model Summary
R           R-sq        MSE                  df1        df2          p
.5645      .3186    22.3035    31.5673     2.0000   135.0000      .0000
Model
              coeff          se          t          p        LLCI       ULCI
constant    -2.5780     3.1714     -.8129      .4177    -8.8500     3.6940
DTST          .1479      .0405     3.6509      .0004      .0678      .2281
CS_TOT        .2917      .0487     5.9916      .0000      .1954      .3880
Covariance matrix of regression parameter estimates:
           constant       DTST     CS_TOT
constant    10.0576     -.0334     -.1341
DTST         -.0334      .0016     -.0005
CS_TOT       -.1341     -.0005      .0024
Test(s) of X by M interaction:
     F          df1          df2                 p
.4658     1.0000    134.0000      .4961
****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************
Direct effect of X on Y
Effect        se         t          p       LLCI       ULCI
.1479      .0405     3.6509      .0004      .0678      .2281
Conditional indirect effects of X on Y:
INDIRECT EFFECT:
DTST        ->     CS_TOT      ->     TRIM_Ben
RHSTOT      Effect     BootSE     BootLLCI      BootULCI
32.7287     -.0146      .0352      -.0827          .0570
42.9203      .0278      .0253      -.0200          .0795
53.1119      .0703      .0283       .0193          .1307
Index of moderated mediation:
           Index      BootSE    BootLLCI   BootULCI
RHSTOT     .0042       .0019       .0001      .0077
Pairwise contrasts between conditional indirect effects (Effect1 minus Effect2)
Effect1     Effect2    Contrast        BootSE    BootLLCI       BootULCI
.0278      -.0146      .0424          .0195      .0014          .0784
.0703      -.0146      .0848          .0389      .0029          .1568
.0703       .0278      .0424          .0195      .0014          .0784
*********** BOOTSTRAP RESULTS FOR REGRESSION MODEL PARAMETERS ************
OUTCOME VARIABLE: CS_TOT
             Coeff    BootMean     BootSE    BootLLCI    BootULCI
constant   74.8582    73.8614    10.7387    49.0463    91.7395
```

```
DTST        -.5170     -.4965      .2944    -1.0333      .1395
RHSTOT      -.3549     -.3371      .2477     -.7660      .2078
Int_1        .0143      .0139      .0062      .0005      .0252
OUTCOME VARIABLE: TRIM_Ben
                  Coeff    BootMean     BootSE   BootLLCI   BootULCI
constant    -2.5780    -2.5068     3.1786    -8.6323     3.8387
DTST          .1479      .1468      .0437      .0584      .2288
CS_TOT        .2917      .2914      .0504      .1920      .3885
********************** ANALYSIS NOTES AND ERRORS ************************
Level of confidence for all confidence intervals in output:  95.0000
Number of bootstrap samples for percentile bootstrap confidence intervals:  10000
W values in conditional tables are the mean and +/- SD from the mean.
------ END MATRIX -----
```

Open practices

The *Open Data* badge was earned because the data of the experiment(s) are available on the journal's web site.

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