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Illustrations of serial mediation using PROCESS, Mplus and R

Laura Lemardelet [a] and Pier-Olivier Caron [b]

[a]Faculté des Sciences de l'Éducation, Université Laval
[b]Université TÉLUQ

Abstract ■ There has been an increased interest among researchers in the behavioral and social sciences for mediation models. This interest is well deserved: mediation can explain via intermediate variables the relationship between an independent variable and a dependent variable. Many software programs are now available to perform such analysis. However, there is a lack of articles to guide users to perform more complex models. The purpose of the current manuscript is to provide a tutorial on serial mediation analysis using software requiring less programming skills like SPSS (PROCESS), and Mplus to more advanced software such as R. In this manuscript, we first introduce the simple mediation analysis. Second, we explain the different parameters and effects of a serial mediation analysis with two mediators. Third, we show how to generate data using R. Fourth, we explain the input and output of PROCESS, Mplus, and R. Finally, a practical example is performed with Mplus.

Keywords ■ mediation, serial mediation. **Tools** ■ PROCESS, Mplus, R.

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laura.lemardelet.1@ulaval.ca

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Introduction

There has been an increasing trend in the behavioral, social, and educational sciences, among others, to unravel the mechanisms through which one variable influence another (MacKinnon, Fairchild, & Fritz, 2007; Preacher, 2015). Mediation analysis is the privileged statistical analysis model to uncover the relation between two variables (a predictor and an outcome) attributed to a third intermediatory variable (the mediator). The wide availability of software, such as PROCESS (Hayes, 2017), Mplus (Muthén & Muthén, 2017), and R (R Core Team, 2021), facilitates its spread among researchers. Despite widespread use, there is a lack of pedagogical articles to guide students and researchers through more complex mediation models, such as serial mediation.

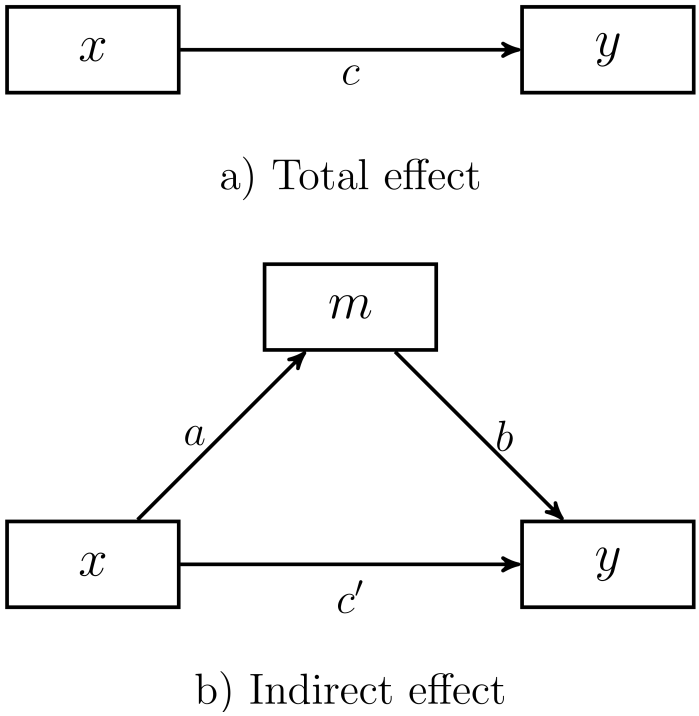
The purpose of the current manuscript is to provide a tutorial on serial mediation analysis for researchers and students in social and behavioral sciences. In this manuscript, we focus on three methods to implement serial mediation as to build on more user-friendly software (SPSS, Mplus) to reach to more technical methods. The sections of the manuscript are as follow: the theoretical foundations of simple and serial mediation are described, an illustrative example to generate data for serial mediation is presented, mediation analysis with PROCESS, Mplus and R is explained, and finally, a practical example is provided with Mplus.

Simple mediation

Simple mediation is the most well-known and prototypical mediation model. It describes the relationship between an independent variable (x) and a dependent variable (y) by adding a third variable called the mediator (m). Methodologically, for all mediation models, a temporal difference between the independent variable (IV; time 1), the mediator variable (MV; time 2) and the dependent variable (DV; time 3) is recommended because cross-sectional models provide biased estimates by omitting the prior values of these variables and the effects of the variables on themselves (Gollob & Reichardt, 1987). Thus, longitudinal models provide better inferences about causal relationships within a mediation model (Cole & Maxwell, 2003).

To illustrate the mediation model, Figure 1 is depicted

Figure 1 ■ Illustration of models. (a) Illustration of the total effect between an independent variable, x, and a dependent variable, y. (b) Illustration of a mediated relation between an independent variable,x, to a dependent variable, y, through a mediator, m.



into two parts: a bivariate regression model and a mediation model. Figure 1a shows the relationship between x and y without accounting for the mediator (m), which is called the total effect, represented using the parameter c. Adding a mediator between x and y yield the path diagram in Figure 1b. Here, the parameter a is the regression of x on m. The parameter b is the regression of m on y accounting for x. The parameter c' is the regression of x on y accounting for m. All parameters are regression coefficients. Three simple effects can be identified:

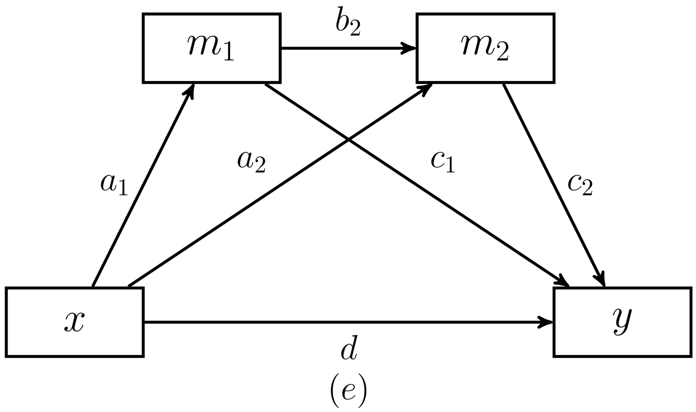
1. The total effect of x on y (c);
2. The simple effect of x on m (a);
3. The simple effect of m on y controlling for x (b).

By adding the mediator, the path diagram includes an indirect effect which is the mediating effect of m between x and y, e.g., the product of paths a and b. If the indirect effect is statistically significant, then m is deemed a mediator.

To determine the significance of the indirect effect, the bootstrap method is privileged by methodological researchers. The bootstrap method (Efron & Tibshriani, 1994) is a computer-intensive method which use random resampling to estimate the sampling distribution of almost any statistics. In a mediation analysis, subjects from the original sample are randomly selected, with replacement, to generate many subsamples, allowing the computation of the two parameters of interest which are a and b. Obtaining these two parameters will allow to obtain their product and to calculate the indirect effect of mediation. The calculation of the indirect effect by boostrapping will allow the estimation of the confidence intervals and the standard errors of the desired effect. This method is recommended over other methods because it follows the empirical distribution of the indirect effect (non-normal) resulting in greater statistical power (Caron & Valois, 2018; Özdil & Kutlu, 2019), more appropriate Type I error rate (Caron, 2019), and robustness when the data are not normal (Cheung & Lau, 2008).

In this manuscript, we will not go deeper on simple mediation as it has been already addressed by other articles (Caron & Valois, 2018; Fairchild & McDaniel, 2017; Kane & Ashbaugh, 2017; Lange, Hansen, Sørensen, & Galatius, 2017), we focus now on serial mediation.

Figure 2 ■ Illustration of serial mediation analysis with two mediators.



Serial mediation

Human behavior is rarely simple. There is a plethora of ongoing processes which can be accounted by models ranging from not so complicated to very convoluted. One way to account for complex human behavior is the addition of multiple mediators, such as parallel mediation or serial mediation. In parallel mediation, at least two mediating variables are non-consecutive in times whereas at least two variables are consecutive in serial mediation. Figure 2 depicts a serial mediation model including two mediators m_1 and m_2. The serial mediation includes many parameters:

- Path a_1 is the regression of x on m_1;
- Path a_2 is the regression of x on m_2;
- Path b_2 is the regression of m_1 on m_2 controlling for the effects of x;
- Path c_1 is the regression of m_1 on y controlling for the effects of x;
- Path c_2 is the regression of m_2 on y by controlling for the effects of x and m_1;
- Path e is the total effect, that is, the regression of x on y;
- Path d is the direct effect which is the effect of x on y by controlling for the effects of m_1 and m_2.

To estimate these parameters, three regressions are necessary to perform a serial mediation analysis and to compute the indirect effect. The first step is to regress x to m_1 to obtain the parameter a_1. The second is to regress x and m_1 to m_2 to obtain a_2 and b_2 respectively. The third step is to regress x, m_1 and m_2 to y to obtain d, c_1 and c_2, respectively. A fourth optional step is to regress x on y, to obtain e, the total effect, which can also be computed from the sum of all primary indirect effects (a_1c_1, a_2c_2, $a_1b_2c_2$) and the total effect; $e = d + a_1c_1 + a_2c_2 + a_1b_2c_2$. The structural equation model has the advantage of running all regressions simultaneously and to yield fit indices when the model is not saturated.

When two mediators are considered, the total effect, e is divided into five indirect effects. There are three primary indirect effects:

- the specific indirect effect of m_1, the product a_1c_1, shown in Figure 3a;
- the specific indirect effect of m_2, the product a_2c_2; shown in Figure 3b;
- the serial indirect effect of m_1 and m_2, the product $a_1b_2c_2$, shown in Figure 3e;

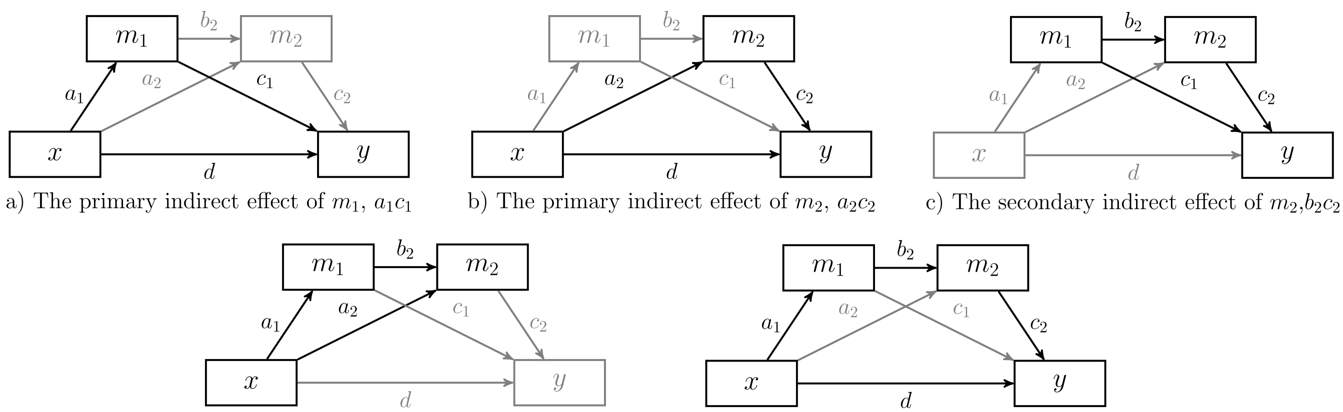
and two secondary indirect effects:

- the specific indirect effect of m_1, the product a_1b_2, shown in Figure 3d;
- the specific indirect effect of m_2, the product b_2c_2, shown in Figure 3c.

The three primary indirect effects are effects that goes from x (the exogenous variable) to y (the outcome). The two secondary effects concern the relationship from x to m_2 (a_1b_2) or from m_1 to y (b_2c_2). Secondary effects are rarely reported in the output but can be of interest, especially if the intermediary path between the two mediators is not significant.

Primary indirect effects are grouped under the total indirect effect. If this effect is significantly different from zero, then there is at least one mediation effect in the model. First, we have to look if the serial indirect effect, $a_1b_2c_2$ is significantly different from zero which suggests a serial mediation effect. Second, if it is not significant, other indirect effects should be investigated. The absence of significant relation between m_1 and m_2 could suggest a parallel mediation or, otherwise, a simple indirect effect from a single mediator.

Figure 3 ■ The five indirect effects included in a serial mediation analysis with two mediators.



a) The primary indirect effect of m_1, a_1c_1 b) The primary indirect effect of m_2, a_2c_2 c) The secondary indirect effect of m_2,b_2c_2

d) The secondary indirect effect of m_1,a_1b_2 e) The primary indirect effect of m_1 and m_2, $a_1b_2c_2$

Illustrative example

To illustrate serial mediation analysis, data were generated with R (R Core Team, 2021) using codes inspired from Caron and Valois (2018). For the sake of simplicity, variables x, m_1, m_2 and y have a normal distribution, with a mean of 0 and a standard deviation of 1. This led population parameters to be standardized coefficients. Listing 1 shows the R code to generate the model data with $n = 432$, and parameters: $a_1 = .5$, $a_2 = .3$, $b_2 = .2$, $c_1 = .7$, $c_2 = .4$, and $d = 0$. In this function, the first step is to calculate the errors (variance of the residuals) from m_1, m_2 and y : ε_{m_1}, ε_{m_2}, and ε_y. Each formula is identified by the lines of R syntax given in Listing 1. The following are the three formulas for the variance of the three residuals errors, ε_{m_1}, ε_{m_2} and ε_y:

$$\text{var}(\varepsilon_{m_1}) = 1 - a_1^2 \qquad \textbf{(line 5)}$$

$$\text{var}(\varepsilon_{m_2}) = 1 - a_2^2 + b_2^2 + 2a_2b_2a_1 \qquad \textbf{(line 6)}$$

$$\begin{aligned}\text{var}(\varepsilon_y) = 1 - (d^2 + c_1^2 + c_2^2 + 2dc_1a_1 + \\ 2dc_2(a_2 + a_1b_2) + \\ 2c_1c_2(b_2 + a_1a_2)) \qquad \textbf{(line 7)}\end{aligned}$$

To achieve a standardized scenario, the explained variance of predictors is subtracted from 1 (the variance of outcome which is set to 1; Caron & Lemardelet, 2021). The variable x is generated **(line 11)** using a standard normal distribution for X so that $X \sim \mathcal{N}(0, 1)$ must be generated, to obtain the data for m_1, m_2 and y . For the computation of m_1, m_2 and y data, the errors are normally distributed with mean 0 and standard deviations $sd(\varepsilon_{m_1})$, $sd(\varepsilon_{m_2})$, and $sd(\varepsilon_y)$. When x is generated, it is possible to obtain the data from m_1, which is the first regression of the serial mediation model. The mathematical formula is as follows:

$$m_1 = a_1x + \varepsilon_{m_1} \qquad \textbf{(line 12)}$$

When m_1 is created, the second regression of the mediation analysis, m_2, can be computed:

$$m_2 = a_2x + b_2m_1 + \varepsilon_{m_2} \qquad \textbf{(line 13)}$$

Finally, having obtained the data for x, m_1 and m_2, we can calculate y, which is the last regression of the model:

$$y = dx + c_1m_1 + c_2m_2 + \varepsilon_y \qquad \textbf{(line 14)}$$

An optional step could be to calculate the parameter e which represents the total effect of x on y:

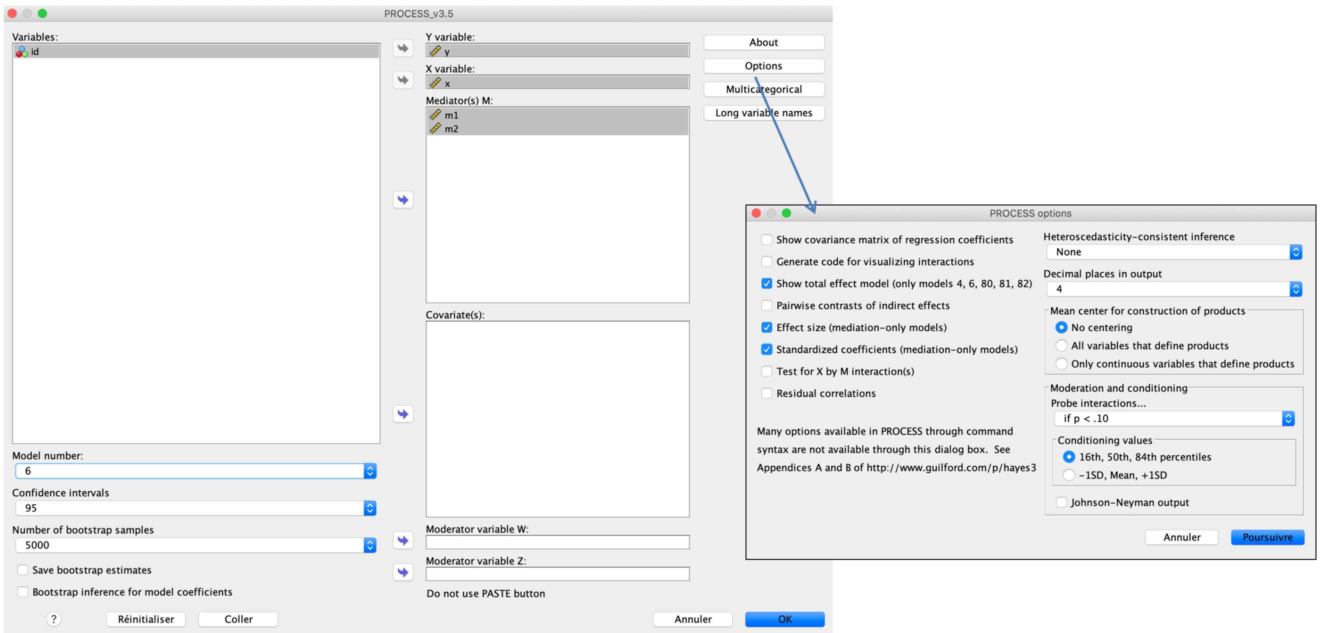
$$e = d + a_1c_1 + a_2c_2 + a_1b_2c_2 \qquad \textbf{(line 17)}$$

The data were generated with the default parameters ($a_1 = .5$, $a_2 = .3$, $b_2 = .2$, $c_1 = .7$, $c_2 = .4$, $d = 0$) with the default sample size $n = 432$ (a sample size appropriate for serial mediation analyses). See supplementary material on the journal's web site for the data file. The data set was then used to perform the analyses with the PROCESS macro of SPSS, Mplus and R.

Analysis in Process

IBM SPSS (IBM Corporation, 2020) is probably the most known and used statistical software in the behavioral science. However, it is not optimized for mediation analysis because it does not allow to run simultaneous several

Figure 4 ■ Main dialog box in PROCESS and dialogue box for options.



linear regressions, which implies that indirect effects and their bootstraping cannot be performed. By adding PROCESS (Hayes, 2017), an SPSS macro that has to be installed by the users, both mediation and moderation analyses can be performed. PROCESS is an add-on, easily and freely available at the following URL: https://www.processmacro.org/download.html. The installation guidelines and the various possible models (more than 75 models) are included in the downloaded file. The input (dialog box) and the output will be presented to understand the serial mediation analysis with PROCESS.

Input

Once installed, we can select PROCESS in the SPSS dialog boxes (`analyze` → `regression`). Figure 4 shows the main dialog box to customize the serial mediation model. First, we have to specify the desired model in `model number`. For serial mediation with two mediators, this is model number 6 (refer to the document provided with PROCESS for an overview of all possible models). Second, the variables of the model are selected in the left section of the dialog box. Finally, we have to specify the confidence interval and the number of resamples we want. By default, SPSS uses a confidence interval of 95% and bootstrap of 5000 replication. Now we have to click on `options` to enter the required parameters.

After clicking on `options`, a new dialog box opens, as shown inset Figure 4. Here PROCESS indicates the optional information for the analysis. We recommend three relevant options: *show total effect model*, *effect size* and *standardized coefficients*.

Once options are chosen, we click on `Continue` and we can carry the analysis by clicking on `OK`.

Output

Appendix A shows the PROCESS output. For an easier interpretation of the results, lines were assigned for all items present in the output file. In addition, yellow allows for quick identification of important results to be located in Appendix A (the output of the SPSS macro analysis). Parameter a_1 is shown at **line 33** ($\beta = .49$ [.410; .576], $p < .001$; hereafter, numbers between brackets denote 95% confidence interval), parameter a_2 is shown at **line 51** ($\beta = .18$ [.090; .265], $p < .001$), parameter b_2 is shown at **line 52** ($\beta = .46$ [.365; .539], $p < .001$), parameter c_1 is shown at **line 72** ($\beta = -.02$ [-.087; .056], $p = .668$), the parameter c_2 is at **line 73** ($\beta = .67$ [.593; .734], $p < .001$), the direct effect d is at **line 71** ($\beta = .25$ [-.093; .019], $p < .001$), the total effect e is at **line 90** ($\beta = .52$ [.425; .583], $p < .001$), and **line 118** shows the total indirect effects ($\beta = .27$ [.210; .318]) which is significant because zero is not included in the confidence interval. The indirect effect, $a_1 b_2 c_2$ (**line 121**), shown in Figure 3e, is deemed significant (β = .15 [.113; .193]). Likely, there is a serial mediation effect with

Table 1 ■ Results produced by the package `pathanalysis` with R.

	Estimate	S.E.	CI Lower 95 %	CI Upper 95 %	p-value
x -> m1	0.492	0.043	0.409	0.580	0.000
x -> m2	0.181	0.040	0.105	0.262	0.000
x -> y	0.252	0.035	0.184	0.318	0.000
m1 -> m2	0.464	0.043	0.379	0.546	0.000
m1 -> y	−0.016	0.038	−0.091	0.059	0.674
m2 -> y	0.666	0.039	0.589	0.744	0.000
x -> m1 -> m2	0.228	0.029	0.172	0.288	0.000
x -> m1 -> y	−0.008	0.019	−0.046	0.029	0.675
x -> m2 -> y	0.121	0.028	0.068	0.177	0.000
m1 -> m2 -> y	0.309	0.035	0.242	0.378	0.000
x -> m1 -> m2 -> y	0.152	0.022	0.111	0.197	0.000
total indirect	0.265	0.033	0.202	0.331	0.000
total effect	0.517	0.041	0.438	0.597	0.000

the mediators m_1 and m_2. As for the two others primary indirect effects: the indirect effect a_1c_1 (Figure 3a) shown to be non-significant [-.046; .028] at **line 119**, which imply there is no mediated effect passing through m_1 and the indirect effect a_2c_2 (Figure 3b) emerges as significant [.068; .174] at **line 120**, so there is a mediation effect when passing through m_2. PROCESS does not provide the secondary indirect effects.

Analysis in Mplus

Mplus (Muthén & Muthén, 2017) is a statistical modelling program that provides researchers with a flexible tool to analyze complex statistical models. Its programming is at the halfway between SPSS and R. Mplus is exclusively based on a syntax, unlike SPSS, but the syntax is easier than R. In this manuscript, the basic principles of the syntax of Mplus will not be discussed (for a detail presentation see Byrne, 2013; Caron, 2018; Geiser, 2013; Kelloway, 2015; Wang & Wang, 2020), we will focus on the commands needed to run a serial mediation analysis and on understanding the output file.

Input

For all analyses in Mplus (version 8.3), shown in listing 2, it is necessary to enter the title (**line 1**), the location of the data (**line 3**), the name of the variables in the file (**line 6**) and the name of the variables to use (**line 7**). As a reminder, each command in Mplus must end with the following punctuation " ; ". To carry out the serial mediation analysis, we have to specify first the bootstrap and the number of bootstraps under ANALYSIS (**line 10**). Here, 5000 bootstrap samples are required. Second, **lines 13 to 15** specify the mediation model. **Line 13** is the path between x and m_1, **line 14** is the relationship between m_1 and m_2 accounting for x and **line 15** is the relationship between x and y through m_1 and m_2. Third, the indirect model is specified between the variables x and y (**line 18**). Finally, **line 20** allows us to obtain the standardized coefficients and the confidence intervals from the Bootstrap. Now the serial mediation analysis can be performed.

Output

Appendix B is the output file of the serial mediation analysis with Mplus. Like previously, we kept the same presentation style (the **lines** and `yellow` color for the parameters). All the estimates are the same; the only differences are with regards to the bootstrap intervals which differs on the second decimals. Such small differences are to be expected as these bootstrap intervals are based on 5000 random subsamples. From **line 236** to **line 250**, the standardized results with Bootstrap are available and from **line 291** to **line 320**, these are the indirect, direct, and total standardized effects with bootstrapping. **Line 241** is the parameter a_1 ($\beta = .49$ [.417; .560]). **Line 244** is the parameter a_2 ($\beta = .18$ [.101; .256]). **Line 245** is the parameter b_2 ($\beta = .46$ [.386; .542]). **Line 249** is the parameter c_1 ($\beta = -.02$ [-.092; .056]). **Line 250** is the parameter c_2 ($\beta = .67$ [.604; .727]). The direct effect, d, is on the **line 248 and 320** ($\beta = .25$ [.183; .320]). Total effect, e, is on the **line 299** ($\beta = .52$ [.445; .581]) and **line 300** shows the total indirect effects (β = .27 [.209; .321]). For primary indirect effects, the **line 305** shows the indirect effect a_1c_1 that is insignificant ($\beta = -.01$ [-.047; .027]), the **line 310** shows the indirect effect a_2c_2 that is significant ($\beta = .12$ [.068; .172]) and the **line 316** shows the indirect effect $a_1b_2c_2$ that is significant ($\beta = .15$ [.116; .196]). Unlike Process, Mplus provides p-values for indirect effects. However, as for Process, Mplus does not provide the secondary indirect effects.

Analysis in R

R is a free programming software for statistical computing and graphics (R Core Team, 2021). It is often use in conjunction with RStudio, an integrated development environment (Team, 2020), which increases the convenience and accessibility of R. Alone, R cannot carry out mediation analyses. However, being a collaborative platform, there are already available package that can be downloaded (`install.packages()`). Packages for mediation analysis are mediation (Tingley, Yamamoto, Hirose, Keele, & Imai, 2014) and Rmediation (Tofighi & Mackinnon, 2011), both coming with its own documentation. The existence of packages should not overshadow the fact that it can be quite easy to develop its own script to perform hypothesis testing of indirect effects with some basic programming skills. Herein, we will describe our own script of bootstrap for indirect effect, which is inspired from Caron and Valois (2018).

Bootstrap method

The bootstrap method (Efron & Tibshriani, 1994) is a computer-intensive method which use random resampling to estimate the sampling distribution of almost any statistics. Its very basic is to randomly select with replacement subjects of the original sample to generate many subsamples and then computing the statistics of interest. Confidence intervals can be computed from the sampling distribution, which can then be used to guide statistical inference.

Listing 3 shows an example of code that can be used to assess the significance of indirect effect in mediation analysis. The code is separated in four main parts: the code to 1) carry a specific indirect effect; 2) use the bootstrap method; 3) run the analysis for a specific indirect effect; 4) the importation of package to carry a complete mediation analysis. One can easily use the code herein (complete code in supplementary file available).

The **lines 1 to 9** specify a function to compute a desired statistic, herein the indirect effect of x through m_1 and m_2 to the outcome y. The function is called `indirect()` and is used within the bootstrap method after. The function extracts the relevant regression estimates to compute the indirect effect and carry their product. It then returns the results. If another indirect effect was of interest, another function should be written to compute this new one. A general case will be describe using a homemade package.

The **lines 11 to 26** is a homemade function to carry the bootstrap method called `boot()`. It works for any statistics specified as the argument stat, like the median for instances, not just `indirect()`. The core of the bootstraps is found in **lines 18-21** where the function `sample()` (**line 19**) randomly selects with replacement the participants among the n participants (recorded at **line 15**). The next line (**line 20**) computes the desired statistics and records it iteratively in the variable est. **Lines 19 and 20** are looped nrep times. Once the resample is finished, the bootstrap samples are used to compute an average estimate, its standard error and its confidence interval. The `boot()` function returns the results. The number of replications and the type I error rate can be specified by the user (by default `nrep = 5000; alpha = .05`).

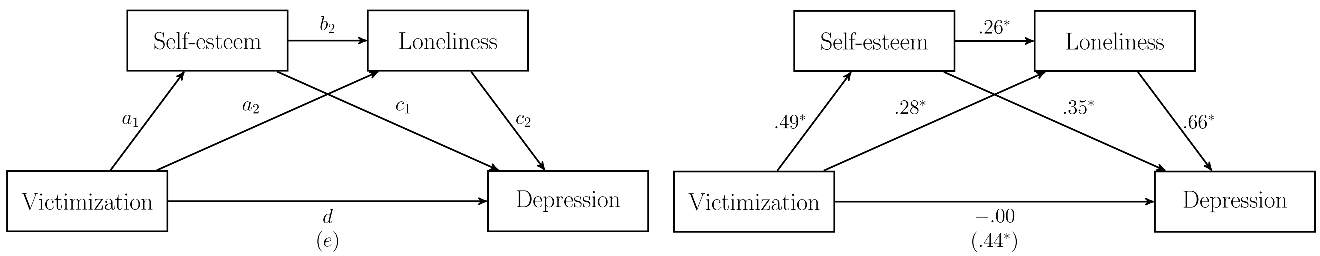
Lines 28-32 shows how to use `boot()` and `indirect()` together. At **line 30**, the data set is imported in R. At **line 32**, the `boot()` function is used with the desired statistics, which is `indirect()`, and the given data set. Its output returns the estimate, its standard error and its confidence interval, which can then be interpreted.

A homemade package, called `pathanalysis`, is in development by the second author (Caron, 2021). The package can be downloaded from GitHub directly into R. The code to do so are presented in the fourth part of the code at **lines 34-47**. At first, the package devtools (or remotes) must be installed, which can be easily done with **line 37**. Once installed, **line 39** imports the package from GitHub and using **line 40** makes the package available in the environment. The package contains the data sets use in this example and so can be imported via **lines 41-42**. The package contains the function `mediation()`. This function needs as an argument the model, that is, the order of the variables in the mediation, outcome to first variable, and a data set. The argument model is a formula like `y ~ m ~ x` which identify the outcome and first variables and all mediator in between. The ~ acts in a similar fashion like other formula in R (such as `lm()`, for instances), it specifies the dependent variable on the left and their independent variables on the right (like the `ON` function in Mplus). Here, the model is `model = y ~ m2 ~ m1 ~ x`. The function `mediation()` returns all indirect effects in the model, which is carried out at **lines 46-47**.

Output

Table 1 is the output file of the serial mediation analysis with package `pathanalysis` with R. **Line 1** is the parameter a_1 ($\beta = .49$, [.409; .580] $p < .001$). **Line 2** is the parameter a_2 ($\beta = .18$, [.105; .262] $p < .001$). **Line 4** is the parameter b_2 ($\beta = .46$ [.379; .546] $p < .001$). **Line 5** is the parameter c_1 ($\beta = -.02$, [-,091; .059] $p = .674$). **Line 6** is the parameter c_2 ($\beta = .67$, [.589; .744] $p < .001$). The direct effect, d, is on the **line 3** ($\beta = .25$, [184; .318] $p < .001$). Total effect, e, is on the **line 13** ($\beta = .52$, [.438; .597] $p < .001$) and **line 12** shows the total indirect effects (β = .27 [.202; .331] $p < .001$). Unlike Process and Mplus, R provides p-values for indirect effects. For primary indirect effects, the

Figure 5 ■ (Left) The theoretical model of the mediating effects of self-esteem and loneliness between victimization and depression; (right) the fitted model.



line 8 shows the indirect effect a_2c_1 that is insignificant ($\beta = -.01$ [-.046; .029], $p = .675$), the **line 9** shows the indirect effect a_2c_2 that is significant ($\beta = .12$ [.068; .177], $p < .001$) and the **line 11** shows the indirect effect $a_1b_2c_2$ that is significant ($\beta = .15$ [.111; .197], $p < .001$). The advantage of R is to provide the secondary indirect effects. The **line 7** shows the secondary indirect effects a_1b_2 that is significant ($\beta = .23$ [.172; .288], $p < .001$) and the line 10 shows the secondary indirect effects b_2c_2 that is significant ($\beta = .31$ [.242; .378], $p < .001$).

Practical example

To provide the reader a better understanding of serial mediation analysis, a fictive example is presented. The data were generated with R like the previous method. In this example, we are interested in whether self-esteem and loneliness mediate the relationship between school victimization and depressive symptoms. In other words, we want to investigate whether low self-esteem and loneliness can explain why victimized adolescents are prone to depressive symptoms. Thus, the variables being studied are:

- Independent variable: Victimization (`victimi`)
- Dependent variable: Depressive symptoms (`dep`)
- Mediators: Low self-esteem (`low_se`) and Loneliness (`lone`).

An illustration of the model is provided in Figure 5, right panel, and the input for Mplus is provided in listing 4. To reproduce the analysis, the data file used is included in the supplementary documents of the manuscript.

Results

For the output of Mplus, to Appendix C, **line 241** is the effect of victimization on low self-esteem (path a_1; $\beta = .49$ [.419; .549]). **Line 244** is the effect of victimization on loneliness (path a_2; $\beta = .28$ [.181; .367]). **Line 245** is the effect of low self-esteem on loneliness controlling for victimization (path b_2; $\beta = .26$ [.170; .344]). **Line 249** is the effect of low self-esteem on depression controlling for victimization (path c_1; $\beta = .35$ [.301; .405]). **Line 250** is the effect of loneliness on depression controlling for victimization and low self-esteem (path c_2; $\beta = .66$ [.617; .708]). The direct effect, the effect of victimization on depression controlling for the effects of low self-esteem and loneliness, is in **lines 248 and 320** (path d; $\beta = -.00$ [-.058; .0,58]). The total effect, the effect of victimization on depression, is in **line 299** (path e; $\beta = .44$ [.355; .511]) and the total indirect effect is in **line 300** ($\beta = .44$ [.372; .504]). Indirect effect, a_1c_1, the effect of victimization on depression through low self-esteem is in **line 305** ($\beta = .17$ [.140; .210]). Indirect effect a_2c_2, the effect of victimization on depression through loneliness is in **line 310** ($\beta = .18$ [.119; .249]). Finally, the indirect effect of serial mediation, $a_1b_2c_2$, the effect of victimization on depression through low self-esteem and loneliness is in **line 316** ($\beta = .08$ [.056; .115]).

Presentation of the results

The purpose of this manuscript has been to test the mediating role of low self-esteem and loneliness in the relationship between victimization and depression. To test our serial mediation model, we used Mplus software with bootstrapping of 5000 replications. The results reveal that victimization has an indirect effect on depression in the presence of low self-esteem and loneliness ($\beta = .08$ [.056; .115]) with a 95% confidence interval not including 0. Specifically, Figure 5, right panel, shows the standardized estimates found between the variables in the model. As observed, victimization has a significant and positive effect on low self-esteem ($\beta = .49$ [.419; .549]) and loneliness ($\beta = .28$ [.181; .367]). In addition, self-esteem has a positive effect on loneliness when the effects of victimization are controlled ($\beta = .26$ [.170; .344]) as does loneliness on depression when victimization and self-esteem are controlled ($\beta = .66$ [.617; .708]) and self-esteem on depression when victimization is controlled ($\beta = .35$ [.301; .405]). The total effect, the effect of victimization on depression, is significantly positive ($\beta = .44$ [.355; .511]). Conversely, the effect of victimization on depression *is non-significant when self-esteem and loneliness are controlled ($\beta = -.00$ [-.058; .0,58]). Finally, simple mediation effects can be observed. Indeed, the indirect effect between victimization and depression is significantly positive in the presence of the low self-esteem mediator ($a_1 \times c_1$= .17 [.140; .210]) and in the presence of the loneliness mediator ($a_2 \times c_2$= .18 [.119; .249]) because 0 is not included in the 95% interval.*

Conclusion

Mediation analyses have been widely used in the human and social sciences. Many articles have dealt with the guidelines of simple mediation. However human complexity leads researchers to investigate more complicated models, such as adding multiple mediators. Thus, this manuscript provides a tutorial for any researcher or student who desires to perform serial mediation analysis with two mediators with PROCESS, Mplus and R. Through this tutorial, we hope to provide a better overview of serial mediation analysis and to encourage the reader to learn more about other types of mediations (e.g., parallel mediation, moderated mediation) or more complex models such as multilevel mediation models.

Authors' note

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Listing 1 ■ Generate data with R

```
Generate_data_mediation_serie <- function(n = 432, a1 = 0.5,
               a2 = 0.3, b2 = 0.2, c1 = 0.7, c2 = 0.4, d = 0){

  # Step to determine the measurement errors of M1, M2 and Y
  em1 <- sqrt(1 - a1^2)
  em2 <- sqrt(sqrt(1 - (a2^2 + b2^2 + 2 * a2 * b2 * a1)))
  ey  <- sqrt(1 - (d^2 + c1^2 + c2^2 + 2 * d * c1 * a1 + 2 * d
         * c2 *(a2 + a1 * b2) + 2 * c1 * c2 * (b2 + a1 * a2)))

  # Step to generate the data
  x  <- rnorm(n, mean = 0, sd = 1)
  m1 <- a1 * x + em1 * (rnorm(n, mean = 0, sd = 1))
  m2 <- a2 * x + b2 * m1 + em2 * (rnorm(n, mean = 0, sd = 1))
  y  <- d * x + c1 * m1 + c2 * m2 +
       ey * (rnorm(n, mean = 0, sd = 1))

  # Optional step to calculate the total effect
  e  <- d + a1 * c1 + a2 * c2 + a1 * b2 * c2

  data <- as.data.frame(cbind(x, y, m1, m2))
  return(data)
}
```

Listing 2 ■ The Mplus input file

```
TITLE: Analysis of serial mediation

DATA: file is data.dat;

VARIABLE:
  names are id x m1 m2 y;
  usevariables are x m1 m2 y;

ANALYSIS:
  bootstrap = 5000;

MODEL:
  m1 on x;
  m2 on x m1;
  y on x m1 m2;

  model indirect:
  y IND x;
```

```
OUTPUT: stdyx cinterval (bcbootstrap);
```

Listing 3 ■ Illustration in R of the serial mediation with two mediators.

```
# Create a function to compute a desired indirect effect
# Carry the necessary regressions, then extract the relevant
# estimates (here a1, b2 and c2), then multiply them.
indirect <- function(data){
  a1 <- coef(lm(m1 ~ x, data = data))["x"]
  b2 <- coef(lm(m2 ~ m1 + x, data = data))["m1"]
  c2 <- coef(lm(y ~ m2 + m1 + x, data = data))["m2"]
  return(a1b2c2 =  a1 * b2 * c2)
}

# Bootstrap method
# Defined a data set and the desired statistic, then compute
# the mean, the standard error and confidence intervals
boot <- function(data, stat, nrep = 5000, alpha = .05){
  n <- nrow(data)                # Number of subjects
  est <- as.numeric()            # Empty variables for recording
  Results <- list()              # Empty variables for recording
  for(k in 1:nrep){              # Loop nrep times
    index <- sample(n, replace = TRUE) # Resampling
    est[k] <- stat(data[index,])       # Desired statistic
  }
  Results$Estimate <- mean(est)        # Computing results
  Results$`S. E.` <- sd(est)
  Results$CI <- quantile(est, prob = c(alpha/2, (1-alpha/2)))
  return(Results = Results)
}

# Carry the computation of the indirect effect
# Import data
data <- read.csv2(file = data.csv)
# Start the analysis
boot(data = data, stat = indirect)

# Carry all indirect effets
# The development version from GitHub:
# The package "devtools" is necessary to download the package
install.packages("devtools")
# Import the package "pathanalysis"
devtools::install_github(repo = "quantmeth/pathanalysis")
library(pathanalysis)
# The data file used is in the package readily available
data <- medEX

# The function mediation is now available
# Specify the model and the data set
mediation(model = y ~ m2 ~ m1 ~ x, data = data,
          standardized = TRUE)
```

Listing 4 ■ The Mplus input file for the application of serial mediation

```
TITLE: Serial mediation analysis between school victimization and depression

DATA: file is data_mediation_application.dat;

VARIABLE:
  names are id victi low_se lone dep;
  usevariables are victi low_se lone dep;

ANALYSIS:
  bootstrap = 5000;

MODEL:
  low_se on victi;
  lone on victi low_se;
  dep on victi low_se lone;

  model indirect:
  dep IND victi;

OUTPUT: stdyx cinterval (bcbootstrap);
```

Appendix A ■ The output file from PROCESS

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 3.5 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 6
    Y  : y
    X  : x
   M1  : m1
   M2  : m2

Sample
Size:  432

**************************************************************************
OUTCOME VARIABLE:
 m1

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,4918      ,2418      ,7711   137,1476     1,0000   430,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     -,0322      ,0423     -,7614      ,4468     -,1154      ,0510
x             ,4936      ,0421    11,7110      ,0000      ,4107      ,5764

Standardized coefficients
       coeff
x !a1  ,4918

```

```
**************************************************************************
OUTCOME VARIABLE:
 m2

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,5750      ,3306      ,6498   105,9262     2,0000   429,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant      ,0248      ,0389      ,6386      ,5234     -,0516      ,1012
x             ,1777      ,0444     4,0001      ,0001      ,0904      ,2651
m1            ,4524      ,0443    10,2186      ,0000      ,3654      ,5394

Standardized coefficients
        coeff
x  !a2  ,1815
m1 !b2  ,4636

**************************************************************************
OUTCOME VARIABLE:
 y

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,7931      ,6291      ,3582   241,9598     3,0000   428,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     -,0370      ,0289    -1,2800      ,2012     -,0937      ,0198
x             ,2461      ,0336     7,3252      ,0000      ,1801      ,3122
m1           -,0157      ,0367     -,4289      ,6682     -,0878      ,0563
m2            ,6635      ,0358    18,5098      ,0000      ,5930      ,7340

Standardized coefficients
        coeff
x  !d    ,2522
m1 !c1  -,0162
m2 !c2   ,6660

************************** TOTAL EFFECT MODEL ****************************
OUTCOME VARIABLE:
 y

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,5170      ,2673      ,7043   156,8355     1,0000   430,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     -,0297      ,0404     -,7332      ,4638     -,1092      ,0498
x             ,5044      ,0403    12,5234      ,0000      ,4253      ,5836

Standardized coefficients
       coeff
x !e   ,5170

************** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y **************

Total effect of X on Y
     Effect         se          t          p       LLCI       ULCI       c_ps       c_cs
      ,5044      ,0403    12,5234      ,0000      ,4253      ,5836      ,5151      ,5170

```

```
Direct effect of X on Y
   Effect         se          t          p       LLCI       ULCI      c'_ps      c'_cs
    ,2461      ,0336     7,3252      ,0000      ,1801      ,3122      ,2513      ,2522

Indirect effect(s) of X on Y:
           Effect     BootSE   BootLLCI   BootULCI
TOTAL       ,2583      ,0318      ,1991      ,3225
Ind1       -,0078      ,0187     -,0453      ,0283
Ind2        ,1179      ,0274      ,0664      ,1741
Ind3        ,1481      ,0216      ,1089      ,1926

Partially standardized indirect effect(s) of X on Y:
           Effect     BootSE   BootLLCI   BootULCI
TOTAL       ,2638      ,0278      ,2110      ,3186
Ind1       -,0079      ,0191     -,0464      ,0286
Ind2        ,1204      ,0267      ,0696      ,1739
Ind3        ,1513      ,0201      ,1147      ,1925

Completely standardized indirect effect(s) of X on Y:
           Effect     BootSE   BootLLCI   BootULCI
TOTAL       ,2647      ,0281      ,2102      ,3188   !Total indirect effects
Ind1       -,0080      ,0192     -,0469      ,0286   !Indirect effect $a_1c_1$
Ind2        ,1209      ,0267      ,0688      ,1749   !Indirect effect $a_2c_2$
Ind3        ,1518      ,0205      ,1137      ,1930   !Indirect effect $a_1b_2c_2$

Indirect effect key:
Ind1 x           ->    m1          ->    y
Ind2 x           ->    m2          ->    y
Ind3 x           ->    m1          ->    m2          ->    y

***************************************************************************
Bootstrap estimates were saved to a file

Map of column names to model coefficients:
          Conseqnt Antecdnt
 COL1     m1       constant
 COL2     m1       x
 COL3     m2       constant
 COL4     m2       x
 COL5     m2       m1
 COL6     y        constant
 COL7     y        x
 COL8     y        m1
 COL9     y        m2

*********** BOOTSTRAP RESULTS FOR REGRESSION MODEL PARAMETERS ************

OUTCOME VARIABLE:
 m1

              Coeff   BootMean     BootSE   BootLLCI   BootULCI
constant     -,0322     -,0326      ,0421     -,1157      ,0505
x             ,4936      ,4938      ,0429      ,4086      ,5797

----------

OUTCOME VARIABLE:
 m2

              Coeff   BootMean     BootSE   BootLLCI   BootULCI
constant      ,0248      ,0248      ,0384     -,0485      ,1013
x             ,1777      ,1785      ,0398      ,1017      ,2562
m1            ,4524      ,4522      ,0423      ,3705      ,5335

----------
OUTCOME VARIABLE:
```

```
 y

                 Coeff    BootMean     BootSE    BootLLCI    BootULCI
constant      -,0370      -,0373      ,0282      -,0943      ,0182
x              ,2461       ,2471      ,0335       ,1787      ,3113
m1            -,0157      -,0158      ,0379      -,0913      ,0564
m2             ,6635       ,6634      ,0388       ,5899      ,7385

********************** ANALYSIS NOTES AND ERRORS ***********************

Level of confidence for all confidence intervals in output:
  95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000

------ END MATRIX -----
```

Appendix B ■ The output file from Mplus

```
Analysis of serial mediation

SUMMARY OF ANALYSIS

Number of groups                                                 1
Number of observations                                         432

Number of dependent variables                                    3
Number of independent variables                                  1
Number of continuous latent variables                            0

Observed dependent variables

  Continuous
   M1          M2          Y

Observed independent variables
   X

Estimator                                                       ML
Information matrix                                        OBSERVED
Maximum number of iterations                                  1000
Convergence criterion                                    0.500D-04
Maximum number of steepest descent iterations                   20
Number of bootstrap draws
    Requested                                                 5000
    Completed                                                 5000

Input data file(s)
  data.dat

Input data format  FREE

[...]

THE MODEL ESTIMATION TERMINATED NORMALLY

MODEL FIT INFORMATION

Number of Free Parameters                        12

Loglikelihood

          H0 Value                        -1463.370
          H1 Value                        -1463.370
```

```
Information Criteria

          Akaike (AIC)                    2950.741
          Bayesian (BIC)                  2999.562
          Sample-Size Adjusted BIC        2961.480
            (n* = (n + 2) / 24)

Chi-Square Test of Model Fit

          Value                              0.000
          Degrees of Freedom                     0
          P-Value                           0.0000

RMSEA (Root Mean Square Error Of Approximation)

          Estimate                           0.000
          90 Percent C.I.                    0.000  0.000
          Probability RMSEA <= .05           0.000

CFI/TLI

          CFI                                1.000
          TLI                                1.000

Chi-Square Test of Model Fit for the Baseline Model

          Value                            721.413
          Degrees of Freedom                     6
          P-Value                           0.0000

SRMR (Standardized Root Mean Square Residual)

          Value                              0.000

MODEL RESULTS

                                                    Two-Tailed
                    Estimate       S.E.  Est./S.E.    P-Value

 M1       ON
    X                  0.494      0.043     11.389      0.000

 M2       ON
    X                  0.178      0.040      4.479      0.000
    M1                 0.452      0.041     10.965      0.000

 Y        ON
    X                  0.246      0.034      7.305      0.000
    M1                -0.016      0.037     -0.425      0.671
    M2                 0.664      0.038     17.248      0.000

 Intercepts
    M1                -0.032      0.042     -0.772      0.440
    M2                 0.025      0.038      0.648      0.517
    Y                 -0.037      0.029     -1.291      0.197

 Residual Variances
    M1                 0.768      0.048     16.056      0.000
    M2                 0.645      0.042     15.456      0.000
    Y                  0.355      0.023     15.355      0.000

STANDARDIZED MODEL RESULTS

STDYX Standardization
```

```
                                                    Two-Tailed
                    Estimate       S.E.  Est./S.E.    P-Value

M1       ON
    X                  0.492      0.037     13.447      0.000

 M2       ON
    X                  0.182      0.039      4.605      0.000
    M1                 0.464      0.040     11.680      0.000

 Y        ON
    X                  0.252      0.035      7.209      0.000
    M1                -0.016      0.038     -0.426      0.670
    M2                 0.666      0.031     21.191      0.000

 Intercepts
    M1                -0.032      0.042     -0.770      0.442
    M2                 0.025      0.039      0.645      0.519
    Y                 -0.038      0.029     -1.290      0.197

 Residual Variances
    M1                 0.758      0.036     21.220      0.000
    M2                 0.669      0.036     18.462      0.000
    Y                  0.371      0.027     13.515      0.000

R-SQUARE

    Observed                                        Two-Tailed
    Variable        Estimate       S.E.  Est./S.E.    P-Value

    M1                 0.242      0.036      6.768      0.000
    M2                 0.331      0.036      9.117      0.000
    Y                  0.629      0.027     22.922      0.000

TOTAL, TOTAL INDIRECT, SPECIFIC INDIRECT, AND DIRECT EFFECTS

                                                    Two-Tailed
                    Estimate       S.E.  Est./S.E.    P-Value

Effects from X to Y

  Total                0.504      0.040     12.581      0.000
  Total indirect       0.258      0.032      8.043      0.000

  Specific indirect 1
    Y
    M1
    X                 -0.008      0.018     -0.424      0.672

  Specific indirect 2
    Y
    M2
    X                  0.118      0.027      4.307      0.000

  Specific indirect 3
    Y
    M2
    M1
    X                  0.148      0.021      6.979      0.000

  Direct
    Y
    X                  0.246      0.034      7.305      0.000

STANDARDIZED TOTAL, TOTAL INDIRECT, SPECIFIC INDIRECT, AND DIRECT EFFECTS
```

```
STDYX Standardization

                                                           Two-Tailed
                    Estimate       S.E.  Est./S.E.    P-Value

Effects from X to Y

  Total                0.517      0.035     14.880      0.000
  Total indirect       0.265      0.028      9.372      0.000

  Specific indirect 1
    Y
    M1
    X                 -0.008      0.019     -0.423      0.672

  Specific indirect 2
    Y
    M2
    X                  0.121      0.026      4.564      0.000

  Specific indirect 3
    Y
    M2
    M1
    X                  0.152      0.020      7.462      0.000

  Direct
    Y
    X                  0.252      0.035      7.209      0.000

CONFIDENCE INTERVALS OF MODEL RESULTS

          Lower .5%  Lower 2.5%  Lower 5%  Estimate  Upper 5%  Upper 2.5%  Upper .5%

 M1       ON
    X      0.378      0.408       0.423      0.494    0.566      0.579       0.606

 M2       ON
    X      0.077      0.098       0.111      0.178    0.242      0.254       0.281
    M1     0.348      0.373       0.385      0.452    0.521      0.535       0.559

 Y        ON
    X      0.158      0.180       0.191      0.246    0.303      0.313       0.334
    M1    -0.118     -0.090      -0.077     -0.016    0.044      0.055       0.077
    M2     0.566      0.591       0.605      0.664    0.729      0.742       0.770

 Intercepts
    M1    -0.144     -0.116      -0.102     -0.032    0.036      0.051       0.077
    M2    -0.082     -0.052      -0.040      0.025    0.086      0.098       0.120
    Y     -0.111     -0.095      -0.084     -0.037    0.010      0.019       0.034

 Residual Variances
    M1     0.653      0.681       0.694      0.768    0.851      0.864       0.895
    M2     0.549      0.572       0.585      0.645    0.721      0.736       0.764
    Y      0.302      0.314       0.321      0.355    0.398      0.407       0.422

CONFIDENCE INTERVALS OF STANDARDIZED MODEL RESULTS

STDYX Standardization

         Lower .5%  Lower 2.5%  Lower 5%  Estimate  Upper 5%  Upper 2.5%  Upper .5%

 M1 ON
  X !a1  0.386      0.417       0.430      0.492    0.550      0.560       0.576

 M2 ON
```

```
  X  !a2   0.080     0.101     0.115     0.182     0.245     0.256     0.281
  M1 !b2   0.358     0.386     0.398     0.464     0.528     0.542     0.565

  Y ON
  X  !d    0.157     0.183     0.194     0.252     0.309     0.320     0.343
  M1 !c1  -0.119    -0.092    -0.079    -0.016     0.046     0.056     0.079
  M2 !c2   0.581     0.604     0.615     0.666     0.717     0.727     0.744

Intercepts
  M1      -0.145    -0.116    -0.102    -0.032     0.035     0.051     0.077
  M2      -0.086    -0.054    -0.041     0.025     0.088     0.100     0.123
  Y       -0.114    -0.096    -0.086    -0.038     0.010     0.020     0.036

Residual Variances
  M1       0.667     0.685     0.698     0.758     0.815     0.826     0.851
  M2       0.578     0.600     0.612     0.669     0.731     0.743     0.764
  Y        0.307     0.321     0.329     0.371     0.421     0.431     0.449

CONFIDENCE INTERVALS OF TOTAL, TOTAL INDIRECT, SPECIFIC INDIRECT, AND DIRECT EFFECTS

         Lower .5%  Lower 2.5%  Lower 5%  Estimate  Upper 5%  Upper 2.5%  Upper .5%

Effects from X to Y

Total           0.399     0.425     0.439     0.504     0.570     0.584     0.608
Total indirect  0.178     0.198     0.209     0.258     0.314     0.326     0.347

  Specific indirect 1
    Y
    M1
    X        -0.059    -0.045    -0.039    -0.008     0.021     0.027     0.040

  Specific indirect 2
    Y
    M2
    X       0.052      0.065     0.074     0.118     0.165     0.174     0.193

  Specific indirect 3
    Y
    M2
    M1
    X       0.098     0.112      0.117     0.148     0.188     0.195     0.212

  Direct
    Y
    X       0.158     0.180      0.191     0.246     0.303     0.313     0.334

CONFIDENCE INTERVALS OF STANDARDIZED TOTAL, TOTAL INDIRECT, SPECIFIC INDIRECT, AND DIRECT EFFECTS

STDYX Standardization

           Lower .5%  Lower 2.5%  Lower 5%  Estimate  Upper 5%  Upper 2.5%  Upper .5%

Effects from X to Y

Total   !e      0.417     0.445     0.457     0.517     0.571     0.581     0.604
Total indirect  0.190     0.209     0.220     0.265     0.313     0.321     0.340

Specific indirect 1 !Indirect effect a1c1
    Y
    M1
    X           -0.061    -0.047    -0.039    -0.008     0.022     0.027     0.041

```

```
Specific indirect 2 !Indirect effect a2c2
    Y
    M2
    X            0.054    0.068    0.077    0.121    0.165    0.172    0.188

Specific indirect 3 !Indirect effect a1b2c2
    Y
    M2
    M1
    X            0.104    0.116    0.122    0.152    0.189    0.196    0.212

Direct
    Y
    X   !d       0.157    0.183    0.194    0.252    0.309    0.320    0.343

[...]

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Appendix C ■ The Mplus output file for the application of serial mediation

```
Serial mediation analysis between school victimization and depression

SUMMARY OF ANALYSIS

Number of groups                                                  1
Number of observations                                          500

Number of dependent variables                                     3
Number of independent variables                                   1
Number of continuous latent variables                             0

Observed dependent variables

  Continuous
   LOW_SE     LONE      DEP

Observed independent variables
   VICTI

Estimator                                                        ML
Information matrix                                         OBSERVED
Maximum number of iterations                                   1000
Convergence criterion                                     0.500D-04
Maximum number of steepest descent iterations                    20
Number of bootstrap draws
    Requested                                                  5000
    Completed                                                  5000

Input data file(s)
  data_mediation6_good.dat

Input data format  FREE

[...]

THE MODEL ESTIMATION TERMINATED NORMALLY

MODEL FIT INFORMATION

Number of Free Parameters                        12

Loglikelihood
```

```

          H0 Value                        -1647.825
          H1 Value                        -1647.825

Information Criteria

          Akaike (AIC)                     3319.651
          Bayesian (BIC)                   3370.226
          Sample-Size Adjusted BIC         3332.137
            (n* = (n + 2) / 24)

Chi-Square Test of Model Fit

          Value                               0.000
          Degrees of Freedom                      0
          P-Value                            0.0000

RMSEA (Root Mean Square Error Of Approximation)

          Estimate                            0.000
          90 Percent C.I.                     0.000  0.000
          Probability RMSEA <= .05            0.000

CFI/TLI

          CFI                                 1.000
          TLI                                 1.000

Chi-Square Test of Model Fit for the Baseline Model

          Value                             950.324
          Degrees of Freedom                      6
          P-Value                            0.0000

SRMR (Standardized Root Mean Square Residual)

          Value                               0.000

MODEL RESULTS

                                                    Two-Tailed
                    Estimate       S.E.  Est./S.E.    P-Value

 LOW_SE   ON
    VICTI              0.471      0.037     12.865      0.000

 LONE     ON
    VICTI              0.302      0.054      5.629      0.000
    LOW_SE             0.290      0.052      5.624      0.000

 DEP      ON
    VICTI             -0.001      0.030     -0.027      0.978
    LOW_SE             0.372      0.028     13.443      0.000
    LONE               0.616      0.025     24.596      0.000

 Intercepts
    LOW_SE             0.044      0.037      1.191      0.233
    LONE              -0.050      0.042     -1.172      0.241
    DEP                0.035      0.023      1.534      0.125

 Residual Variances
    LOW_SE             0.675      0.042     16.095      0.000
    LONE               0.896      0.053     16.839      0.000
    DEP                0.242      0.015     15.681      0.000

STANDARDIZED MODEL RESULTS
```

```
STDYX Standardization

                                                    Two-Tailed
                    Estimate       S.E.  Est./S.E.    P-Value

 LOW_SE   ON
    VICTI              0.488      0.033     14.608      0.000

 LONE     ON
    VICTI              0.276      0.048      5.796      0.000
    LOW_SE             0.256      0.045      5.741      0.000

 DEP      ON
    VICTI             -0.001      0.029     -0.027      0.978
    LOW_SE             0.355      0.026     13.450      0.000
    LONE               0.665      0.023     28.547      0.000

 Intercepts
    LOW_SE             0.046      0.039      1.190      0.234
    LONE              -0.047      0.040     -1.162      0.245
    DEP                0.036      0.023      1.537      0.124

 Residual Variances
    LOW_SE             0.762      0.032     23.533      0.000
    LONE               0.789      0.033     24.089      0.000
    DEP                0.248      0.020     12.658      0.000

R-SQUARE

    Observed                                        Two-Tailed
    Variable        Estimate       S.E.  Est./S.E.    P-Value

    LOW_SE             0.238      0.032      7.343      0.000
    LONE               0.211      0.033      6.431      0.000
    DEP                0.752      0.020     38.287      0.000

TOTAL, TOTAL INDIRECT, SPECIFIC INDIRECT, AND DIRECT EFFECTS

                                                    Two-Tailed
                    Estimate       S.E.  Est./S.E.    P-Value

Effects from VICTI to DEP

  Total                0.444      0.042     10.612      0.000
  Total indirect       0.445      0.038     11.810      0.000

  Specific indirect 1
    DEP
    LOW_SE
    VICTI              0.175      0.019      9.382      0.000

  Specific indirect 2
    DEP
    LONE
    VICTI              0.186      0.034      5.538      0.000

  Specific indirect 3
    DEP
    LONE
    LOW_SE
    VICTI              0.084      0.017      5.093      0.000

  Direct
    DEP
    VICTI             -0.001      0.030     -0.027      0.978
```

```

STANDARDIZED TOTAL, TOTAL INDIRECT, SPECIFIC INDIRECT, AND DIRECT EFFECTS

STDYX Standardization

                                                    Two-Tailed
                    Estimate       S.E.  Est./S.E.    P-Value

Effects from VICTI to DEP

  Total                0.439      0.039     11.193      0.000
  Total indirect       0.439      0.034     12.957      0.000

  Specific indirect 1
    DEP
    LOW_SE
    VICTI              0.173      0.018      9.563      0.000

  Specific indirect 2
    DEP
    LONE
    VICTI              0.183      0.033      5.532      0.000

  Specific indirect 3
    DEP
    LONE
    LOW_SE
    VICTI              0.083      0.015      5.539      0.000

  Direct
    DEP
    VICTI             -0.001      0.029     -0.027      0.978

CONFIDENCE INTERVALS OF MODEL RESULTS

           Lower .5%  Lower 2.5%  Lower 5%  Estimate  Upper 5%  Upper 2.5%  Upper .5%

 LOW_SE   ON
    VICTI    0.375      0.399      0.411      0.471      0.532      0.542      0.563

 LONE     ON
    VICTI    0.160      0.196      0.214      0.302      0.388      0.408      0.440
    LOW_SE   0.166      0.192      0.207      0.290      0.376      0.392      0.423

 DEP      ON
    VICTI   -0.078     -0.059     -0.049     -0.001      0.048      0.058      0.075
    LOW_SE   0.301      0.317      0.325      0.372      0.415      0.425      0.442
    LONE     0.550      0.564      0.573      0.616      0.656      0.663      0.679

 Intercepts
    LOW_SE  -0.053     -0.030     -0.019      0.044      0.102      0.112      0.134
    LONE    -0.158     -0.131     -0.119     -0.050      0.023      0.037      0.060
    DEP     -0.024     -0.010     -0.002      0.035      0.073      0.081      0.095

 Residual Variances
    LOW_SE   0.577      0.601      0.614      0.675      0.752      0.767      0.796
    LONE     0.769      0.801      0.818      0.896      0.994      1.010      1.045
    DEP      0.206      0.215      0.219      0.242      0.270      0.275      0.285

CONFIDENCE INTERVALS OF STANDARDIZED MODEL RESULTS

STDYX Standardization

           Lower .5%  Lower 2.5%  Lower 5%  Estimate  Upper 5%  Upper 2.5%  Upper .5%

 LOW_SE   ON
```

```
    VICTI   !a1  0.398     0.419     0.430     0.488      0.540      0.549      0.569

 LONE     ON
    VICTI   !a2  0.149     0.181     0.196     0.276      0.352      0.367      0.397
    LOW_SE  !b2  0.146     0.170     0.184     0.256      0.330      0.344      0.370

 DEP      ON
    VICTI   !d  -0.076    -0.058    -0.049    -0.001      0.047      0.058      0.076
    LOW_SE  !c1  0.285     0.301     0.310     0.355      0.397      0.405      0.422
    LONE    !c2  0.601     0.617     0.625     0.665      0.702      0.708      0.722

 Intercepts
    LOW_SE -0.055     -0.032     -0.020     0.046      0.108      0.119      0.143
    LONE   -0.146     -0.124     -0.112    -0.047      0.021      0.034      0.056
    DEP    -0.025     -0.010     -0.003     0.036      0.073      0.081      0.096

 Residual Variances
    LOW_SE  0.676      0.699      0.709     0.762      0.815      0.825      0.842
    LONE    0.706      0.727      0.737     0.789      0.845      0.854      0.873
    DEP     0.202      0.213      0.218     0.248      0.283      0.290      0.303

CONFIDENCE INTERVALS OF TOTAL, TOTAL INDIRECT, SPECIFIC INDIRECT, AND DIRECT EFFECTS

           Lower .5%  Lower 2.5%  Lower 5%  Estimate  Upper 5%  Upper 2.5%  Upper .5%

Effects from VICTI to DEP

  Total           0.334     0.359     0.373     0.444     0.513      0.525     0.547
  Total indirect 0.351     0.371     0.384     0.445     0.508      0.519     0.544

  Specific indirect 1
    DEP
    LOW_SE
    VICTI         0.130     0.140     0.146     0.175     0.207      0.214     0.225

  Specific indirect 2
    DEP
    LONE
    VICTI         0.101     0.122     0.132      0.186    0.242      0.254     0.275

  Specific indirect 3
    DEP
    LONE
    LOW_SE
    VICTI         0.047     0.055     0.060      0.084     0.115     0.121     0.134

  Direct
    DEP
    VICTI        -0.078    -0.059    -0.049     -0.001     0.048     0.058     0.075

CONFIDENCE INTERVALS OF STANDARDIZED TOTAL, TOTAL INDIRECT, SPECIFIC INDIRECT, AND DIRECT EFFECTS

STDYX Standardization

           Lower .5%  Lower 2.5%  Lower 5%  Estimate  Upper 5%  Upper 2.5%  Upper .5%

Effects from VICTI to DEP

  Total     !e    0.327     0.355     0.368     0.439      0.500     0.511     0.531
  Total indirect 0.348     0.372     0.383     0.439      0.494     0.504     0.524

  Specific indirect 1 !Indirect effect a1c1
    DEP
```

```
    LOW_SE
    VICTI         0.128     0.140      0.144      0.173       0.204      0.210      0.222

  Specific indirect 2 !Indirect effect a2c2
    DEP
    LONE
    VICTI         0.097     0.119      0.130      0.183       0.238      0.249      0.269

  Specific indirect 3 !Indirect effect a1b2c2
    DEP
    LONE
    LOW_SE
    VICTI         0.049     0.056      0.061      0.083       0.110      0.115      0.125

  Direct
    DEP
    VICTI   !d  -0.076    -0.058     -0.049     -0.001       0.047      0.058      0.076

[...]

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Open practices

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

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