

PSC205A Assignment 07: Longitudinal Multivariate

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Read in data

```
library(lavaan)
library(ggplot2)

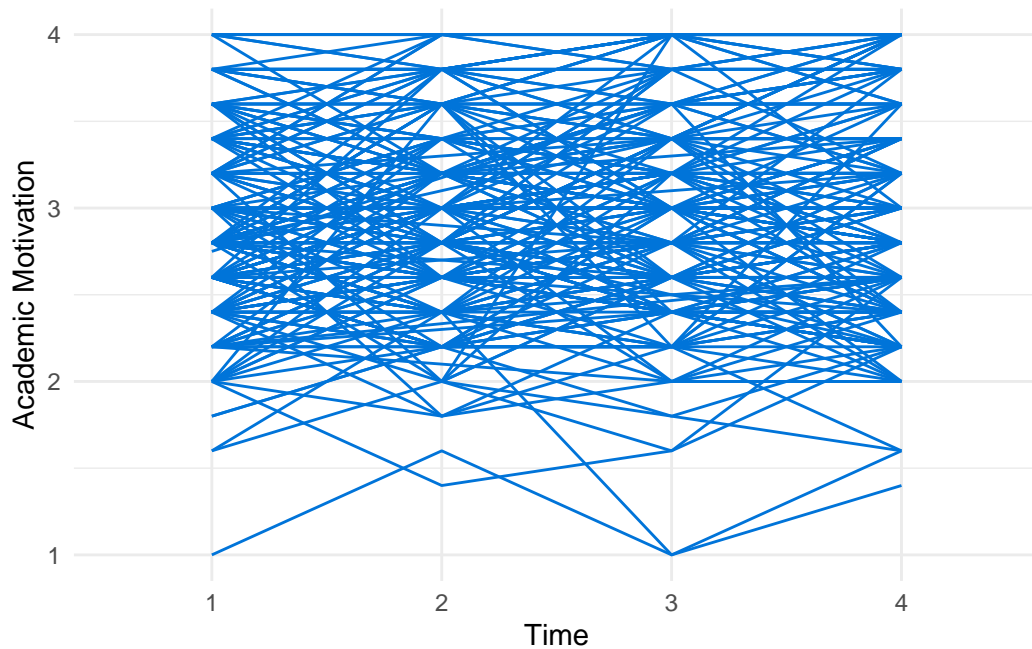
mhs <- read.csv("mhs.csv", na.strings = ".")
```

1. Individual trajectories plot

These plots show us that we should not expect an accentuated change over time in academic motivation and perceived competence. It is possible that the results show these variables remain stable over the four time points.

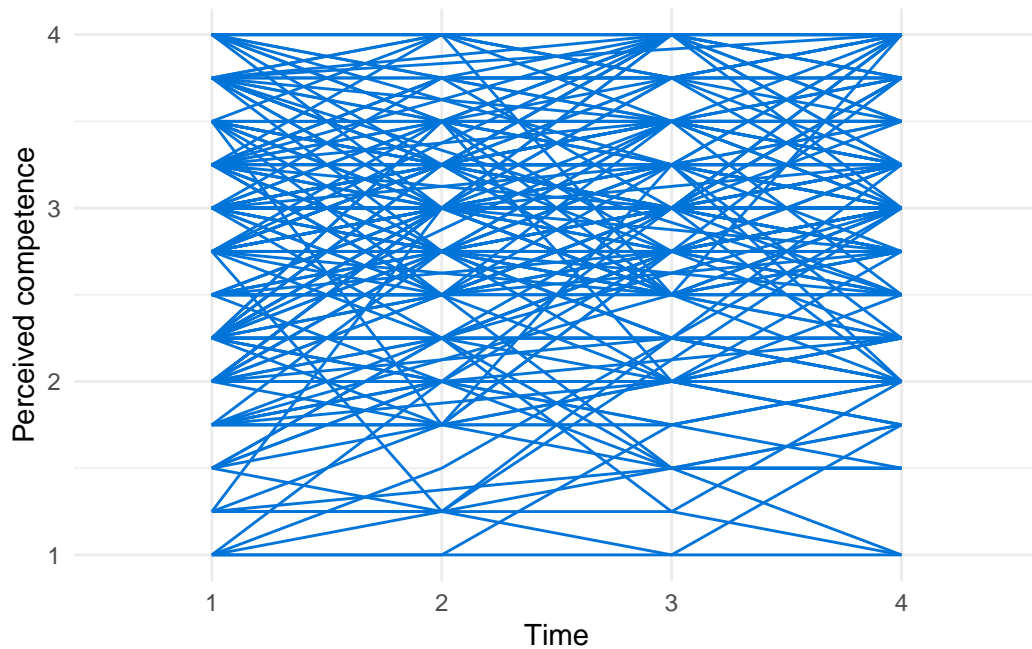
```
mot_data <- mhs |>
  dplyr::select(id, mot1:mot4) |>
  tidyr::pivot_longer(cols = c(mot1:mot4),
                      names_to = "timepoint",
                      names_prefix = "mot",
                      names_transform = as.factor,
                      values_to = "motivation") |>
  dplyr::filter(!is.na(motivation))

ggplot(mot_data, aes(x = timepoint, y = motivation, group = id)) +
  #geom_point()+
  geom_line(color = "#0074D9")+
  theme_minimal()+
  labs(x = "Time", y = "Academic Motivation")
```



```
pc_data <- mhs |>
  dplyr::select(id, pc1:pc4) |>
  tidyr::pivot_longer(cols = c(pc1:pc4),
    names_to = "timepoint",
    names_prefix = "pc",
    names_transform = as.factor,
    values_to = "competence") |>
  dplyr::filter(!is.na(competence))

ggplot(pc_data, aes(x = timepoint, y = competence, group = id)) +
  #geom_point()+
  geom_line(color = "#0074D9")+
  theme_minimal()+
  labs(x = "Time", y = "Perceived competence")
```



2. Latent Growth model

Both models show a small positive slope, suggesting a slight positive growth of academic motivation and perceived competence over time. Additionally, for both models, the covariance between slope and intercept is non-significantly different from zero, meaning that initial values on the target variable do not influence the expected growth over time.

```
mod_mot <- "i =~ 1*mot1 + 1*mot2 + 1*mot3 + 1*mot4
            s =~ 0*mot1 + 1*mot2 + 2*mot3 + 3*mot4"

fit_mot <- growth(mod_mot, missing="fiml", data=mhs)
```

Warning in lav_data_full(data = data, group = group, cluster = cluster, : lavaan WARNING: some observed variables have missing values
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```
summary(fit_mot, standardized=TRUE)
```

lavaan 0.6.16 ended normally after 43 iterations

Estimator	ML	
Optimization method	NLMINB	
Number of model parameters	9	
	Used	Total
Number of observations	261	263
Number of missing patterns	14	

Model Test User Model:

Test statistic	4.980
Degrees of freedom	5
P-value (Chi-square)	0.418

Parameter Estimates:

Standard errors	Standard
Information	Observed
Observed information based on	Hessian

Latent Variables:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
i =~						
mot1	1.000				0.453	0.823
mot2	1.000				0.453	0.790
mot3	1.000				0.453	0.765
mot4	1.000				0.453	0.735
s =~						
mot1	0.000				0.000	0.000
mot2	1.000				0.098	0.171
mot3	2.000				0.196	0.331
mot4	3.000				0.295	0.477

Covariances:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
i ~~						
s	0.005	0.008	0.559	0.576	0.104	0.104

Intercepts:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
.mot1	0.000				0.000	0.000
.mot2	0.000				0.000	0.000
.mot3	0.000				0.000	0.000

.mot4	0.000				0.000	0.000
i	2.836	0.034	83.492	0.000	6.254	6.254
s	0.043	0.011	3.838	0.000	0.440	0.440

Variances:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
.mot1	0.098	0.020	4.939	0.000	0.098	0.323
.mot2	0.105	0.014	7.667	0.000	0.105	0.318
.mot3	0.089	0.013	7.005	0.000	0.089	0.253
.mot4	0.061	0.018	3.370	0.001	0.061	0.160
i	0.206	0.029	7.109	0.000	1.000	1.000
s	0.010	0.004	2.318	0.020	1.000	1.000

```
mod_pc <- "i =~ 1*pc1 + 1*pc2 + 1*pc3 + 1*pc4
          s =~ 0*pc1 + 1*pc2 + 2*pc3 + 3*pc4"

fit_pc <- growth(mod_pc, missing="fiml", data=mhs)
```

Warning in lav_data_full(data = data, group = group, cluster = cluster, : lavaan WARNING: some observed variables have missing values
160 162

```
summary(fit_pc , standardized=TRUE)
```

lavaan 0.6.16 ended normally after 46 iterations

Estimator	ML	
Optimization method	NLMINB	
Number of model parameters	9	
	Used	Total
Number of observations	261	263
Number of missing patterns	14	

Model Test User Model:

Test statistic	15.293
Degrees of freedom	5
P-value (Chi-square)	0.009

Parameter Estimates:

Standard errors
Information
Observed information based on

Standard
Observed
Hessian

Latent Variables:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
i =~						
pc1	1.000				0.660	0.876
pc2	1.000				0.660	0.904
pc3	1.000				0.660	0.951
pc4	1.000				0.660	0.932
s =~						
pc1	0.000				0.000	0.000
pc2	1.000				0.097	0.133
pc3	2.000				0.194	0.279
pc4	3.000				0.291	0.410

Covariances:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
i ~~						
s	-0.018	0.012	-1.538	0.124	-0.279	-0.279

Intercepts:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
.pc1	0.000				0.000	0.000
.pc2	0.000				0.000	0.000
.pc3	0.000				0.000	0.000
.pc4	0.000				0.000	0.000
i	2.767	0.046	59.858	0.000	4.192	4.192
s	0.066	0.012	5.343	0.000	0.680	0.680

Variances:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
.pc1	0.132	0.024	5.498	0.000	0.132	0.233
.pc2	0.123	0.017	7.320	0.000	0.123	0.232
.pc3	0.080	0.013	6.209	0.000	0.080	0.166
.pc4	0.088	0.020	4.487	0.000	0.088	0.175
i	0.436	0.051	8.552	0.000	1.000	1.000
s	0.009	0.005	2.049	0.041	1.000	1.000

3. Group differences

Testing for differences in trajectories of perceived competence between males and females, it was found that males (`female = 0`) start at higher values in T1 than females (`female = 1`) but have a less steep slope of latent growth compared to the target group. That indicates that although males start with higher perceived competence, the change over time is more accentuated for females. For both groups, the covariance between intercept and slope is non-significantly different from zero, following the group trend of non-association between rate of change and initial values of perceived competence.

```
fit_pc_inv <- growth(mod_pc, group = "female", data=mhs)
```

Warning in lav_data_full(data = data, group = group, cluster = cluster, : lavaan WARNING: gr

```
summary(fit_pc_inv)
```

lavaan 0.6.16 ended normally after 67 iterations

Estimator	ML	
Optimization method	NLMINB	
Number of model parameters	18	
Number of observations per group:	Used	Total
1	68	106
0	85	147

Model Test User Model:

Test statistic	17.332
Degrees of freedom	10
P-value (Chi-square)	0.067
Test statistic for each group:	
1	1.650
0	15.682

Parameter Estimates:

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

Group 1 [1]:

Latent Variables:

	Estimate	Std.Err	z-value	P(> z)
i =~				
pc1	1.000			
pc2	1.000			
pc3	1.000			
pc4	1.000			
s =~				
pc1	0.000			
pc2	1.000			
pc3	2.000			
pc4	3.000			

Covariances:

	Estimate	Std.Err	z-value	P(> z)
i ~~				
s	-0.000	0.013	-0.016	0.987

Intercepts:

	Estimate	Std.Err	z-value	P(> z)
.pc1	0.000			
.pc2	0.000			
.pc3	0.000			
.pc4	0.000			
i	2.459	0.081	30.407	0.000
s	0.083	0.017	4.834	0.000

Variances:

	Estimate	Std.Err	z-value	P(> z)
.pc1	0.116	0.033	3.513	0.000
.pc2	0.089	0.020	4.529	0.000
.pc3	0.078	0.018	4.292	0.000
.pc4	0.026	0.021	1.233	0.218
i	0.375	0.077	4.849	0.000
s	0.008	0.005	1.447	0.148

Group 2 [0]:

Latent Variables:

	Estimate	Std.Err	z-value	P(> z)
i =~				
pc1	1.000			
pc2	1.000			
pc3	1.000			
pc4	1.000			
s =~				
pc1	0.000			
pc2	1.000			
pc3	2.000			
pc4	3.000			

Covariances:

	Estimate	Std.Err	z-value	P(> z)
i ~~				
s	-0.004	0.013	-0.309	0.757

Intercepts:

	Estimate	Std.Err	z-value	P(> z)
.pc1	0.000			
.pc2	0.000			
.pc3	0.000			
.pc4	0.000			
i	3.108	0.063	49.471	0.000
s	0.055	0.017	3.296	0.001

Variances:

	Estimate	Std.Err	z-value	P(> z)
.pc1	0.116	0.031	3.737	0.000
.pc2	0.131	0.025	5.340	0.000
.pc3	0.061	0.015	4.033	0.000
.pc4	0.114	0.027	4.282	0.000
i	0.253	0.054	4.681	0.000
s	0.001	0.005	0.183	0.855

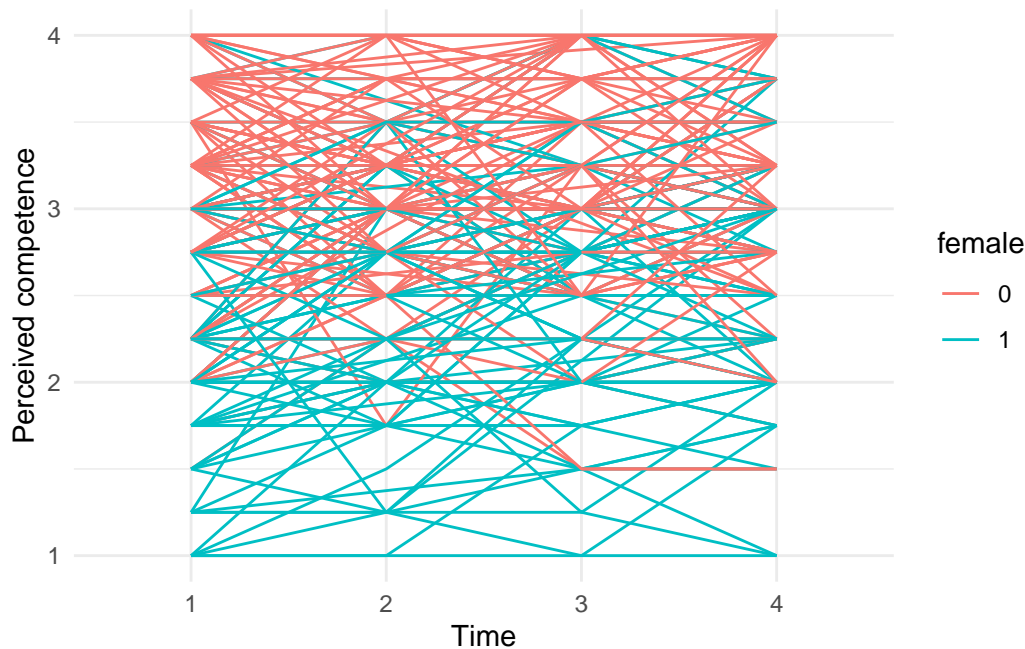
```
pc_data_sex <- mhs |>
  dplyr::select(id, female, pc1:pc4) |>
  tidyr::pivot_longer(cols = c(pc1:pc4),
    names_to = "timepoint",
    names_prefix = "pc",
    names_transform = as.factor,
```

```

      values_to = "competence") |>
dplyr::mutate(female = factor(female)) |>
dplyr::filter(!is.na(competence), !is.na(female))

ggplot(pc_data_sex, aes(x = timepoint, y = competence, group = id, color=female)) +
  #geom_point()+
  geom_line()+
  theme_minimal()+
  labs(x = "Time", y = "Perceived competence")

```



4. Interrelations between perceived competence and motivation

The correlation between motivation and competence intercepts is large and positive, suggesting that participants with higher starting values on motivation also start with higher values on perceived competence and vice-versa. Similar to the individual model analyses, none of the intercepts were significantly associated with the slopes, indicating no relation between starting values and change. However, as with the intercepts, the slopes' correlations of the two latent growths are significant, and positive, meaning that participants who change on one variable tend to change in the other in the same direction.

```

mod_complete <-
" mot_i =~ 1*mot1 + 1*mot2 + 1*mot3 + 1*mot4
  mot_s =~ 0*mot1 + 1*mot2 + 2*mot3 + 3*mot4

  pc_i =~ 1*pc1 + 1*pc2 + 1*pc3 + 1*pc4
  pc_s =~ 0*pc1 + 1*pc2 + 2*pc3 + 3*pc4
"

fit_complete <- growth(mod_complete,missing="fiml", data=mhs)

```

Warning in lav_data_full(data = data, group = group, cluster = cluster, : lavaan WARNING: some observed variables are missing
160 162

```
summary(fit_complete, standardized=TRUE)
```

lavaan 0.6.16 ended normally after 87 iterations

Estimator	ML	
Optimization method	NLMINB	
Number of model parameters	22	
	Used	Total
Number of observations	261	263
Number of missing patterns	18	

Model Test User Model:

Test statistic	43.624
Degrees of freedom	22
P-value (Chi-square)	0.004

Parameter Estimates:

Standard errors	Standard
Information	Observed
Observed information based on	Hessian

Latent Variables:

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

mot1	1.000	0.460	0.836
mot2	1.000	0.460	0.793
mot3	1.000	0.460	0.771
mot4	1.000	0.460	0.743
mot_s =~			
mot1	0.000	0.000	0.000
mot2	1.000	0.104	0.180
mot3	2.000	0.208	0.349
mot4	3.000	0.312	0.505
pc_i =~			
pc1	1.000	0.663	0.878
pc2	1.000	0.663	0.908
pc3	1.000	0.663	0.941
pc4	1.000	0.663	0.936
pc_s =~			
pc1	0.000	0.000	0.000
pc2	1.000	0.102	0.140
pc3	2.000	0.205	0.291
pc4	3.000	0.307	0.434

Covariances:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
mot_i ~~						
mot_s	0.003	0.008	0.373	0.709	0.064	0.064
pc_i	0.200	0.028	7.077	0.000	0.656	0.656
pc_s	-0.002	0.007	-0.371	0.711	-0.053	-0.053
mot_s ~~						
pc_i	0.010	0.008	1.179	0.238	0.141	0.141
pc_s	0.003	0.002	1.217	0.224	0.241	0.241
pc_i ~~						
pc_s	-0.018	0.011	-1.609	0.108	-0.266	-0.266

Intercepts:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
.mot1	0.000				0.000	0.000
.mot2	0.000				0.000	0.000
.mot3	0.000				0.000	0.000
.mot4	0.000				0.000	0.000
.pc1	0.000				0.000	0.000
.pc2	0.000				0.000	0.000
.pc3	0.000				0.000	0.000
.pc4	0.000				0.000	0.000
mot_i	2.838	0.034	83.412	0.000	6.171	6.171

mot_s	0.043	0.011	3.843	0.000	0.413	0.413
pc_i	2.764	0.046	59.764	0.000	4.172	4.172
pc_s	0.064	0.012	5.233	0.000	0.627	0.627

Variances:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
.mot1	0.091	0.019	4.839	0.000	0.091	0.301
.mot2	0.108	0.014	7.923	0.000	0.108	0.321
.mot3	0.089	0.012	7.310	0.000	0.089	0.249
.mot4	0.056	0.017	3.317	0.001	0.056	0.145
.pc1	0.131	0.023	5.644	0.000	0.131	0.230
.pc2	0.120	0.016	7.298	0.000	0.120	0.224
.pc3	0.087	0.013	6.838	0.000	0.087	0.175
.pc4	0.076	0.019	4.121	0.000	0.076	0.152
mot_i	0.211	0.029	7.263	0.000	1.000	1.000
mot_s	0.011	0.004	2.690	0.007	1.000	1.000
pc_i	0.439	0.051	8.644	0.000	1.000	1.000
pc_s	0.010	0.004	2.337	0.019	1.000	1.000

5. Perceived competence growth curve analysis

```
mod_pc_latent <- "

PC_1 =~ pc1_1 + pc2_1 + pc3_1 + pc4_1
PC_2 =~ pc1_2 + pc2_2 + pc3_2 + pc4_2
PC_3 =~ pc1_3 + pc2_3 + pc3_3 + pc4_3
PC_4 =~ pc1_4 + pc2_4 + pc3_4 + pc4_4

PCi =~ 1*PC_1 + 1*PC_2 + 1*PC_3 + 1*PC_4
PCs =~ 0*PC_1 + 1*PC_2 + 2*PC_3 + 3*PC_4

"
```

Group invariance

Given the non-significant difference in the chi squared tests across the more restricted models, it is possible to assume that males and females are invariant in perceived competence across all levels of measurement invariance, except for the residuals.

```

fit.configural = sem(mod_pc_latent,data=mhs, group="female", missing="fiml", group.equal=c
fit.loadings   = sem(mod_pc_latent,data=mhs, group="female", missing="fiml", group.equal=c
fit.intercepts = sem(mod_pc_latent,data=mhs, group="female", missing="fiml", group.equal=c
fit.varcov     = sem(mod_pc_latent,data=mhs, group="female", missing="fiml", group.equal=c
fit.regress    = sem(mod_pc_latent,data=mhs, group="female", missing="fiml", group.equal=c
fit.invariant  = sem(mod_pc_latent,data=mhs, group="female",
                    group.equal=c("loadings","intercepts", "lv.variances","lv.covariances

anova(fit.configural, fit.loadings, fit.intercepts, fit.varcov, fit.regress, fit.invariant
knitr::kable(caption = "Multiple group invariance test.", digits=3)

```

Table 1: Multiple group invariance test.

	Df	AIC	BIC	Chisq	Chisq diff	RMSEA	Df diff	Pr(>Chisq)
fit.configural	202	6564.273	6923.869	441.993	NA	NA	NA	NA
fit.loadings	214	6545.497	6862.788	447.217	5.224	0.000	12	0.950
fit.intercepts	224	6531.768	6813.804	453.489	6.271	0.000	10	0.792
fit.varcov	231	6524.699	6782.058	460.420	6.931	0.000	7	0.436
fit.regress	231	6524.699	6782.058	460.420	0.000	0.000	0	NA
fit.invariant	247	4384.317	4555.542	532.668	72.248	0.167	16	0.000

Growth curve

Similar to the results found in Q2, the correlation between intercept and slope is negative but non-significant. The growth curve slope of this model was positive, just as found in the analysis using composite scores. However, the statistical significance was not computed because the model failed to converge. We can suppose that this model also shows a positive growth of perceived competence over time.

```

fit_growth <- growth(mod_pc_latent, missing="fiml", data=mhs)
summary(fit_growth, standardized=TRUE, fit.measures=TRUE)

```

lavaan 0.6.16 ended normally after 62 iterations

Estimator	ML	
Optimization method	NLMINB	
Number of model parameters	41	
	Used	Total
Number of observations	261	263

Number of missing patterns	16
----------------------------	----

Model Test User Model:

Test statistic	278.215
Degrees of freedom	111
P-value (Chi-square)	0.000

Model Test Baseline Model:

Test statistic	2240.393
Degrees of freedom	120
P-value	0.000

User Model versus Baseline Model:

Comparative Fit Index (CFI)	0.921
Tucker-Lewis Index (TLI)	0.915
Robust Comparative Fit Index (CFI)	NA
Robust Tucker-Lewis Index (TLI)	NA

Loglikelihood and Information Criteria:

Loglikelihood user model (H0)	-3320.338
Loglikelihood unrestricted model (H1)	-3181.230
Akaike (AIC)	6722.675
Bayesian (BIC)	6868.820
Sample-size adjusted Bayesian (SABIC)	6738.833

Root Mean Square Error of Approximation:

RMSEA	0.076
90 Percent confidence interval - lower	0.065
90 Percent confidence interval - upper	0.087
P-value H ₀ : RMSEA ≤ 0.050	0.000
P-value H ₀ : RMSEA ≥ 0.080	0.285
Robust RMSEA	NA
90 Percent confidence interval - lower	NA
90 Percent confidence interval - upper	NA
P-value H ₀ : Robust RMSEA ≤ 0.050	NA

P-value H_0: Robust RMSEA >= 0.080 NA

Standardized Root Mean Square Residual:

SRMR 0.088

Parameter Estimates:

Standard errors	Standard
Information	Observed
Observed information based on	Hessian

Latent Variables:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
PC_1 =~						
pc1_1	1.000				0.696	0.725
pc2_1	0.972	0.020	49.752	0.000	0.676	0.760
pc3_1	0.930	0.019	47.974	0.000	0.647	0.736
pc4_1	0.978	0.022	45.169	0.000	0.680	0.695
PC_2 =~						
pc1_2	1.000				0.679	0.786
pc2_2	0.983	0.018	54.136	0.000	0.668	0.764
pc3_2	0.979	0.017	57.268	0.000	0.664	0.797
pc4_2	0.989	0.020	50.356	0.000	0.672	0.724
PC_3 =~						
pc1_3	1.000				0.652	0.826
pc2_3	0.973	0.016	61.017	0.000	0.635	0.749
pc3_3	0.973	0.014	67.379	0.000	0.635	0.801
pc4_3	0.997	0.017	59.037	0.000	0.650	0.733
PC_4 =~						
pc1_4	1.000				0.670	0.856
pc2_4	0.969	0.015	66.808	0.000	0.649	0.777
pc3_4	0.929	0.015	60.098	0.000	0.623	0.725
pc4_4	0.978	0.016	61.529	0.000	0.656	0.737
PCi =~						
PC_1	1.000				0.951	0.951
PC_2	1.000				0.974	0.974
PC_3	1.000				1.014	1.014
PC_4	1.000				0.987	0.987
PCs =~						
PC_1	0.000				0.000	0.000
PC_2	1.000				0.140	0.140
PC_3	2.000				0.291	0.291

PC_4	3.000				0.425	0.425
Covariances:						
	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
PCi ~~						
PCs	-0.015	0.012	-1.253	0.210	-0.242	-0.242
Intercepts:						
	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
.pc1_1	0.000				0.000	0.000
.pc2_1	0.000				0.000	0.000
.pc3_1	0.000				0.000	0.000
.pc4_1	0.000				0.000	0.000
.pc1_2	0.000				0.000	0.000
.pc2_2	0.000				0.000	0.000
.pc3_2	0.000				0.000	0.000
.pc4_2	0.000				0.000	0.000
.pc1_3	0.000				0.000	0.000
.pc2_3	0.000				0.000	0.000
.pc3_3	0.000				0.000	0.000
.pc4_3	0.000				0.000	0.000
.pc1_4	0.000				0.000	0.000
.pc2_4	0.000				0.000	0.000
.pc3_4	0.000				0.000	0.000
.pc4_4	0.000				0.000	0.000
.PC_1	1.093	31412.608	0.000	1.000	1.570	1.570
.PC_2	0.635	29527.481	0.000	1.000	0.934	0.934
.PC_3	0.221	24972.703	0.000	1.000	0.339	0.339
.PC_4	-0.194	15557.734	-0.000	1.000	-0.289	-0.289
PCi	1.754	31412.608	0.000	1.000	2.652	2.652
PCs	0.495	NA			5.218	5.218
Variances:						
	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
.pc1_1	0.437	0.048	9.042	0.000	0.437	0.475
.pc2_1	0.334	0.039	8.594	0.000	0.334	0.422
.pc3_1	0.355	0.040	8.965	0.000	0.355	0.459
.pc4_1	0.496	0.053	9.409	0.000	0.496	0.517
.pc1_2	0.285	0.034	8.405	0.000	0.285	0.382
.pc2_2	0.318	0.037	8.584	0.000	0.318	0.416
.pc3_2	0.253	0.031	8.261	0.000	0.253	0.365
.pc4_2	0.409	0.046	8.853	0.000	0.409	0.476
.pc1_3	0.198	0.024	8.208	0.000	0.198	0.318

.pc2_3	0.315	0.035	9.101	0.000	0.315	0.439
.pc3_3	0.225	0.026	8.720	0.000	0.225	0.359
.pc4_3	0.364	0.039	9.236	0.000	0.364	0.462
.pc1_4	0.164	0.023	7.285	0.000	0.164	0.268
.pc2_4	0.277	0.032	8.719	0.000	0.277	0.396
.pc3_4	0.349	0.038	9.175	0.000	0.349	0.474
.pc4_4	0.361	0.040	9.099	0.000	0.361	0.457
.PC_1	0.047	0.027	1.711	0.087	0.096	0.096
.PC_2	0.045	0.018	2.515	0.012	0.097	0.097
.PC_3	0.013	0.014	0.923	0.356	0.030	0.030
.PC_4	0.021	0.021	1.043	0.297	0.048	0.048
PCi	0.438	0.053	8.203	0.000	1.000	1.000
PCs	0.009	0.005	1.915	0.055	1.000	1.000

6. Extra

Modeling motivation and competence as latent variables and examining their change yielded results similar to what was found by examining the growth change using composite scores. That is, there is a positive correlation between motivation and competence intercepts but no significant correlation between intercepts and slopes. The slopes of the two latent growths are correlated significantly and positively, just as the results using composite scores. Overall, that means that using composites or modeling the latent factors gives comparable results with little loss of information.

```
mod_complete_latent <- "

MOT_1 =~ mot1_1 + mot2_1 + mot3_1 + mot4_1
MOT_2 =~ mot1_2 + mot2_2 + mot3_2 + mot4_2
MOT_3 =~ mot1_3 + mot2_3 + mot3_3 + mot4_3
MOT_4 =~ mot1_4 + mot2_4 + mot3_4 + mot4_4

MOTi =~ 1*MOT_1 + 1*MOT_2 + 1*MOT_3 + 1*MOT_4
MOTs =~ 0*MOT_1 + 1*MOT_2 + 2*MOT_3 + 3*MOT_4

PC_1 =~ pc1_1 + pc2_1 + pc3_1 + pc4_1
PC_2 =~ pc1_2 + pc2_2 + pc3_2 + pc4_2
PC_3 =~ pc1_3 + pc2_3 + pc3_3 + pc4_3
PC_4 =~ pc1_4 + pc2_4 + pc3_4 + pc4_4

PCi =~ 1*PC_1 + 1*PC_2 + 1*PC_3 + 1*PC_4
PCs =~ 0*PC_1 + 1*PC_2 + 2*PC_3 + 3*PC_4
```

"

```
fit_growth_complete <- growth(mod_complete_latent, missing="fiml", data=mhs)
summary(fit_growth_complete, standardized=TRUE, fit.measures=TRUE)
```

lavaan 0.6.16 ended normally after 106 iterations

Estimator	ML	
Optimization method	NLMINB	
Number of model parameters	86	
	Used	Total
Number of observations	261	263
Number of missing patterns	21	

Model Test User Model:

Test statistic	1117.411
Degrees of freedom	474
P-value (Chi-square)	0.000

Model Test Baseline Model:

Test statistic	3880.742
Degrees of freedom	496
P-value	0.000

User Model versus Baseline Model:

Comparative Fit Index (CFI)	0.810
Tucker-Lewis Index (TLI)	0.801
Robust Comparative Fit Index (CFI)	NA
Robust Tucker-Lewis Index (TLI)	NA

Loglikelihood and Information Criteria:

Loglikelihood user model (H0)	-7131.999
Loglikelihood unrestricted model (H1)	-6573.293
Akaike (AIC)	14435.997

Bayesian (BIC)	14742.546
Sample-size adjusted Bayesian (SABIC)	14469.890

Root Mean Square Error of Approximation:

RMSEA	0.072
90 Percent confidence interval - lower	0.067
90 Percent confidence interval - upper	0.078
P-value H ₀ : RMSEA ≤ 0.050	0.000
P-value H ₀ : RMSEA ≥ 0.080	0.009

Robust RMSEA	NA
90 Percent confidence interval - lower	NA
90 Percent confidence interval - upper	NA
P-value H ₀ : Robust RMSEA ≤ 0.050	NA
P-value H ₀ : Robust RMSEA ≥ 0.080	NA

Standardized Root Mean Square Residual:

SRMR	0.095
------	-------

Parameter Estimates:

Standard errors	Standard
Information	Observed
Observed information based on	Hessian

Latent Variables:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
MOT_1 =~						
mot1_1	1.000				0.466	0.632
mot2_1	0.646	0.019	33.438	0.000	0.301	0.328
mot3_1	0.919	0.019	49.674	0.000	0.428	0.504
mot4_1	0.862	0.019	46.497	0.000	0.401	0.468
MOT_2 =~						
mot1_2	1.000				0.493	0.570
mot2_2	0.753	0.021	36.075	0.000	0.371	0.428
mot3_2	0.980	0.022	44.501	0.000	0.483	0.556
mot4_2	0.911	0.021	43.382	0.000	0.449	0.538
MOT_3 =~						
mot1_3	1.000				0.506	0.662
mot2_3	0.709	0.019	37.163	0.000	0.359	0.393
mot3_3	0.945	0.018	52.679	0.000	0.478	0.568

mot4_3	0.874	0.017	50.570	0.000	0.442	0.544
MOT_4 =~						
mot1_4	1.000				0.553	0.651
mot2_4	0.714	0.019	37.661	0.000	0.395	0.436
mot3_4	0.912	0.019	48.454	0.000	0.504	0.572
mot4_4	0.875	0.018	48.146	0.000	0.484	0.568
MOTi =~						
MOT_1	1.000				0.980	0.980
MOT_2	1.000				0.927	0.927
MOT_3	1.000				0.903	0.903
MOT_4	1.000				0.826	0.826
MOTs =~						
MOT_1	0.000				0.000	0.000
MOT_2	1.000				0.176	0.176
MOT_3	2.000				0.343	0.343
MOT_4	3.000				0.470	0.470
PC_1 =~						
pc1_1	1.000				0.697	0.725
pc2_1	0.973	0.019	49.925	0.000	0.678	0.765
pc3_1	0.930	0.019	47.793	0.000	0.649	0.735
pc4_1	0.978	0.022	45.075	0.000	0.682	0.695
PC_2 =~						
pc1_2	1.000				0.679	0.789
pc2_2	0.984	0.018	54.408	0.000	0.668	0.765
pc3_2	0.979	0.017	57.291	0.000	0.665	0.795
pc4_2	0.989	0.020	50.457	0.000	0.672	0.723
PC_3 =~						
pc1_3	1.000				0.664	0.833
pc2_3	0.971	0.016	61.549	0.000	0.645	0.756
pc3_3	0.971	0.014	67.613	0.000	0.645	0.804
pc4_3	0.995	0.017	59.011	0.000	0.661	0.736
PC_4 =~						
pc1_4	1.000				0.670	0.853
pc2_4	0.970	0.015	66.627	0.000	0.650	0.778
pc3_4	0.930	0.015	60.113	0.000	0.623	0.728
pc4_4	0.979	0.016	61.277	0.000	0.656	0.737
PCi =~						
PC_1	1.000				0.953	0.953
PC_2	1.000				0.979	0.979
PC_3	1.000				1.001	1.001
PC_4	1.000				0.993	0.993
PCs =~						
PC_1	0.000				0.000	0.000

PC_2	1.000	0.150	0.150
PC_3	2.000	0.306	0.306
PC_4	3.000	0.456	0.456

Covariances:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
MOTi ~~						
MOTs	0.011	0.012	0.940	0.347	0.279	0.279
PCi	0.225	0.032	7.124	0.000	0.741	0.741
PCs	-0.005	0.008	-0.601	0.548	-0.098	-0.098
MOTs ~~						
PCi	0.006	0.010	0.552	0.581	0.096	0.096
PCs	0.004	0.003	1.475	0.140	0.432	0.432
PCi ~~						
PCs	-0.016	0.012	-1.346	0.178	-0.234	-0.234

Intercepts:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
.mot1_1	0.000				0.000	0.000
.mot2_1	0.000				0.000	0.000
.mot3_1	0.000				0.000	0.000
.mot4_1	0.000				0.000	0.000
.mot1_2	0.000				0.000	0.000
.mot2_2	0.000				0.000	0.000
.mot3_2	0.000				0.000	0.000
.mot4_2	0.000				0.000	0.000
.mot1_3	0.000				0.000	0.000
.mot2_3	0.000				0.000	0.000
.mot3_3	0.000				0.000	0.000
.mot4_3	0.000				0.000	0.000
.mot1_4	0.000				0.000	0.000
.mot2_4	0.000				0.000	0.000
.mot3_4	0.000				0.000	0.000
.mot4_4	0.000				0.000	0.000
.pc1_1	0.000				0.000	0.000
.pc2_1	0.000				0.000	0.000
.pc3_1	0.000				0.000	0.000
.pc4_1	0.000				0.000	0.000
.pc1_2	0.000				0.000	0.000
.pc2_2	0.000				0.000	0.000
.pc3_2	0.000				0.000	0.000
.pc4_2	0.000				0.000	0.000
.pc1_3	0.000				0.000	0.000

.pc2_3	0.000		0.000	0.000
.pc3_3	0.000		0.000	0.000
.pc4_3	0.000		0.000	0.000
.pc1_4	0.000		0.000	0.000
.pc2_4	0.000		0.000	0.000
.pc3_4	0.000		0.000	0.000
.pc4_4	0.000		0.000	0.000
.MOT_1	1.282	NA	2.752	2.752
.MOT_2	0.627	NA	1.272	1.272
.MOT_3	0.274	NA	0.541	0.541
.MOT_4	-0.214	NA	-0.387	-0.387
MOTi	1.968	NA	4.310	4.310
MOTs	0.532	NA	6.138	6.138
.PC_1	1.093	NA	1.567	1.567
.PC_2	0.630	NA	0.927	0.927
.PC_3	0.223	NA	0.335	0.335
.PC_4	-0.194	NA	-0.289	-0.289
PCi	1.752	NA	2.634	2.634
PCs	0.494	NA	4.856	4.856

Variances:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
.mot1_1	0.326	0.037	8.826	0.000	0.326	0.600
.mot2_1	0.752	0.073	10.240	0.000	0.752	0.893
.mot3_1	0.538	0.059	9.098	0.000	0.538	0.746
.mot4_1	0.574	0.060	9.591	0.000	0.574	0.781
.mot1_2	0.505	0.055	9.197	0.000	0.505	0.676
.mot2_2	0.612	0.063	9.660	0.000	0.612	0.816
.mot3_2	0.522	0.060	8.697	0.000	0.522	0.691
.mot4_2	0.494	0.054	9.166	0.000	0.494	0.710
.mot1_3	0.328	0.036	9.006	0.000	0.328	0.562
.mot2_3	0.703	0.070	10.005	0.000	0.703	0.845
.mot3_3	0.481	0.053	9.136	0.000	0.481	0.678
.mot4_3	0.465	0.048	9.587	0.000	0.465	0.704
.mot1_4	0.417	0.046	9.098	0.000	0.417	0.577
.mot2_4	0.666	0.068	9.808	0.000	0.666	0.810
.mot3_4	0.522	0.057	9.144	0.000	0.522	0.672
.mot4_4	0.491	0.052	9.475	0.000	0.491	0.677
.pc1_1	0.440	0.049	9.064	0.000	0.440	0.475
.pc2_1	0.326	0.038	8.580	0.000	0.326	0.415
.pc3_1	0.358	0.040	8.999	0.000	0.358	0.460
.pc4_1	0.498	0.053	9.431	0.000	0.498	0.517
.pc1_2	0.279	0.033	8.430	0.000	0.279	0.377

.pc2_2	0.317	0.037	8.624	0.000	0.317	0.415
.pc3_2	0.258	0.031	8.332	0.000	0.258	0.368
.pc4_2	0.412	0.046	8.891	0.000	0.412	0.477
.pc1_3	0.195	0.024	8.187	0.000	0.195	0.306
.pc2_3	0.311	0.034	9.090	0.000	0.311	0.428
.pc3_3	0.228	0.026	8.725	0.000	0.228	0.353
.pc4_3	0.369	0.040	9.246	0.000	0.369	0.458
.pc1_4	0.169	0.023	7.477	0.000	0.169	0.273
.pc2_4	0.275	0.031	8.802	0.000	0.275	0.394
.pc3_4	0.345	0.037	9.223	0.000	0.345	0.470
.pc4_4	0.361	0.039	9.165	0.000	0.361	0.456
.MOT_1	0.008	0.031	0.277	0.782	0.039	0.039
.MOT_2	0.005	0.022	0.208	0.835	0.019	0.019
.MOT_3	-0.027	0.018	-1.465	0.143	-0.105	-0.105
.MOT_4	-0.036	0.028	-1.319	0.187	-0.119	-0.119
MOTi	0.208	0.037	5.653	0.000	1.000	1.000
MOTs	0.008	0.006	1.286	0.198	1.000	1.000
.PC_1	0.044	0.026	1.697	0.090	0.091	0.091
.PC_2	0.041	0.017	2.365	0.018	0.088	0.088
.PC_3	0.021	0.014	1.536	0.124	0.048	0.048
.PC_4	0.008	0.020	0.423	0.672	0.018	0.018
PCi	0.442	0.053	8.315	0.000	1.000	1.000
PCs	0.010	0.005	2.252	0.024	1.000	1.000