

# Assignment 5: SEM

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## 1 Reading the Data

We first create a Wave variable that bins the months into 4-month intervals, so that we have 3 time points for each person.

---

```
> cell_demo = read.csv("cell_demo.csv", header = TRUE, sep = ",")
> cell = read.csv("cell_withitems_complete.csv", header = TRUE, sep = ",")
> cell = merge(cell, cell_demo, by = "ID")
> cell$ID = as.factor(as.character(cell$ID))
> for(i in 1:nrow(cell)){
+   if(cell[i,12] <= 4){
+     cell[i,20] = 1
+   }
+   else if(cell[i,12] > 4 & cell[i,12]<= 8){
+     cell[i,20] = 2
+   }
+   else
+     cell[i,20] = 3
+ }
> colnames(cell)[20] = "Wave"
```

---

## 2 Converting Data to Wide Format

---

```
> library(plyr)
> library(dplyr)
> accuracy_time = group_by(cell, ID, Wave) %>%
+   summarise_at(vars(Accuracy), mean)
> messages_time = group_by(cell, ID, Wave) %>%
+   summarise_at(vars(Messages), mean)
> memorability_time = group_by(cell, ID, Wave) %>%
+   summarise_at(vars(Memorablity), mean)
> td_time = group_by(cell, ID, Wave) %>%
+   summarise_at(vars(TimeJudgmentDistance), mean)
> vivid_time = group_by(cell, ID, Wave) %>%
+   summarise_at(vars(Vividness), mean)
> ## long to wide
>
> acc_wide = tidyr::spread(accuracy_time, Wave, Accuracy)
> colnames(acc_wide) = c("Subject", "Q1_Acc", "Q2_Acc", "Q3_Acc")
> messages_wide = tidyr::spread(messages_time, Wave, Messages)
> colnames(messages_wide) = c("Subject", "Q1_mess", "Q2_mess", "Q3_mess")
> mem_wide = tidyr::spread(memorability_time, Wave, Memorablity)
> colnames(mem_wide) = c("Subject", "Q1_mem", "Q2_mem", "Q3_mem")
> td_wide = tidyr::spread(td_time, Wave, TimeJudgmentDistance)
```

```

> colnames(td_wide) = c("Subject", "Q1_td", "Q2_td", "Q3_td")
> vivid_wide = tidyr::spread(td_time, Wave, TimeJudgmentDistance)
> colnames(vivid_wide) = c("Subject", "Q1_v", "Q2_v", "Q3_v")
> cell_wide = Reduce(function(x,y) merge(x,y, all = TRUE), list(acc_wide, messages_wide, mem_wide, t
> cell_wide[,c(5:10)] = cell_wide[,c(5:10)]/100
> cell_wide[,c(11:16)] = cell_wide[,c(11:16)]/10
>

```

---

### 3 Measurement Model with 1 Time Point

#### Default Marker Variable Loading

```

> cell.model.1 <- 'NameMemory =~ Q1_Acc + Q1_mem + Q1_mess + Q1_v'
> library(lavaan)
> library(semPlot)
> library(semTools)
> m_marker = lavaan::cfa(cell.model.1, data = cell_wide)
> summary(m_marker, fit.measures = TRUE)

```

---

*lavaan (0.5-23.1097) converged normally after 60 iterations*

<i>Number of observations</i>	<i>44</i>
<i>Estimator</i>	<i>ML</i>
<i>Minimum Function Test Statistic</i>	<i>0.639</i>
<i>Degrees of freedom</i>	<i>2</i>
<i>P-value (Chi-square)</i>	<i>0.726</i>

*Model test baseline model:*

<i>Minimum Function Test Statistic</i>	<i>3.326</i>
<i>Degrees of freedom</i>	<i>6</i>
<i>P-value</i>	<i>0.767</i>

*User model versus baseline model:*

<i>Comparative Fit Index (CFI)</i>	<i>1.000</i>
<i>Tucker-Lewis Index (TLI)</i>	<i>-0.527</i>

*Loglikelihood and Information Criteria:*

<i>Loglikelihood user model (H0)</i>	<i>182.765</i>
<i>Loglikelihood unrestricted model (H1)</i>	<i>183.084</i>
<i>Number of free parameters</i>	<i>8</i>
<i>Akaike (AIC)</i>	<i>-349.529</i>
<i>Bayesian (BIC)</i>	<i>-335.256</i>
<i>Sample-size adjusted Bayesian (BIC)</i>	<i>-360.325</i>

*Root Mean Square Error of Approximation:*

<i>RMSEA</i>	<i>0.000</i>
<i>90 Percent Confidence Interval</i>	<i>0.000 0.213</i>
<i>P-value RMSEA &lt;= 0.05</i>	<i>0.751</i>

*Standardized Root Mean Square Residual:*

SRMR

0.035

Parameter Estimates:

Information	Expected
Standard Errors	Standard

Latent Variables:

	Estimate	Std.Err	z-value	P(> z )
NameMemory =~				
Q1_Acc	1.000			
Q1_mem	-0.648	0.874	-0.742	0.458
Q1_mess	-0.609	1.084	-0.562	0.574
Q1_v	-0.461	0.637	-0.724	0.469

Variances:

	Estimate	Std.Err	z-value	P(> z )
.Q1_Acc	0.010	0.003	3.006	0.003
.Q1_mem	0.005	0.002	3.371	0.001
.Q1_mess	0.019	0.004	4.383	0.000
.Q1_v	0.002	0.001	2.943	0.003
NameMemory	0.002	0.003	0.581	0.561

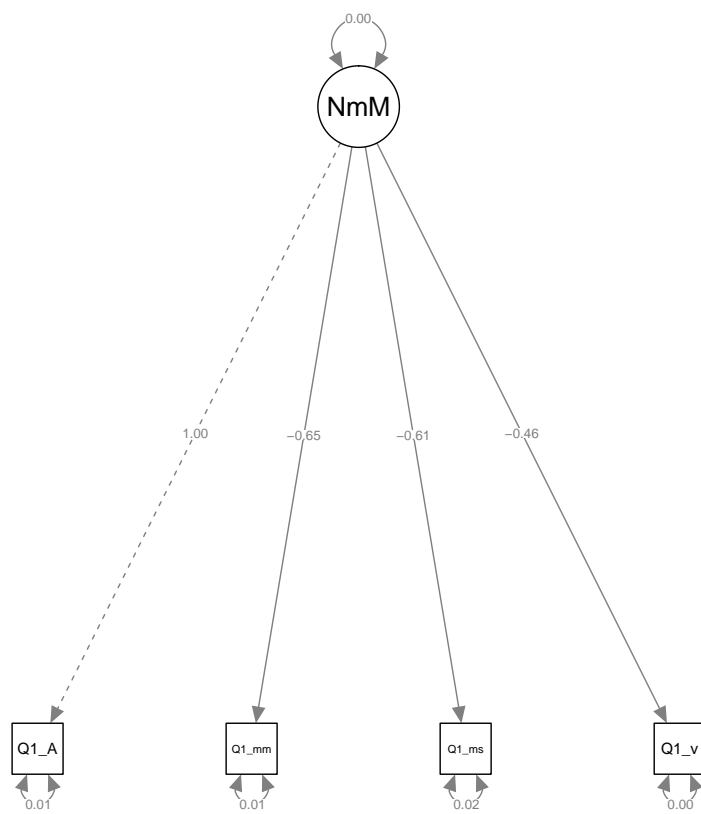
---

Plotting

---

```
> semPaths(m_marker, whatLabels = "est")
```

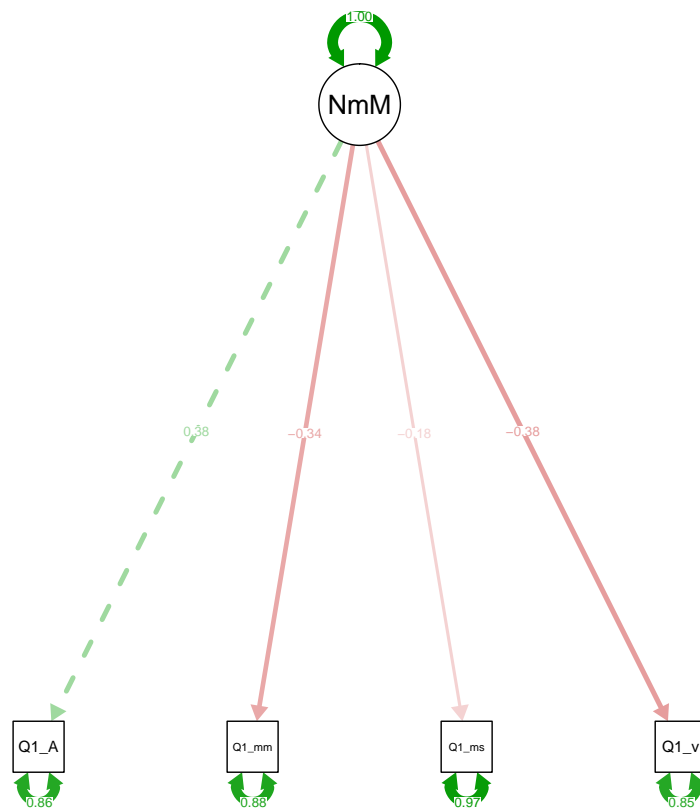
---




---

```
> semPaths(m_marker, what = "std")
```

---



## Fixed Factor Loading

---

```
> m_fixed = lavaan::cfa(cell.model.1, data = cell_wide, std.lv = TRUE)
> summary(m_fixed, fit.measures = TRUE)
```

---

*lavaan (0.5-23.1097) converged normally after 51 iterations*

<i>Number of observations</i>	<i>44</i>
<i>Estimator</i>	<i>ML</i>
<i>Minimum Function Test Statistic</i>	<i>0.639</i>
<i>Degrees of freedom</i>	<i>2</i>
<i>P-value (Chi-square)</i>	<i>0.726</i>

*Model test baseline model:*

<i>Minimum Function Test Statistic</i>	<i>3.326</i>
<i>Degrees of freedom</i>	<i>6</i>
<i>P-value</i>	<i>0.767</i>

*User model versus baseline model:*

<i>Comparative Fit Index (CFI)</i>	<i>1.000</i>
<i>Tucker-Lewis Index (TLI)</i>	<i>-0.527</i>

#### Loglikelihood and Information Criteria:

Loglikelihood user model (H0)	182.765
Loglikelihood unrestricted model (H1)	183.084
Number of free parameters	8
Akaike (AIC)	-349.529
Bayesian (BIC)	-335.256
Sample-size adjusted Bayesian (BIC)	-360.325

#### Root Mean Square Error of Approximation:

RMSEA	0.000
90 Percent Confidence Interval	0.000 0.213
P-value RMSEA <= 0.05	0.751

#### Standardized Root Mean Square Residual:

SRMR	0.035
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#### Parameter Estimates:

Information	Expected
Standard Errors	Standard

#### Latent Variables:

	Estimate	Std.Err	z-value	P(> z )
NameMemory =~				
Q1_Acc	0.040	0.035	1.162	0.245
Q1_mem	-0.026	0.023	-1.119	0.263
Q1_mess	-0.025	0.037	-0.662	0.508
Q1_v	-0.019	0.016	-1.169	0.243

#### Variances:

	Estimate	Std.Err	z-value	P(> z )
.Q1_Acc	0.010	0.003	3.006	0.003
.Q1_mem	0.005	0.002	3.371	0.001
.Q1_mess	0.019	0.004	4.383	0.000
.Q1_v	0.002	0.001	2.943	0.003
NameMemory	1.000			

---

When we keep the marker loading, the first indicator variable is weighted 1, and all the other estimates are compared to that first indicator. In fixed-factor loading we constrain the variance of the latent variable to 1. Thus, we see in the summary() output for both models that the variance estimates are different for the latent variable. Also note that the estimates for each of the indicator variables is different, which makes sense because the estimates in the are relative to Q1acc and they are not constrained in the fixed-factor model.

Note, however, that the overall fit statistics do not change i.e. both have the same values for SRMR and RMSEA.

## 4 Fit Statistics

The fit statistics for the marker model are as follows: RMSEA is 0, SRMR is 0.035, thus this a fairly good fitting model. CFI=1, TLI = -.527, high CFI indicates a good fit.

The degrees of freedom are 2.

## 5 Longitudinal CFA Model

### Correlating Latent Factors

---

```
> long_model = 'NameMem_1 =~ Q1_Acc + Q1_mem + Q1_mess + Q1_v
+               NameMem_2 =~ Q2_Acc + Q2_mem + Q2_mess + Q2_v
+               NameMem_3 =~ Q3_Acc + Q3_mem + Q3_mess + Q3_v'
> long_model_fit = lavaan::cfa(long_model, missing = "ML", data = cell_wide)
> summary(long_model_fit, fit.measures = TRUE)
```

---

*lavaan (0.5-23.1097) converged normally after 175 iterations*

<i>Number of observations</i>	<i>44</i>
<i>Number of missing patterns</i>	<i>2</i>
<i>Estimator</i>	<i>ML</i>
<i>Minimum Function Test Statistic</i>	<i>68.879</i>
<i>Degrees of freedom</i>	<i>51</i>
<i>P-value (Chi-square)</i>	<i>0.048</i>

*Model test baseline model:*

<i>Minimum Function Test Statistic</i>	<i>119.370</i>
<i>Degrees of freedom</i>	<i>66</i>
<i>P-value</i>	<i>0.000</i>

*User model versus baseline model:*

<i>Comparative Fit Index (CFI)</i>	<i>0.665</i>
<i>Tucker-Lewis Index (TLI)</i>	<i>0.566</i>

*Loglikelihood and Information Criteria:*

<i>Loglikelihood user model (H0)</i>	<i>467.107</i>
<i>Loglikelihood unrestricted model (H1)</i>	<i>501.547</i>
<i>Number of free parameters</i>	<i>39</i>
<i>Akaike (AIC)</i>	<i>-856.215</i>
<i>Bayesian (BIC)</i>	<i>-786.631</i>
<i>Sample-size adjusted Bayesian (BIC)</i>	<i>-908.842</i>

*Root Mean Square Error of Approximation:*

<i>RMSEA</i>	<i>0.089</i>
<i>90 Percent Confidence Interval</i>	<i>0.008 0.139</i>
<i>P-value RMSEA &lt;= 0.05</i>	<i>0.137</i>

*Standardized Root Mean Square Residual:*

<i>SRMR</i>	<i>0.122</i>
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*Parameter Estimates:*

<i>Information</i>	<i>Observed</i>
<i>Standard Errors</i>	<i>Standard</i>

Latent Variables:

	Estimate	Std.Err	z-value	P(> z )
NameMem_1 =~				
Q1_Acc	1.000			
Q1_mem	0.428	0.336	1.272	0.203
Q1_mess	-0.771	0.577	-1.337	0.181
Q1_v	-0.051	0.147	-0.346	0.729
NameMem_2 =~				
Q2_Acc	1.000			
Q2_mem	0.056	0.119	0.472	0.637
Q2_mess	0.022	0.047	0.456	0.648
Q2_v	-0.380	0.137	-2.776	0.006
NameMem_3 =~				
Q3_Acc	1.000			
Q3_mem	0.026	0.031	0.826	0.409
Q3_mess	0.015	0.018	0.820	0.412
Q3_v	-0.228	0.173	-1.313	0.189

Covariances:

	Estimate	Std.Err	z-value	P(> z )
NameMem_1 ~~				
NameMem_2	0.009	0.004	2.132	0.033
NameMem_3	0.002	0.004	0.512	0.608
NameMem_2 ~~				
NameMem_3	0.035	0.012	2.824	0.005

Intercepts:

	Estimate	Std.Err	z-value	P(> z )
.Q1_Acc	0.865	0.016	53.583	0.000
.Q1_mem	0.237	0.012	20.510	0.000
.Q1_mess	0.160	0.021	7.616	0.000
.Q1_v	0.099	0.007	13.458	0.000
.Q2_Acc	0.688	0.037	18.576	0.000
.Q2_mem	0.242	0.015	15.699	0.000
.Q2_mess	0.064	0.006	10.203	0.000
.Q2_v	0.212	0.020	10.360	0.000
.Q3_Acc	0.625	0.046	13.633	0.000
.Q3_mem	0.229	0.015	15.184	0.000
.Q3_mess	0.056	0.005	11.701	0.000
.Q3_v	0.307	0.034	9.072	0.000
NameMem_1	0.000			
NameMem_2	0.000			
NameMem_3	0.000			

Variances:

	Estimate	Std.Err	z-value	P(> z )
.Q1_Acc	0.013	0.004	3.480	0.001
.Q1_mem	0.006	0.001	4.328	0.000
.Q1_mess	0.020	0.005	4.384	0.000
.Q1_v	0.002	0.001	4.683	0.000
.Q2_Acc	0.032	0.013	2.581	0.010
.Q2_mem	0.010	0.002	4.662	0.000
.Q2_mess	0.002	0.000	4.665	0.000
.Q2_v	0.014	0.003	4.368	0.000
.Q3_Acc	-0.052	0.098	-0.537	0.591
.Q3_mem	0.010	0.002	4.656	0.000
.Q3_mess	0.001	0.000	4.600	0.000
.Q3_v	0.042	0.010	4.157	0.000

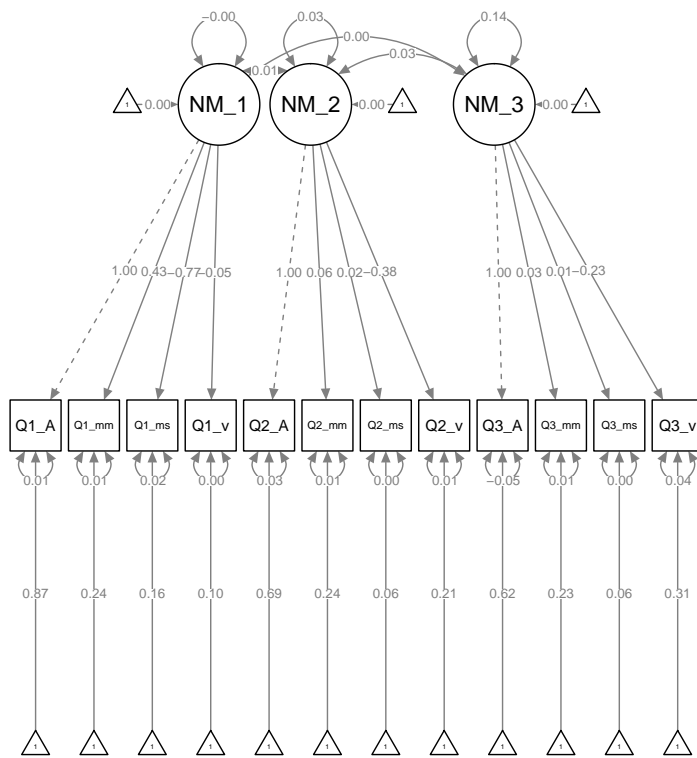


NameMem_1	-0.001	0.002	-0.514	0.607
NameMem_2	0.028	0.015	1.851	0.064
NameMem_3	0.143	0.098	1.457	0.145

---

```
> semPaths(long_model_fit, whatLabels = "est")
```

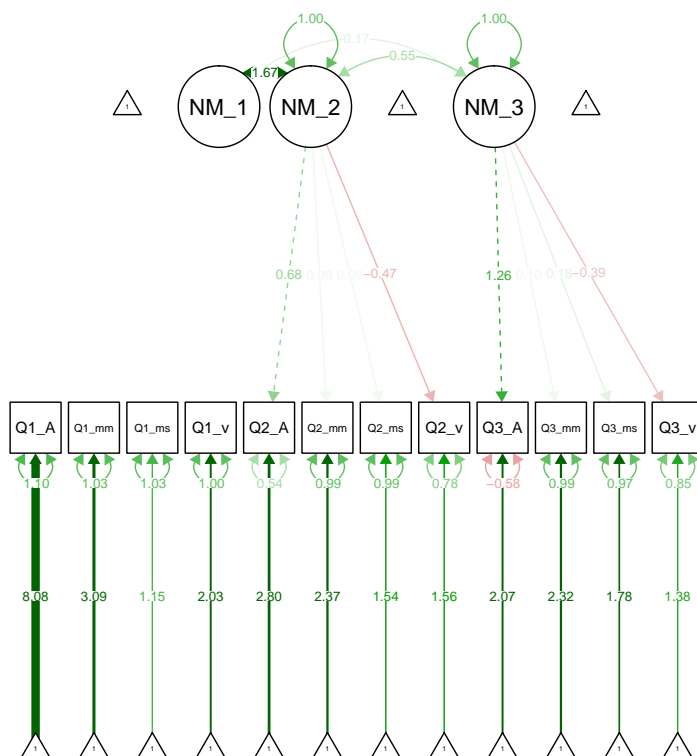
---




---

```
> semPaths(long_model_fit, what = "std")
```

---



When we correlate the latent factors across time, we find Name Memory at Wave 2 is strongly predicted by Name Memory at Wave 1. We also find that the auto-regressive model fails to converge.

## Auto-regressive

```
> long_model.2 = 'NameMem_1 =~ Q1_Acc + Q1_mem + Q1_mess + Q1_v
+
+           NameMem_2 =~ Q2_Acc + Q2_mem + Q2_mess + Q2_v
+           NameMem_3 =~ Q3_Acc + Q3_mem + Q3_mess + Q3_v
+
+           NameMem_2 ~ NameMem_1
+
+
>
> #auto_fit = lavaan::cfa(long_model.2, missing = "ML", data = cell_wide)
> #summary(auto_fit, fit.measures = TRUE) ## does not converge!
```

## Plotting

```
> #semPaths(auto_fit, what = "est")

> #semPaths(auto_fit, what = "std")
```

## 6 SEM and HLM

### HLM Models

---

```
> library(lme4)
> hlm_model_fixed = lmer(data = accuracy_time, Accuracy ~ Wave + (1|ID))
> summary(hlm_model_fixed)
```

---

Linear mixed model fit by REML ['lmerMod']

Formula: Accuracy ~ Wave + (1 | ID)

Data: accuracy\_time

REML criterion at convergence: -8.3

Scaled residuals:

Min	1Q	Median	3Q	Max
-2.58275	-0.56533	0.03377	0.63264	1.82296

Random effects:

Groups	Name	Variance	Std.Dev.
ID	(Intercept)	0.01714	0.1309
	Residual	0.03855	0.1964

Number of obs: 131, groups: ID, 44

Fixed effects:

	Estimate	Std. Error	t value
(Intercept)	0.96754	0.04945	19.567
Wave	-0.12115	0.02108	-5.747

Correlation of Fixed Effects:

(Intr)	
Wave	-0.849

---

```
> hlm_model_random = lmer(data = accuracy_time, Accuracy ~ Wave + (Wave|ID))
> summary(hlm_model_random)
```

---

Linear mixed model fit by REML ['lmerMod']

Formula: Accuracy ~ Wave + (Wave | ID)

Data: accuracy\_time

REML criterion at convergence: -33.3

Scaled residuals:

Min	1Q	Median	3Q	Max
-2.37678	-0.50800	0.01226	0.76407	1.61472

Random effects:

Groups	Name	Variance	Std.Dev.	Corr
ID	(Intercept)	0.005708	0.07555	
	Wave	0.012534	0.11196	-1.00
	Residual	0.025525	0.15977	

Number of obs: 131, groups: ID, 44

Fixed effects:

	Estimate	Std. Error	t value
--	----------	------------	---------

(Intercept)	0.96814	0.03870	25.018
Wave	-0.12159	0.02414	-5.036

Correlation of Fixed Effects:

(Intr)	
Wave	-0.838

## SEM Models

### Fixed SEM Model

---

```
> ### FIXED SLOPE
>
> sem_fixed = 'intercept =~ 1*Q1_Acc + 1*Q2_Acc + 1*Q3_Acc
+               slope =~ 0*Q1_Acc + 1*Q2_Acc + 2*Q3_Acc
+               slope ~~ 0*slope'
> sem_fixed_model = growth(sem_fixed, missing = "ML", data = cell_wide)
> summary(sem_fixed_model, fit.measures = TRUE)
```

---



---

lavaan (0.5-23.1097) converged normally after 46 iterations

Number of observations	44
Number of missing patterns	2
Estimator	ML
Minimum Function Test Statistic	9.596
Degrees of freedom	2
P-value (Chi-square)	0.008

Model test baseline model:

Minimum Function Test Statistic	18.464
Degrees of freedom	3
P-value	0.000

User model versus baseline model:

Comparative Fit Index (CFI)	0.509
Tucker-Lewis Index (TLI)	0.263

Loglikelihood and Information Criteria:

Loglikelihood user model (H0)	30.097
Loglikelihood unrestricted model (H1)	34.895
Number of free parameters	7
Akaike (AIC)	-46.193
Bayesian (BIC)	-33.704
Sample-size adjusted Bayesian (BIC)	-55.639

Root Mean Square Error of Approximation:

RMSEA	0.294
90 Percent Confidence Interval	0.127 0.491
P-value RMSEA <= 0.05	0.013

Standardized Root Mean Square Residual:

SRMR 0.138

Parameter Estimates:

Information	Observed
Standard Errors	Standard

Latent Variables:

	Estimate	Std.Err	z-value	P(> z )
intercept =~				
Q1_Acc	1.000			
Q2_Acc	1.000			
Q3_Acc	1.000			
slope =~				
Q1_Acc	0.000			
Q2_Acc	1.000			
Q3_Acc	2.000			

Covariances:

	Estimate	Std.Err	z-value	P(> z )
intercept ~~				
slope	0.005	0.004	1.149	0.251

Intercepts:

	Estimate	Std.Err	z-value	P(> z )
.Q1_Acc	0.000			
.Q2_Acc	0.000			
.Q3_Acc	0.000			
intercept	0.860	0.017	51.079	0.000
slope	-0.135	0.020	-6.599	0.000

Variances:

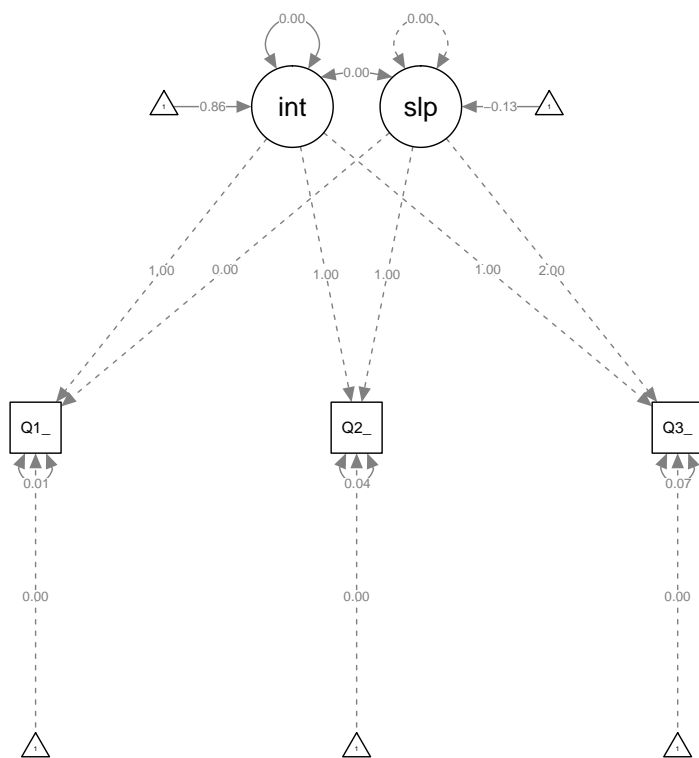
	Estimate	Std.Err	z-value	P(> z )
slope	0.000			
.Q1_Acc	0.010	0.006	1.595	0.111
.Q2_Acc	0.042	0.012	3.661	0.000
.Q3_Acc	0.074	0.020	3.801	0.000
intercept	0.002	0.006	0.349	0.727

Plotting

---

```
> semPaths(sem_fixed_model, whatLabels = "est")
```

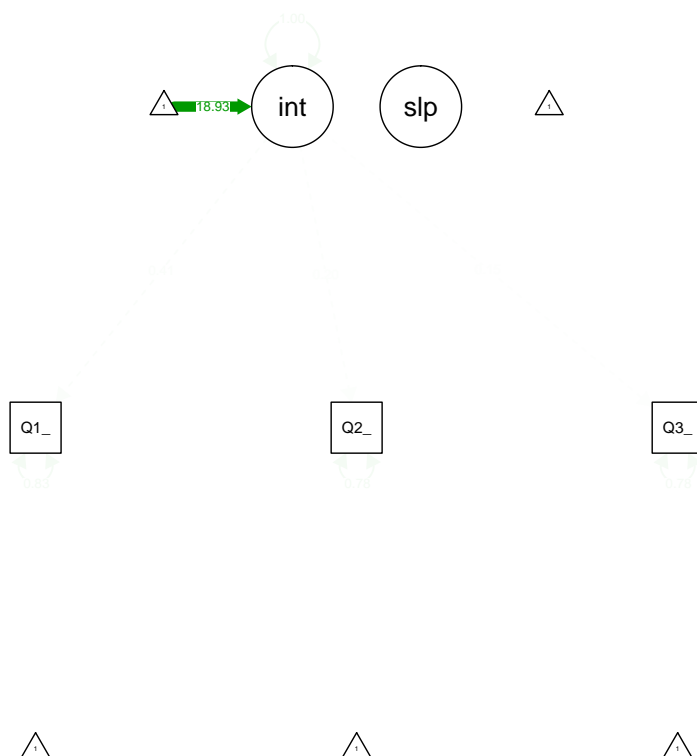
---




---

```
> semPaths(sem_fixed_model, what = "std")
```

---



## Random SEM Model

---

```
> ### RANDOM SLOPE
>
> sem_random = 'intercept =~ 1*Q1_Acc + 1*Q2_Acc + 1*Q3_Acc
+               slope =~ 0*Q1_Acc + 1*Q2_Acc + 2*Q3_Acc'
> sem_random_model = growth(sem_random, missing = "ML", data = cell_wide)
> summary(sem_random_model, fit.measures = TRUE)
```

---



---

*lavaan (0.5-23.1097) converged normally after 67 iterations*

<i>Number of observations</i>	<i>44</i>
<i>Number of missing patterns</i>	<i>2</i>
<i>Estimator</i>	<i>ML</i>
<i>Minimum Function Test Statistic</i>	<i>3.004</i>
<i>Degrees of freedom</i>	<i>1</i>
<i>P-value (Chi-square)</i>	<i>0.083</i>

*Model test baseline model:*

<i>Minimum Function Test Statistic</i>	<i>18.464</i>
<i>Degrees of freedom</i>	<i>3</i>
<i>P-value</i>	<i>0.000</i>

User model versus baseline model:

Comparative Fit Index (CFI)	0.870
Tucker-Lewis Index (TLI)	0.611

Loglikelihood and Information Criteria:

Loglikelihood user model (H0)	33.393
Loglikelihood unrestricted model (H1)	34.895
Number of free parameters	8
Akaike (AIC)	-50.785
Bayesian (BIC)	-36.512
Sample-size adjusted Bayesian (BIC)	-61.581

Root Mean Square Error of Approximation:

RMSEA	0.213
90 Percent Confidence Interval	0.000 0.509
P-value RMSEA <= 0.05	0.100

Standardized Root Mean Square Residual:

SRMR	0.070
------	-------

Parameter Estimates:

Information	Observed
Standard Errors	Standard

Latent Variables:

	Estimate	Std.Err	z-value	P(> z )
intercept =~				
Q1_Acc	1.000			
Q2_Acc	1.000			
Q3_Acc	1.000			
slope =~				
Q1_Acc	0.000			
Q2_Acc	1.000			
Q3_Acc	2.000			

Covariances:

	Estimate	Std.Err	z-value	P(> z )
intercept ~~				
slope	-0.005	0.005	-1.023	0.306

Intercepts:

	Estimate	Std.Err	z-value	P(> z )
.Q1_Acc	0.000			
.Q2_Acc	0.000			
.Q3_Acc	0.000			
intercept	0.868	0.017	52.132	0.000
slope	-0.132	0.023	-5.713	0.000

Variances:

	Estimate	Std.Err	z-value	P(> z )
.Q1_Acc	-0.004	0.007	-0.576	0.565



<i>.Q2_Acc</i>	0.040	0.010	3.933	0.000
<i>.Q3_Acc</i>	0.029	0.021	1.376	0.169
<i>intercept</i>	0.016	0.008	1.962	0.050
<i>slope</i>	0.017	0.006	2.590	0.010

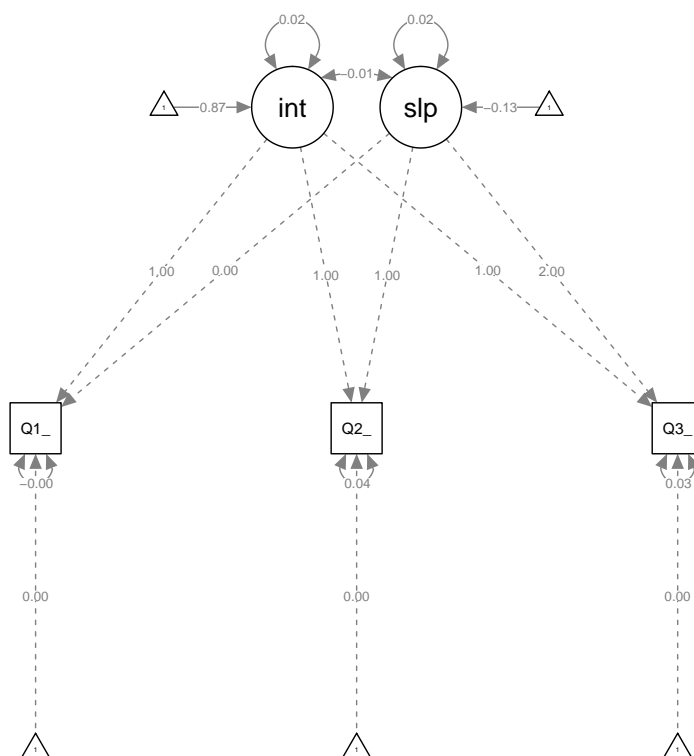
Changing from random to fixed (or the other way), changes the variance estimate of the slope. In the fixed SEM model, the variance estimate for the slope is 0 i.e. it is fixed, whereas is 0.017 in the random SEM model. Further, also note that the estimates themselves of the intercept and slope change, although only slightly.

## Plotting

---

```
> semPaths(sem_random_model, whatLabels = "est")
```

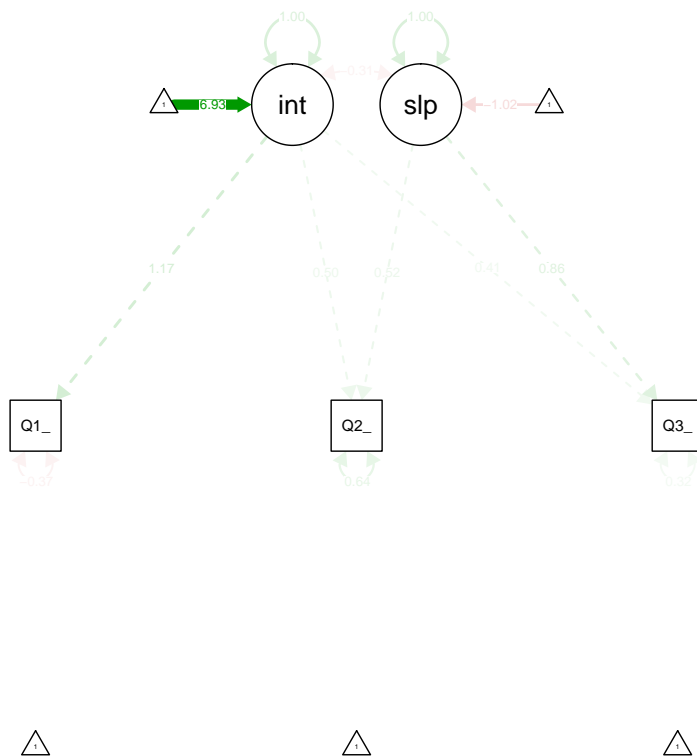
---




---

```
> semPaths(sem_random_model, what = "std")
```

---



## 6.1 Model Comparison

---

```
> anova(sem_fixed_model, sem_random_model) ## FIXED MODEL IS BETTER
```

---

Chi Square Difference Test

---

	Df	AIC	BIC	Chisq	Chisq diff
sem_random_model	1	-50.785	-36.512	3.0037	
sem_fixed_model	2	-46.193	-33.704	9.5956	6.5919

	Df	diff	Pr(>Chisq)
sem_random_model			
sem_fixed_model	1		0.01024 *

---  
 Signif. codes:  
 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

---

Comparing SEM and HLM models we realize that the estimates for the slope and intercept are close to each other in both models.

## 7 Constraining Residual Variances

---

```
> sem_res = 'intercept =~ 1*Q1_Acc + 1*Q2_Acc + 1*Q3_Acc
+           slope =~ 0*Q1_Acc + 1*Q2_Acc + 2*Q3_Acc
+           Q1_Acc ~~ a*Q1_Acc'
```

```

+           Q2_Acc ~~ a*Q2_Acc
+           Q3_Acc ~~ a*Q3_Acc'
> sem_res_model = growth(sem_res, missing = "ML", data = cell_wide)
> summary(sem_res_model, fit.measures =TRUE)

```

---

lavaan (0.5-23.1097) converged normally after 52 iterations

Number of observations	44
Number of missing patterns	2
Estimator	ML
Minimum Function Test Statistic	22.578
Degrees of freedom	3
P-value (Chi-square)	0.000

Model test baseline model:

Minimum Function Test Statistic	18.464
Degrees of freedom	3
P-value	0.000

User model versus baseline model:

Comparative Fit Index (CFI)	0.000
Tucker-Lewis Index (TLI)	-0.266

Loglikelihood and Information Criteria:

Loglikelihood user model (H0)	23.606
Loglikelihood unrestricted model (H1)	34.895
Number of free parameters	6
Akaike (AIC)	-35.211
Bayesian (BIC)	-24.506
Sample-size adjusted Bayesian (BIC)	-43.308

Root Mean Square Error of Approximation:

RMSEA	0.385
90 Percent Confidence Interval	0.247 0.541
P-value RMSEA <= 0.05	0.000

Standardized Root Mean Square Residual:

SRMR	0.365
------	-------

Parameter Estimates:

Information	Observed
Standard Errors	Standard

Latent Variables:

	Estimate	Std.Err	z-value	P(> z )
intercept =~				
Q1_Acc	1.000			
Q2_Acc	1.000			

```

      Q3_Acc          1.000
slope =~
      Q1_Acc          0.000
      Q2_Acc          1.000
      Q3_Acc          2.000

```

Covariances:

	Estimate	Std.Err	z-value	P(> z )
intercept ~~				
slope	0.010	0.005	2.207	0.027

Intercepts:

	Estimate	Std.Err	z-value	P(> z )
.Q1_Acc	0.000			
.Q2_Acc	0.000			
.Q3_Acc	0.000			
intercept	0.846	0.020	42.344	0.000
slope	-0.121	0.023	-5.294	0.000

Variances:

		Estimate	Std.Err	z-value	P(> z )
.Q1_Acc	(a)	0.031	0.007	4.668	0.000
.Q2_Acc	(a)	0.031	0.007	4.668	0.000
.Q3_Acc	(a)	0.031	0.007	4.668	0.000
intercept		-0.008	0.007	-1.251	0.211
slope		0.007	0.006	1.201	0.230

---

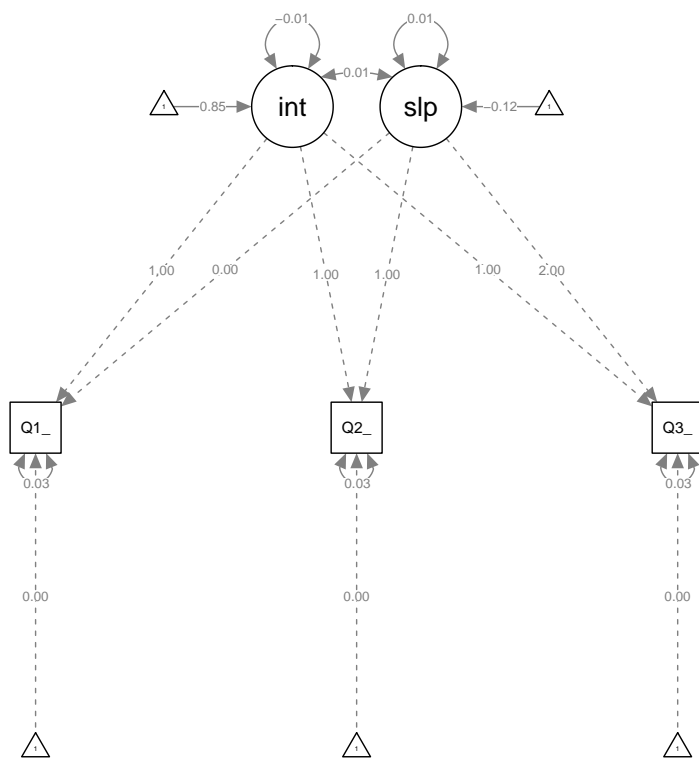
Constraining the residual variances changes the estimate of the slope and intercept, as well as the variance estimates of the slope and intercept. Note also that the variance estimate for the indicator variables is the same now, because we constrained it to be so.

## Plotting

---

```
> semPaths(sem_res_model, whatLabels = "est")
```

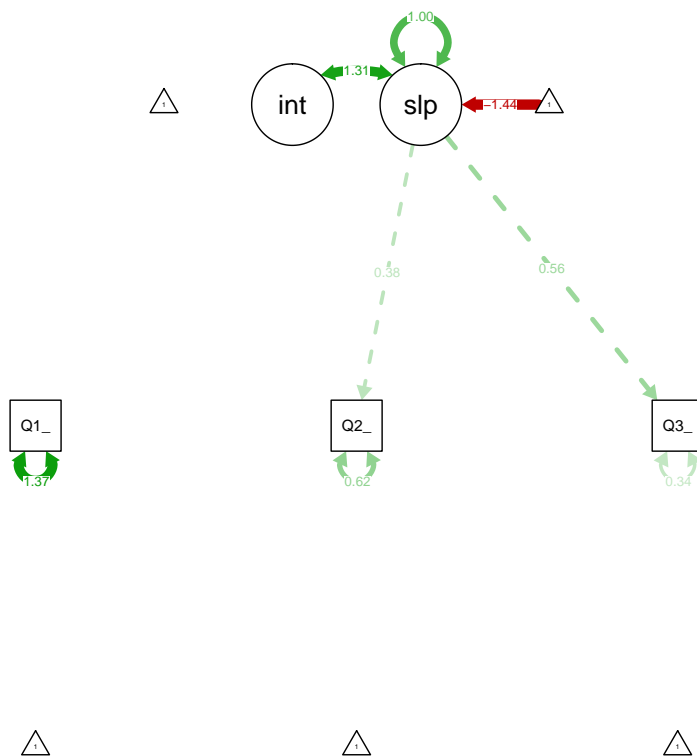
---




---

```
> semPaths(sem_res_model, what = "std")
```

---



## 7.1 Model Comparison

---

```
> anova(sem_random_model, sem_res_model) ## random model is better
```

---

Chi Square Difference Test

---

	Df	AIC	BIC	Chisq	Chisq diff
sem_random_model	1	-50.785	-36.512	3.0037	
sem_res_model	3	-35.211	-24.506	22.5775	19.574

	Df	diff	Pr(>Chisq)
sem_random_model			
sem_res_model	2	5.618e-05	***

---  
 Signif. codes:  
 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

---

## 8 Changing the Time Metric

We change centering to last wave instead of first wave. Note that we will use the random slope model as it has the lowest SRMR and RMSEA fit statistics.

---

```
> sem_time_model = 'intercept =~ 1*Q1_Acc + 1*Q2_Acc + 1*Q3_Acc
+ slope =~ -2*Q1_Acc + -1*Q2_Acc + 0*Q3_Acc'
```

---

```
> sem_time_model = growth(sem_time_model, missing = "ML", data = cell_wide)
> summary(sem_time_model, fit.measures = TRUE)
```

---

lavaan (0.5-23.1097) converged normally after 49 iterations

Number of observations	44
Number of missing patterns	2
Estimator	ML
Minimum Function Test Statistic	3.004
Degrees of freedom	1
P-value (Chi-square)	0.083

Model test baseline model:

Minimum Function Test Statistic	18.464
Degrees of freedom	3
P-value	0.000

User model versus baseline model:

Comparative Fit Index (CFI)	0.870
Tucker-Lewis Index (TLI)	0.611

Loglikelihood and Information Criteria:

Loglikelihood user model (H0)	33.393
Loglikelihood unrestricted model (H1)	34.895
Number of free parameters	8
Akaike (AIC)	-50.785
Bayesian (BIC)	-36.512
Sample-size adjusted Bayesian (BIC)	-61.581

Root Mean Square Error of Approximation:

RMSEA	0.213
90 Percent Confidence Interval	0.000 0.509
P-value RMSEA <= 0.05	0.100

Standardized Root Mean Square Residual:

SRMR	0.070
------	-------

Parameter Estimates:

Information	Observed
Standard Errors	Standard

Latent Variables:

	Estimate	Std.Err	z-value	P(> z )
intercept =~				
Q1_Acc	1.000			
Q2_Acc	1.000			
Q3_Acc	1.000			
slope =~				

<i>Q1_Acc</i>	-2.000			
<i>Q2_Acc</i>	-1.000			
<i>Q3_Acc</i>	0.000			
Covariances:				
	<i>Estimate</i>	<i>Std.Err</i>	<i>z-value</i>	<i>P(&gt; z )</i>
<i>intercept</i> ~~				
<i>slope</i>	0.028	0.012	2.476	0.013
Intercepts:				
	<i>Estimate</i>	<i>Std.Err</i>	<i>z-value</i>	<i>P(&gt; z )</i>
<i>.Q1_Acc</i>	0.000			
<i>.Q2_Acc</i>	0.000			
<i>.Q3_Acc</i>	0.000			
<i>intercept</i>	0.604	0.046	13.064	0.000
<i>slope</i>	-0.132	0.023	-5.713	0.000
Variances:				
	<i>Estimate</i>	<i>Std.Err</i>	<i>z-value</i>	<i>P(&gt; z )</i>
<i>.Q1_Acc</i>	-0.004	0.007	-0.576	0.565
<i>.Q2_Acc</i>	0.040	0.010	3.933	0.000
<i>.Q3_Acc</i>	0.029	0.021	1.376	0.169
<i>intercept</i>	0.062	0.024	2.643	0.008
<i>slope</i>	0.017	0.006	2.590	0.010

## 8.1 Model Comparison

---

```
> anova(sem_random_model, sem_time_model) ## no difference
```

---

### Chi Square Difference Test

---

	<i>Df</i>	<i>AIC</i>	<i>BIC</i>	<i>Chisq</i>	<i>Chisq diff</i>
<i>sem_random_model</i>	1	-50.785	-36.512	3.0037	
<i>sem_time_model</i>	1	-50.785	-36.512	3.0037	3.908e-14

---

	<i>Df diff</i>	<i>Pr(&gt;Chisq)</i>
<i>sem_random_model</i>		
<i>sem_time_model</i>	0	< 2.2e-16 ***

---

---  
Signif. codes:  
0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

---

## 8.2 Evaluating Fits

### 8.2.1 Fixed SEM Model

RMSEA: .294, SRMR = .138

### 8.2.2 Random SEM Model

RMSEA: .213, SRMR = .07

### 8.2.3 Constrained residual variances SEM Model

RMSEA: .385, SRMR = .365



### 8.2.4 Changed Time Metric SEM Model

RMSEA: .213, SRMR = .07

Thus, as we notice, changing the time metric for the random slope model does not change the overall fit of the SEM model. However, there is a change in the intercept, since we are now looking at differences in name accuracy in the LAST wave, as opposed to the first wave. Also note that there is NO change in the estimate of the slope variable, i.e. the overall association between Name Accuracy and Time doesn't change by changing the time metric. Also, the slope estimate is negative, which means there's a negative association between naming accuracy and time, which is consistent with the MLM models run previously.

## 9 Different Estimators

Our final model is the random slopes model. We now use a different estimation technique for this model to see if there are any differences. Since our data is not complete, we will only use estimators that don't require complete data: MLF and MLR.

---

```
> sem_random = 'intercept =~ 1*Q1_Acc + 1*Q2_Acc + 1*Q3_Acc
+               slope =~ 0*Q1_Acc + 1*Q2_Acc + 2*Q3_Acc'
> sem_random_mlf = growth(sem_random, data = cell_wide, estimator = "MLF")
> summary(sem_random_mlf, fit.measures = TRUE)
```

---

---

*lavaan (0.5-23.1097) converged normally after 91 iterations*

---

	<i>Used</i>	<i>Total</i>
<i>Number of observations</i>	43	44
<i>Estimator</i>	ML	
<i>Minimum Function Test Statistic</i>	2.742	
<i>Degrees of freedom</i>	1	
<i>P-value (Chi-square)</i>	0.098	

*Model test baseline model:*

<i>Minimum Function Test Statistic</i>	18.711
<i>Degrees of freedom</i>	3
<i>P-value</i>	0.000

*User model versus baseline model:*

<i>Comparative Fit Index (CFI)</i>	0.889
<i>Tucker-Lewis Index (TLI)</i>	0.667

*Loglikelihood and Information Criteria:*

<i>Loglikelihood user model (H0)</i>	32.672
<i>Loglikelihood unrestricted model (H1)</i>	34.043
<i>Number of free parameters</i>	8
<i>Akaike (AIC)</i>	-49.343
<i>Bayesian (BIC)</i>	-35.253
<i>Sample-size adjusted Bayesian (BIC)</i>	-60.314

*Root Mean Square Error of Approximation:*

<i>RMSEA</i>	0.201
<i>90 Percent Confidence Interval</i>	0.000 0.503
<i>P-value RMSEA &lt;= 0.05</i>	0.116

Standardized Root Mean Square Residual:

SRMR 0.067

Parameter Estimates:

Information Observed  
Standard Errors First.order

Latent Variables:

	Estimate	Std.Err	z-value	P(> z )
intercept =~				
Q1_Acc	1.000			
Q2_Acc	1.000			
Q3_Acc	1.000			
slope =~				
Q1_Acc	0.000			
Q2_Acc	1.000			
Q3_Acc	2.000			

Covariances:

	Estimate	Std.Err	z-value	P(> z )
intercept ~~				
slope	-0.005	0.007	-0.756	0.449

Intercepts:

	Estimate	Std.Err	z-value	P(> z )
.Q1_Acc	0.000			
.Q2_Acc	0.000			
.Q3_Acc	0.000			
intercept	0.865	0.023	38.076	0.000
slope	-0.129	0.032	-4.016	0.000

Variances:

	Estimate	Std.Err	z-value	P(> z )
.Q1_Acc	-0.005	0.010	-0.460	0.646
.Q2_Acc	0.041	0.017	2.422	0.015
.Q3_Acc	0.028	0.028	0.991	0.322
intercept	0.016	0.012	1.324	0.186
slope	0.017	0.009	1.797	0.072

---

```
> sem_random_mlr = growth(sem_random, data = cell_wide, estimator = "MLR")
> summary(sem_random_mlr, fit.measures = TRUE)
```

---

lavaan (0.5-23.1097) converged normally after 91 iterations

	Used	Total
Number of observations	43	44
Estimator	ML	Robust
Minimum Function Test Statistic	2.742	3.176
Degrees of freedom	1	1
P-value (Chi-square)	0.098	0.075
Scaling correction factor		0.863
for the Yuan-Bentler correction		

Model test baseline model:

Minimum Function Test Statistic	18.711	18.489
Degrees of freedom	3	3
P-value	0.000	0.000

User model versus baseline model:

Comparative Fit Index (CFI)	0.889	0.859
Tucker-Lewis Index (TLI)	0.667	0.578
Robust Comparative Fit Index (CFI)		0.880
Robust Tucker-Lewis Index (TLI)		0.640

Loglikelihood and Information Criteria:

Loglikelihood user model (H0)	32.672	32.672
Scaling correction factor for the MLR correction		1.020
Loglikelihood unrestricted model (H1)	34.043	34.043
Scaling correction factor for the MLR correction		1.003
Number of free parameters	8	8
Akaike (AIC)	-49.343	-49.343
Bayesian (BIC)	-35.253	-35.253
Sample-size adjusted Bayesian (BIC)	-60.314	-60.314

Root Mean Square Error of Approximation:

RMSEA	0.201	0.225
90 Percent Confidence Interval	0.000 0.503	0.000 0.000
P-value RMSEA <= 0.05	0.116	0.095
Robust RMSEA		0.209
90 Percent Confidence Interval		0.000 0.000

Standardized Root Mean Square Residual:

SRMR	0.067	0.067
------	-------	-------

Parameter Estimates:

Information	Observed
Standard Errors	Robust.huber.white

Latent Variables:

	Estimate	Std.Err	z-value	P(> z )
intercept =~				
Q1_Acc	1.000			
Q2_Acc	1.000			
Q3_Acc	1.000			
slope =~				
Q1_Acc	0.000			
Q2_Acc	1.000			
Q3_Acc	2.000			

Covariances:

	Estimate	Std.Err	z-value	P(> z )
intercept ~~				
slope	-0.005	0.005	-1.128	0.259

Intercepts:

	Estimate	Std.Err	z-value	P(> z )
.Q1_Acc	0.000			
.Q2_Acc	0.000			
.Q3_Acc	0.000			
intercept	0.865	0.017	51.187	0.000
slope	-0.129	0.023	-5.636	0.000

Variances:

	Estimate	Std.Err	z-value	P(> z )
.Q1_Acc	-0.005	0.006	-0.762	0.446
.Q2_Acc	0.041	0.007	5.741	0.000
.Q3_Acc	0.028	0.017	1.605	0.108
intercept	0.016	0.006	2.611	0.009
slope	0.017	0.006	2.737	0.006

Note that the estimates of slope and intercept slightly change if we change the estimator, but the overall fit remains the same.

## 10 Adding New Latent Variable

```
> sem_two_lv = 'name_intercept =~ 1*Q1_Acc + 1*Q2_Acc + 1*Q3_Acc
+               name_slope =~ 0*Q1_Acc + 1*Q2_Acc + 2*Q3_Acc
+               time_intercept =~ 1*Q1_td + 1*Q2_td + 1*Q3_td
+               time_slope =~ 0*Q1_td + 1*Q2_td + 2*Q3_td'
> sem_twolv_model = growth(sem_two_lv, data = cell_wide, estimator = "MLF")
> summary(sem_twolv_model, fit.measures = TRUE)
```

lavaan (0.5-23.1097) converged normally after 160 iterations

	Used	Total
Number of observations	43	44
Estimator	ML	
Minimum Function Test Statistic	8.663	
Degrees of freedom	7	
P-value (Chi-square)	0.278	

Model test baseline model:

Minimum Function Test Statistic	43.590
Degrees of freedom	15
P-value	0.000

User model versus baseline model:

Comparative Fit Index (CFI)	0.942
Tucker-Lewis Index (TLI)	0.875

Loglikelihood and Information Criteria:

Loglikelihood user model (H0)	141.135
Loglikelihood unrestricted model (H1)	145.466
Number of free parameters	20
Akaike (AIC)	-242.270
Bayesian (BIC)	-207.046
Sample-size adjusted Bayesian (BIC)	-269.697

Root Mean Square Error of Approximation:

RMSEA	0.074
90 Percent Confidence Interval	0.000 0.211
P-value RMSEA <= 0.05	0.349

Standardized Root Mean Square Residual:

SRMR	0.080
------	-------

Parameter Estimates:

Information	Observed
Standard Errors	First.order

Latent Variables:

	Estimate	Std.Err	z-value	P(> z )
name_intercept =~				
Q1_Acc	1.000			
Q2_Acc	1.000			
Q3_Acc	1.000			
name_slope =~				
Q1_Acc	0.000			
Q2_Acc	1.000			
Q3_Acc	2.000			
time_intercept =~				
Q1_td	1.000			
Q2_td	1.000			
Q3_td	1.000			
time_slope =~				
Q1_td	0.000			
Q2_td	1.000			
Q3_td	2.000			

Covariances:

	Estimate	Std.Err	z-value	P(> z )
name_intercept ~~				
name_slope	-0.005	0.008	-0.631	0.528
time_intercept	-0.001	0.002	-0.463	0.644
time_slope	-0.002	0.003	-0.804	0.422
name_slope ~~				
time_intercept	0.001	0.002	0.477	0.633
time_slope	-0.007	0.005	-1.245	0.213
time_intercept ~~				
time_slope	0.001	0.005	0.298	0.766

Intercepts:

	Estimate	Std.Err	z-value	P(> z )
.Q1_Acc	0.000			
.Q2_Acc	0.000			

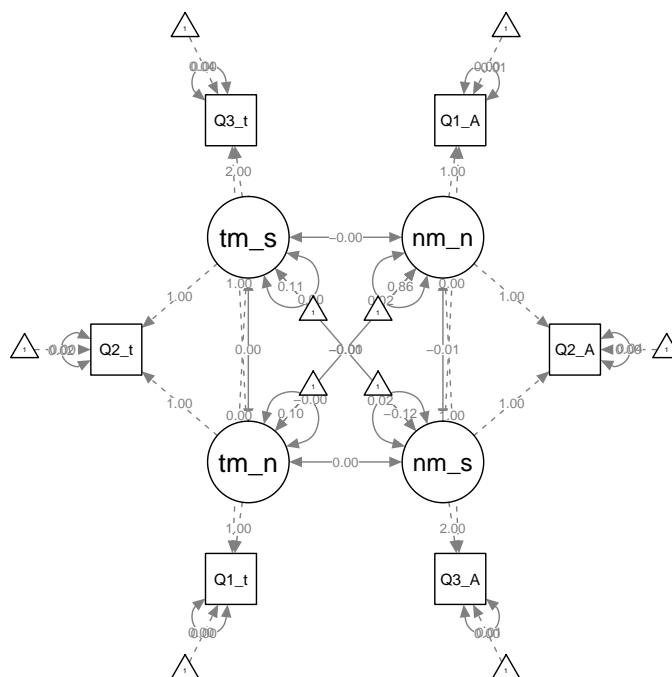
.Q3_Acc	0.000			
.Q1_td	0.000			
.Q2_td	0.000			
.Q3_td	0.000			
name_intercept	0.865	0.026	33.263	0.000
name_slope	-0.125	0.047	-2.665	0.008
time_intercept	0.101	0.014	7.389	0.000
time_slope	0.108	0.028	3.800	0.000

Variances:

	Estimate	Std.Err	z-value	P(> z )
.Q1_Acc	-0.005	0.014	-0.371	0.710
.Q2_Acc	0.045	0.024	1.901	0.057
.Q3_Acc	0.013	0.038	0.336	0.737
.Q1_td	0.005	0.006	0.791	0.429
.Q2_td	0.016	0.006	2.548	0.011
.Q3_td	0.042	0.015	2.758	0.006
name_intercept	0.016	0.015	1.134	0.257
name_slope	0.020	0.014	1.430	0.153
time_intercept	-0.002	0.006	-0.407	0.684
time_slope	0.001	0.007	0.166	0.868

## Plotting

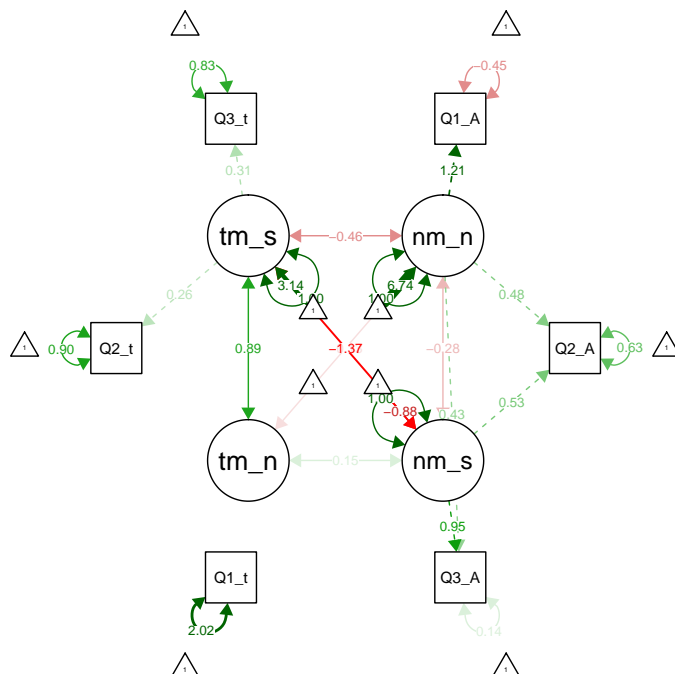
```
> semPaths(sem_twolv_model, layout = "circle2", whatLabels = "est")
```



---

```
> semPaths(sem_twolv_model, layout = "circle2", what = "std")
```

---



## 11 Adding Another Predictor

---

```
> sem_newpred = 'name_intercept =~ 1*Q1_Acc + 1*Q2_Acc + 1*Q3_Acc
+
+       name_slope =~ 0*Q1_Acc + 1*Q2_Acc + 2*Q3_Acc
+
+       time_intercept =~ 1*Q1_td + 1*Q2_td + 1*Q3_td
+
+       time_slope =~ 0*Q1_td + 1*Q2_td + 2*Q3_td
+
+       Q1_Acc ~ Q1_v
+       Q2_Acc ~ Q2_v
+       Q3_Acc ~ Q3_v'
> sem_newpred = growth(sem_newpred, data = cell_wide, estimator = "MLF")
> summary(sem_newpred, fit.measures = TRUE)
```

---

lavaan (0.5-23.1097) converged normally after 157 iterations

	Used	Total
Number of observations	43	44
Estimator	ML	
Minimum Function Test Statistic	920.951	
Degrees of freedom	22	
P-value (Chi-square)	0.000	

Model test baseline model:

Minimum Function Test Statistic	962.853
Degrees of freedom	33
P-value	0.000

User model versus baseline model:

Comparative Fit Index (CFI)	0.033
Tucker-Lewis Index (TLI)	-0.450

Loglikelihood and Information Criteria:

Loglikelihood user model (H0)	244.531
Loglikelihood unrestricted model (H1)	705.007
Number of free parameters	23
Akaike (AIC)	-443.063
Bayesian (BIC)	-402.555
Sample-size adjusted Bayesian (BIC)	-474.605

Root Mean Square Error of Approximation:

RMSEA	0.975
90 Percent Confidence Interval	0.922 1.029
P-value RMSEA <= 0.05	0.000

Standardized Root Mean Square Residual:

SRMR	0.325
------	-------

Parameter Estimates:

Information	Observed
Standard Errors	First.order

Latent Variables:

	Estimate	Std.Err	z-value	P(> z )
name_intercept =~				
Q1_Acc	1.000			
Q2_Acc	1.000			
Q3_Acc	1.000			
name_slope =~				
Q1_Acc	0.000			
Q2_Acc	1.000			
Q3_Acc	2.000			
time_intercept =~				
Q1_td	1.000			
Q2_td	1.000			
Q3_td	1.000			
time_slope =~				
Q1_td	0.000			
Q2_td	1.000			
Q3_td	2.000			

Regressions:

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



Q1_Acc ~				
Q1_v	1.483	1.406	1.055	0.291
Q2_Acc ~				
Q2_v	-0.127	0.286	-0.446	0.655
Q3_Acc ~				
Q3_v	-0.322	0.367	-0.878	0.380

Covariances:

	Estimate	Std.Err	z-value	P(> z )
name_intercept ~~				
name_slope	-0.010	0.009	-1.047	0.295
time_intercept	-0.004	0.004	-1.083	0.279
time_slope	0.001	0.004	0.148	0.883
name_slope ~~				
time_intercept	0.003	0.002	1.366	0.172
time_slope	-0.006	0.006	-0.871	0.384
time_intercept ~~				
time_slope	0.001	0.005	0.181	0.856

Intercepts:

	Estimate	Std.Err	z-value	P(> z )
.Q1_Acc	0.000			
.Q2_Acc	0.000			
.Q3_Acc	0.000			
.Q1_td	0.000			
.Q2_td	0.000			
.Q3_td	0.000			
name_intercept	0.713	0.154	4.629	0.000
name_slope	0.004	0.121	0.035	0.972
time_intercept	0.101	0.015	6.972	0.000
time_slope	0.108	0.031	3.499	0.000

Variances:

	Estimate	Std.Err	z-value	P(> z )
.Q1_Acc	-0.003	0.012	-0.280	0.780
.Q2_Acc	0.038	0.023	1.630	0.103
.Q3_Acc	0.010	0.037	0.267	0.789
.Q1_td	0.004	0.006	0.656	0.512
.Q2_td	0.015	0.007	2.281	0.023
.Q3_td	0.044	0.022	1.994	0.046
name_intercept	0.022	0.018	1.224	0.221
name_slope	0.021	0.012	1.648	0.099
time_intercept	-0.001	0.006	-0.260	0.795
time_slope	0.002	0.007	0.229	0.819

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>

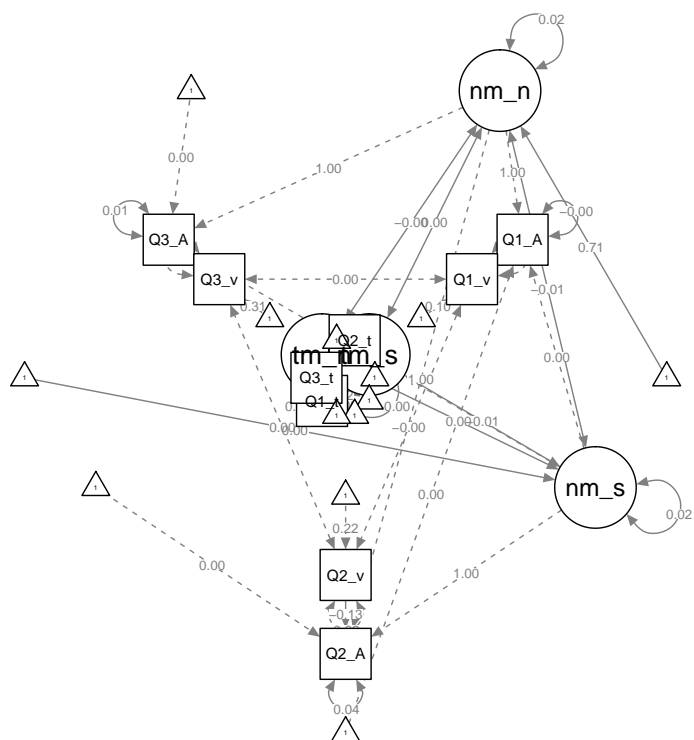
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---

> semPaths(sem\_newpred, layout = "circle2", whatLabels = "est")

---




---

```
> semPaths(sem_newpred, layout = "circle2", what = "std")
```

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