Condition 9 and 10 Tests of Model Confirmation with SEM Techniques

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Honoring the SEM Contributions of Larry James
I. Introduction

A. 1960s-1980s: regression > path analysis > latent variable models
   Duncan (1975); Kenny (1979); Joreskog & Sorbom (1979); Bagozzi (1980)
   James, Mulaik, & Brett (1982): “conditions for confirmatory inference”
   Condition 9: empirical support for equations of model paths in the model
   Condition 10: fit between model and empirical data paths not in the model

B. Prior reviews of latent variable models in organizational research
   James & James (1989); Harris & Schaubroeck (1990), Medsker, Williams, & Holahan (1994)

C. No reviews since in spite of dramatic increase in use
D. Overview of presentation

Review James et al. (1982) condition 9 and 10 tests
Review recent substantive applications (311 studies)
  focus on author(s) approaches to model confirmation
Present reanalyses of 116 studies using new techniques
Provide suggestions for improved condition 9 and 10 assessment

II. Overview of Conditions 9 and 10

See Figures 1a and 1b for example path analysis and latent variable multiple indicator models
Figure 1a. Example Path Analysis Model (Full Mediation)
Proposes $b_1 \neq 0$, $b_2 \neq 0$, $b_3 = 0$

**Condition 9:**
Requires $b_1 \neq 0$ and $b_2 \neq 0$
1) Met if $b_1$ and $b_2$ confidence intervals do not include 0

**Condition 10:**
Requires $b_3 = 0$
1) Met if $b_3$ confidence interval includes 0
   (omitted parameter test)
   Let $r^*_{xy} =$ reproduced correlation $= b_1 \times b_2$
2) Met if $r_{xy} - r^*_{xy} = 0$ (reproduced correlation test)
Figure 1b. Example Latent Variable Model (Full Mediation)
Proposes $\gamma_1 \neq 0$, $\beta_1 \neq 0$, $\gamma_2 = 0$

**Condition 9:**
Requires $\gamma_1 \neq 0$ and $\beta_1 \neq 0$
1) Met if $\gamma_1$ and $\beta_1$ confidence intervals do not include 0
   Let $M_{T-2}$ constrain $\gamma_1$ and $\beta_1 = 0$
2) Met if $\chi^2_{T-2} - \chi^2_T$ significant

**Condition 10:**
Requires $\gamma_2 = 0$
1) Met if $\gamma_2$ confidence interval includes 0
   Let $M_{T+1}$ include $\gamma_2 \neq 0$
2) Met if $\chi^2_T - \chi^2_{T+1}$ not significant
3) Met if $M_T$ goodness of fit is adequate
III. Summary: Conditions 9 and 10 with Latent Variables

A. Condition 9: path estimates different from zero? (support for equation)
   Does confidence interval include zero (are parameters significant)
   Chi-square test of nested models
   $M_T$ (theory) vs. $M_{SN}$ (structural null, theory paths set to zero)
   Hope test significant, if so reject null hypothesis about fixed parameters
   Theory supported
B. Condition 10: fit between model and data

Chi-square test of nested models
$M_T$ vs. $M_{SS}$ (saturated structural, adds paths predicted to be zero)
Hope test non-significant, fail to reject null paths predicted as zero
Theory supported
Also recommended fit index NFI (Bentler & Bonett, 1980)
Also recommended efficiency index (Khattab & Hocevar, 1982)
C. Condition 10 from then to now
   Many global fit indices proposed, three survive
   CFI (Bentler, 1990)
       Based on NFI, avoids sample size bias
   RMSEA (Steiger & Lind, 1980)
       Like efficiency index (accounts for number of parameters)
       Also yields confidence interval
   SRMR (Bentler, 1995)
       Based on reproduced correlation test of James et al. (1982)
   Guidelines (*cut-off values*): CFI >.95, RMSEA<.08, SRMR<.10

D. Which condition more important, which should be established first?
   Quality of model must be established first (Condition 10)
   Path estimates from poor model can’t be trusted (Condition 9)
IV. Review of recent applications in management research

A. All models tested with SEM between 2001-2014
   AMJ, JAP, PPsy, JoM, OBHDP, SMJ
   Only single level of analysis, path model, multiple indicators
   Resulted in 311 included studies

B. Coded
   Sample size
   Chi-square and df of CFA and composite path model
   Values of CFI, RMSEA, SRMR (and other indices)

C. Results (Table 1)
Table 1. Results for reviewed studies

<table>
<thead>
<tr>
<th>Condition 9 Tests</th>
<th>k</th>
<th>%</th>
<th>Mean(SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>T-test parameters</td>
<td>304</td>
<td>98%</td>
<td>--</td>
</tr>
<tr>
<td>Nested Model Comparison</td>
<td>197</td>
<td>63%</td>
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</table>

<table>
<thead>
<tr>
<th>Condition 10 Tests</th>
<th>(\chi^2)</th>
<th>k</th>
<th>%</th>
<th>Mean(SD)</th>
</tr>
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<tbody>
<tr>
<td></td>
<td></td>
<td>287</td>
<td>92%</td>
<td>594.73(1066.85)</td>
</tr>
<tr>
<td>CFI</td>
<td></td>
<td>280</td>
<td>90%</td>
<td>0.95 (0.03)</td>
</tr>
<tr>
<td>RMSEA</td>
<td></td>
<td>243</td>
<td>78%</td>
<td>0.06 (0.02)</td>
</tr>
<tr>
<td>RMSEA CI</td>
<td></td>
<td>29</td>
<td>9%</td>
<td>--</td>
</tr>
<tr>
<td>SRMR</td>
<td></td>
<td>133</td>
<td>43%</td>
<td>0.06 (0.02)</td>
</tr>
</tbody>
</table>
D. Summary

High number of studies that just meet criteria

CFI: .93-.949 (41), .95-.97 (111)
RMSEA: .06-.079 (82), .08 (21), >.08 (13)

Confidence intervals used infrequently (9%)
SRMR: .08-.10 (20), >.10 (4)

Reflects role of criteria in acceptance? Or drive authors practices?

E. Use of multiple fit indices- not been investigated with sample data

Correlations among values

CFI and RMSEA: -.28 (n=227)
CFI and SRMR: -.26 (n=121)
RMSEA and SRMR: .43 (n=96)

Summary of conclusions using common thresholds
CFI >.95, RMSEA<.08, SRMR<.10 (see Table 2)
# Table 2 part 1: Meet one threshold

<table>
<thead>
<tr>
<th>Indices reported</th>
<th>k</th>
<th>did NOT meet threshold(s)</th>
<th>met CFI threshold only</th>
<th>met RMSEA threshold only</th>
<th>met SRMR threshold only</th>
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</thead>
<tbody>
<tr>
<td>1. CFI only</td>
<td>21</td>
<td>8</td>
<td>13</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>2. RMSEA only</td>
<td>9</td>
<td>0</td>
<td>-</td>
<td>9</td>
<td>-</td>
</tr>
<tr>
<td>3. SRMR only</td>
<td>5</td>
<td>0</td>
<td>-</td>
<td>-</td>
<td>5</td>
</tr>
<tr>
<td>4. CFI &amp; RMSEA</td>
<td>138</td>
<td>3</td>
<td>6</td>
<td>43</td>
<td>-</td>
</tr>
<tr>
<td>5. CFI &amp; SRMR</td>
<td>32</td>
<td>3</td>
<td>1</td>
<td>-</td>
<td>7</td>
</tr>
<tr>
<td>6. RMSEA &amp; SRMR</td>
<td>7</td>
<td>0</td>
<td>-</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>7. CFI, RMSEA, &amp; SRMR</td>
<td>89</td>
<td>0</td>
<td>0</td>
<td>5</td>
<td>0</td>
</tr>
</tbody>
</table>
Table 2 part 2: Meet two or three thresholds

<table>
<thead>
<tr>
<th>Indices reported</th>
<th>k</th>
<th>met CFI &amp; RMSEA thresholds</th>
<th>met CFI &amp; SRMR thresholds</th>
<th>met RMSEA &amp; SRMR thresholds</th>
<th>met all 3 indices' thresholds</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. CFI only</td>
<td>21</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
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<tr>
<td>2. RMSEA only</td>
<td>9</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>3. SRMR only</td>
<td>5</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>4. CFI &amp; RMSEA</td>
<td>138</td>
<td>86</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>5. CFI &amp; SRMR</td>
<td>32</td>
<td>-</td>
<td>21</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>6. RMSEA &amp; SRMR</td>
<td>7</td>
<td>-</td>
<td>-</td>
<td>7</td>
<td>-</td>
</tr>
<tr>
<td>7. CFI, RMSEA, &amp; SRMR</td>
<td>89</td>
<td>5</td>
<td>4</td>
<td>26</td>
<td>49</td>
</tr>
</tbody>
</table>
F. But, use of *cut-offs*? .......West, Taylor, & Wu (2012)

“we caution readers that the reification of specific cutoff standards for the acceptance or rejection of a hypothesized model can be fraught with peril” (p.219)

“current standards for interpreting acceptable model fit are only rough guidelines; they become increasingly less reasonable as they are extrapolated to models and data further from the CFA models...” (p.220)

“attempting to meet cutoff standards for adequate fit encourages post hoc model modification and the use of a relatively small number of indicators of each latent construct, practices which are often non optimal from a scientific standpoint” (p.221)
G. And, ....global Fit Indices: tell us about entire model, but our focus on three paths linking LVs most closely linked to theory
V. So Big Problem: CFI & RMSEA Do Not Assess “Path” Model Fit

A. Composite model- “path” component (causal arrows linking LVs)

Can lack of focus of CFI and RMSEA on path component lead to incorrect decisions about models – models with adequate values but misspecified path components?

Requires simulation analysis- know “true model”, evaluate misspecified models, examine their CFI and RMSEA values

Results discussed in Williams & O’Boyle (2011), replicated in Lance et al. (2016) - See Figure 2
Figure 2. Example Model for Simulations
B. Results: Are there misspecified models with CFI>.95 or RMSEA<.08?

Example 1: \( M_{T-4} \)
Example 2: \( M_{T-6} \)
Example 3 (2 indicators): \( M_{T-5} \)
Example 3 (4 indicators): \( M_{T-7} \)
Example 4 (2 indicators): \( M_{T-2} \)
Example 4 (4 indicators): \( M_{T-4} \)

Conclusion: multiple indicator models with severe misspecifications can have CFI and RMSEA values that meet the standards used to indicate adequate fit; replicated by Lance et al. (2016)
VI. Two New Fit Indices for Path Models

A. Background

Based on previous work by Sobel and Bohnstedt (1985), Mulaik et al. (1989), Williams & Holahan (1994) and McDonald & Ho (2002)

Goal is to develop indices that more accurately reflect the adequacy of the path model component of a composite model

Focus on latent variable path relations can allow for better theory evaluation

Consider different components of total composite model
    See Figure 3 Hierarchy of models
Figure 3. CFI: a/b  RMSEA: c  NSCI-P: f/g  RMSEA-P: h

AN: Absolute Null
Worst possible model, highest $\chi^2$ and df

UF: Uncorrelated Factors
Latent variables unrelated

SN: Structural Null
No causal paths linking latent variables
[no gammas ($\gamma$) or betas ($\beta$), does include correlations among exogenous latent variables]

T: Theoretical (Composite)

SS: Saturated Structural
All possible causal paths linking latent variables; $\chi^2$, df = Measurement Model ($M_M$)

CS: Completely Saturated
Best possible model $\chi^2$ and df = 0
$M_{UF} = \text{Uncorrelated Factor Model}$
\[ M_{SN} = \text{Structural Null Model} \]
$M_T = \text{Theoretical Model}$
$M_{SS} = \text{Saturated Structural Model}$
First new index was originally introduced as NSCI as part of a parsimony fit index (Williams & Holahan, 1994), given label of NSCI-P by Williams and O’Boyle (2011)

$$\text{NSCI-P} = \frac{(d_{SN} - d_T)}{(d_{SN} - d_{SS})}$$

$$= \frac{[(\chi^2_{SN} - \chi^2_{T}) - (df_{SN} - df_T)]}{[(\chi^2_{SN} - \chi^2_{SS}) - (df_{SN} - df_{SS})]}$$

Judges fit of M_T relative to range of possible path model fit defined by M_{SN} and M_{SS}

Reviewed favorably by Lance et al. (2017), no more today
Second originally presented by McDonald & Ho (2002), given label of RMSEA-P by O’Boyle & Williams (JAP, 2011)

\[
\text{RMSEA-P} = \left\{\frac{\chi^2_p - df_p}{df_p (N-1)}\right\}^{1/2},
\]
where \(\chi^2_p\) and \(df_p\) are calculated as \(\chi^2\) and \(df\) differences between measurement (\(M_{SS}\)) and composite (\(M_T\)) models

\[
= \left\{\frac{(\chi^2_T - \chi^2_{SS}) - (df_T - df_{SS})}{[(df_T - df_{SS})^*(N-1)]}\right\}^{1/2}
\]

Reviewed not so favorably by Lance et al. (2016)

Focus here because used in our reanalyses, requires results for two models we often have (\(M_T, M_{SS}\))
Frank Goeddeke  RMSEA-P website calculator
https://fgoeddeke.shinyapps.io/rmseap

<table>
<thead>
<tr>
<th>Sample size</th>
<th>793</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chi-Square of Measurement Model</td>
<td>562.25</td>
</tr>
<tr>
<td>Degrees of Freedom in Measurement Model</td>
<td>209</td>
</tr>
<tr>
<td>Chi-Square of Structural Model</td>
<td>729.29</td>
</tr>
<tr>
<td>Degrees of Freedom in Structural Model</td>
<td>280</td>
</tr>
</tbody>
</table>

Your RMSEA-P value is: 0.0367730192369927
Your RMSEA-P 90% C.I. Lower limit is: 0.0276161603513608
Your RMSEA-P 90% C.I. Upper limit is: 0.0446769298274733
B. Does RMSEA-P work?:
Remember null \( H_0 \) is that \( M_T \) is true, hope is to not reject
\( M_T \) should have value <.08 (if not Type I error),
\( M_{T-x} \) should have values >.08 (if not Type II error)

Return to simulation results- RMSEA-P (Williams & O’Boyle, 2011, ORM)
Across 6 example models, \( M_T \) had values < .08 (no Type I errors)
Misspecified models (\( M_{T-x} \)):
   success (all values >.08) with 5 of 6 examples (also CIs supportive)
   Examples 2-6: \( M_{T-1} \) and all other \( M_{T-x} \) had RMSEA-P>.08
      Note: Indicator to LV ratios all > 2.0
   Example 1: \( M_{T-2} \) and \( M_{T-1} \) retained
      (RMSEA-P<.08)  Note: Indicator to LV ratio 1.25:1
C. Lance, Beck, Fan, and Carter (2016)- less favorable towards RMSEA-P
Used same 6 examples as Williams & O’Boyle (2011)
good- also manipulated sample size (100, 200, 500, 1000)
good- also focused on individual study outcomes
goal: identify % of studies for which $M_{T-?}$ had $RMSEA-P < .08$
for each cell of design, % of 1000 random sample $RMSEA-P$
Results for $RMSEA-P$ one part of large set of results
Conclusion: $RMSEA-P$ does NOT work
   many misspecified models ($M_{T-#}$) retained ($RMSEA-P < .08$)
But, they collapsed results across 6 examples
   Williams & O’Boyle found differences across examples
   $RMSEA-P$ success with models with mostly multiple indicators
   Examples 2-6: Indicator to LV ratios all $> 2.0$
Key point: results hard to judge, $RMSEA-P$ values not reported
D. Williams & Williams (2017 AOM)

Same 6 examples as Williams & O’Boyle (2011) and Lance et al. (2016)
Keep focus on individual study outcomes
identify % of samples (of 1000) for which $M_{T-?}$ had RMSEA-P<.08
6 examples, range of models ($M_{T-X}$, $M_T$, $M_{T+X}$), 4 sample sizes
Used mean $\chi^2$ from Lance et al. as population $\chi^2$ value for each cell
Generated 1000 sample $\chi^2$ values per cell to compute RMSEA-P
Several steps to confirm appropriateness of simulated data
Report results for each sample separately (given role of # indicators)
Count of number of samples with RMSEA-P <.08
Also examine mean RMSEA-P and CI endpoints within each cell
KEY: See if effectiveness different based on number of indicators per LV
## Table 9. RMSEA-P works Examples 1-4 (Multiple Indicators), not Examples 5-6 (not all multiple indicators)

<table>
<thead>
<tr>
<th>EX</th>
<th>Model</th>
<th>n=100</th>
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<th>n=500</th>
<th>n=1000</th>
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<tr>
<td>1-4</td>
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<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>5-6</td>
<td>T-3</td>
<td>46</td>
<td>37</td>
<td>22</td>
<td>17</td>
</tr>
<tr>
<td>1-4</td>
<td>T-1 (MI)</td>
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<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
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<td>T-1</td>
<td>73</td>
<td>77</td>
<td>78</td>
<td>76</td>
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<tr>
<td>1-4</td>
<td>T (MI)</td>
<td>80</td>
<td>91</td>
<td>97</td>
<td>100</td>
</tr>
<tr>
<td>5-6</td>
<td>T</td>
<td>83</td>
<td>91</td>
<td>99</td>
<td>100</td>
</tr>
<tr>
<td>1-4</td>
<td>T+1 (MI)</td>
<td>80</td>
<td>94</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>5-6</td>
<td>T+1</td>
<td>78</td>
<td>90</td>
<td>97</td>
<td>100</td>
</tr>
<tr>
<td>1-4</td>
<td>T+3 (MI)</td>
<td>79</td>
<td>91</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>5-6</td>
<td>T+3</td>
<td>78</td>
<td>86</td>
<td>96</td>
<td>100</td>
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</tbody>
</table>
Example 1. MacCallum (1986) 2 indicators RMSEA-P works
Example 2. MacCallum (1986) 4 indicators RMSEA-P works
Example 3. Mulaik et al. (1989) 2 indicators RMSEA-P works
Example 4. Mulaik et al. (1989) 4 indicators RMSEA-P works
Example 5. Duncan et al. (1971)- RMSEA-P DOES NOT WORK
Example 6. Ecob (1987) **RMSEA-P DOES NOT WORK**
Conclusions:

With multiple indicator models, RMSEA-P correctly identifies misspecified models with true paths omitted.

For true models, RMSEA-P may incorrectly reject in some cases, especially with small sample sizes (work of David Kenny with small df models).

RMSEA-P confidence intervals should not be ignored.

RMSEA-P results should be considered along with other Condition 10 tests (chi-square difference test, omitted parameter test).
VII. RMSEA-P and real data: O’Boyle & Williams (2011, JAP)

Of 91 articles, 45 samples with information needed to do RMSEA decomposition and obtain RMSEA-P.

Results from these 45 samples: Path model fit poor
Mean value of RMSEA-P = .111
Only 3 < .05, 15 < .08 recommended values
RMSEA-P Confidence intervals (CI):
  19 (42%) have lower bound of CI > .08
  Reject close and reasonable fit, models bad
Only 5 (11%) have upper bound of CI < .08
  Fail to reject close fit, models good
What about global fit for 30 “bad” path models (of 30 with RMSEA-P > .08):
22 had RMSEA (composite) < .08
14 had CFI > .95
9 of 9 reporting SRMR < .10

What about nested model comparison ($M_T$ vs. $M_{ss}$)?
O’Boyle & Williams (2011)
Report only 3 of 43 did this test!!!
Williams & O’Boyle (2011): did the tests, 30 were significant
$M_T$ includes significant misspecifications
For 26 of these, CFI and RMSEA values met criteria
“good” fit conclusion counter to $\chi^2$ difference test
VIII. New Results on Path Model Fit: Williams, O’Boyle, & Yu (ORM 2018)

A. A subsample of 116 of our 311 studies provided information we needed
   Fit information for CFA and theoretical models
B. Summary of key results
   Path model fit (RMSEA-P) weak/moderate correlations with global fit
   Results using cut-off values
   Of those with bad path model fit (RMSEA-P) > .08
      75% retained using RMSEA (<.08)
      50% retained using CFI (> .95)
      70% retained using SRMS (<.10)
   Agreement among measures of global and path model fit
   RMSEA-P, RMSEA-P confidence interval, chi-square diff test
Comparison of Global Fit Decisions with Path Model Fit Decisions

<table>
<thead>
<tr>
<th></th>
<th>No accept</th>
<th>Partial accept</th>
<th>All accept</th>
<th>Total</th>
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<tbody>
<tr>
<td>K</td>
<td>5</td>
<td>47</td>
<td>64</td>
<td>116</td>
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<tr>
<td>Path model fit decision (individual)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RMSEA-P accept</td>
<td>1 (20%)</td>
<td>17 (36%)</td>
<td>44 (69%)</td>
<td></td>
</tr>
<tr>
<td>RMSEA-P&lt;sub&gt;UB&lt;/sub&gt; accept</td>
<td>0 (0%)</td>
<td>18 (38%)</td>
<td>31 (48%)</td>
<td></td>
</tr>
<tr>
<td>$\Delta \chi^2_{p$-value (M&lt;sub&gt;T&lt;/sub&gt;-M&lt;sub&gt;SS&lt;/sub&gt;)} test accept</td>
<td>0 (0%)</td>
<td>10 (21%)</td>
<td>38 (59%)</td>
<td></td>
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<tr>
<td>Path model fit decision (combined)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No accept</td>
<td>4 (80%)</td>
<td>27 (57%)</td>
<td>17 (27%)</td>
<td>48</td>
</tr>
<tr>
<td>Partial accept</td>
<td>1 (20%)</td>
<td><strong>12 (26%)</strong></td>
<td>27 (42%)</td>
<td>40</td>
</tr>
<tr>
<td>All accept</td>
<td>0 (0%)</td>
<td>8 (17%)</td>
<td><strong>20 (31%)</strong></td>
<td>28</td>
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</tbody>
</table>
IX. Summary Comments

A. Condition 10 has priority: estimates from bad models can’t be trusted
B. Cut-offs only guidelines, should not be used as “gold standard”
C. Agreement among conclusions of 3 measures using cut-off values?
   Not interchangeable, don’t reflect unitary concept of model quality
   Lai & Green (2016): two watches disagree but no known standard
D. Investigate measurement model first
   Content adequacy before collect data, EFA, CFA
E. Path model fit
   Remember: What you don’t see just as important as what you see
   SEM: hypotheses test constrained parameters (Mulaik, 2009)
   Don’t forget nested model comparison of $M_T$ vs. $M_{SS}$
   Also don’t forget RMSEA-P confidence interval
F. Table 5 from Williams, O’Boyle, & Yu (2018, ORM)

Path model fit Condition 10 tests (testing restrictions of paths not $M_T$)

1. Add paths to $M_T$ to create saturated structural model ($M_{SS}$),
   $M_{SS}$ compared to $M_T$ with chi-square difference test
   $\chi^2_T - \chi^2_{SS}$ should be statistically and/or practically non-significant

2. Examine path model fit indices (RMSEA-P, RMSEA-P confidence interval)
   RMSEA-P < .05 indicates good fit
   RMSEA-P > .05 and < .08 indicates adequate fit
   RMSEA-P > .10 indicates poor fit
   RMSEA-P confidence interval < .05 or high end < .10 indicates retain model

3. Examine individual significance of paths added to form $M_{SS}$
   t-values should NOT be statistically significant
Path model fit Condition 9 tests (testing restrictions of paths included in model)

4. Drop paths in $M_T$ to create structural null model ($M_{SN}$)
   $M_{SS}$ compared to $M_T$ with chi-square difference test
   $\chi^2_{SN} - \chi^2_T$ should be statistically and practically significant

5. Examine individual statistical and practical significance of paths in $M_T$
   $t$-values should be statistically significant
Thank you Larry James!