

# Full Structural Equation Modeling

## Theory Construction and Statistical Modeling



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# Outline

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Structural Equation Modeling  
Measurement Model  
Structural Model

Mediation with SEM

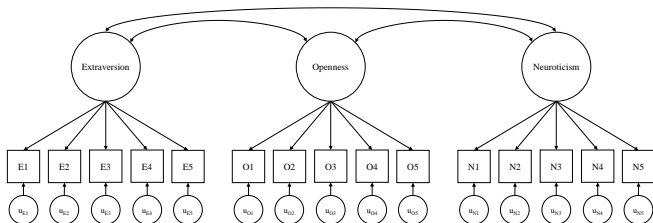


# Full SEM

A full structural equation model (SEM) simply combines path analysis and CFA.

- SEM allows us to model complicated structural relations among latent variables.

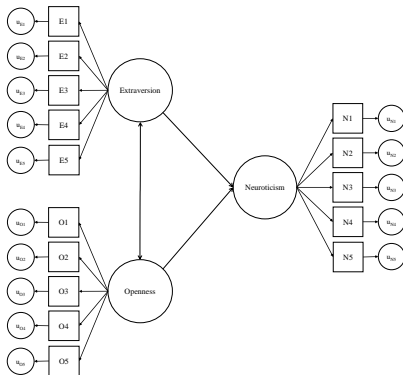
Let's consider a simple, three-factor CFA model.



# CFA → SEM

We first evaluate the validity of the measurement model via CFA.

- We then convert the CFA to an SEM by converting some covariances to latent regression paths.



# CFA Example

```
## Load the lavaan package and some data:
```

```
library(lavaan)
```

```
data(bfi, package = "psych")
```

```
## Specify the CFA model:
```

```
cfaMod <- '
```

```
extra =~ E1 + E2 + E3 + E4 + E5
```

```
open  =~ O1 + O2 + O3 + O4 + O5
```

```
neuro =~ N1 + N2 + N3 + N4 + N5
```

```
'
```

```
## Estimate the model:
```

```
cfaOut <- cfa(cfaMod, data = bfi, missing = "fiml", std.lv = TRUE)
```

```
## Check the fit:
```

```
fitMeasures(cfaOut,
```

```
  c("chisq", "df", "pvalue", "cfi", "tli", "rmsea", "srmr")  
)
```

chisq	df	pvalue	cfi	tli	rmsea	srmr
2251.679	87.000	0.000	0.809	0.769	0.094	0.081

# CFA Example

```
partSummary(cfaOut, 7)
```

Latent Variables:

	Estimate	Std.Err	z-value	P(> z )
extra =~				
E1	0.973	0.032	30.607	0.000
E2	1.163	0.030	38.171	0.000
E3	-0.815	0.027	-30.358	0.000
E4	-0.979	0.028	-35.254	0.000
E5	-0.714	0.027	-26.638	0.000
open =~				
O1	0.630	0.025	24.886	0.000
O2	-0.605	0.036	-16.781	0.000
O3	0.897	0.029	30.765	0.000
O4	0.290	0.028	10.402	0.000
O5	-0.602	0.031	-19.734	0.000
neuro =~				
N1	1.272	0.027	47.254	0.000
N2	1.218	0.026	46.491	0.000
N3	1.157	0.029	40.195	0.000
N4	0.892	0.030	29.356	0.000
N5	0.823	0.031	26.163	0.000

# CFA Example

---

```
partSummary(cfaOut, 8)
```

Covariances:

	Estimate	Std.Err	z-value	P(> z )
extra ~~				
open	-0.444	0.024	-18.472	0.000
neuro	0.240	0.023	10.551	0.000
open ~~				
neuro	-0.117	0.025	-4.667	0.000

# CFA Example

```
partSummary(cfaOut, 9)
```

Intercepts:

	Estimate	Std.Err	z-value	P(> z )
.E1	2.974	0.031	96.223	0.000
.E2	3.143	0.030	103.424	0.000
.E3	4.002	0.026	156.117	0.000
.E4	4.421	0.028	160.350	0.000
.E5	4.417	0.025	174.595	0.000
.01	4.816	0.021	224.964	0.000
.02	2.713	0.030	91.745	0.000
.03	4.436	0.023	191.555	0.000
.04	4.892	0.023	211.519	0.000
.05	2.490	0.025	98.932	0.000
.N1	2.932	0.030	98.589	0.000
.N2	3.508	0.029	121.459	0.000
.N3	3.217	0.030	106.147	0.000
.N4	3.185	0.030	106.894	0.000
.N5	2.969	0.031	96.663	0.000
extra	0.000			
open	0.000			
neuro	0.000			



# CFA Example

```
partSummary(cfaOut, 10)
```

Variances:

	Estimate	Std.Err	z-value	P(> z )
.E1	1.713	0.054	31.442	0.000
.E2	1.224	0.049	24.952	0.000
.E3	1.163	0.038	30.388	0.000
.E4	1.166	0.041	28.522	0.000
.E5	1.272	0.039	32.789	0.000
.O1	0.878	0.031	28.320	0.000
.O2	2.083	0.062	33.705	0.000
.O3	0.686	0.043	16.130	0.000
.O4	1.407	0.039	36.236	0.000
.O5	1.401	0.044	31.837	0.000
.N1	0.848	0.037	23.029	0.000
.N2	0.842	0.035	24.184	0.000
.N3	1.228	0.043	28.308	0.000
.N4	1.666	0.051	32.808	0.000
.N5	1.942	0.056	34.465	0.000
extra	1.000			
open	1.000			
neuro	1.000			

# SEM Example

```
## Add structural paths:
```

```
semMod <- '  
extra =~ E1 + E2 + E3 + E4 + E5  
open  =~ O1 + O2 + O3 + O4 + O5  
neuro =~ N1 + N2 + N3 + N4 + N5  
  
neuro ~ extra + open  
,
```

```
## Estimate the model:
```

```
semOut <- sem(semMod, data = bfi, missing = "fiml", std.lv = TRUE)
```

```
## Check the fit:
```

```
fitMeasures(semOut,  
             c("chisq", "df", "pvalue", "cfi", "tli", "rmsea", "srmr")  
             )
```

chisq	df	pvalue	cfi	tli	rmsea	srmr
2251.679	87.000	0.000	0.809	0.769	0.094	0.081

# SEM Example

```
partSummary(semOut, 7)
```

Latent Variables:

	Estimate	Std.Err	z-value	P(> z )
extra =~				
E1	0.973	0.032	30.607	0.000
E2	1.163	0.030	38.172	0.000
E3	-0.815	0.027	-30.358	0.000
E4	-0.979	0.028	-35.254	0.000
E5	-0.714	0.027	-26.638	0.000
open =~				
O1	0.630	0.025	24.886	0.000
O2	-0.605	0.036	-16.781	0.000
O3	0.897	0.029	30.765	0.000
O4	0.290	0.028	10.402	0.000
O5	-0.602	0.031	-19.734	0.000
neuro =~				
N1	1.235	0.027	45.916	0.000
N2	1.183	0.026	45.360	0.000
N3	1.123	0.028	39.976	0.000
N4	0.866	0.029	29.605	0.000
N5	0.799	0.031	26.204	0.000

# SEM Example

---

```
partSummary(semOut, 8:9)
```

## Regressions:

	Estimate	Std.Err	z-value	P(> z )
neuro ~				
extra	0.241	0.030	8.169	0.000
open	-0.014	0.031	-0.448	0.654

## Covariances:

	Estimate	Std.Err	z-value	P(> z )
extra ~~				
open	-0.444	0.024	-18.472	0.000

# SEM Example

```
partSummary(semOut, 10)
```

Intercepts:

	Estimate	Std.Err	z-value	P(> z )
.E1	2.974	0.031	96.223	0.000
.E2	3.143	0.030	103.424	0.000
.E3	4.002	0.026	156.117	0.000
.E4	4.421	0.028	160.350	0.000
.E5	4.417	0.025	174.595	0.000
.01	4.816	0.021	224.964	0.000
.02	2.713	0.030	91.745	0.000
.03	4.436	0.023	191.555	0.000
.04	4.892	0.023	211.520	0.000
.05	2.490	0.025	98.932	0.000
.N1	2.932	0.030	98.589	0.000
.N2	3.508	0.029	121.459	0.000
.N3	3.217	0.030	106.146	0.000
.N4	3.185	0.030	106.894	0.000
.N5	2.969	0.031	96.663	0.000
extra	0.000			
open	0.000			
.neuro	0.000			

# SEM Example

```
partSummary(semOut, 11)
```

Variances:

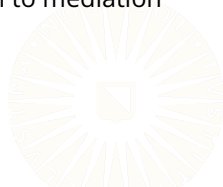
	Estimate	Std.Err	z-value	P(> z )
.E1	1.713	0.054	31.442	0.000
.E2	1.224	0.049	24.952	0.000
.E3	1.163	0.038	30.388	0.000
.E4	1.166	0.041	28.522	0.000
.E5	1.272	0.039	32.789	0.000
.O1	0.878	0.031	28.320	0.000
.O2	2.083	0.062	33.705	0.000
.O3	0.686	0.043	16.130	0.000
.O4	1.407	0.039	36.236	0.000
.O5	1.401	0.044	31.837	0.000
.N1	0.848	0.037	23.029	0.000
.N2	0.842	0.035	24.184	0.000
.N3	1.228	0.043	28.308	0.000
.N4	1.666	0.051	32.808	0.000
.N5	1.942	0.056	34.465	0.000
extra	1.000			
open	1.000			
.neuro	1.000			

# Why SEM?

---

The beauty of SEM is that we get to model the types of complex relations we can specify via path models while leveraging all the strengths of latent variables.

- Multiple-group SEM models moderation by group.
  - The latent variables give us the ability to evaluate measurement invariance across groups.
  - We'll see more of these ideas in the next lecture.
- Path analysis and SEM lend themselves especially well to mediation analysis and conditional process analysis.



# MEDIATION WITH SEM

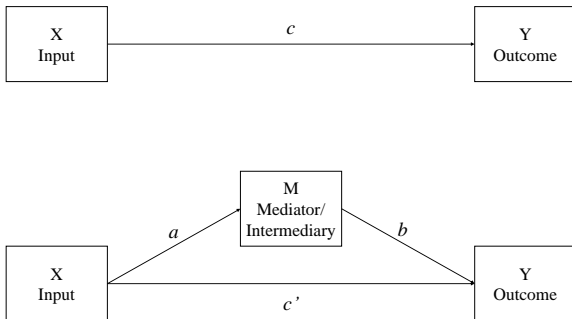




# Boring Model

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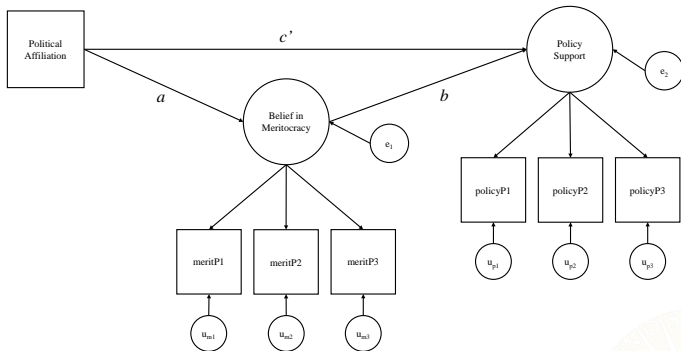
In Week 3, all of our models have looked something like:



But there is no reason that we need to restrict ourselves to mucking around with observed variables.

# Better Model

We can (and should) test for indirect effects using full SEMs such as as:



Measurement error can be a big problem for mediation analysis, so latent variable modeling is highly recommended.

# Example

```
dat1 <- readRDS("../data/adamsKlpsData.rds") %>% select(-merit, -policy)

## Specify the CFA model:
mod5.1 <- '
merit =~ meritP1 + meritP2 + meritP3
policy =~ policyP1 + policyP2 + policyP3
'

## Fit the CFA and check model:
out5.1 <- cfa(mod5.1, data = dat1, std.lv = TRUE)

## Check model fit:
fitMeasures(out5.1,
             c("chisq", "df", "pvalue", "cfi", "tli", "rmsea", "srmr"))

```

chisq	df	pvalue	cfi	tli	rmsea	srmr
16.869	8.000	0.031	0.922	0.853	0.113	0.065

# Example

```
partSummary(out5.1, 7)
```

Latent Variables:

	Estimate	Std.Err	z-value	P(> z )
merit =~				
meritP1	0.690	0.134	5.155	0.000
meritP2	0.968	0.142	6.830	0.000
meritP3	0.748	0.137	5.458	0.000
policy =~				
policyP1	0.851	0.186	4.570	0.000
policyP2	0.996	0.167	5.967	0.000
policyP3	1.121	0.177	6.339	0.000



# Example

```
partSummary(out5.1, 8:9)
```

Covariances:

	Estimate	Std.Err	z-value	P(> z )
merit ~~ policy	-0.336	0.131	-2.563	0.010

Variances:

	Estimate	Std.Err	z-value	P(> z )
.meritP1	0.865	0.165	5.248	0.000
.meritP2	0.445	0.201	2.211	0.027
.meritP3	0.833	0.172	4.857	0.000
.policyP1	1.836	0.324	5.671	0.000
.policyP2	0.942	0.256	3.683	0.000
.policyP3	0.857	0.297	2.882	0.004
merit	1.000			
policy	1.000			

# Example

---

```
## Specify the structural model:
mod5.2 <- '
merit  =~ meritP1 + meritP2 + meritP3
policy =~ policyP1 + policyP2 + policyP3

policy ~ b*merit + polAffil
merit  ~ a*polAffil

ab := a*b
'

## Fit the structural model and test the indirect effect:
out5.2 <-
  sem(mod5.2, data = dat1, std.lv = TRUE, se = "boot", bootstrap = 500)
```



# Example

```
partSummary(out5.2, 7:8)
```

Latent Variables:

	Estimate	Std.Err	z-value	P(> z )
merit =~				
meritP1	0.545	0.132	4.136	0.000
meritP2	0.858	0.133	6.452	0.000
meritP3	0.609	0.128	4.776	0.000
policy =~				
policyP1	0.799	0.186	4.303	0.000
policyP2	0.924	0.161	5.749	0.000
policyP3	1.001	0.277	3.614	0.000

Regressions:

		Estimate	Std.Err	z-value	P(> z )
policy ~					
merit	(b)	-0.195	0.203	-0.962	0.336
polAffil		0.169	0.141	1.203	0.229
merit ~					
polAffil	(a)	-0.411	0.100	-4.093	0.000

# Example

```
partSummary(out5.2, 9:10)
```

Variances:

	Estimate	Std.Err	z-value	P(> z )
.meritP1	0.922	0.175	5.262	0.000
.meritP2	0.341	0.213	1.599	0.110
.meritP3	0.869	0.182	4.783	0.000
.policyP1	1.801	0.325	5.548	0.000
.policyP2	0.918	0.304	3.023	0.003
.policyP3	0.922	0.598	1.542	0.123
.merit	1.000			
.policy	1.000			

Defined Parameters:

	Estimate	Std.Err	z-value	P(> z )
ab	0.080	0.092	0.872	0.383



# Example

---

```
parameterEstimates(out5.2, boot.ci.type = "bca.simple") %>%  
  select(c("label", "est", "ci.lower", "ci.upper")) %>%  
  filter(label != "")
```

	label	est	ci.lower	ci.upper
1	b	-0.195	-0.667	0.170
2	a	-0.411	-0.637	-0.241
3	ab	0.080	-0.074	0.293

