Estimating and Comparing Specific Mediation Effects in Complex Latent Variable Models

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Abstract
This teaching note starts with a demonstration of a straightforward procedure using Mplus Version 6 to produce a bias-corrected (BC) bootstrap confidence interval for testing a specific mediation effect in a complex latent variable model. The procedure is extended to constructing a BC bootstrap confidence interval for the difference between two specific mediation effects. The extended procedure not only tells whether the strengths of any direct and mediation effects or any two specific mediation effects in a latent variable model are significantly different but also provides an estimate and a confidence interval for the difference. However, the Mplus procedures do not allow the estimation of a BC bootstrap confidence interval for the difference between two standardized mediation effects. This teaching note thus demonstrates the LISREL procedures for constructing BC confidence intervals for specific standardized mediation effects and for comparing two standardized mediation effects. Finally, procedures combining Mplus and PRELIS are demonstrated for constructing BC bootstrap confidence intervals for the difference between the between-part and within-part path coefficients in multilevel models and for examining models with interactions of latent variables.

Keywords
structural equation modeling, computer simulation procedures, Monte Carlo, bootstrapping, quantitative research, multiple regression

Mediators—also known as intervening variables—play a critical role in organizational studies, as they help us to gain a better understanding of the processes underlying organizational phenomena (Mathieu, DeShon, & Bergh, 2008). Mediational analysis allows researchers to conduct scientific investigations, which in turn provide researchers with an understanding of the sequence of effects that lead to certain consequences (Kenny, 2008). Because of advances in knowledge, organization theories and models developed in recent years usually contain multiple mediators to represent the

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complexity of organizational phenomena. This inclusion of additional mediators makes the models less vulnerable to specification errors (Mathieu et al., 2008; Preacher & Hayes, 2008). In these complex models, there is usually more than one structural path from the predictor variable to the outcome variable (Mathieu et al., 2008; Stone-Romero & Rosopa, 2008), leading to a collection of direct and specific mediation effects. The terms indirect effect and specific indirect effect are sometimes used in the literature and software programs instead of mediation effect and specific mediation effect, respectively. In this article, these terms are used interchangeably. MacKinnon and his colleagues (MacKinnon, Lockwood, & Williams, 2004; Williams & MacKinnon, 2008) suggested using the bias-corrected (BC) bootstrap confidence interval method to examine the significance of the mediation effects in path analysis. In an extension of their work, G. W. Cheung and Lau (2008) demonstrated an AMOS procedure of developing BC bootstrap confidence intervals for mediation effects in complex latent variable models. Their procedure, however, only estimates the BC confidence intervals for total mediation effects and not the specific mediation effects. Hence, researchers cannot determine whether a particular mediator in a model of multiple mediators is playing a mediating role.

In addition to testing specific mediation effects, researchers are usually interested in comparing the strengths of direct and mediation effects. They are also increasingly interested in comparing the strengths of mediation effects in complex models, which is particularly important in applied social science because it allows identification of the more crucial path from the independent variable to the dependent variable. For example, in a study of interfirm relationships among small- to medium-size enterprises (SMEs) in developing economies, it was hypothesized that the impact of horizontal relational governance on SME access to global markets was mediated by SME sourcing of collective resources and by product innovation, along two causal pathways (Mesquita & Lazzarini, 2008). Researchers may be interested in determining which mediation effect is stronger in studies of this type. Determining the relative strengths of mediators allows researchers not only to give better explanations of processes and thus to make even more specific predictions but also to offer more specific recommendations to practitioners regarding various managerial approaches that can be taken to alter processes or achieve the desired outcomes (Williams & MacKinnon, 2008). In this SME study, the comparison of the strengths of SME sourcing of collective resources and product innovation as mediators may shed light on practitioners’ business strategies. Furthermore, the inclusion of multiple mediators in the same model followed by a comparison of their specific mediation effects represents a method for pitting competing theories against one another—a scientific practice that is encouraged in the literature (Preacher & Hayes, 2008).

This teaching note serves three purposes. First, it extends G. W. Cheung and Lau’s (2008) study by demonstrating a simple Mplus procedure (Muthén & Muthén, 1998-2010) to estimate the BC bootstrap confidence intervals for specific mediation effects in complex latent variable models. The procedure is further extended to estimate the BC bootstrap confidence interval for a new parameter, $D_M$, to examine the difference between two specific mediation effects or the difference between any direct and mediation effects within a single group and across groups. Second, this teaching note gives a tutorial illustrating the LISREL procedures of constructing BC bootstrap confidence intervals for testing specific standardized/unstandardized mediation effects and comparing two standardized/unstandardized mediation effects. Although it is powerful, Mplus is not without limitations: It does not support bootstrapping with complex latent variable models, such as multilevel models and models involving interactions of latent variables. The final purpose of this note is to propose procedures combining Mplus and PRELIS with which researchers can use bootstrapping to test the significance of the difference between the between part and the within part of a multilevel model and the significance of mediated moderation effects or moderated mediation effects in models involving interactions of latent variables.
We first demonstrate a procedure to test the effect of a specific meditational path with Mplus Version 6. Mplus is advantageous in that its syntax is simple and it allows researchers to use simple commands to obtain total indirect, specific indirect, and total effects directly in the output file. The Mplus User’s Guide (Muthén & Muthén, 1998-2010) sets out a syntax on how to construct a bootstrap confidence interval for the specific mediation effects in a path model (Example 3.16, p. 37). The following demonstration extends this example by illustrating the construction of the BC bootstrap confidence interval for a specific mediation effect in a structural equation model.

Figure 1 shows the model employed in this demonstration, which contains two exogenous variables and four endogenous variables. There are several specific mediation effects in this model, including the one from $\eta_1$ through $\eta_2$ to $\eta_4$ (i.e., $b_{21}b_{42}$) and the one from $\eta_1$ through $\eta_3$ to $\eta_4$ (i.e., $b_{31}b_{43}$). The Mplus syntax for this demonstration can be found in Appendix A. The DATA and VARIABLE commands provide information about the data set and the variables to be analyzed. The MODEL command describes the structural equation model to be estimated. The MODEL INDIRECT command specifies the specific mediation effects needed. The ANALYSIS command requests a bootstrap procedure, and the statement of “BOOTSTRAP = 1000” requests a bootstrap analysis with 1,000 bootstrap samples. One limitation of using the bootstrap approach to generate BC confidence intervals is that even when they use the same data set, two researchers may establish different confidence intervals due to the fact that the bootstrap samples generated by each researcher may be different when bootstrap sample sizes are too small (Gleser, 1996; MacKinnon et al., 2004). To minimize this problem, G. W. Cheung and Lau (2008) recommended using a bootstrap sample size of 500 to 1,000. Finally, to obtain the BC bootstrap confidence intervals for the specific mediation effects, “CINTERVAL(BCBOOTSTRAP)” is specified in the OUTPUT command.
Table 1. Sample Output File of Bias-Corrected Confidence Intervals for Specific Mediation Effects From Mplus

<table>
<thead>
<tr>
<th>Effects From ETA1 to ETA4</th>
<th>Lower 0.5%</th>
<th>Lower 2.5%</th>
<th>Lower 5%</th>
<th>Estimate</th>
<th>Upper 5%</th>
<th>Upper 2.5%</th>
<th>Upper 0.5%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sum of indirect</td>
<td>0.494</td>
<td>0.534</td>
<td>0.563</td>
<td>0.796</td>
<td>1.120</td>
<td>1.175</td>
<td>1.285</td>
</tr>
<tr>
<td>Specific indirect ETA4 ETA2 ETA1</td>
<td>0.038</td>
<td>0.057</td>
<td>0.066</td>
<td>0.124</td>
<td>0.203</td>
<td>0.218</td>
<td>0.255</td>
</tr>
<tr>
<td>ETA4 ETA3 ETA1</td>
<td>0.356</td>
<td>0.414</td>
<td>0.450</td>
<td>0.672</td>
<td>0.959</td>
<td>1.018</td>
<td>1.184</td>
</tr>
</tbody>
</table>

Table 1 presents the output file that details the estimated specific mediation effects, together with their BC bootstrap confidence intervals. It is shown that the 95% BC confidence interval for the mediation effect $b_{21}b_{42}$ does not contain zero (lower 2.5% limit = 0.057; upper 2.5% limit = 0.218), which indicates that the mediation effect is significantly different from zero. Likewise, the 95% BC confidence interval for the mediation effect $b_{31}b_{43}$ does not contain zero (lower 2.5% limit = 0.414; upper 2.5% limit = 1.018). Hence, the mediation effect from $\eta_1$ to $\eta_4$ via $\eta_3$ is significantly different from zero.

Sometimes researchers may want to test different mediation models on the same data set. To do so, they need to use the same seed number across various hypothesized models to ensure that the same set of bootstrap data sets is generated. The seed number is the initial seed value for data generation. As the seed number is fixed at zero in the bootstrapping process in Mplus, researchers need not make any change in the seed number when using Mplus to test different mediation models. If they want to generate independent sets of bootstrap samples, different seed numbers are required. As there is no option to select the seed number used with the BOOTSTRAP option in Mplus, researchers need to turn to PRELIS and set the seed number in the PRELIS program by including IX = 123456 (where 123456 is the seed number) on the OU line.

Comparing Two Mediation Effects With Mplus

Thus far, a few procedures have been recommended in the literature for comparing the strengths of two specific mediation effects or the strengths of direct and mediation effects in complex latent variable models. One common approach is to add a nonlinear constraint in the model, such that the strengths of the direct and mediation effects being compared are constrained to be equal (e.g., Preacher & Hayes, 2008). The chi-square statistic values of the unconstrained and constrained models are then compared using a chi-square difference (Wald) test. If the chi-square difference is statistically significant, then the strengths of the direct and mediation effects are significantly different. Another approach involves the use of latent phantom variables (M. W.-L. Cheung, 2007), which are latent variables containing zero variance. Researchers have first to create a phantom variable. The independent variable is then regressed on the phantom variable such that the path coefficient from the phantom variable to the independent variable is constrained to be the same as the difference between the direct and mediation effects in examination, by imposing a nonlinear constraint. By obtaining the BC bootstrap confidence interval for this path coefficient, the BC bootstrap confidence interval for the difference between the direct and mediation effects can also be obtained.
Here, we demonstrate a simple Mplus procedure for comparisons of the strengths of two mediational paths in a latent variable model that does not require the creation of phantom variables. Specifically, the previous demonstration of how to develop a BC bootstrap confidence interval for a specific mediation effect is extended by using the NEW parameter option to test the significance of the difference between two specific mediation effects, which is defined as $D_M$:

$$D_M = M_1 - M_2,$$

where $M_1$ is the first specific mediation effect and $M_2$ is the second mediation effect. In fact, $M_1$ can also be a direct effect and $M_2$ a mediation effect. Following from the previous demonstration, three $D_M$s can be defined in the hypothetical model for demonstration. The first is the difference between the direct effect from $Z_1$ to $Z_4$ and the specific mediation effect from $Z_1$ through $Z_2$ to $Z_4$ ($DM_1 = b_{41} - b_{21}b_{42}$). The second is the difference between the direct effect from $Z_1$ to $Z_4$ and the specific mediation effect from $Z_1$ through $Z_3$ to $Z_4$ ($DM_2 = b_{41} - b_{31}b_{43}$). The third is the difference between two specific mediation effects ($DM_3 = b_{21}b_{42} - b_{31}b_{43}$).

To examine the confidence interval for each $D_M$, one needs first to describe and specify the data, variables, and analysis model in the DATA, VARIABLE, MODEL, and MODEL INDIRECT commands. The Mplus syntax is shown in Appendix B, whereas the sample outputs are presented in Table 2. We use the MODEL CONSTRAINT command and the NEW option to assign labels to the two specific mediation effects (MED1, MED2) and the three $D_M$s ($DM_1$, $DM_2$, $DM_3$). Again, in the ANALYSIS command, the statement “BOOTSTRAP = 1000” is used to generate 1,000 bootstrap samples. In the OUTPUT command, the statement “CINTERVAL (BCCBOOTSTRAP)” is specified.

As shown in Table 2, the confidence interval for $DM_1$ is between $-0.481$ and $0.213$, suggesting that the specific mediation effect $b_{21}b_{42}$ is not significantly different from the direct effect $b_{41}$. The confidence interval for $DM_2$ is between $-1.293$ and $-0.107$, which does not contain zero. Hence, the specific mediation effect $b_{31}b_{43}$ is significantly larger than the direct effect. Similarly, the BC confidence interval for $DM_3$ is between $-0.884$ and $-0.275$, which does not contain zero. We thus conclude that the specific mediation effect $b_{31}b_{43}$ is significantly larger than the specific mediation effect $b_{21}b_{42}$.
effect $b_{21}b_{42}$. We also conducted the same comparisons with chi-square difference tests by imposing equivalent constraints on the structural paths. The corresponding $\Delta \chi^2$ values with 1 degree of freedom for comparisons represented by $D_M1$, $D_M2$, and $D_M3$ were 0.425 ($p = .5144$), 5.331 ($p = .0210$), and 13.869 ($p = .0002$), respectively. Although these test results provide the same conclusion as the BC bootstrap confidence interval method, they include less information than in the confidence intervals.

Researchers may use the Mplus procedure to compare the strengths of mediational paths in opposite directions. One such circumstance is the presence of a suppression effect. When a model contains multiple mediational paths, suppression effects are more likely to exist. Consider a mediation model with two specific mediational paths: Path 1 ($b_{42}b_{21}$), with a coefficient of 0.2, and Path 2 ($b_{43}b_{31}$), with a coefficient of $-0.2$. Researchers can use the following command to compare the two mediation effects:

```
MODEL CONSTRAINT:
NEW (DM1, DM2);
DM1 = PATH 1 - PATH 2;
DM2 = PATH 1 + PATH 2.
```

In this case, DM1 compares the effects of these two mediational paths, whereas DM2 compares the absolute magnitudes of these two paths.

The Mplus procedure can be further extended to a cross-group comparison in a multigroup analysis. An example of the Mplus syntax is shown in Appendix C. Under the ANALYSIS option, “MODEL = NOMEANSTRUCTURE” and “INFORMATION = EXPECTED” are added so that a covariance structure model is estimated. The direct paths in different groups are given different labels under the MODEL command. As the default for Mplus in multigroup analysis is measurement invariance (equal factor loadings and intercepts across groups), the noninvariant factor loadings and/or intercepts need to be specified in the second group. For instance, in the syntax in Appendix C, the factor loading of item x3 in the female group is free for estimation. Finally, DM can be created under MODEL CONSTRAINT as in a single group model. This procedure can be used to analyze the moderated mediation effect when the moderator is a categorical variable.

Although Mplus does provide standardized solutions, it does not allow constraint of the variance of the endogenous latent variables to unity in the model. Although M. W.-L. Cheung (2009) suggests constraining the residual variance of the endogenous variables with the following equation (Cohen & Cohen, 1983, p. 101),

$$1 - \sum \beta_i^2 - 2 \sum \beta_i \beta_j r_{ij},$$

(2)

to provide standardized path coefficients, that only works in simple mediation models with one mediator. Hence, $D_M$ of standardized mediational paths in complex latent variable models cannot be estimated with Mplus. Researchers need to use the LISREL procedure described below to compare standardized mediational paths.

**Testing Specific Mediation Effects and Comparing Two Mediation Effects With LISREL**

The test for specific mediation effect and comparison of two specific mediation effects can also be implemented with LISREL together with PRELIS and Microsoft Excel. Although the LISREL procedure is much more tedious than the Mplus procedure, LISREL can test both standardized and unstandardized mediation effects. This LISREL procedure consists of seven steps.
In Step 1, one has to test the proposed structural model with LISREL, as usual, and obtain the sample estimates of $b$s and $g$s from the output file. To obtain unstandardized mediation effects, one has to fix the factor loading of the reference item of each latent variable to 1. If one is to test standardized mediation effects, all exogenous and endogenous variables are standardized by estimating all factor loadings instead, which, in effect, sets the variance of the latent variables to 1.

In Step 2, one has to bootstrap the covariance matrices with PRELIS. To carry out this step, it is first necessary to prepare a PRELIS data file that contains the raw data for the observed variables. To set the number of bootstrap samples to 1,000, open the PRELIS file containing the raw data for the observed variables, then go to Statistics, Bootstrapping, fill in the number of bootstrap samples (1000, e.g.) and the sample fraction (100, e.g.). Next, in the Output Options screen, choose Covariances in the Moment Matrix section, and fill in the file name for the file where the covariance matrices to be saved. The following syntax can also be used to generate a file of 1,000 covariance matrices:

\[ \text{SY} = \text{file name of the PRELIS data file} \]
\[ \text{OU MA} = \text{CM BS} = 1000 \text{ SF} = 100 \text{ BM} = (\text{file name of the covariance matrix file created}). \]

The SY line indicates the PRELIS data file to be analyzed in the bootstrap procedure. On the OU line, the MA keyword specifies the type of matrix to be generated (in this case, a covariance matrix). The BS keyword specifies the number of bootstrap samples to be generated, whereas the SF keyword specifies the sample fraction of each bootstrap sample as a percentage. Finally, the BM keyword indicates the file name of the covariance matrix file created.

Step 3 involves a process of generating parameter estimates using the 1,000 covariance matrices created in the previous step. Specifically, the LISREL model is run again with 1,000 replications. On the DA line in the syntax, “RP = 1000” should be added to the end to run 1,000 replications of the model. The parameter estimates—particularly the estimated $b$s and $g$s used for calculating the mediation effects—have to be saved in a separate PRELIS data file (*.psf) so that once the syntax has been run, PRELIS can be used to read the output. To save the parameter estimates, specify a file name with the keyword PV on the OU line.

Then, in Step 4, the PRELIS data file is opened. As there are 1,000 bootstrap samples, the PRELIS data file should consist of 1,000 rows of data, with each row containing the parameter estimates generated from one repetition in the bootstrap process. The first three columns reveal information related to the bootstrap results: The first column shows the repetition number in the bootstrap process, the second column shows whether there was convergence in the repetition, and the third column shows whether an admissible solution was obtained in the repetition. The parameter estimates generated in the bootstrap process are shown from the fourth column onward. Because further calculations based on the data generated are necessary for estimating the confidence intervals and PRELIS does not support such calculations, these data have to be exported to an Excel file (*.xls). Go to File, Export Data, then select Excel (*.xls) as the Save As Type in the dialog box. Type in the file name and save.

From Step 5 onward, all calculations are done with the Excel file created in Step 4. Specific mediation effect estimates are calculated in Step 5. Open the file generated in Step 4 in Excel. In this step, one can calculate any bootstrap mediation effect or any $D_M$ (the difference between two mediation effects or the difference between a direct effect and a mediation effect) one wishes to examine ($\hat{b}'$). As an example, if a BC confidence interval for the specific mediation effect from $\eta_1$ to $\eta_4$ through $\eta_2$ in Figure 1 is to be generated, the mediation effect to be examined is $b_{21}b_{42}$.

Alternatively, one can include the additional parameter function (add $AP = 2$ at the end of the DA line for two additional parameters) and the following nonlinear constraints in the LISREL program.
in Steps 1 and 3 to estimate the specific mediation effect and the difference between the direct and specific mediation effects for each sample:

\[ \text{CO PAR}(1) = \text{BE}(4,2) \times \text{BE}(2,1) \]
\[ \text{CO PAR}(2) = \text{BE}(4,1) - \text{BE}(4,2) \times \text{BE}(2,1). \]

However, calculation of the mediation effects and the difference in mediation effects with Excel is preferred because that provides greater flexibility in estimating any new parameter as a function of any estimated direct paths.

After calculating the product terms, copy the values to a new column, select the column of the copied values, go to Data, Sort, and choose the order of Smallest to Largest. In so doing, the column of bootstrap mediation effects is sorted in ascending order.

The biasing constant \( z_0 \) is estimated in Step 6:

\[ z_0 = \Phi^{-1} \{ \text{Prob} \left( \hat{\theta}^* \leq \bar{\theta} \right) \}, \tag{3} \]

where \( \Phi^{-1} \) is the inverse of the cumulative distribution function for the standard normal variable (Efron & Tibshirani, 1993). First, look up the original sample mediation effect (\( \bar{\theta} \)) from the LISREL output generated in Step 1. Then use the COUNTIF function in the Excel file to count the number of bootstrap mediation effects that are less than or equal to the sample value (\( \hat{\theta}^* \leq \bar{\theta} \)). Next, divide the count by 1,000 to convert that into probability \( \text{Prob}(\hat{\theta}^* \leq \bar{\theta}) \). The \( z_0 \) value can then be estimated using the NORMSINV \( (\text{Prob}(\hat{\theta}^* \leq \bar{\theta})) \) function. Finally, with this biasing constant, one can estimate the upper and lower endpoint percentiles, their locations, and their corresponding values for the BC confidence interval.

\[ \text{Lower BC endpoint} = \text{the value of } \hat{\theta}^* \text{ at the } \left\{ \left\lfloor \Phi(2z_0 + z_{a/2}) \right\rfloor \times 100 \right\} \text{ percentile}; \tag{4} \]
\[ \text{Upper BC endpoint} = \text{the value of } \hat{\theta}^* \text{ at the } \left\lfloor \Phi(2z_0 + z_{1-a/2}) \right\rfloor \times 100 \right\} \text{ percentile}. \tag{5} \]

Equations 4 and 5 can be used to calculate the lower and upper endpoints, respectively, of the BC confidence interval. In the Excel file, the endpoints are estimated with the NORMSDIST function. The location of an endpoint is estimated by multiplying the number of bootstrap estimates by the endpoint percentile. With the location of an endpoint, one can refer back to the column of bootstrap mediation effects or DM sorted in ascending order to identify the corresponding value as the endpoint value.

Testing the Difference Between the Between-Part and Within-Part Path Coefficients in Multilevel Models

Although the NEW parameter option of Mplus is very powerful in creating linear and nonlinear constraints and it is easy to estimate the BC confidence intervals, there are still some limitations in the bootstrapping analysis of Mplus. In organizational studies, researchers may investigate individuals within groups in an organization. They may want to know how the association between a person-level covariate and the dependent variable (i.e., within-group association) may differ from the association between the group means of the covariate and the dependent variable (i.e., between-group association). The difference in path coefficient between the between part and the within part in a multilevel model corresponds to a contextual effect (Raudenbush & Bryk, 2002, p. 140). However, bootstrapping with multilevel models is not allowed with Mplus. As a consequence, the BC bootstrap confidence intervals for contextual effects in multilevel models cannot be estimated directly.
Hence, we suggest a procedure that combines Mplus and PRELIS to estimate BC bootstrap confidence intervals for contextual effects in multilevel models. The Mplus User’s Guide (Mutheén & Mutheén, 1998-2010) provides an example for comparing parameters in the between part and the within part in a two-level model (Example 9.1b, pp. 242-243).

In Step 1, Mplus is used to estimate the sample parameters that are to be used to estimate the BC bootstrap confidence intervals in Step 6. In Step 2, one has to prepare a PRELIS data file (*.psf). With this data file, one then conducts a bootstrap process in which bootstrap samples are generated (e.g., a bootstrap sample size of 1,000). Instead of saving the covariance matrix, the data of the bootstrap samples are saved (*.dat). As PRELIS saves the 1,000 bootstrap samples in a single file, before moving to Step 3 one needs to partition the large data file into 1,000 smaller data files, each with the data of one bootstrap sample. This is a tedious procedure but can be easily done with any word processor or spreadsheet with the Copy and Paste functions. The file names should be ended with a number indicating the number of the bootstrap sample and with a “.dat” extension. For example, if the large data file is named MLB.dat, the small data files can be named MLB1.dat, MLB2.dat, and so on, such that MLB1.dat contains the data of the first bootstrap sample. Then a data list file is created with the file name MLBlist.dat. Entries of this file are the file names of the bootstrap sample files, with one file name on each line. To continue with the example, in this data list file, the file name MLB1.dat is on line one, MLB2.dat on line two, and continues to MLB1000.dat on the last line.

In Step 3, the Mplus program is run with slight modifications. The program will be run as an external Monte Carlo simulation using the bootstrap sample files by including the following commands:

```
DATA: FILE = MLBlist.dat;
TYPE = MONTECARLO;
```

The results are then saved in a data file using the SAVEDATA command and RESULTS option. In Step 4, the data generated in the previous step is imported into PRELIS and further exported to an Excel file. All calculations are then conducted in this Excel file, and the calculations are similar to those in the previously described LISREL procedure. In Step 5, one locates the column of the parameter in the Excel file that corresponds to the contextual effect under examination. By copying the values to a new column, one can sort the values in ascending order. Step 6 involves the estimation of the biasing constant using the sample estimate from the Mplus output obtained in Step 1. Finally, with the biasing constant, one can estimate the lower and upper endpoint percentiles, locations, and values for the BC bootstrap confidence interval in Step 7.

While this demonstration shows the construction of BC bootstrap confidence intervals for the difference between the between-part and within-part path coefficients in multilevel models, it can be easily extended to test the difference of mediation effects between the between part and the within part in multilevel models.

**Testing Specific Mediation Effects in Models With Interactions of Latent Variables**

Similarly, Mplus does not allow bootstrapping with models involving interactions of latent variables. The BC bootstrap confidence intervals for the mediated moderation effects or the moderated mediation effects in models with interactions of latent variables cannot, therefore, be estimated. One alternative is to conduct a multigroup structural equation model by using the moderator as the grouping variable and comparing the mediation effects across groups using the syntax shown in Appendix C. Although this subgroup approach can be used to compare mediation effects across levels of the moderator, other drawbacks of the subgroup approach, such as lower power and loss of information in the
grouping variable, remain (Edwards & Lambert, 2007). We recommend running the analysis for
mediated moderation or moderated mediation models using a procedure that combines Mplus and
PRELIS. The Mplus User’s Guide (Muthén & Muthén, 1998-2010) provides an example in which an
interaction between two latent variables is included in a model (Example 5.13, pp. 71-72). This model
is one with mediated moderation effect.

The procedure is similar to that of testing the difference between the between part and the within
part in multilevel models. In Step 1, one first runs the program on the data file in Mplus. The param-
eter estimates are saved for further use in Step 6. In Step 2, the data in the data file are imported into
PRELIS and saved as a PRELIS data file (*.psf). With this data file, one can conduct a bootstrap
process (e.g., a bootstrap sample size of 1,000 bootstrap samples) and save the results in a data file
(e.g., MMB.dat). With the use of any word processor or spreadsheet, one then breaks down the large
data file into 1,000 small data files. The file name of each small data file should reflect the bootstrap
sample to which it is related. For example, MMB1.dat is the data file containing the data of the first
bootstrap sample, whereas MMB2.dat contains the data of the second bootstrap sample. When these
separate data files are ready, one can create a data list file (MMBlist.dat) that contains the file names
of these files, with one file name on each line.

Step 3 involves rerunning the model with the slightly modified Mplus program. An external
Monte Carlo simulation is conducted using the bootstrap sample files with the following commands:

```
DATA: FILE = MMBlist.dat;
TYPE = MONTECARLO;
```

The results are then saved in a data file using the SAVEDATA command and RESULTS option. The
data generated in the external Monte Carlo simulation are exported to an Excel file through PRELIS
in Step 4. In Step 5, one first locates the column of the bootstrap interaction effects in the Excel file
and then locates the column of any direct effect to be examined. By copying these values to two new
columns and calculating their product terms, one can estimate the bootstrap mediated moderation
effects. Then, one can sort these bootstrap-mediated moderation effects in ascending order. Step
6 involves using the parameter estimates to calculate the biasing constant, which is then used to esti-
mate the BC bootstrap confidence interval in Step 7.

Preacher and his colleagues (Preacher, Rucker, & Hayes, 2007) recently discussed the
various forms of mediated moderation and moderated mediation models, all of which involve interac-
tions of latent variables. Although the above procedure was based upon a mediated moderation model,
it can be extended to test any model containing mediated moderators or moderated mediators.

**Discussion**

With the increasing complexity of models examined in organizational research, it is increasingly
common to examine multiple mediator models in which there is more than one structural path
between the independent variable and the dependent variable. This teaching note demonstrates a
procedure of testing the significance of specific mediation effects using simple syntax in Mplus.
It also demonstrates that comparisons of two specific mediation effects or comparisons of the
strengths of direct and mediation effects in a complex latent variable model within a single group
or across groups can be easily conducted using a similar procedure. As Mplus does not allow boot-
strapping of standardized mediation effects in complex latent variable models, an alternative set of
LISREL procedures is illustrated, which can examine both standardized and unstandardized media-
tion effects. Finally, procedures combining Mplus and PRELIS for testing the difference between
the between-part and within-part path coefficients (i.e., a contextual effect) in multilevel models,
and models with interactions of latent variables are presented.
Mediators in a complex latent variable model are interdependent, such that the role of one mediator can hardly be disentangled from the roles played by others. Hence, even if researchers realize that one or more mediational path is not statistically significant using any of the procedures presented in the article, it is not recommended that they take away these mediators and rerun the analysis, as doing so may alter the path coefficients in the models.

The proposed procedures are different from and have several advantages over various methods for examining mediation effects currently existing in the literature. First, the procedures for establishing BC bootstrap confidence intervals avoid the problems that stem from the normality assumption—an assumption that is often violated (MacKinnon et al., 2004), thus enabling them to outperform not only those approaches that rely on null hypothesis testing (e.g., the Sobel test; Sobel, 1982) but also those in which confidence intervals are derived under the normality assumption. Second, the use of BC bootstrap confidence intervals corrects the bias in the bootstrapped sampling distribution. As the bootstrapped sampling distribution may be a biased estimator of the sampling distribution, adjustment of the bootstrapped sampling distribution ensures the accuracy of inferences made about the true population value of the mediation effect. The BC bootstrap method thus provides more accurate confidence intervals than those methods without such bias correction, such as the percentile method. Third, the bootstrap confidence interval procedures for comparing mediation effects outperform the chi-square difference test. The chi-square difference test mainly provides a p value that indicates whether the difference between two mediation effects is statistically significant. Although researchers can also estimate the magnitude of the difference, the standard error of the difference is not readily available. Our proposed procedures, on the other hand, offer more specific detail: an estimate of the difference and a confidence interval for the difference. With these benefits, our procedures are preferable to alternatives in the literature.

One potential drawback of the use of BC bootstrap confidence intervals for analyzing or comparing specific mediation effects concerns the slightly inflated Type I error rate (8% instead of 5%) in some special occasions (G. W. Cheung & Lau, 2008; Taylor, MacKinnon, & Tein, 2008). Specifically, among the two paths from the predictor to the mediator and from the mediator to the outcome variable, when one path is large and the other is small, the overall mediation effect tends to be trivial. In this situation, the Type I error rate may be inflated. However, the extra power provided by the BC bootstrap confidence interval method might outweigh the slight increase in Type I error rate (Taylor et al., 2008). In addition, as the sample size is 200 or above, the Type I error rate becomes closer to expected values. Researchers may cross-validate their results with the confidence intervals based on the bootstrap percentile method, which has a lower Type I error rate (G. W. Cheung & Lau, 2008), by replacing the CINTERVAL(BCBOOTSTRAP) option with CINTERVAL(BOOTSTRAP) under the OUTPUT command in the Mplus syntax.

Appendix A

Sample Mplus Syntax for Estimating Bias-Corrected Confidence Intervals for Specific Mediation Effects

```
TITLE: Example of Bootstrapping Confidence Intervals for Mediation Effects
DATA: FILE IS Example1.DAT;
VARIABLE: NAMES ARE y1-y12 x1-x6;
MODEL: eta1 BY y1-y3;
  eta2 BY y4-y6;
  eta3 BY y7-y9;
  eta4 BY y10-y12;
  ksi1 BY x1-x3;
```
ksi2 BY x4-x6;
eta1 ON ksi1 ksi2;
eta2 ON eta1;
eta3 ON eta1;
eta4 ON eta1 eta2 eta3;

MODEL INDIRECT:
eta4 IND eta2 eta1;
eta4 IND eta3 eta1;

ANALYSIS: BOOTSTRAP = 1000;
OUTPUT: CINTERVAL(BCBOOTSTRAP);

Appendix B

Sample Mplus Syntax for Estimating Bias-Corrected Confidence Intervals for Differences in Direct/Indirect and Indirect/Indirect Effects

TITLE: Example of Bootstrapping Confidence Intervals for Differences in Mediation Effects
DATA: FILE IS Example1.DAT;
VARIABLE: NAMES ARE y1-y12 x1-x6;
MODEL: eta1 BY y1-y3;
eta2 BY y4-y6;
eta3 BY y7-y9;
eta4 BY y10-y12;
ksi1 BY x1-x3;
ksi2 BY x4-x6;
eta1 ON ksi1 (a11)
ksi2 (a12);
eta2 ON eta1 (b21);
eta3 ON eta1 (b31);
eta4 ON eta1 (b41)
eta2 (b42)
eta3 (b43);
MODEL INDIRECT:
eta4 IND eta2 eta1;
eta4 IND eta3 eta1;
MODEL CONSTRAINT:
NEW (MED1 MED2 DM1 DM2 DM3);
MED1 = b21*b42;
MED2 = b31*b43;
DM1 = b41 - b21*b42;
DM2 = b41 - b31*b43;
DM3 = b21*b42 - b31*b43;
ANALYSIS: BOOTSTRAP = 1000;
OUTPUT: CINTERVAL(BCBOOTSTRAP);
Appendix C

Sample Mplus Syntax for Estimating Bias-Corrected Confidence Intervals for Differences in Direct/Indirect and Indirect/Indirect Effects Across Groups

TITLE: Example of Bootstrapping CI for Difference of Mediation Effects in 2 Samples
DATA: FILE is Example2.DAT;
VARIABLE: NAMES ARE y1-y9 x1-x3 g;
GROUPING IS g (1 = male 2 = female);
ANALYSIS: MODEL = NOMEANSTRUCTURE;
INFORMATION = EXPECTED;
MODEL:
ksi1 BY x1-x3;
eta1 BY y1-y3;
eta2 BY y4-y6;
eta3 BY y7-y9;
eta1 ON ksi1 (a11m);
eta2 ON ksi1 (a21m);
eta3 ON ksi1 (a31m)
eta1 (b31m)
eteta2 (b32m);
MODEL female:
ksi1 BY x3;
eteta1 ON ksi1 (a11f);
eteta2 ON ksi1 (a21f);
eteta3 ON ksi1 (a31f)
eteta1 (b31f)
eteta2 (b32f);
MODEL CONSTRAINT:
NEW (MED1m MED1f DM1 DM2);
MED1m = b31m*a11m;
MED1f = b31f*a11f;
DM1 = MED1m − MED1f;  ! Comparison of indirect effects across groups
DM2 = a31m − a31f;  ! Comparison of direct effects across groups
ANALYSIS: BOOTSTRAP = 1000;
OUTPUT: CINTERVAL(BCBOOTSTRAP);

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Note
All syntax files, data files, output files, and detailed demonstrations of the procedures presented in this article are available from the website of the second author (http://www3.baf.cuhk.edu.hk/download/TNote.zip).
References

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