|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Workflow:**  **Principal Components Analysis (PCA)** | | | | | | |
|  |  | | | |  |  |
|  | **Structure-up your dataframe(s)** | | | | | |
|  | ● | | Reverse-score any items are negatively worded (i.e., the item is scaled opposite the other items) | | | |
|  | ● | | Create a df with *only* the items (scaled in the proper direction) | | | |
|  |  | | | |  |  |
|  | **Check the assumptions associated with PCA** | | | | | |
|  | ● | | Kaiser-Meyer-Olkin (KMO) for sampling adequacy (KMO should be > .50) | | | |
|  | ● | | Barlett’s to rule out the possibility of an *identity matrix* (Barlett’s *p-value* should be < .05) | | | |
|  | ● | | Determinant of the correlation matrix to rule out *multicollinearity*  or *singularity* (the determinant should be > 0.00001) | | | |
|  |  | | | |  |  |
|  | **Determine the Number of Components to Extract** | | | | | |
|  | ● | | Run a PCA with the number of components equal to the number of variables/items in the data | | | |
|  | ● | | Examine **eigenvalues** (“SS loadings” in the psych package), consider the eigenvalues-greater-than-1 criteria for determining the number of components to extract | | | |
|  | ● | | Examine the **scree plot**, consider extracting the number of components above the plateau | | | |
|  | ● | | Consider the proportion of variance accounted for. How much additional variance does each additional component add? | | | |
|  | ● | | Consider any a priori theory regarding the number of factors | | | |
|  |  | | | |  |  |
|  | **Specify and Evaluate the Solution with the Specified Number of Components** | | | | | |
|  | ● | | Rerun the PA with the determined number of components | | | |
|  | ● | | Examine **communalities** individually and as an average.Criteria for acceptability range from being greater than .40 to being greater than .70 | | | |
|  | ● | | Examine **residuals**. Determine the number and percentage that are greater than .05. A common practice is to stay below 50% larger than .05. | | | |
|  |  | | | |  |  |
|  | **Component Rotation: Orthogonal or Oblique?** Expect to run both (with varying component structures), report only one. | | | | | |
|  | **Orthogonal** – to be used when we think the components are independent/unrelated; this approach minimizes cross-loadings | | | | | |
|  |  | ● | | Examine the components loadings. Are they above .3? Do any cross-load on other components (the highest loading should be on their theorized subscale)? | | |
|  |  | ● | | Are the communalities greater than at least .4? (ideally higher). Consider removing items when the communalities are .2 or lower. | | |
|  | **Oblique** – to be used when we expect the components to be correlated; this approach may be *truer* to our overarching hypothese (i.e., subscales are likely related to each other), but add complexity because cross-loadings are more likely | | | | | |
|  |  | ● | | Examine the components loadings. Are they above .3? Do any cross-load on other components (the highest loading should be on their theorized subscale)? | | |
|  |  | ● | | Are the communalities greater than at least .4? (ideally higher). Consider removing items when the communalities are .2 or lower. | | |
|  |  | ● | | The **pattern matrix** reports component loadings and is most comparable to the orthogonal output. | | |
|  |  | ● | | The **structure matrix** is a product of the pattern matrix and matrix containing the correlation coefficients between the components/scales). This can serve as a useful check to the pattern matrix. | | |
|  |  | |  | | | |
|  | **Engage in the *iterative* nature of this process** | | | | | |
|  | ● | | Try different models and evaluate their results before determining which model (number of components, orthogonal or oblique rotation) best fits the data | | | |
|  |  | |  | | |  |

Diagram

Description automatically generatedA picture containing text, antenna

Description automatically generated

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Workflow:**  **Principal Axis Factoring (PAF)** | | | | | | |
|  |  | | | |  |  |
|  | **Structure-up your dataframe(s)** | | | | | |
|  | ● | | Reverse-score any items are negatively worded (i.e., the item is scaled opposite the other items) | | | |
|  | ● | | Create a df with *only* the items (scaled in the proper direction) | | | |
|  |  | | | |  |  |
|  | **Check the assumptions associated with PAF** | | | | | |
|  | ● | | Kaiser-Meyer-Olkin (KMO) for sampling adequacy (KMO should be > .50) | | | |
|  | ● | | Barlett’s to rule out the possibility of an *identity matrix* (Barlett’s *p-value* should be < .05) | | | |
|  | ● | | Determinant of the correlation matrix to rule out *multicollinearity*  or *singularity* (the determinant should be > 0.00001) | | | |
|  |  | | | |  |  |
|  | **Determine the Number of Factors to Extract** | | | | | |
|  | ● | | Run a PAF with the number of factors *fewer than* the number of variables/items in the data | | | |
|  | ● | | Examine **eigenvalues** (“SS loadings” in the psych package), consider the eigenvalues-greater-than-1 criteria for determining the number of factors to extract | | | |
|  | ● | | Examine the **scree plot**, consider extracting the number of factors above the plateau | | | |
|  | ● | | Consider the proportion of variance accounted for. How much additional variance does each additional factor add? | | | |
|  | ● | | Consider any a priori theory regarding the number of factors | | | |
|  |  | | | |  |  |
|  | **Specify and Evaluate the Solution with the Specified Number of Factors** | | | | | |
|  | ● | | Rerun the PA with the determined number of factors | | | |
|  | ● | | Examine **communalities** individually and as an average.Criteria for acceptability range from being greater than .40 to being greater than .70 | | | |
|  | ● | | Examine **residuals**. Determine the number and percentage that are greater than .05. A common practice is to stay below 50% larger than .05. | | | |
|  |  | | | |  |  |
|  | **Factor Rotation: Orthogonal or Oblique?** Expect to run both (with varying factor structures), report only one. | | | | | |
|  | **Orthogonal** – to be used when we think the factors are independent/unrelated; this approach minimizes cross-loadings | | | | | |
|  |  | ● | | Examine the factors loadings. Are they above .3? Do any cross-load on other factors (the highest loading should be on their theorized subscale)? | | |
|  |  | ● | | Are the communalities greater than at least .4? (ideally higher). Consider removing items when the communalities are .2 or lower. | | |
|  | **Oblique** – to be used when we expect the factors to be correlated; this approach may be *truer* to our overarching hypothese (i.e., subscales are likely related to each other), but add complexity because cross-loadings are more likely | | | | | |
|  |  | ● | | Examine the factors loadings. Are they above .3? Do any cross-load on other factors (the highest loading should be on their theorized subscale)? | | |
|  |  | ● | | Are the communalities greater than at least .4? (ideally higher). Consider removing items when the communalities are .2 or lower. | | |
|  |  | ● | | The **pattern matrix** reports factor loadings and is most comparable to the orthogonal output. | | |
|  |  | ● | | The **structure matrix** is a product of the pattern matrix and matrix containing the correlation coefficients between the factors/scales). This can serve as a useful check to the pattern matrix. | | |
|  |  | |  | | | |
|  | **Engage in the *iterative* nature of this process** | | | | | |
|  | ● | | Try different models and evaluate their results before determining which model (number of factors, orthogonal or oblique rotation) best fits the data | | | |
|  |  | |  | | |  |

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Workflow:**  **Confirmatory Factor Analysis (CFA)** | | | | | | | | | | |
|  |  | | | | | | | |  |  |
|  | **Structure-up your dataframe(s)** | | | | | | | | | |
|  | ● | | Reverse-score any items are negatively worded (i.e., the item is scaled opposite the other items) | | | | | | | |
|  |  | | | | | | | |  |  |
|  | **Apriorily, determine your factor structure (i.e., which items belong to each scale)** | | | | | | | | | |
|  | ● | | Is it identified? | | | | | | | |
|  |  | | ○ | | | | | A single factor model has at least three items/indicators | | |
|  |  | | ○ | | | | | Multidimensional models have at least two items per factor | | |
|  |  | | | | | | | |  |  |
|  | **Specify a Series of Models, a typical scenario includes** | | | | | | | | | |
|  | ● | | Unidimensional (all items on a single factor) | | | | | | | |
|  | ● | | Single order structure with correlated factors (e.g., “correlated traits”, oblique) | | | | | | | |
|  |  | | ○ | | | | If the subscales are theorized to be independent (orthogonal), then respecify as an uncorrelated single order model | | | |
|  | ● | | Second order structure | | | | | | | |
|  | ● | | Bifactor structure | | | | | | | |
|  |  | | | | | | | |  |  |
|  | **Evaluate Model Fit with a Variety of Indicators, a common scenario includes** | | | | | | | | | |
|  | ● | | Each indicator has a factor loading (pattern coefficient) that is strong ( > .30), statistically significant, and consistently in the desired direction (positive or negative valence) | | | | | | | |
|  | ● | | Fit indices are within the pre-specified criteria | | | | | | | |
|  |  | | ○ | | | 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 | | | | |
|  |  | | | | | | | |  |  |
|  | **Compare Models** | | | | | | | | | |
|  |  | ● | | AIC and BIC are compared; the lowest values suggest better models | | | | | | |
|  |  | ● | | Χ2Δ is statistically significant; the model with the superior fit is the better model | | | | | | |
|  |  | |  | | | | | | | |
|  | **In the Event of Inferior Fit** | | | | | | | | | |
|  | ● | | Evaluate modification indices, note those that are substantially higher than the rest. Options: | | | | | | | |
|  |  | | ○ | | Consider eliminating items that have substantial crossloadings | | | | | |
|  |  | | ○ | | If theoretically (or rationally) justified, consider allowing errors to covary | | | | | |
|  |  | |  | | | | | | |  |

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Workflow:**  **Multigroup Invariance Testing** | | | | | | | | | | | | | | |
|  |  | | | | | |  | | | | | | |  |
|  | **Structure-up your dataframe(s)** | | | | | | | | | | | | | |
|  | ● | Reverse-score any items are negatively worded (i.e., the item is scaled opposite the other items) | | | | | | | | | | | | |
|  |  | | | | | |  | | | | | | |  |
|  | **Prior to invariance testing, specify and evaluate a *baseline model* that meets acceptable standards for model fit for the groups of interest** | | | | | | | | | | | | | |
|  | ● | Theoretically and statistically identified | | | | | | | | | | | | |
|  | ● | Magnitude and direction of factor loadings | | | | | | | | | | | | |
|  | ● | Acceptability of fit indices | | | | | | | | | | | | |
|  |  | | | | | |  | | | | | | |  |
|  | **Specify and compare a series of increasingly restrictive models. A typical hierarchy includes** | | | | | | | | | | | | | |
|  | ● | Configural invariance (the same CFA model) | | | | | | | | | | | | |
|  |  | ○ | If model fit is acceptable, proceed to the next step. |  | | | | ○ | | | | | If the model fit is unacceptable, stop. Reconsider your baseline model. | |
|  | ● | Weak invariance (configural + pattern/factor loadings) | | | | | | | | | | | | |
|  | ● | Conduct Χ2 difference and ΔCFI tests between the weak and configural specifications | | | | | | | | | | | | |
|  |  | ○ | If there are non-significant differences (and model fit remains acceptable) proceed to the next step. |  | | | | ○ | | | | If the constraints for weak invariance lead to unacceptable fit and/or there are statistically significant differences, stop. Consider partial measurement invariance testing to determine the source of the invariance (e.g., which pattern/factor loadings are noninvariant). | | |
|  | ● | Strong invariance (weak + item intercepts) | | | | | | | | | | | | |
|  | ● | Conduct Χ2 difference and ΔCFI tests between the strong and weak specifications | | | | | | | | | | | | |
|  |  | ○ | Conduct Χ2 difference and ΔCFI tests. If there are non-significant differences (and model fit remains acceptable) proceed to the next step. | |  | | | | ○ | | | If the constraints for strong invariance lead to unacceptable fit and/or there are statistically significant differences, stop. Consider partial measurement invariance testing to determine the source of the invariance (i.e., which item intercepts are noninvariant). | | |
|  | ● | Strict invariance (strong + error variances and covariances) | | | | | | | | | | | | |
|  | ● | Conduct Χ2 difference and ΔCFI tests between the strict and strong specifications | | | | | | | | | | | | |
|  |  | ○ | Conduct Χ2 difference and ΔCFI tests. If there are non-significant differences declare the model to be invariant for the two groups. | | |  | | | | ○ | If the constraints for strict invariance lead to unacceptable fit, consider partial measurement invariance testing to determine the source of the invariance (i.e., which error variances or covariance are noninvariant). | | | |
|  |  | | | | | | | | | | | | | |

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Workflow:**  **Incorporating Your Psychometrically Sound Measure(s) into a Hybrid Model** | | | | |
|  |  |  | | |
|  | **Structure-up your dataframe(s)** | | | |
|  | ● | Reverse-score any items are negatively worded (i.e., the item is scaled opposite the other items) | | |
|  | ● | Ensure proper formatting of variables (e.g., numerical, factor) | | |
|  | ● | Conduct a missing data analysis and manage missing data. | | |
|  |  | * I use Parent’s (2013) available item analysis approach, by eliminating all variables with 20% or more data missing at the item-level; creating scale scores when ~80% of items are present; and specifying *fiml* in the *lavaan::cfa* and *lavaan::sem* models. | | |
|  |  |  | | |
|  | **Preliminary analyses** | | | |
|  | ● | Evaluate assumptions for multivariate analyses. This typically includes skew, kurtosis, normality, identification of outliers, multivariate normality | | |
|  | ● | Calculate internal consistency coefficients for any measures that are “scales” | | |
|  | ● | Create a correlation table with means and standard deviations | | |
|  |  |  | | |
|  | **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) | |
|  | ● | In the event of poor fit, respecify LVs with multiple indicators with parcels. | | |
|  |  |  | | |
|  | **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. |
|  |  | | | |