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| **Workflow:**  **Simple Mediation in a Path Analytic Framework** | | |
|  | **A Priori Power Analysis** | |
|  | ● | Conduct an a priori power analysis to determine the appropriate sample size. |
|  | ● | Draw estimates of effect from pilot data and/or the literature. |
|  |  |  |
|  | **Scrubbing & Scoring** | |
|  | ● | Import data and format (i.e., variable naming, reverse-scoring) item level variables. |
|  | ● | Analyze item-level missingness. |
|  | ● | If using scales, create the mean scores of the scales. |
|  | ● | Determine and execute approach for managing missingness. Popular choices are available item analysis (e.g., Parent, 2013) and multiple imputation. |
|  | ● | Analyze scale-level missingness. |
|  | ● | Create a df with *only* the items (scaled in the proper direction). |
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|  | **Data Diagnostics** | |
|  | ● | Evaluate univariate normality (i.e., one variable at a time) with Shapiro-Wilks tests; *p* < .05 indicates a violation of univariate normality. |
|  | ● | Evaluate multivariate normality (i.e., all continuously scaled variables simultaneously) with Mahalanobis test. Identify outliers (e.g., cases with Mahal values > 3 *SDx* from the centroid). Consider deleting (or transforming *if* there is an extreme-ish “jump” in the sorted values. |
|  | ● | Evaluate internal consistency of the scaled scores with Cronbach’s alpha or omega; the latter is increasingly preferred. |
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|  | **Specify and Run Model to be Analyzed (this workflow presumes lavaan)** | |
|  | ● | The dependent variable should be predicted by the independent, mediating, and covarying (if any) variables. |
|  | ● | “Labels” can facilitate interpretation by naming the a, b, and c’ paths. |
|  | ● | Additional script provides labels for the indirect, direct, and total effects. |
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|  | **Post Hoc Power Analysis** | |
|  | ● | With the values from your study, repeat the power analysis and report the degree to which you were adequately powered. |
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|  | **Interpret the Results** | |
|  | ● | Attend to ALL the paths (a, b, c’, direct, indirect, total) and their patterns. |
|  | ● | Table the results. |
|  | ● | Create a figure. |
|  | ● | Prepare the results appropriate for the audience who will receive it. |

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| **Workflow:**  **Complex Mediation in a Path Analytic Framework** | | |
|  | **A Priori Power Analysis** | |
|  | ● | Conduct an a priori power analysis to determine the appropriate sample size. |
|  | ● | Draw estimates of effect from pilot data and/or the literature. |
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|  | **Scrubbing & Scoring** | |
|  | ● | Import data and format (i.e., variable naming, reverse-scoring) item level variables. |
|  | ● | Analyze item-level missingness. |
|  | ● | If using scales, create the mean scores of the scales. |
|  | ● | Determine and execute approach for managing missingness. Popular choices are available item analysis (e.g., Parent, 2013) and multiple imputation. |
|  | ● | Analyze scale-level missingness. |
|  | ● | Create a df with *only* the items (scaled in the proper direction). |
|  |  |  |
|  | **Data Diagnostics** | |
|  | ● | Evaluate univariate normality (i.e., one variable at a time) with Shapiro-Wilks tests; *p* < .05 indicates a violation of univariate normality. |
|  | ● | Evaluate multivariate normality (i.e., all continuously scaled variables simultaneously) with Mahalanobis test. Identify outliers (e.g., cases with Mahal values > 3 *SDx* from the centroid). Consider deleting (or transforming *if* there is an extreme-ish “jump” in the sorted values. |
|  | ● | Evaluate internal consistency of the scaled scores with Cronbach’s alpha or omega; the latter is increasingly preferred. |
|  |  |  |
|  | **Specify and Run Model to be Analyzed (this workflow presumes lavaan)** | |
|  | ● | The dependent variable should be predicted by the independent, mediating, and covarying (if any) variables. |
|  | ● | “Labels” can facilitate interpretation by naming the a, b, and c’ paths. |
|  | ● | Additional script provides labels for the indirect, direct, and total effects. |
|  | ● | Add script to calculate “contrasts” – that is to ask if there are statistically significant differences between indirect effects. |
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|  | **Post Hoc Power Analysis** | |
|  | ● | With the values from your study, repeat the power analysis and report the degree to which you were adequately powered. |
|  |  |  |
|  | **Interpret the Results** | |
|  | ● | Attend to ALL the paths (a, b, c’, direct, indirect, total) and their patterns. |
|  | ● | Report if some indirect effects are stronger than other (i.e., are contrasts statistically significant). |
|  | ● | Table the results. |
|  | ● | Create a figure. |
|  | ● | Prepare the results appropriate for the audience who will receive it. |

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| **Workflow:**  **Moderated Mediation in a Path Analytic Framework** | | |
|  | **A Priori Power Analysis** | |
|  | ● | Conduct an a priori power analysis to determine the appropriate sample size. |
|  | ● | Draw estimates of effect from pilot data and/or the literature. |
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|  | **Scrubbing & Scoring** | |
|  | ● | Import data and format (i.e., variable naming, reverse-scoring) item level variables. |
|  | ● | Analyze item-level missingness. |
|  | ● | If using scales, create the mean scores of the scales. |
|  | ● | Determine and execute approach for managing missingness. Popular choices are available item analysis (e.g., Parent, 2013) and multiple imputation. |
|  | ● | Analyze scale-level missingness. |
|  | ● | Create a df with *only* the items (scaled in the proper direction). |
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|  | **Data Diagnostics** | |
|  | ● | Evaluate univariate normality (i.e., one variable at a time) with Shapiro-Wilks tests; *p* < .05 indicates a violation of univariate normality. |
|  | ● | Evaluate multivariate normality (i.e., all continuously scaled variables simultaneously) with Mahalanobis test. Identify outliers (e.g., cases with Mahal values > 3 *SDs* from the centroid). Consider deleting (or transforming *if* there is an extreme-ish “jump” in the sorted values. |
|  | ● | Evaluate internal consistency of the scaled scores with Cronbach’s alpha or omega; the latter is increasingly preferred. |
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|  | **Specify and Run Piecewise and Full Models (this workflow presumes lavaan)** | |
|  | ● | Conduct a piecewise analysis of each simple mediation and simple moderation(s), separately. |
|  | ● | Specify and analyze a model with all the paths, including the interaction terms of the moderator. |
|  |  | “Labels” can facilitate interpretation by naming the a, b, and c’ paths. |
|  | ● | The code should also include calculations for the index of moderated mediation and conditional indirect and direct (if included) effects. |
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|  | **Post Hoc Power Analysis** | |
|  | ● | With the values from your study, repeat the power analysis and report the degree to which you were adequately powered. |
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|  | **Interpret the Results** | |
|  | ● | Attend to ALL the paths (a, b, c’, direct, indirect, total) and their patterns. |
|  | ● | Table the results. |
|  | ● | Create a figure. |
|  | ● | Prepare the results appropriate for the audience who will receive it. |

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|  | **Specify and evaluate a *measurement model*** | | | |
|  | ● | In this just-identified (saturated) model, all latent variables are specified as covarying | | |
|  |  | ○ | For LVs with 3 items or more, remember to set a marker/reference variable. | |
|  | ● | In the event of poor fit, respecify LVs with multiple indicators with parcels. | | |
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|  | **Specify and evaluate a *structural model*** | | | |
|  | ● | Replace the covariances with paths that represent the a priori hypotheses. | | |
|  |  | ○ | | These models could take a variety of forms. |
|  |  | ○ | | It is possible to respecify models through trimming or building approaches. |
|  |  | ○ | | Nested models can be compared with Χ2 difference and ΔCFI tests. |
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| **Workflow:**  **Evaluating a Structural Model** | | | | | | | | | |
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|  | **A Priori Power Analysis** | | | | | | | | |
|  | ● | | Conduct an a priori power analysis to determine the appropriate sample size. | | | | | | |
|  | ● | | Draw estimates of effect from pilot data and/or the literature. | | | | | | |
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|  | **Scrubbing & Scoring** | | | | | | | | |
|  | ● | | Import data and format (i.e., variable naming, reverse-scoring) item level variables. | | | | | | |
|  | ● | | Analyze item-level missingness. | | | | | | |
|  | ● | | If using scales, create the mean scores of the scales. | | | | | | |
|  | ● | | Determine and execute approach for managing missingness. Popular choices are available item analysis (e.g., Parent, 2013) and multiple imputation. | | | | | | |
|  | ● | | Analyze scale-level missingness. | | | | | | |
|  | ● | | Create a df with *only* the items (scaled in the proper direction). | | | | | | |
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|  | **Data Diagnostics** | | | | | | | | |
|  | ● | | Evaluate univariate normality (i.e., one variable at a time) with Shapiro-Wilks tests; *p* < .05 indicates a violation of univariate normality. | | | | | | |
|  | ● | | Evaluate multivariate normality (i.e., all continuously scaled variables simultaneously) with Mahalanobis test. Identify outliers (e.g., cases with Mahal values > 3 *SDs* from the centroid). Consider deleting (or transforming *if* there is an extreme-ish “jump” in the sorted values. | | | | | | |
|  | ● | | Evaluate internal consistency of the scaled scores with Cronbach’s alpha or omega; the latter is increasingly preferred. | | | | | | |
|  |  | | | | | | |  |  |
|  | **Specify and evaluate a *measurement model*** | | | | | | | | |
|  | ● | | In this just-identified (saturated) model, all latent variables are specified as covarying | | | | | | |
|  |  | | ○ | | | | For LVs with 3 items or more, remember to set a marker/reference variable. | | |
|  |  | | ○ | | | | For LVs with 2 items, constrain the loadings to be equal | | |
|  |  | | ○ | | | | For single-item indicators fix the error variance to zero (or a non-zero estimate of unreliability) | | |
|  | ● | | Evaluate results with *global* (e.g., X2, CFI, RMSEA, SRMR) and *local* (i.e., factor loadings and covariances) fit indices | | | | | | |
|  | ● | | In the event of poor fit, respecify LVs with multiple indicators with parcels. | | | | | | |
|  | ● | | Nested alternative measurement models can be compared with Χ2 difference, ΔCFI tests; non-nested models with AIC, and BIC tests | | | | | | |
|  |  | | | | | | |  |  |
|  | **Specify and evaluate a *structural model*** | | | | | | | | |
|  | ● | Replace the covariances with paths that represent the a priori hypotheses | | | | | | | |
|  |  | ○ | | | | These models could take a variety of forms. | | | |
|  |  | ○ | | | | It is possible to respecify models through trimming or building approaches. | | | |
|  | ● | Evaluate results using: | | | | | | | |
|  |  | ○ | | | global fit indices (e.g., X2, CFI, RMSEA, SRMS), | | | | |
|  |  | ○ | | | local fit indices (i.e., strength and significance of factor loadings, covariances, and additional model parameters [e.g., indirect effects]) | | | | |
|  | ● | Consider respecifying and evaluating one or more *alternative* models: | | | | | | | |
|  |  | ○ | | nested models can be compared with Χ2 difference, ΔCFI tests | | | | | |
|  |  | ○ | | non-nested models can use AIC, and BIC comparisons (lower values suggest better fit) | | | | | |
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|  | **Quick Guide for Global and Comparative Fit Statistics** | | | | | | | | |
|  | ● | | Χ2, *p >* .05; this test is sensitive to sample size and this value can be difficult to attain | | | | | | |
|  | ● | | CFI > .95 (or at least .90) | | | | | | |
|  | ● | | RMSEA (and associated 90%CI) are < .05 (< .08, or at least < .10) | | | | | | |
|  | ● | | SRMR < .08 (or at least <.10) | | | | | | |
|  | ● | | Combination rule: CFI < .95 and SRMR < .08 | | | | | | |
|  | ● | | AIC and BIC are compared; the lowest values suggest better models | | | | | | |
|  | ● | | Χ2Δ is statistically significant; the model with the superior global fit is the better model | | | | | | |
|  | ● | | ΔCFI is greater than 0.01; the model with CFI values closest to 1.0 has better fit | | | | | | |
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| **Workflow:**  **Template** | | | | | | |
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