

# template: References

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## References

**Baron et al.: The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations**

**Lib-Mediation-Causal-Steps-Baron-1986**

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Reuben M. Baron and David A. Kenny. “The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations”. In: *Journal of Personality and Social Psychology* 51.6 (1986), pp. 1173–1182. DOI: [10.1037/0022-3514.51.6.1173](https://doi.org/10.1037/0022-3514.51.6.1173).

Annotations: Lib-Mediation-Causal-Steps.

Abstract: In this article, we attempt to distinguish between the properties of moderator and mediator variables at a number of levels. First, we seek to make theorists and researchers aware of the importance of not using the terms moderator and mediator interchangeably by carefully elaborating, both conceptually and strategically, the many ways in which moderators and mediators differ. We then go beyond this largely pedagogical function and delineate the conceptual and strategic implications of making use of such distinctions with regard to a wide range of phenomena, including control and stress, attitudes, and personality traits. We also provide a specific compendium of analytic procedures appropriate for making the most effective use of the moderator and mediator distinction, both separately and in terms of a broader causal system that includes both moderators and mediators.

File: [references/10.1037%2F0022-3514.51.6.1173.pdf](#).

**M. W.-L. Cheung: Comparison of approaches to constructing confidence intervals for mediating effects using structural equation models**

**Lib-Confidence-Intervals-Profile-Likelihood-Cheung-2007**

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Mike W.-L. Cheung. "Comparison of approaches to constructing confidence intervals for mediating effects using structural equation models". In: *Structural Equation Modeling: A Multidisciplinary Journal* 14.2 (May 2007), pp. 227–246. DOI: [10.1080/10705510709336745](#).

Annotations: Lib-Confidence-Intervals-Profile-Likelihood.

**M. W.-L. Cheung: Comparison of methods for constructing confidence intervals of standardized indirect effects**

**Lib-Confidence-Intervals-Profile-Likelihood-Cheung-2009a**

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Mike W.-L. Cheung. "Comparison of methods for constructing confidence intervals of standardized indirect effects". In: *Behavior Research Methods* 41.2 (May 2009), pp. 425–438. DOI: [10.3758/brm.41.2.425](#).

Annotations: Lib-Confidence-Intervals-Profile-Likelihood.

**M. W.-L. Cheung: Constructing approximate confidence intervals for parameters with structural equation models**

**Lib-Confidence-Intervals-Profile-Likelihood-Cheung-2009b**

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Mike W.-L. Cheung. "Constructing approximate confidence intervals for parameters with structural equation models". In: *Structural Equation Modeling: A Multidisciplinary Journal* 16.2 (Apr. 2009), pp. 267–294. DOI: [10.1080/10705510902751291](#).

Annotations: Lib-Confidence-Intervals-Profile-Likelihood.

**Dudgeon: Some improvements in confidence intervals for standardized regression coefficients**  
**Lib-Regression-Standardized-Coefficients-HC-Dudgeon-2017**

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Paul Dudgeon. “Some improvements in confidence intervals for standardized regression coefficients”. In: *Psychometrika* 82.4 (Mar. 2017), pp. 928–951. DOI: [10.1007/s11336-017-9563-z](https://doi.org/10.1007/s11336-017-9563-z).

Annotations: Lib-Regression-Standardized-Coefficients-HC.

Abstract: Yuan and Chan (Psychometrika 76:670–690, 2011. doi:10.1007/S11336-011-9224-6) derived consistent confidence intervals for standardized regression coefficients under fixed and random score assumptions. Jones and Waller (Psychometrika 80:365–378, 2015. doi:10.1007/S11336-013-9380-Y) extended these developments to circumstances where data are non-normal by examining confidence intervals based on Browne’s (Br J Math Stat Psychol 37:62–83, 1984. doi:10.1111/j.2044-8317.1984.tb00789.x) asymptotic distribution-free (ADF) theory. Seven different heteroscedastic-consistent (HC) estimators were investigated in the current study as potentially better solutions for constructing confidence intervals on standardized regression coefficients under non-normality. Normal theory, ADF, and HC estimators were evaluated in a Monte Carlo simulation. Findings confirmed the superiority of the HC3 (MacKinnon and White, J Econ 35:305–325, 1985. doi:10.1016/0304-4076(85)90158-7) and HC5 (Cribari-Neto and Da Silva, Adv Stat Anal 95:129–146, 2011. doi:10.1007/s10182-010-0141-2) interval estimators over Jones and Waller’s ADF estimator under all conditions investigated, as well as over the normal theory method. The HC5 estimator was more robust in a restricted set of conditions over the HC3 estimator. Some possible extensions of HC estimators to other effect size measures are considered for future developments.

File: [references/10.1007%2Fs11336-017-9563-z.pdf](#).

**Ghosh et al.: Likelihood-based Inference for the ratios of regression coefficients in linear models**  
**Lib-Confidence-Intervals-Profile-Likelihood-Ghosh-2006**

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Malay Ghosh et al. “Likelihood-based Inference for the ratios of regression coefficients in linear

models”. In: *Annals of the Institute of Statistical Mathematics* 58.3 (June 2006), pp. 457–473. DOI: [10.1007/s10463-005-0027-3](https://doi.org/10.1007/s10463-005-0027-3).

Annotations: Lib-Confidence-Intervals-Profile-Likelihood.

**Hayes et al.: The relative trustworthiness of inferential tests of the indirect effect in statistical mediation analysis**      **Lib-Mediation-Monte-Carlo-Method-Hayes-2013**

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Andrew F. Hayes and Michael Scharkow. “The relative trustworthiness of inferential tests of the indirect effect in statistical mediation analysis”. In: *Psychological Science* 24.10 (Aug. 2013), pp. 1918–1927. DOI: [10.1177/0956797613480187](https://doi.org/10.1177/0956797613480187).

Annotations: Lib-Mediation-Monte-Carlo-Method.

Abstract: A content analysis of 2 years of Psychological Science articles reveals inconsistencies in how researchers make inferences about indirect effects when conducting a statistical mediation analysis. In this study, we examined the frequency with which popularly used tests disagree, whether the method an investigator uses makes a difference in the conclusion he or she will reach, and whether there is a most trustworthy test that can be recommended to balance practical and performance considerations. We found that tests agree much more frequently than they disagree, but disagreements are more common when an indirect effect exists than when it does not. We recommend the bias-corrected bootstrap confidence interval as the most trustworthy test if power is of utmost concern, although it can be slightly liberal in some circumstances. Investigators concerned about Type I errors should choose the Monte Carlo confidence interval or the distribution-of-the-product approach, which rarely disagree. The percentile bootstrap confidence interval is a good compromise test.

File: [references/10.1177/0956797613480187.pdf](https://doi.org/10.1177/0956797613480187).

**Kisbu-Sakarya et al.: The distribution of the product explains normal theory mediation confidence interval estimation**

**Lib-Mediation-Monte-Carlo-Method-Kisbu-Sakarya-2014**

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Yasemin Kisbu-Sakarya, David P. MacKinnon, and Milica Miočević. “The distribution of the product explains normal theory mediation confidence interval estimation”. In: *Multivariate Behavioral Research* 49.3 (May 2014), pp. 261–268. DOI: [10.1080/00273171.2014.903162](https://doi.org/10.1080/00273171.2014.903162).

Annotations: Lib-Mediation-Monte-Carlo-Method.

Abstract: The distribution of the product has several useful applications. One of these applications is its use to form confidence intervals for the indirect effect as the product of 2 regression coefficients. The purpose of this article is to investigate how the moments of the distribution of the product explain normal theory mediation confidence interval coverage and imbalance. Values of the critical ratio for each random variable are used to demonstrate how the moments of the distribution of the product change across values of the critical ratio observed in research studies. Results of the simulation study showed that as skewness in absolute value increases, coverage decreases. And as skewness in absolute value and kurtosis increases, imbalance increases. The difference between testing the significance of the indirect effect using the normal theory versus the asymmetric distribution of the product is further illustrated with a real data example. This article is the first study to show the direct link between the distribution of the product and indirect effect confidence intervals and clarifies the results of previous simulation studies by showing why normal theory confidence intervals for indirect effects are often less accurate than those obtained from the asymmetric distribution of the product or from resampling methods.

File: [references/10.1080/00273171.2014.903162.pdf](https://doi.org/10.1080/00273171.2014.903162).

**MacKinnon et al.: Confidence limits for the indirect effect: Distribution of the product and resampling methods**      **Lib-Mediation-Monte-Carlo-Method-MacKinnon-2004**

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David P. MacKinnon, Chondra M. Lockwood, and Jason Williams. “Confidence limits for the indirect effect: Distribution of the product and resampling methods”. In: *Multivariate Behavioral Research* 39.1 (Jan. 2004), pp. 99–128. DOI: [10.1207/s15327906mbr3901\\_4](https://doi.org/10.1207/s15327906mbr3901_4).

Annotations: Lib-Mediation-Monte-Carlo-Method.

Abstract: The most commonly used method to test an indirect effect is to divide the estimate of the indirect effect by its standard error and compare the resulting  $z$  statistic with a critical value from the standard normal distribution. Confidence limits for the indirect effect are also typically based on critical values from the standard normal distribution. This article uses a simulation study to demonstrate that confidence limits are imbalanced because the distribution of the indirect effect is normal only in special cases. Two alternatives for improving the performance of confidence limits for the indirect effect are evaluated: (a) a method based on the distribution of the product of two normal random variables, and (b) resampling methods. In Study 1, confidence limits based on the distribution of the product are more accurate than methods based on an assumed normal distribution but confidence limits are still imbalanced. Study 2 demonstrates that more accurate confidence limits are obtained using resampling methods, with the bias-corrected bootstrap the best method overall.

File: [references/10.1207%2Fs15327906mbr3901\\_4.pdf](#).

**Murphy et al.: On Profile Likelihood**

**Lib-Confidence-Intervals-Profile-Likelihood-Murphy-2000**

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S. A. Murphy and A. W. Van Der Vaart. “On Profile Likelihood”. In: *Journal of the American Statistical Association* 95.450 (June 2000), pp. 449–465. DOI: [10.1080/01621459.2000.10474219](https://doi.org/10.1080/01621459.2000.10474219).

Annotations: Lib-Confidence-Intervals-Profile-Likelihood.

**Neale et al.: The use of likelihood-based confidence intervals in genetic models**

**Lib-Confidence-Intervals-Profile-Likelihood-Neale-1997**

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Michael C. Neale and Michael B. Miller. “The use of likelihood-based confidence intervals in genetic models”. In: *Behavior Genetics* 27.2 (1997), pp. 113–120. DOI: [10.1023/a:1025681223921](https://doi.org/10.1023/a:1025681223921).

Annotations: Lib-Confidence-Intervals-Profile-Likelihood.

**Pawitan: In all likelihood: statistical modelling and inference using likelihood**

**Lib-Confidence-Intervals-Profile-Likelihood-Pawitan-2013**

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Yudi Pawitan. *In all likelihood: statistical modelling and inference using likelihood*. Oxford University Press, Jan. 17, 2013. 544 pp. ISBN: 9780199671229.

Annotations: Lib-Confidence-Intervals-Profile-Likelihood.

**Pek et al.: Profile likelihood-based confidence intervals and regions for structural equation models**

**Lib-Confidence-Intervals-Profile-Likelihood-Pek-2015**

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Jolynn Pek and Hao Wu. “Profile likelihood-based confidence intervals and regions for structural equation models”. In: *Psychometrika* 80.4 (Apr. 2015), pp. 1123–1145. DOI: [10.1007/s11336-015-9461-1](https://doi.org/10.1007/s11336-015-9461-1).

Annotations: Lib-Confidence-Intervals-Profile-Likelihood.

**Pesigan et al.: SEM-based methods to form confidence intervals for indirect effect: Still applicable given nonnormality, under certain conditions**

**Lib-Confidence-Intervals-Profile-Likelihood-Pesigan-2020**

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Ivan Jacob Agaloos Pesigan and Shu Fai Cheung. “SEM-based methods to form confidence intervals

for indirect effect: Still applicable given nonnormality, under certain conditions”. In: *Frontiers in Psychology* 11 (Dec. 2020). DOI: [10.3389/fpsyg.2020.571928](https://doi.org/10.3389/fpsyg.2020.571928).

Annotations: Lib-Confidence-Intervals-Profile-Likelihood.

**Pesigan et al.: SEM-based methods to form confidence intervals for indirect effect:  
Still applicable given nonnormality, under certain conditions**

**Lib-Mediation-Monte-Carlo-Method-Pesigan-2020**

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Ivan Jacob Agaloos Pesigan and Shu Fai Cheung. “SEM-based methods to form confidence intervals for indirect effect: Still applicable given nonnormality, under certain conditions”. In: *Frontiers in Psychology* 11 (Dec. 2020). DOI: [10.3389/fpsyg.2020.571928](https://doi.org/10.3389/fpsyg.2020.571928).

Annotations: Lib-Mediation-Monte-Carlo-Method.

**Abstract:** A SEM-based approach using likelihood-based confidence interval (LBCI) has been proposed to form confidence intervals for unstandardized and standardized indirect effect in mediation models. However, when used with the maximum likelihood estimation, this approach requires that the variables are multivariate normally distributed. This can affect the LBCIs of unstandardized and standardized effect differently. In the present study, the robustness of this approach when the predictor is not normally distributed but the error terms are conditionally normal, which does not violate the distributional assumption of ordinary least squares (OLS) estimation, is compared to four other approaches: nonparametric bootstrapping, two variants of LBCI, LBCI assuming the predictor is fixed (LBCI-Fixed-X) and LBCI based on ADF estimation (LBCI-ADF), and Monte Carlo. A simulation study was conducted using a simple mediation model and a serial mediation model, manipulating the distribution of the predictor. The Monte Carlo method performed worst among the methods. LBCI and LBCI-Fixed-X had suboptimal performance when the distributions had high kurtosis and the population indirect effects were medium to large. In some conditions, the problem was severe even when the sample size was large. LBCI-ADF and nonparametric bootstrapping had coverage probabilities close to the nominal value in nearly all conditions, although



the coverage probabilities were still suboptimal for the serial mediation model when the sample size was small with respect to the model. Implications of these findings in the context of this special case of nonnormal data were discussed.

File: [references/10.3389%2Ffpsyg.2020.571928.pdf](#).

**Preacher et al.: Advantages of Monte Carlo confidence intervals for indirect effects**  
**Lib-Mediation-Monte-Carlo-Method-Preacher-2012**

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Kristopher J. Preacher and James P. Selig. “Advantages of Monte Carlo confidence intervals for indirect effects”. In: *Communication Methods and Measures* 6.2 (Apr. 2012), pp. 77–98. DOI: [10.1080/19312458.2012.679848](#).

Annotations: Lib-Mediation-Monte-Carlo-Method.

Abstract: Monte Carlo simulation is a useful but underutilized method of constructing confidence intervals for indirect effects in mediation analysis. The Monte Carlo confidence interval method has several distinct advantages over rival methods. Its performance is comparable to other widely accepted methods of interval construction, it can be used when only summary data are available, it can be used in situations where rival methods (e.g., bootstrapping and distribution of the product methods) are difficult or impossible, and it is not as computer-intensive as some other methods. In this study we discuss Monte Carlo confidence intervals for indirect effects, report the results of a simulation study comparing their performance to that of competing methods, demonstrate the method in applied examples, and discuss several software options for implementation in applied settings.

File: [references/10.1080%2F19312458.2012.679848.pdf](#).

**Pritikin et al.: Likelihood-based confidence intervals for a parameter with an upper or lower bound**  
**Lib-Confidence-Intervals-Profile-Likelihood-Pritikin-2017**

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Joshua N. Pritikin, Lance M. Rappaport, and Michael C. Neale. “Likelihood-based confidence intervals for a parameter with an upper or lower bound”. In: *Structural Equation Modeling: A Multidisciplinary Journal* 24.3 (Jan. 2017), pp. 395–401. DOI: [10.1080/10705511.2016.1275969](https://doi.org/10.1080/10705511.2016.1275969).

Annotations: Lib-Confidence-Intervals-Profile-Likelihood.

**R Core Team: R: A language and environment for statistical computing**  
**Lib-R-Manual-2021**

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R Core Team. *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. Vienna, Austria, 2021. URL: <https://www.R-project.org/>.

Annotations: Lib-R-Manual.

**R Core Team: R: A language and environment for statistical computing**  
**Lib-R-Manual-2022**

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R Core Team. *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. Vienna, Austria, 2022. URL: <https://www.R-project.org/>.

Annotations: Lib-R-Manual.

**Sobel: Asymptotic confidence intervals for indirect effects in structural equation models**  
**Lib-Mediation-Delta-Method-Sobel-1982**

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Michael E. Sobel. “Asymptotic confidence intervals for indirect effects in structural equation models”. In: *Sociological Methodology* 13 (1982), p. 290. DOI: [10.2307/270723](https://doi.org/10.2307/270723).

**Sobel: Some new results on indirect effects and their standard errors in covariance structure models**  
**Lib-Mediation-Delta-Method-Sobel-1986**

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Michael E. Sobel. “Some new results on indirect effects and their standard errors in covariance structure models”. In: *Sociological Methodology* 16 (1986), p. 159. DOI: [10.2307/270922](https://doi.org/10.2307/270922).

**Sobel: Direct and indirect effects in linear structural equation models**  
**Lib-Mediation-Delta-Method-Sobel-1987**

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Michael E. Sobel. “Direct and indirect effects in linear structural equation models”. In: *Sociological Methods & Research* 16.1 (Aug. 1987), pp. 155–176. DOI: [10.1177/0049124187016001006](https://doi.org/10.1177/0049124187016001006).

Abstract: This article discusses total indirect effects in linear structural equation models. First, I define these effects. Second, I show how the delta method may be used to obtain the standard errors of the sample estimates of these effects and test hypotheses about the magnitudes of the indirect effects. To keep matters simple, I focus throughout on a particularly simple linear structural equation system; for a treatment of the general case, see Sobel (1986). To illustrate the ideas and results, a detailed example is presented.

**Tofighi et al.: Indirect effects in sequential mediation models: Evaluating methods for hypothesis testing and confidence interval formation**  
**Lib-Mediation-Monte-Carlo-Method-Tofighi-2019**

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Davood Tofighi and Ken Kelley. “Indirect effects in sequential mediation models: Evaluating methods for hypothesis testing and confidence interval formation”. In: *Multivariate Behavioral Research* 55.2 (June 2019), pp. 188–210. DOI: [10.1080/00273171.2019.1618545](https://doi.org/10.1080/00273171.2019.1618545).

Annotations: Lib-Mediation-Monte-Carlo-Method.

Abstract: Complex mediation models, such as a two-mediator sequential model, have become more prevalent in the literature. To test an indirect effect in a two-mediator model, we conducted a large-

scale Monte Carlo simulation study of the Type I error, statistical power, and confidence interval coverage rates of 10 frequentist and Bayesian confidence/credible intervals (CIs) for normally and nonnormally distributed data. The simulation included never-studied methods and conditions (e.g., Bayesian CI with flat and weakly informative prior methods, two model-based bootstrap methods, and two nonnormality conditions) as well as understudied methods (e.g., profile-likelihood, Monte Carlo with maximum likelihood standard error [MC-ML] and robust standard error [MC-Robust]). The popular BC bootstrap showed inflated Type I error rates and CI under-coverage. We recommend different methods depending on the purpose of the analysis. For testing the null hypothesis of no mediation, we recommend MC-ML, profile-likelihood, and two Bayesian methods. To report a CI, if data has a multivariate normal distribution, we recommend MC-ML, profile-likelihood, and the two Bayesian methods; otherwise, for multivariate nonnormal data we recommend the percentile bootstrap. We argue that the best method for testing hypotheses is not necessarily the best method for CI construction, which is consistent with the findings we present.

File: [references/10.1080%2F00273171.2019.1618545.pdf](#).

**Tofighi et al.: Monte Carlo confidence intervals for complex functions of indirect effects**  
**Lib-Mediation-Monte-Carlo-Method-Tofighi-2015**

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Davood Tofighi and David P. MacKinnon. “Monte Carlo confidence intervals for complex functions of indirect effects”. In: *Structural Equation Modeling: A Multidisciplinary Journal* 23.2 (Aug. 2015), pp. 194–205. DOI: [10.1080/10705511.2015.1057284](#).

Annotations: Lib-Mediation-Monte-Carlo-Method.

Abstract: One challenge in mediation analysis is to generate a confidence interval (CI) with high coverage and power that maintains a nominal significance level for any well-defined function of indirect and direct effects in the general context of structural equation modeling (SEM). This study discusses a proposed Monte Carlo extension that finds the CIs for any well-defined function of the coefficients of SEM such as the product of k coefficients and the ratio of the contrasts of

indirect effects, using the Monte Carlo method. Finally, we conduct a small-scale simulation study to compare CIs produced by the Monte Carlo, nonparametric bootstrap, and asymptotic-delta methods. Based on our simulation study, we recommend researchers use the Monte Carlo method to test a complex function of indirect effects.

File: [references/10.1080%2F10705511.2015.1057284.pdf](#).

**Venzon et al.: A method for computing profile-likelihood-based confidence intervals**  
**Lib-Confidence-Intervals-Profile-Likelihood-Venzon-1988**

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D. J. Venzon and S. H. Moolgavkar. “A method for computing profile-likelihood-based confidence intervals”. In: *Applied Statistics* 37.1 (1988), p. 87. DOI: [10.2307/2347496](#).

Annotations: Lib-Confidence-Intervals-Profile-Likelihood.

**Wu et al.: Adjusted confidence intervals for a bounded parameter**  
**Lib-Confidence-Intervals-Profile-Likelihood-Wu-2012**

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Hao Wu and Michael C. Neale. “Adjusted confidence intervals for a bounded parameter”. In: *Behavior Genetics* 42.6 (Sept. 2012), pp. 886–898. DOI: [10.1007/s10519-012-9560-z](#).

Annotations: Lib-Confidence-Intervals-Profile-Likelihood.

**Yzerbyt et al.: New recommendations for testing indirect effects in mediational models:  
The need to report and test component paths**  
**Lib-Mediation-Monte-Carlo-Method-Yzerbyt-2018**

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Vincent Yzerbyt et al. “New recommendations for testing indirect effects in mediational models: The need to report and test component paths”. In: *Journal of Personality and Social Psychology* 115.6 (Dec. 2018), pp. 929–943. DOI: [10.1037/pspa0000132](#).

Annotations: Lib-Mediation-Monte-Carlo-Method.

Abstract: In light of current concerns with replicability and reporting false-positive effects in psychology, we examine Type I errors and power associated with 2 distinct approaches for the assessment of mediation, namely the component approach (testing individual parameter estimates in the model) and the index approach (testing a single mediational index). We conduct simulations that examine both approaches and show that the most commonly used tests under the index approach risk inflated Type I errors compared with the joint-significance test inspired by the component approach. We argue that the tendency to report only a single mediational index is worrisome for this reason and also because it is often accompanied by a failure to critically examine the individual causal paths underlying the mediational model. We recommend testing individual components of the indirect effect to argue for the presence of an indirect effect and then using other recommended procedures to calculate the size of that effect. Beyond simple mediation, we show that our conclusions also apply in cases of within-participant mediation and moderated mediation. We also provide a new R-package that allows for an easy implementation of our recommendations.

File: [references/10.1037%2Fpspa0000132.pdf](#).