

SEM mediation models

Paul Johnson¹, Terry Jorgensen, and others²

¹Center for Research Methods and Data Analysis ²Previous GRAs, including but not limited to Ben Kite, Sunthud Pornprasertmanit, Jared Harpole

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Outline

- 1 R warmups
- 2 Path Model of Mediation
- 3 Mediation among Latent Variables
 - CFA Review
 - SEM with mediation
- 4 Supplementary Hypothesis Test
- 5 Conclusion

For examples: we will use the affect data

The affect data is available in the SEM workshop `data` folder

```
ddir <- "../..//data"
fn <- "affect-2.csv"
dat <- read.csv(file.path(ddir, fn))
```

```
head(dat)
```

	Agency1	Agency2	Agency3	Intrin1	Intrin2	Intrin3	Extrin1	Extrin2	Extrin3	PosAFF1	PosAFF2	PosAFF3
1	3.5000	4.0000	4.0000	4.0000	4.0	4	1.0000	1.0000	1.5000	4.0000	4.0	4.0
2	2.5000	3.1667	3.0000	3.2123	2.0	3	1.8333	2.6667	1.8333	3.0000	3.5	2.5
3	1.8333	2.0000	1.5000	3.0000	3.0	2	1.0000	1.0000	1.0000	3.0184	2.5	3.0
4	2.7714	3.0602	2.3639	3.1337	4.0	3	1.0774	1.1667	1.0000	3.0000	2.5	3.0
5	3.1667	3.3333	2.8333	3.5000	4.0	4	1.8333	2.0000	1.8333	3.7804	3.5	3.0
6	2.3333	2.8333	2.3333	3.0000	2.5	3	3.0588	2.4125	2.6667	4.0000	3.0	3.0
	NegAFF1	NegAFF2	NegAFF3	Sex	gender	ethnicity	race					
1	1.0	1.0000	1.0	1	male	Hispanic	Nonwhite					
2	1.5	1.6858	1.5	1	male	White	White					
3	1.0	1.0000	1.0	1	male	White	White					
4	2.5	2.5000	1.5	1	male	White	White					
5	2.5	2.0000	3.0	1	male	White	White					
6	2.0	1.5000	2.0	1	male	White	White					

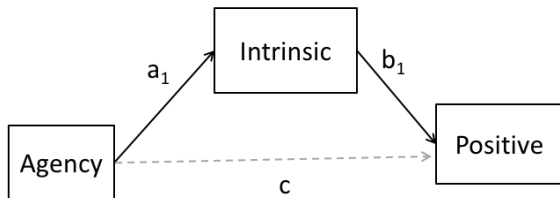
For examples: we will use the affect data ...

The primary R (R Core Team, 2017) package we use is `lavaan`, but also will illustrate `semPlot`.

```
library(lavaan)
library(semPlot)
```

A model with observed variables

This is a “usual” kind of regression story



$$Positive_i = c \cdot Agency_i + b_1 Intrinsic_i + \varepsilon 1_i \quad (1)$$

$$Intrinsic_i = a_1 Agency_i + \varepsilon 2_i \quad (2)$$

- c is the *direct effect* of Agency on Positive affect
- The product “ $a_1 \cdot b_1$ ” is the *indirect effect* of Agency on Positive affect

A model with observed variables ...

- See why “ $a_1 \cdot b_1$ ” is the *indirect effect*?
 - Insert equation (2) into (1):

$$\begin{aligned}
 \text{Positive} &= c \cdot \text{Agency}_i + b_1 \{a_1 \text{Agency}_i + \varepsilon_{2i}\} + \varepsilon_{1i} & (3) \\
 &= c \cdot \text{Agency}_i + \{b_1 \cdot a_1\} \text{Agency}_i + \{\varepsilon_{1i} + b_1 \varepsilon_{2i}\}
 \end{aligned}$$

The coefficients in that one-liner cannot be estimated, they are not identifiable.

$$\{b_1 \cdot a_1 + c\} \text{Agency}_i + \{\varepsilon_{1i} + b_1 \varepsilon_{2i}\} \quad (4)$$

A model with observed variables ...

- The primary research question is whether the “direct” path c is more/less important than the indirect path a_1b_1
- To estimate this with ordinary regression analysis, we would need to calculate 2 regression models:

$$Positive_i = c \cdot Agency_i + b_1 Intrinsic_i + \varepsilon 1_i \quad (5)$$

$$Intrinsic_i = a_1 Agency_i + \varepsilon 2_i \quad (6)$$

- From the output, take the individual estimates, \hat{a}_1 and \hat{b}_1 , and multiply to create $\hat{a}_1\hat{b}_1$ and interpret that as an estimate of a_1b_1 .
 - (We just asserted that $\hat{a}_1\hat{b}_1$ is a consistent/unbiased estimator of $\widehat{a_1b_1}$, and I'm not entirely sure how that is justified. But assume it is OK)
- But...

A model with observed variables ...

More problems present themselves:

- 1 Are the error terms ε_{1i} and ε_{2i} uncorrelated with each other? If not, a system-wide estimation procedure is needed
 - 1 “seemingly unrelated regression” (3SLS), so-called “limited information maximum likelihood”
 - 2 system-wide maximum Likelihood (ML), often called “full information maximum likelihood”

A model with observed variables ...

- ② How can we conduct a hypothesis test for the product $\hat{a}_1 \cdot \hat{b}_1$?
 Does anybody know if we can do a t-test of a product of 2 variables?
 What would we plug in for the standard error, $s.e.(\widehat{a_1 b_1})$ in a formula like

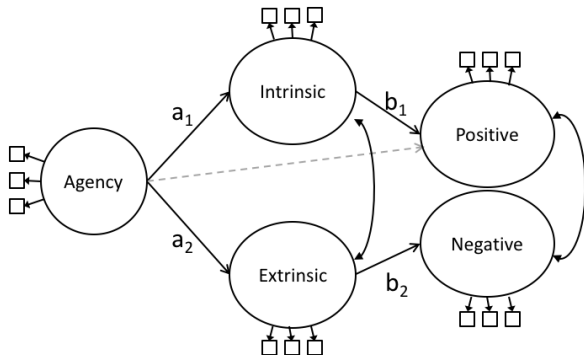
$$\hat{t} = \frac{\widehat{a_1 b_1}}{s.e.(\widehat{a_1 b_1})} = \frac{\hat{a}_1 \hat{b}_1}{?} \quad (7)$$

- ① Think about what the 'nil' hypo means:
 - ① $H_0 : a_1 \cdot b_1 = 0$
 - ② Means that either $H_0 : a_1 = 0$ and/or $b_1 = 0$
- ② Tough to visualize, no known statistical distribution can be used for a direct test. Various methods have been proposed.

Latent Variable Model with Mediation

The circles are unmeasured variables.

Mediation among Latent Variables



Latent Variable Model with Mediation

- The SEM integrates
 - “measurement error” analysis (correlation of error terms for Positive and Negative terms, with
 - analysis of the underlying relationships.
- We’ve spiced this example with correlations between
 - latent variables Intrinsic and Extrinsic
 - error terms for Positive and Negative affect outcomes

Recall SEM assumptions

- 1 observed indicators reflect unmeasured latent variables.
- 2 the latent variables are multivariate normal distributions (with inter-correlations we'd like to estimate)

In the “big picture”, there are 2 chores.

- 1 Find a way to test the indirect effect's importance, and
- 2 Decide if the path model we sketched above is “good enough”. We end up doing a χ^2 “diff test” to contrast the “full” CFA and a simpler SEM.
 - CFA:** correlations among latent traits exist, allow those correlations to be freely estimated.
 - uses “most” parameters because all links are estimated
 - SEM:** structural equation model: Limit estimation of linkages to a theoretically inspired set of connections.

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The CFA model procedure

```
cfa.mod <- '  
Agency =~ Agency1 + Agency2 + Agency3  
Intrinsic =~ Intrin1 + Intrin2 + Intrin3  
Extrinsic =~ Extrin1 + Extrin2 + Extrin3  
Positive =~ PosAFF1 + PosAFF2 + PosAFF3  
Negative =~ NegAFF1 + NegAFF2 + NegAFF3  
,  
cfa3 <- cfa(cfa.mod, data = dat, std.lv = TRUE)
```

The CFA model procedure ...

```
summary(cfa3)
```

```
lavaan 0.6-3 ended normally after 58 iterations
```

Optimization method	NLMINB
Number of free parameters	40
Number of observations	380
Estimator	ML
Model Fit Test Statistic	106.847
Degrees of freedom	80
P-value (Chi-square)	0.024

```
Parameter Estimates:
```

Information	Expected
Information saturated (h1) model	Structured
Standard Errors	Standard

```
Latent Variables:
```

	Estimate	Std.Err	z-value	P(> z)
Agency =~				
Agency1	0.466	0.021	22.560	0.000

The CFA model procedure ...

Agency2	0.492	0.021	23.774	0.000
Agency3	0.497	0.022	22.815	0.000
Intrinsic ≈				
Intrin1	0.541	0.039	13.960	0.000
Intrin2	0.581	0.043	13.489	0.000
Intrin3	0.615	0.038	16.201	0.000
Extrinsic ≈				
Extrin1	0.388	0.022	17.606	0.000
Extrin2	0.456	0.027	17.168	0.000
Extrin3	0.471	0.026	18.100	0.000
Positive ≈				
PosAFF1	0.569	0.028	20.132	0.000
PosAFF2	0.603	0.029	21.150	0.000
PosAFF3	0.632	0.029	21.648	0.000
Negative ≈				
NegAFF1	0.634	0.029	21.670	0.000
NegAFF2	0.585	0.027	21.457	0.000
NegAFF3	0.598	0.026	22.805	0.000
Covariances:				
	Estimate	Std.Err	z-value	P(> z)
Agency ~				
Intrinsic	0.507	0.047	10.782	0.000
Extrinsic	0.270	0.054	5.028	0.000
Positive	0.302	0.051	5.950	0.000
Negative	0.017	0.055	0.312	0.755

The CFA model procedure ...

Intrinsic ~				
Extrinsic	-0.028	0.063	-0.441	0.659
Positive	0.414	0.052	7.918	0.000
Negative	0.021	0.060	0.341	0.733
Extrinsic ~				
Positive	-0.029	0.058	-0.503	0.615
Negative	0.209	0.056	3.764	0.000
Positive ~				
Negative	-0.071	0.056	-1.274	0.203
Variances:				
	Estimate	Std.Err	z-value	P(> z)
.Agency1	0.048	0.005	9.649	0.000
.Agency2	0.036	0.005	7.604	0.000
.Agency3	0.051	0.005	9.278	0.000
.Intrin1	0.298	0.029	10.204	0.000
.Intrin2	0.386	0.036	10.620	0.000
.Intrin3	0.214	0.029	7.474	0.000
.Extrin1	0.080	0.009	8.924	0.000
.Extrin2	0.123	0.013	9.465	0.000
.Extrin3	0.103	0.012	8.264	0.000
.PosAFF1	0.121	0.012	9.921	0.000
.PosAFF2	0.104	0.012	8.615	0.000
.PosAFF3	0.099	0.013	7.869	0.000
.NegAFF1	0.107	0.012	9.202	0.000
.NegAFF2	0.096	0.010	9.498	0.000

The CFA model procedure ...

```
75 .NegAFF3      0.067      0.009      7.369      0.000
    Agency      1.000
    Intrinsic   1.000
    Extrinsic   1.000
    Positive    1.000
80    Negative    1.000
```

Make a nice table with semTable

Start by creating a label vector `vl`

```
vl <- c("Intrin1" = "Intrinsic1", "Intrin2" =  
  "Intrinsic2", "Intrin3" = "Intrinsic3",  
  "Extrin1" = "Extrinsic1", "Extrin2" =  
  "Extrinsic2", "Extrin3" = "Extrinsic3",  
  "PosAFF1" = "Positive1", "PosAFF2" =  
  "Positive2", "PosAFF3" = "Positive3",  
  "NegAFF1" = "Negative1", "NegAFF2" =  
  "Negative2", "NegAFF3" = "Negative3")
```

Not much customization needed:

```
library(semTable)  
cfa3.tab <- semTable(list("Confirmatory Factor  
  Analysis" = cfa3), columns = c("estsestars"),  
  varLabels = vl, longtable = TRUE,  
  print.results = FALSE)
```

And results are

```
cat(cfa3.tab)
```

		Confirmatory Factor Analysis	
		Estimate(Std.Err.)	
		<u>Factor Loadings</u>	
<u>Agency</u>			
	Agency1	0.47(0.02)	***
	Agency2	0.49(0.02)	***
	Agency3	0.50(0.02)	***
<u>Intrinsic</u>			
	Intrinsic1	0.54(0.04)	***
	Intrinsic2	0.58(0.04)	***
	Intrinsic3	0.62(0.04)	***
<u>Extrinsic</u>			
	Extrinsic1	0.39(0.02)	***
	Extrinsic2	0.46(0.03)	***

And results are ...

	Extrinsic3	0.47(0.03)***
<u>Positive</u>		
	Positive1	0.57(0.03)***
	Positive2	0.60(0.03)***
	Positive3	0.63(0.03)***
<u>Negative</u>		
	Negative1	0.63(0.03)***
	Negative2	0.59(0.03)***
	Negative3	0.60(0.03)***
		<u>Residual Variances</u>
	Agency1	0.05(0.00)***
	Agency2	0.04(0.00)***
	Agency3	0.05(0.01)***
	Intrinsic1	0.30(0.03)***
	Intrinsic2	0.39(0.04)***
	Intrinsic3	0.21(0.03)***
	Extrinsic1	0.08(0.01)***

And results are ...

Extrinsic2	0.12(0.01)***
Extrinsic3	0.10(0.01)***
Positive1	0.12(0.01)***
Positive2	0.10(0.01)***
Positive3	0.10(0.01)***
Negative1	0.11(0.01)***
Negative2	0.10(0.01)***
Negative3	0.07(0.01)***

Latent Variances

Agency	1.00 ⁺
Intrinsic	1.00 ⁺
Extrinsic	1.00 ⁺
Positive	1.00 ⁺
Negative	1.00 ⁺

Latent Covariances

Agency w/Intrinsic	0.51(0.05)***
Agency w/Extrinsic	0.27(0.05)***

And results are ...

Agency w/Positive	0.30(0.05)***
Agency w/Negative	0.02(0.05)
Intrinsic w/Extrinsic	-0.03(0.06)
Intrinsic w/Positive	0.41(0.05)***
Intrinsic w/Negative	0.02(0.06)
Extrinsic w/Positive	-0.03(0.06)
Extrinsic w/Negative	0.21(0.06)***
Positive w/Negative	-0.07(0.06)
	<u>Fit Indices</u>
χ^2 (df)	106.85(80)*
CFI	0.99
TLI	0.99
RMSEA	0.03

+Fixed parameter

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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Equations we need to estimate

Going by the path diagram, write out the equations:

$$Positive_i = c \cdot Agency_i + b_1 Intrinsic_i + \varepsilon 1_i \quad (8)$$

$$Intrinsic_i = a_1 Agency_i + \varepsilon 2_i \quad (9)$$

$$Negative_i = b_2 Extrinsic_i + \varepsilon 3_i \quad (10)$$

$$Extrinsic_i = a_2 Agency_i + \varepsilon 4_i \quad (11)$$

- Agency affects Intrinsic motivation (equation 9)
- Positive affect is predicted by Intrinsic motivation and Agency (equation 8)
- Negative affect is driven by Agency *only indirectly*
- And we inserted also correlations that should be estimated,
 - $Cov(\varepsilon 1, \varepsilon 3) \neq 0$
 - $Cov(Intrinsic, Extrinsic) \neq 0$

Equations we need to estimate ...

- But we assert there is no direct link from
 - Extrinsic to Positive
 - Intrinsic to Negative
 - Agency to Negative

Estimate mediation with lavaan

The distinctive feature is that our `lavaan` code introduces 4 named parameters, `a1`, `a2`, `b1`, `b2`.

We will create two “constructed” variables, `ind1` and `ind2`, to represent the indirect path estimates.

Estimate mediation with lavaan ...

```
mediat.mod.2 <- '  
  Agency =~ Agency1 + Agency2 + Agency3  
  Intrinsic =~ Intrin1 + Intrin2 + Intrin3  
  Extrinsic =~ Extrin1 + Extrin2 + Extrin3  
  Positive =~ PosAFF1 + PosAFF2 + PosAFF3  
  Negative =~ NegAFF1 + NegAFF2 + NegAFF3  
  Positive ~ b1*Intrinsic + Agency  
  Negative ~ b2*Extrinsic  
  Intrinsic ~ a1*Agency  
  Extrinsic ~ a2*Agency  
  Intrinsic ~ Extrinsic  
  ## define mediation parameters (indirect effects)  
  ind1 := a1 * b1  
  ind2 := a2 * b2  
'
```

Estimate mediation with lavaan ...

```
mediat.mod.2 <- '  
  Agency =~ Agency1 + Agency2 + Agency3  
  Intrinsic =~ Intrin1 + Intrin2 + Intrin3  
  Extrinsic =~ Extrin1 + Extrin2 + Extrin3  
  Positive =~ PosAFF1 + PosAFF2 + PosAFF3  
  Negative =~ NegAFF1 + NegAFF2 + NegAFF3  
  Positive ~ b1*Intrinsic + Agency  
  Negative ~ b2*Extrinsic  
  Intrinsic ~ a1*Agency  
  Extrinsic ~ a2*Agency  
  Intrinsic ~ Extrinsic  
  ## define mediation parameters (indirect effects)  
  ind1 := a1 * b1  
  ind2 := a2 * b2  
'
```

1. Named parameters for indirect effect $ind1 = a_1 \cdot b_1$

```
Positive ~ b1*Intrinsic + Agency
Negative ~ b2*Extrinsic
Intrinsic ~ a1*Agency
Extrinsic ~ a2*Agency
## define mediation parameters (indirect effects)
ind1 := a1 * b1
ind2 := a2 * b2
```

- The product $a_1 \cdot b_1$ can be tested because we represent it by `ind1`

2. Bootstrap the estimate of a_1b_1

- The null hypothesis we would like to test,

$$H_0 : a_1b_1 = 0$$

- At the current time, no analytical “formula” exists for testing that. Instead, it is necessary to use ‘bootstrapped standard errors’.
- The disadvantage of the bootstrap method is that the model must be calculated 100s or 1000s of times (slow!)

Structural Regressions among Latent Constructs

We will set the number of bootstrap resampling exercises as `Nboot`

```
Nboot <- 500
```

```
sem(mediat.mod.2, data = dat, std.lv = TRUE, se =  
  "boot", bootstrap = Nboot)
```

- The arguments in `sem()` that concern the bootstrap are
 - `se="boot"` , and
 - `bootstrap = Nboot` .
- Rather than analytically approximate standard errors, the standard deviations of the bootstrapped estimates are used as standard errors.

Make a nice table

```
semcfa.tab <- semTable(list("SEM" = mediat.out.2,  
  "CFA" = cfa3), columns = c("estsestars"),  
  varLabels = vl, longtable = TRUE,  
  print.results = FALSE)
```

And results are

```
cat(semcfa.tab)
```

		SEM	CFA
		Estimate(Std.Err.)	Estimate(Std.Err.)
		<u>Factor Loadings</u>	
<u>Agency</u>			
	Agency1	0.47(0.02)***	0.47(0.02)***
	Agency2	0.49(0.02)***	0.49(0.02)***
	Agency3	0.50(0.02)***	0.50(0.02)***
<u>Intrinsic</u>			
	Intrinsic1	0.47(0.04)***	0.54(0.04)***
	Intrinsic2	0.50(0.04)***	0.58(0.04)***
	Intrinsic3	0.53(0.03)***	0.62(0.04)***
<u>Extrinsic</u>			
	Extrinsic1	0.37(0.02)***	0.39(0.02)***
	Extrinsic2	0.44(0.03)***	0.46(0.03)***

And results are ...

<u>Positive</u>	Extrinsic3	0.45(0.03)***	0.47(0.03)***
	Positive1	0.51(0.03)***	0.57(0.03)***
	Positive2	0.54(0.03)***	0.60(0.03)***
	Positive3	0.57(0.03)***	0.63(0.03)***
<u>Negative</u>	Negative1	0.62(0.04)***	0.63(0.03)***
	Negative2	0.57(0.04)***	0.59(0.03)***
	Negative3	0.59(0.03)***	0.60(0.03)***
		<u>Regression Slopes</u>	
<u>Positive</u>	Intrinsic	0.34(0.08)***	
	Agency	0.13(0.07)	
<u>Negative</u>	Extrinsic	0.20(0.07)**	
<u>Intrinsic</u>	Agency	0.59(0.08)***	

And results are ...

Extrinsic

Agency	0.28(0.06)***	
	<u>Residual Variances</u>	
Agency1	0.05(0.01)***	0.05(0.00)***
Agency2	0.04(0.00)***	0.04(0.00)***
Agency3	0.05(0.01)***	0.05(0.01)***
Intrinsic1	0.30(0.03)***	0.30(0.03)***
Intrinsic2	0.39(0.04)***	0.39(0.04)***
Intrinsic3	0.21(0.04)***	0.21(0.03)***
Extrinsic1	0.08(0.01)***	0.08(0.01)***
Extrinsic2	0.12(0.02)***	0.12(0.01)***
Extrinsic3	0.10(0.02)***	0.10(0.01)***
Positive1	0.12(0.02)***	0.12(0.01)***
Positive2	0.10(0.02)***	0.10(0.01)***
Positive3	0.10(0.01)***	0.10(0.01)***
Negative1	0.11(0.02)***	0.11(0.01)***
Negative2	0.10(0.01)***	0.10(0.01)***

And results are ...

Negative3	0.07(0.01)***	0.07(0.01)***
	<u>Latent Variances</u>	
Agency	1.00 ⁺	1.00 ⁺
Intrinsic	1.00 ⁺	1.00 ⁺
Extrinsic	1.00 ⁺	1.00 ⁺
Positive	1.00 ⁺	1.00 ⁺
Negative	1.00 ⁺	1.00 ⁺
	<u>Latent Covariances</u>	
Intrinsic w/Extrinsic	-0.20(0.06)**	-0.03(0.06)
Positive w/Negative	-0.08(0.07)	-0.07(0.06)
Agency w/Intrinsic		0.51(0.05)***
Agency w/Extrinsic		0.27(0.05)***
Agency w/Positive		0.30(0.05)***
Agency w/Negative		0.02(0.05)
Intrinsic w/Positive		0.41(0.05)***
Intrinsic w/Negative		0.02(0.06)
Extrinsic w/Positive		-0.03(0.06)

And results are ...

Extrinsic w/Negative		0.21(0.06)***
		<u>Constructed</u>
ind1	0.20(0.05)***	
ind2	0.06(0.02)*	
		<u>Fit Indices</u>
$\chi^2(df)$	109.15(83)*	106.85(80)*
CFI	0.99	0.99
TLI	0.99	0.99
RMSEA	0.03	0.03

+ Fixed parameter

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Use lavaan's anova function

- The mediation model with latent variables estimates fewer parameters than the CFA, but it fits just as well as the CFA.

```
anova(cfa3, mediat.out.2)
```

```
Chi Square Difference Test
```

	Df	AIC	BIC	Chisq	Chisq diff	Df diff	Pr(>Chisq)
cfa3	80	7478.2	7635.8	106.85			
mediat.out.2	83	7474.5	7620.3	109.15	2.3051	3	0.5116

```
anova(cfa3, mediat.out.2)
```

```
Chi Square Difference Test
```

	Df	AIC	BIC	Chisq	Chisq diff	Df diff	Pr(>Chisq)
cfa3	80	7478.2	7635.8	106.85			
mediat.out.2	83	7474.5	7620.3	109.15	2.3051	3	0.5116

Make a pleasant table with compareLavaan (semTable)

```
# if nesting is not specified, the diff is not
  reported
compareLavaan(list("CFA" = cfa3, "SEM" =
  mediat.out.2), nesting = "CFA > SEM", fitmeas
  = c("chisq", "df", "pvalue", "rmsea", "cfi",
  "bic"), type="latex")
```

	χ^2	df	<i>p</i> -value	rmsea	cfi	bic	$\Delta\chi^2$	Δdf	<i>p</i>
CFA	106.85	80.00	0.02	0.03	0.99	7635.83	-	-	-
SEM	109.15	83.00	0.03	0.03	0.99	7620.31	2.305a	3	0.51

a = SEM vs CFA

Make a pleasant table with compareLavaan (semTable) ...

```
mediat.mod.3 <- '  
## measurement model  
Agency =~ Agency1 + Agency2 + Agency3  
Intrinsic =~ Intrin1 + Intrin2 + Intrin3  
Extrinsic =~ Extrin1 + Extrin2 + Extrin3  
Positive =~ PosAFF1 + PosAFF2 + PosAFF3  
Negative =~ NegAFF1 + NegAFF2 + NegAFF3  
## structural model  
Positive ~ b1*Intrinsic + Agency  
Negative ~ b2*Extrinsic  
Intrinsic ~ a1*Agency  
Extrinsic ~ a2*Agency  
Intrinsic ~ Extrinsic  
## define mediation parameters (indirect effects)  
c1 := a1 * b1  
c2 := a2 * b2  
c1 == c2
```

Make a pleasant table with compareLavaan (semTable) ...

```
,
```

Compare Standardized factor loadings

- We have standardized latent variables, but we did not standardize the observed variables.
- Various methods are available

Method 1: Refit from scratch:

```
mediat.out.2.std.A <- sem(mediat.mod.2, data
  = dat, std.lv = TRUE, std.ov=TRUE, se =
  "boot", bootstrap = Nboot)
summary(mediat.out.2.std.A, fit = TRUE)
```

Compare Standardized factor loadings ...

```

lavaan 0.6-3 ended normally after 31 iterations

  Optimization method           NLMINB
  Number of free parameters      37
5
  Number of observations         380

  Estimator                      ML
  Model Fit Test Statistic       109.152
10
  Degrees of freedom             83
  P-value (Chi-square)          0.029

Model test baseline model:

15
  Minimum Function Test Statistic 3749.411
  Degrees of freedom              105
  P-value                          0.000

User model versus baseline model:

20
  Comparative Fit Index (CFI)     0.993
  Tucker-Lewis Index (TLI)       0.991

Loglikelihood and Information Criteria:

25

```

Compare Standardized factor loadings ...

```

Loglikelihood user model (H0)                -6260.310
Loglikelihood unrestricted model (H1)        -6205.734

Number of free parameters                    37
30 Akaike (AIC)                             12594.621
Bayesian (BIC)                             12740.407
Sample-size adjusted Bayesian (BIC)        12623.013

Root Mean Square Error of Approximation:
35 RMSEA                                     0.029
90 Percent Confidence Interval              0.010 0.043
P-value RMSEA <= 0.05                     0.996

Standardized Root Mean Square Residual:
40 SRMR                                     0.034

Parameter Estimates:
45 Standard Errors                          Bootstrap
Number of requested bootstrap draws        500
Number of successful bootstrap draws       500

50 Latent Variables:
Estimate Std.Err z-value P(>|z|)

```

Compare Standardized factor loadings ...

	Agency =~				
	Agency1	0.904	0.042	21.531	0.000
	Agency2	0.932	0.042	22.325	0.000
55	Agency3	0.910	0.044	20.914	0.000
	Intrinsic =~				
	Intrin1	0.605	0.052	11.579	0.000
	Intrin2	0.587	0.045	13.046	0.000
	Intrin3	0.689	0.041	16.750	0.000
60	Extrinsic =~				
	Extrin1	0.777	0.048	16.079	0.000
	Extrin2	0.763	0.049	15.634	0.000
	Extrin3	0.795	0.053	14.918	0.000
	Positive =~				
65	PosAFF1	0.770	0.037	20.728	0.000
	PosAFF2	0.796	0.041	19.302	0.000
	PosAFF3	0.807	0.039	20.575	0.000
	Negative =~				
	NegAFF1	0.869	0.051	16.875	0.000
70	NegAFF2	0.864	0.057	15.044	0.000
	NegAFF3	0.897	0.051	17.756	0.000
	Regressions :				
		Estimate	Std.Err	z-value	P(> z)
75	Positive ~				
	Intrinsic (b1)	0.343	0.073	4.684	0.000
	Agency	0.129	0.074	1.739	0.082

Compare Standardized factor loadings ...

	Negative ~				
80	Extrinsic (b2)	0.199	0.068	2.939	0.003
	Intrinsic ~				
	Agency (a1)	0.588	0.087	6.788	0.000
	Extrinsic ~				
	Agency (a2)	0.278	0.062	4.450	0.000
85	Covariances:				
		Estimate	Std.Err	z-value	P(> z)
	.Intrinsic ~				
	.Extrinsic	-0.202	0.060	-3.350	0.001
90	.Positive ~				
	.Negative	-0.076	0.073	-1.052	0.293
	Variances:				
		Estimate	Std.Err	z-value	P(> z)
95	.Agency1	0.181	0.022	8.400	0.000
	.Agency2	0.129	0.017	7.696	0.000
	.Agency3	0.169	0.018	9.134	0.000
	.Intrin1	0.505	0.056	8.949	0.000
	.Intrin2	0.534	0.056	9.600	0.000
	.Intrin3	0.358	0.062	5.793	0.000
100	.Extrin1	0.347	0.047	7.445	0.000
	.Extrin2	0.371	0.045	8.278	0.000
	.Extrin3	0.316	0.051	6.232	0.000
	.PosAFF1	0.271	0.034	7.846	0.000

Compare Standardized factor loadings ...

105	.PosAFF2	0.221	0.034	6.437	0.000
	.PosAFF3	0.199	0.028	6.978	0.000
	.NegAFF1	0.210	0.030	6.972	0.000
	.NegAFF2	0.219	0.030	7.261	0.000
	.NegAFF3	0.157	0.025	6.405	0.000
	Agency	1.000			
110	.Intrinsic	1.000			
	.Extrinsic	1.000			
	.Positive	1.000			
	.Negative	1.000			
115	Defined Parameters:				
		Estimate	Std.Err	z-value	P(> z)
	ind1	0.202	0.045	4.515	0.000
	ind2	0.055	0.023	2.445	0.014

Method 2: R update function (re-specify standardization)

```
mediat.out.2.std.B <- update(mediat.out.2,
  std.lv = TRUE, std.ov = TRUE)
summary(mediat.out.2.std.B, fit = TRUE)
```


Compare Standardized factor loadings ...

```

lavaan 0.6-3 ended normally after 31 iterations

  Optimization method           NLMINB
  Number of free parameters      37
5
  Number of observations         380

  Estimator                      ML
  Model Fit Test Statistic       109.152
10
  Degrees of freedom             83
  P-value (Chi-square)           0.029

Model test baseline model:

15
  Minimum Function Test Statistic 3749.411
  Degrees of freedom              105
  P-value                          0.000

User model versus baseline model:

20
  Comparative Fit Index (CFI)     0.993
  Tucker-Lewis Index (TLI)       0.991

Loglikelihood and Information Criteria:

25

```

Compare Standardized factor loadings ...

```

Loglikelihood user model (H0)                -6260.310
Loglikelihood unrestricted model (H1)        -6205.734

Number of free parameters                    37
30 Akaike (AIC)                             12594.621
Bayesian (BIC)                             12740.407
Sample-size adjusted Bayesian (BIC)        12623.013

Root Mean Square Error of Approximation:
35 RMSEA                                    0.029
90 Percent Confidence Interval              0.010 0.043
P-value RMSEA <= 0.05                     0.996

Standardized Root Mean Square Residual:
40 SRMR                                    0.034

Parameter Estimates:
45 Standard Errors                        Bootstrap
Number of requested bootstrap draws        500
Number of successful bootstrap draws        500

50 Latent Variables:
Estimate Std.Err z-value P(>|z|)

```

Compare Standardized factor loadings ...

	Agency =~				
	Agency1	0.904	0.039	23.380	0.000
	Agency2	0.932	0.039	23.715	0.000
55	Agency3	0.910	0.040	22.895	0.000
	Intrinsic =~				
	Intrin1	0.605	0.050	12.100	0.000
	Intrin2	0.587	0.041	14.319	0.000
	Intrin3	0.689	0.042	16.423	0.000
60	Extrinsic =~				
	Extrin1	0.777	0.046	16.848	0.000
	Extrin2	0.763	0.046	16.560	0.000
	Extrin3	0.795	0.053	15.124	0.000
	Positive =~				
65	PosAFF1	0.770	0.038	20.246	0.000
	PosAFF2	0.796	0.043	18.540	0.000
	PosAFF3	0.807	0.040	20.015	0.000
	Negative =~				
	NegAFF1	0.869	0.055	15.779	0.000
70	NegAFF2	0.864	0.057	15.247	0.000
	NegAFF3	0.897	0.051	17.522	0.000
	Regressions :				
		Estimate	Std.Err	z-value	P(> z)
75	Positive ~				
	Intrinsic (b1)	0.343	0.075	4.582	0.000
	Agency	0.129	0.072	1.777	0.076

Compare Standardized factor loadings ...

	Negative ~				
80	Extrinsic (b2)	0.199	0.070	2.862	0.004
	Intrinsic ~				
	Agency (a1)	0.588	0.085	6.916	0.000
	Extrinsic ~				
	Agency (a2)	0.278	0.064	4.354	0.000
85	Covariances:				
		Estimate	Std.Err	z-value	P(> z)
	.Intrinsic ~				
	.Extrinsic	-0.202	0.065	-3.106	0.002
90	.Positive ~				
	.Negative	-0.076	0.070	-1.092	0.275
	Variances:				
		Estimate	Std.Err	z-value	P(> z)
95	.Agency1	0.181	0.021	8.428	0.000
	.Agency2	0.129	0.017	7.707	0.000
	.Agency3	0.169	0.019	9.060	0.000
	.Intrin1	0.505	0.055	9.131	0.000
	.Intrin2	0.534	0.052	10.253	0.000
	.Intrin3	0.358	0.065	5.514	0.000
100	.Extrin1	0.347	0.046	7.482	0.000
	.Extrin2	0.371	0.047	7.863	0.000
	.Extrin3	0.316	0.051	6.158	0.000
	.PosAFF1	0.271	0.036	7.458	0.000

Compare Standardized factor loadings ...

105	.PosAFF2	0.221	0.033	6.719	0.000
	.PosAFF3	0.199	0.028	6.981	0.000
	.NegAFF1	0.210	0.031	6.799	0.000
	.NegAFF2	0.219	0.031	7.168	0.000
	.NegAFF3	0.157	0.026	5.937	0.000
	Agency	1.000			
110	.Intrinsic	1.000			
	.Extrinsic	1.000			
	.Positive	1.000			
	.Negative	1.000			
115	Defined Parameters:				
		Estimate	Std.Err	z-value	P(> z)
	ind1	0.202	0.043	4.700	0.000
	ind2	0.055	0.022	2.496	0.013

Method 3: Insert “standardized = TRUE” in the summary,

```
summary(mediat.out.2, standardized = TRUE)
```

See far-right column.

A shortcoming is that it does not give us a “model object,” which I want to make a nice table.

Compare Standardized factor loadings ...

```
summary(mediat.out.2, standardized = TRUE)
```

```
lavaan 0.6-3 ended normally after 58 iterations
```

```

Optimization method           NLMINB
Number of free parameters      37

Number of observations         380

Estimator                      ML
Model Fit Test Statistic      109.152
Degrees of freedom             83
P-value (Chi-square)          0.029

```

```
Parameter Estimates:
```

```

Standard Errors                Bootstrap
Number of requested bootstrap draws  500
Number of successful bootstrap draws  500

```

```
Latent Variables:
```

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
Agency =~						
Agency1	0.466	0.021	22.563	0.000	0.466	0.905

Compare Standardized factor loadings ...

Agency2	0.492	0.022	22.567	0.000	0.492	0.933
Agency3	0.497	0.024	20.885	0.000	0.497	0.912
Intrinsic ≈						
Intrin1	0.466	0.039	11.831	0.000	0.540	0.703
Intrin2	0.500	0.035	14.134	0.000	0.580	0.682
Intrin3	0.531	0.032	16.501	0.000	0.616	0.800
Extrinsic ≈						
Extrin1	0.373	0.023	16.125	0.000	0.388	0.808
Extrin2	0.440	0.028	15.701	0.000	0.457	0.793
Extrin3	0.454	0.030	15.022	0.000	0.471	0.827
Positive ≈						
PosAFF1	0.514	0.026	19.694	0.000	0.569	0.854
PosAFF2	0.545	0.029	19.014	0.000	0.604	0.882
PosAFF3	0.570	0.028	20.177	0.000	0.632	0.895
Negative ≈						
NegAFF1	0.620	0.040	15.591	0.000	0.633	0.889
NegAFF2	0.573	0.038	15.159	0.000	0.585	0.883
NegAFF3	0.586	0.032	18.293	0.000	0.598	0.918
Regressions:						
	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
Positive ~						
Intrinsic (b1)	0.343	0.077	4.432	0.000	0.359	0.359
Agency	0.129	0.072	1.784	0.074	0.116	0.116
Negative ~						
Extrinsic (b2)	0.199	0.069	2.868	0.004	0.202	0.202

Compare Standardized factor loadings ...

Intrinsic ~							
Agency	(a1)	0.588	0.085	6.930	0.000	0.507	0.507
Extrinsic ~							
Agency	(a2)	0.278	0.063	4.415	0.000	0.268	0.268
Covariances:							
		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
.Intrinsic ~							
.Extrinsic							
		-0.202	0.061	-3.283	0.001	-0.202	-0.202
.Positive ~							
.Negative							
		-0.076	0.073	-1.051	0.293	-0.076	-0.076
Variances:							
		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
.Agency1							
		0.048	0.005	8.914	0.000	0.048	0.181
.Agency2							
		0.036	0.005	7.726	0.000	0.036	0.129
.Agency3							
		0.050	0.005	9.207	0.000	0.050	0.169
.Intrin1							
		0.299	0.033	9.179	0.000	0.299	0.506
.Intrin2							
		0.387	0.040	9.796	0.000	0.387	0.535
.Intrin3							
		0.213	0.036	5.836	0.000	0.213	0.359
.Extrin1							
		0.080	0.011	7.004	0.000	0.080	0.348
.Extrin2							
		0.123	0.016	7.734	0.000	0.123	0.372
.Extrin3							
		0.103	0.016	6.253	0.000	0.103	0.317
.PosAFF1							
		0.121	0.017	7.301	0.000	0.121	0.271
.PosAFF2							
		0.104	0.016	6.536	0.000	0.104	0.222
.PosAFF3							
		0.099	0.015	6.824	0.000	0.099	0.199

Compare Standardized factor loadings ...

.NegAFF1	0.107	0.016	6.571	0.000	0.107	0.210
.NegAFF2	0.096	0.013	7.157	0.000	0.096	0.219
.NegAFF3	0.067	0.011	6.104	0.000	0.067	0.158
Agency	1.000				1.000	1.000
.Intrinsic	1.000				0.743	0.743
.Extrinsic	1.000				0.928	0.928
.Positive	1.000				0.815	0.815
.Negative	1.000				0.959	0.959

Defined Parameters:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
ind1	0.202	0.049	4.092	0.000	0.182	0.182
ind2	0.055	0.022	2.509	0.012	0.054	0.054

Why did we bother to standardize?

- We went into the standardization exercise because one of the GRAs thought that there were “weak” loadings that complicate the estimation of the mediator
 - Possible that measurement error variance translates into low standardized factor loadings
- Perhaps difficulty in latent regressions is due to simple measurement errors in the observed outcomes

Compare fits for standardized and non-standardized

```
mediat.out.2.std = update(mediat.out.2, std.lv =  
  TRUE, std.ov = TRUE, meanstructure=TRUE)  
semTable(list("Standardized" = mediat.out.2.std,  
  "Not Standardized" = mediat.out.2),  
  longtable = TRUE, columns = c("estsestars"),  
  varLabels = vl)
```

	Standardized	Not Standardized
	Estimate(Std.Err.)	Estimate(Std.Err.)

Compare fits for standardized and non-standardized ...

	<u>Factor Loadings</u>	
<u>Agency</u>		
Agency1	0.90(0.04)***	0.47(0.02)***
Agency2	0.93(0.04)***	0.49(0.02)***
Agency3	0.91(0.04)***	0.50(0.02)***
<u>Intrinsic</u>		
Intrinsic1	0.61(0.05)***	0.47(0.04)***
Intrinsic2	0.59(0.04)***	0.50(0.04)***
Intrinsic3	0.69(0.04)***	0.53(0.03)***
<u>Extrinsic</u>		
Extrinsic1	0.78(0.05)***	0.37(0.02)***
Extrinsic2	0.76(0.05)***	0.44(0.03)***
Extrinsic3	0.80(0.05)***	0.45(0.03)***
<u>Positive</u>		
Positive1	0.77(0.04)***	0.51(0.03)***
Positive2	0.80(0.04)***	0.54(0.03)***

Compare fits for standardized and non-standardized ...

	Positive3	0.81(0.04)***	0.57(0.03)***
<u>Negative</u>			
	Negative1	0.87(0.05)***	0.62(0.04)***
	Negative2	0.86(0.06)***	0.57(0.04)***
	Negative3	0.90(0.05)***	0.59(0.03)***
		<u>Regression Slopes</u>	
<u>Positive</u>			
	Intrinsic	0.34(0.08)***	0.34(0.08)***
	Agency	0.13(0.07)	0.13(0.07)
<u>Negative</u>			
	Extrinsic	0.20(0.07)**	0.20(0.07)**
<u>Intrinsic</u>			
	Agency	0.59(0.09)***	0.59(0.08)***
<u>Extrinsic</u>			
	Agency	0.28(0.06)***	0.28(0.06)***
		<u>Intercepts</u>	
	Agency1	0.00(0.05)	

Compare fits for standardized and non-standardized ...

Agency2	0.00(0.05)	
Agency3	0.00(0.05)	
Intrinsic1	0.00(0.05)	
Intrinsic2	0.00(0.05)	
Intrinsic3	0.00(0.05)	
Extrinsic1	0.00(0.05)	
Extrinsic2	0.00(0.05)	
Extrinsic3	0.00(0.05)	
Positive1	0.00(0.05)	
Positive2	0.00(0.05)	
Positive3	0.00(0.05)	
Negative1	0.00(0.05)	
Negative2	0.00(0.05)	
Negative3	0.00(0.05)	
	<u>Residual Variances</u>	
Agency1	0.18(0.02) ^{***}	0.05(0.01) ^{***}
Agency2	0.13(0.02) ^{***}	0.04(0.00) ^{***}

Compare fits for standardized and non-standardized ...

Agency3	0.17(0.02)***	0.05(0.01)***
Intrinsic1	0.50(0.05)***	0.30(0.03)***
Intrinsic2	0.53(0.05)***	0.39(0.04)***
Intrinsic3	0.36(0.06)***	0.21(0.04)***
Extrinsic1	0.35(0.05)***	0.08(0.01)***
Extrinsic2	0.37(0.05)***	0.12(0.02)***
Extrinsic3	0.32(0.05)***	0.10(0.02)***
Positive1	0.27(0.03)***	0.12(0.02)***
Positive2	0.22(0.03)***	0.10(0.02)***
Positive3	0.20(0.03)***	0.10(0.01)***
Negative1	0.21(0.03)***	0.11(0.02)***
Negative2	0.22(0.03)***	0.10(0.01)***
Negative3	0.16(0.02)***	0.07(0.01)***

Latent Intercepts

Agency	0.00 ⁺
Intrinsic	0.00 ⁺
Extrinsic	0.00 ⁺

Compare fits for standardized and non-standardized ...

Positive	0.00 ⁺	
Negative	0.00 ⁺	
	<u>Latent Variances</u>	
Agency	1.00 ⁺	1.00 ⁺
Intrinsic	1.00 ⁺	1.00 ⁺
Extrinsic	1.00 ⁺	1.00 ⁺
Positive	1.00 ⁺	1.00 ⁺
Negative	1.00 ⁺	1.00 ⁺
	<u>Latent Covariances</u>	
Intrinsic w/Extrinsic	-0.20(0.06) ^{***}	-0.20(0.06) ^{**}
Positive w/Negative	-0.08(0.07)	-0.08(0.07)
	<u>Constructed</u>	
ind1	0.20(0.05) ^{***}	0.20(0.05) ^{***}
ind2	0.06(0.02) [*]	0.06(0.02) [*]
	<u>Fit Indices</u>	
χ^2 (df)	109.15(83) [*]	109.15(83) [*]
CFI	0.99	0.99

Compare fits for standardized and non-standardized ...

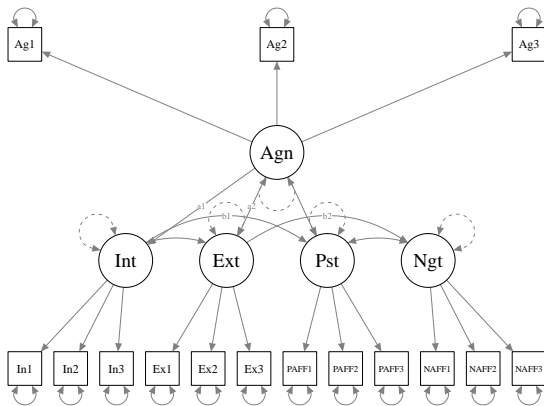
TLI	0.99	0.99
RMSEA	0.03	0.03

[†] Fixed parameter

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

plot

```
semPaths(mediat.out.2)
```



Check if c1 and c2 are significantly different

- Did you wonder if c1 is significantly different from c2?
- The assumption that they are the same is another restriction we can put on the model.
- We re-fit, and then run the anova test.

```
# if nesting is not specified, the diff is not reported
compareLavaan(list("CFA" = cfa3, "SEM" =
  mediat.out.2), nesting = "CFA > SEM", fitmeas
  = c("chisq", "df", "pvalue", "rmsea", "cfi",
  "bic"), type="latex")
```

	χ^2	df	p-value	rmsea	cfi	bic	$\Delta\chi^2$	Δdf	p
CFA	106.85	80.00	0.02	0.03	0.99	7635.83	-	-	-
SEM	109.15	83.00	0.03	0.03	0.99	7620.31	2.305a	3	0.5

a = SEM vs CFA

Check if c1 and c2 are significantly different ...

```

mediat.mod.3 <- '
  ## measurement model
  Agency =~ Agency1 + Agency2 + Agency3
  Intrinsic =~ Intrin1 + Intrin2 + Intrin3
  Extrinsic =~ Extrin1 + Extrin2 + Extrin3
  Positive =~ PosAFF1 + PosAFF2 + PosAFF3
  Negative =~ NegAFF1 + NegAFF2 + NegAFF3
  ## structural model
  Positive ~ b1*Intrinsic + Agency
  Negative ~ b2*Extrinsic
  Intrinsic ~ a1*Agency
  Extrinsic ~ a2*Agency
  Intrinsic ~ Extrinsic
  ## define mediation parameters (indirect effects)
  c1 := a1 * b1
  c2 := a2 * b2
  c1 == c2

```

Check if c1 and c2 are significantly different ...

,

```
# if nesting is not specified, the diff is not
  reported
compareLavaan(list("CFA" = cfa3, "SEM" =
  mediat.out.2), nesting = "CFA > SEM", fitmeas
  = c("chisq", "df", "pvalue", "rmsea", "cfi",
  "bic"), type="latex")
```

	χ^2	df	p-value	rmsea	cfi	bic	$\Delta\chi^2$	Δdf	p
CFA	106.85	80.00	0.02	0.03	0.99	7635.83	-	-	-
SEM	109.15	83.00	0.03	0.03	0.99	7620.31	2.305a	3	0.5

a = SEM vs CFA

Check if c1 and c2 are significantly different ...

```

mediat.mod.3 <- '
## measurement model
Agency =~ Agency1 + Agency2 + Agency3
Intrinsic =~ Intrin1 + Intrin2 + Intrin3
Extrinsic =~ Extrin1 + Extrin2 + Extrin3
Positive =~ PosAFF1 + PosAFF2 + PosAFF3
Negative =~ NegAFF1 + NegAFF2 + NegAFF3
## structural model
Positive ~ b1*Intrinsic + Agency
Negative ~ b2*Extrinsic
Intrinsic ~ a1*Agency
Extrinsic ~ a2*Agency
Intrinsic ~ Extrinsic
## define mediation parameters (indirect effects)
c1 := a1 * b1
c2 := a2 * b2
c1 == c2

```

Check if c1 and c2 are significantly different ...

,

```
Nboot <- 500
mediat.out.3 <- sem(mediat.mod.3, data = dat,
                    std.lv = TRUE, se = "boot",
                    bootstrap = Nboot)
summary(mediat.out.3, standardized = TRUE, fit =
        TRUE)
```

```
lavaan 0.6-3 ended normally after 461 iterations
```

Optimization method	NLMINB
Number of free parameters	37
Number of observations	380
Estimator	ML
Model Fit Test Statistic	118.955
Degrees of freedom	84
P-value (Chi-square)	0.007

Check if c1 and c2 are significantly different ...

Model test baseline model:

Minimum Function Test Statistic	3749.411
Degrees of freedom	105
P-value	0.000

User model versus baseline model:

Comparative Fit Index (CFI)	0.990
Tucker-Lewis Index (TLI)	0.988

Loglikelihood and Information Criteria:

Loglikelihood user model (H0)	-3705.163
Loglikelihood unrestricted model (H1)	-3645.686
Number of free parameters	36
Akaike (AIC)	7482.326
Bayesian (BIC)	7624.172
Sample-size adjusted Bayesian (BIC)	7509.951

Root Mean Square Error of Approximation:

RMSEA	0.033
90 Percent Confidence Interval	0.018 0.046
P-value RMSEA <= 0.05	0.986

Check if c1 and c2 are significantly different ...

Standardized Root Mean Square Residual:

SRMR 0.051

Parameter Estimates:

Standard Errors	Bootstrap
Number of requested bootstrap draws	500
Number of successful bootstrap draws	500

Latent Variables:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
Agency =~						
Agency1	0.467	0.021	22.277	0.000	0.467	0.905
Agency2	0.491	0.021	23.539	0.000	0.491	0.933
Agency3	0.497	0.023	21.758	0.000	0.497	0.911
Intrinsic =~						
Intrin1	0.468	0.038	12.199	0.000	0.528	0.693
Intrin2	0.508	0.037	13.809	0.000	0.573	0.679
Intrin3	0.540	0.032	17.093	0.000	0.609	0.801
Extrinsic =~						
Extrin1	0.373	0.023	16.540	0.000	0.395	0.813
Extrin2	0.439	0.029	15.055	0.000	0.465	0.798
Extrin3	0.452	0.028	15.863	0.000	0.478	0.829
Positive =~						

Check if c1 and c2 are significantly different ...

55	PosAFF1	0.530	0.024	22.141	0.000	0.564	0.853
	PosAFF2	0.562	0.028	20.274	0.000	0.598	0.881
	PosAFF3	0.587	0.028	21.227	0.000	0.624	0.892
	Negative =~						
	NegAFF1	0.614	0.037	16.448	0.000	0.639	0.890
70	NegAFF2	0.567	0.038	14.815	0.000	0.590	0.885
	NegAFF3	0.579	0.032	18.377	0.000	0.603	0.919
	Regressions:						
		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
75	Positive ~						
	Intrinsic (b1)	0.183	0.074	2.485	0.013	0.194	0.194
	Agency	0.218	0.074	2.952	0.003	0.205	0.205
	Negative ~						
	Extrinsic (b2)	0.275	0.058	4.745	0.000	0.280	0.280
80	Intrinsic ~						
	Agency (a1)	0.523	0.102	5.147	0.000	0.463	0.463
	Extrinsic ~						
	Agency (a2)	0.348	0.066	5.263	0.000	0.328	0.328
85	Covariances:						
		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
	.Intrinsic ~						
	.Extrinsic	-0.202	0.060	-3.388	0.001	-0.202	-0.202
	.Positive ~						
90	.Negative	-0.063	0.069	-0.918	0.359	-0.063	-0.063

Check if c1 and c2 are significantly different ...

Variances:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
.Agency1	0.048	0.005	8.896	0.000	0.048	0.181
.Agency2	0.036	0.004	8.028	0.000	0.036	0.129
.Agency3	0.050	0.006	8.848	0.000	0.050	0.170
.Intrin1	0.301	0.034	8.886	0.000	0.301	0.519
.Intrin2	0.383	0.039	9.771	0.000	0.383	0.539
.Intrin3	0.208	0.038	5.498	0.000	0.208	0.359
.Extrin1	0.080	0.010	7.751	0.000	0.080	0.339
.Extrin2	0.123	0.016	7.838	0.000	0.123	0.363
.Extrin3	0.104	0.017	6.241	0.000	0.104	0.312
.PosAFF1	0.120	0.015	8.068	0.000	0.120	0.273
.PosAFF2	0.103	0.016	6.654	0.000	0.103	0.224
.PosAFF3	0.100	0.014	7.103	0.000	0.100	0.205
.NegAFF1	0.107	0.016	6.578	0.000	0.107	0.207
.NegAFF2	0.096	0.014	7.051	0.000	0.096	0.216
.NegAFF3	0.067	0.011	6.361	0.000	0.067	0.156
Agency	1.000				1.000	1.000
.Intrinsic	1.000				0.785	0.785
.Extrinsic	1.000				0.892	0.892
.Positive	1.000				0.883	0.883
.Negative	1.000				0.922	0.922

Defined Parameters:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
--	----------	---------	---------	---------	--------	---------

Check if c1 and c2 are significantly different ...

c1	0.096	0.026	3.634	0.000	0.090	0.090
c2	0.096	0.026	3.634	0.000	0.092	0.092
Constraints:						
c1 - (c2)				Slack		
				0.000		

```
Nboot <- 500
mediat.out.3 <- sem(mediat.mod.3, data = dat,
                    std.lv = TRUE, se = "boot",
                    bootstrap = Nboot)
summary(mediat.out.3, standardized = TRUE, fit =
        TRUE)
```

Check if c1 and c2 are significantly different ...

```

lavaan 0.6-3 ended normally after 461 iterations

  Optimization method           NLMINB
  Number of free parameters      37
5
  Number of observations         380

  Estimator                      ML
  Model Fit Test Statistic       118.955
10
  Degrees of freedom             84
  P-value (Chi-square)           0.007

Model test baseline model:

15
  Minimum Function Test Statistic 3749.411
  Degrees of freedom              105
  P-value                          0.000

User model versus baseline model:

20
  Comparative Fit Index (CFI)     0.990
  Tucker-Lewis Index (TLI)       0.988

Loglikelihood and Information Criteria:
25

```

Check if c1 and c2 are significantly different ...

```

Loglikelihood user model (H0)                -3705.163
Loglikelihood unrestricted model (H1)        -3645.686

Number of free parameters                    36
Akaike (AIC)                                7482.326
Bayesian (BIC)                              7624.172
Sample-size adjusted Bayesian (BIC)         7509.951

Root Mean Square Error of Approximation:

RMSEA                                        0.033
90 Percent Confidence Interval              0.018  0.046
P-value RMSEA <= 0.05                     0.986

Standardized Root Mean Square Residual:

SRMR                                        0.051

Parameter Estimates:

Standard Errors                            Bootstrap
Number of requested bootstrap draws        500
Number of successful bootstrap draws        500

Latent Variables:
      Estimate  Std.Err  z-value  P(>|z|)  Std.lv  Std.all

```

Check if c1 and c2 are significantly different ...

Agency =~						
Agency1	0.467	0.021	22.277	0.000	0.467	0.905
Agency2	0.491	0.021	23.539	0.000	0.491	0.933
Agency3	0.497	0.023	21.758	0.000	0.497	0.911
Intrinsic =~						
Intrin1	0.468	0.038	12.199	0.000	0.528	0.693
Intrin2	0.508	0.037	13.809	0.000	0.573	0.679
Intrin3	0.540	0.032	17.093	0.000	0.609	0.801
Extrinsic =~						
Extrin1	0.373	0.023	16.540	0.000	0.395	0.813
Extrin2	0.439	0.029	15.055	0.000	0.465	0.798
Extrin3	0.452	0.028	15.863	0.000	0.478	0.829
Positive =~						
PosAFF1	0.530	0.024	22.141	0.000	0.564	0.853
PosAFF2	0.562	0.028	20.274	0.000	0.598	0.881
PosAFF3	0.587	0.028	21.227	0.000	0.624	0.892
Negative =~						
NegAFF1	0.614	0.037	16.448	0.000	0.639	0.890
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NegAFF3	0.579	0.032	18.377	0.000	0.603	0.919
Regressions:						
	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
Positive ~						
Intrinsic (b1)	0.183	0.074	2.485	0.013	0.194	0.194
Agency	0.218	0.074	2.952	0.003	0.205	0.205

Check if c1 and c2 are significantly different ...

Negative ~						
Extrinsic (b2)	0.275	0.058	4.745	0.000	0.280	0.280
Intrinsic ~						
Agency (a1)	0.523	0.102	5.147	0.000	0.463	0.463
Extrinsic ~						
Agency (a2)	0.348	0.066	5.263	0.000	0.328	0.328
Covariances:						
	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
.Intrinsic ~						
.Extrinsic	-0.202	0.060	-3.388	0.001	-0.202	-0.202
.Positive ~						
.Negative	-0.063	0.069	-0.918	0.359	-0.063	-0.063
Variances:						
	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
.Agency1	0.048	0.005	8.896	0.000	0.048	0.181
.Agency2	0.036	0.004	8.028	0.000	0.036	0.129
.Agency3	0.050	0.006	8.848	0.000	0.050	0.170
.Intrin1	0.301	0.034	8.886	0.000	0.301	0.519
.Intrin2	0.383	0.039	9.771	0.000	0.383	0.539
.Intrin3	0.208	0.038	5.498	0.000	0.208	0.359
.Extrin1	0.080	0.010	7.751	0.000	0.080	0.339
.Extrin2	0.123	0.016	7.838	0.000	0.123	0.363
.Extrin3	0.104	0.017	6.241	0.000	0.104	0.312
.PosAFF1	0.120	0.015	8.068	0.000	0.120	0.273

Check if c1 and c2 are significantly different ...

.PosAFF2	0.103	0.016	6.654	0.000	0.103	0.224
.PosAFF3	0.100	0.014	7.103	0.000	0.100	0.205
.NegAFF1	0.107	0.016	6.578	0.000	0.107	0.207
.NegAFF2	0.096	0.014	7.051	0.000	0.096	0.216
.NegAFF3	0.067	0.011	6.361	0.000	0.067	0.156
Agency	1.000				1.000	1.000
.Intrinsic	1.000				0.785	0.785
.Extrinsic	1.000				0.892	0.892
.Positive	1.000				0.883	0.883
.Negative	1.000				0.922	0.922
Defined Parameters:						
	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
c1	0.096	0.026	3.634	0.000	0.090	0.090
c2	0.096	0.026	3.634	0.000	0.092	0.092
Constraints:						
c1 - (c2)				Slack		
				0.000		

```
anova(mediat.out.3, mediat.out.2)
```

Check if c1 and c2 are significantly different ...

```
Chi Square Difference Test
```

```

          Df      AIC      BIC  Chisq  Chisq diff  Df  diff  Pr(>Chisq)
mediat.out.2 83 7474.5 7620.3 109.15
mediat.out.3 84 7482.3 7624.2 118.95      9.8021      1  0.001743 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```
anova(mediat.out.3, mediat.out.2)
```

```
Chi Square Difference Test
```

```

          Df      AIC      BIC  Chisq  Chisq diff  Df  diff  Pr(>Chisq)
mediat.out.2 83 7474.5 7620.3 109.15
mediat.out.3 84 7482.3 7624.2 118.95      9.8021      1  0.001743 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

Mediation is

- Mediation is a comparison of *direct* versus *indirect effects*
- SEM are help in mediation analysis because the integrate
 - analysis of several equations with correlated errors
 - allow for hypothesis testing (bootstrap).
- The “gold standard” software for SEM modeling has been Mplus.
- However, as we see in this example, `lavaan` is completely capable of doing the necessary calculations.

References

R Core Team (2017). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria.

Session

```
sessionInfo()
```

```
R version 3.6.0 (2019-04-26)
Platform: x86_64-pc-linux-gnu (64-bit)
Running under: Ubuntu 19.04

Matrix products: default
BLAS:   /usr/lib/x86_64-linux-gnu/atlas/libblas.so.3.10.3
LAPACK: /usr/lib/x86_64-linux-gnu/atlas/liblapack.so.3.10.3

locale:
 [1] LC_CTYPE=en_US.UTF-8      LC_NUMERIC=C
      LC_TIME=en_US.UTF-8
 [4] LC_COLLATE=en_US.UTF-8   LC_MONETARY=en_US.UTF-8
      LC_MESSAGES=en_US.UTF-8
 [7] LC_PAPER=en_US.UTF-8     LC_NAME=C              LC_ADDRESS=C
[10] LC_TELEPHONE=C           LC_MEASUREMENT=en_US.UTF-8
      LC_IDENTIFICATION=C

attached base packages:
[1] stats      graphics  grDevices  utils      datasets  methods   base

other attached packages:
[1] semTable_1.4  semPlot_1.1.1 lavaan_0.6-3
```

Session ...

```

loaded via a namespace (and not attached):
 [1] nlme_3.1-140          stationery_0.98.6    RColorBrewer_1.1-2  mi_1.0
 [5] tools_3.6.0          backports_1.1.4     R6_2.4.0
    rpart_4.1-15
 [9] d3Network_0.5.2.1   Hmisc_4.2-0        lazyeval_0.2.2
    colorspace_1.4-1
[13] nnet_7.3-12         tidyselect_0.2.5    gridExtra_2.3
    mnormt_1.5-5
[17] compiler_3.6.0      qgraph_1.6.2        fdrtool_1.2.15
    htmlTable_1.13.1
[21] regsem_1.3.9        scales_1.0.0        checkmate_1.9.3
    psych_1.8.12
[25] pbapply_1.4-0       sem_3.1-9           stringr_1.4.0
    digest_0.6.18
[29] pbivnorm_0.6.0     foreign_0.8-71     minqa_1.2.4
    rmarkdown_1.12
[33] base64enc_0.1-3     jpeg_0.1-8          pkgconfig_2.0.2
    htmltools_0.3.6
[37] lme4_1.1-21         lisrelToR_0.1.4     htmlwidgets_1.3
    rlang_0.3.4
[41] rstudioapi_0.10     huge_1.3.2          gtools_3.8.1
    acepack_1.4.1
[45] dplyr_0.8.1         zip_2.0.2           magrittr_1.5
    OpenMx_2.13.2

```

Session ...

[49]	Formula_1.2-3 munsell_0.5.0	Matrix_1.2-17	Rcpp_1.0.1
[53]	abind_1.4-5 whisker_0.3-2	rockchalk_1.8.144	stringi_1.4.3
[57]	carData_3.0-2 matrixcalc_1.0-3	MASS_7.3-51.4	plyr_1.8.4
[61]	grid_3.6.0 lattice_0.20-38	parallel_3.6.0	crayon_1.3.4
[65]	kutils_1.69 pillar_1.4.0	splines_3.6.0	knitr_1.22
[69]	igraph_1.2.4.1 corpcor_1.6.9	boot_1.3-22	rjson_0.2.20
[73]	BDgraph_2.59 XML_3.98-1.19	reshape2_1.4.3	stats4_3.6.0
[77]	glue_1.3.1 data.table_1.12.2	evaluate_0.13	latticeExtra_0.6-28
[81]	png_0.1-7 purrr_0.3.2	nloptr_1.2.1	gtable_0.3.0
[85]	assertthat_0.2.1 openxlsx_4.1.0	ggplot2_3.1.1	xfun_0.7
[89]	xtable_1.8-4 Rsolnp_1.16	semTools_0.5-1	coda_0.19-2
[93]	survival_2.44-1.1 tibble_2.1.1	glasso_1.10	truncnorm_1.0-8
[97]	arm_1.10-1	ggm_2.3	cluster_2.0.9