Multi-level SEM – part 1

SEM for between-subjects and mixed designs

Intro

Today's goal:

Teach how to do multi-level CFA and SEM in R and Mplus

Outline:

- Intro to Mplus (including common method bias!)
- Why multi-level?
- Multi-level CFA and SEM in R
- Multi-level CFA and SEM in Mplus

Intro to Mplus

Confirmatory Factor Analysis

Specifying a CFA

```
DATA: FILE IS twq.datm;
VARIABLE:
 names are s1 s2 s3 s4 s5 s6 s7 q1 q2 q3 q4 q5 q6
  c1 c2 c3 c4 c5 u1 u2 u3 u4 u5 cgraph citem cfriend;

 usevariables are s1-s7 q1-q6 c1-c4 u2 u4 u5;
 categorical are all;

MODEL:
 satisf  by s1-s7;
 quality by q1-q6;
 control by c1-c4;
 underst by u2 u4 u5;

OUTPUT:
 standardized;
 modindices(3.84);
```

Run the model

Running the model:

- Save file as model.inp
- Run the model, this will create and open model.out
- Inspect model output file (for UVI results, look under STDYX, STDY, or STD)
- Iterate (not needed here)

Tip: When trimming, remove items from usevariables as well!

Method bias

To test common method bias, change the following:

```
MODEL:
 satisf  by s1-s7*;
 quality by q1-q6*;
 control by c1-c4*;
 underst by u2* u4 u5;

 method by s1-u5* (a);
 satisf-method@1;
 method with satisf-underst@0;
```

Interpretation

We force UVI in the main model

- Using stars to free up the first loading and satisf-method@1 to set the factor variances to 1

We create a "method" factor with all items

- They all load equally on the factor (a)
- We make the factor orthogonal to the other factors (method with satsif-underst@0)

The bias is significant, but not strong

- It doesn't affect the factor model much

Specifying an SEM

VARIABLE:
names are s1 s2 s3 s4 s5 s6 s7 q1 q2 q3 q4 q5 q6
c1 c2 c3 c4 c5 u1 u2 u3 u4 u5 cgraph citem cfriend;

usevariables are s1-s7 q1-q6 c1-c4 u2 u4 u5 **cgraph citem cfriend;**
categorical are **s1-u5;**

MODEL:
satisf by s1-s7;
quality by q1-q6;
control by c1-c4;
underst by u2 u4 u5;

satisf on quality control;
quality on control;
control on underst;
underst on cgraph citem cfriend (p1-p3);

Tips

Different outputs:

- Regular results: not standardized
- STDYX standardization: standardizes factors, and any single-time variables that are either x or y
- STDY standardization: same, but does not standardize single-item variables that are x (experimental conditions!)
- STD standardization: standardizes only the factors

Here, we use STDY

Or STD, same thing!

Tips

You can test omnibus effects like this:

```
MODEL TEST:
 p2=0;
 p3=0;
```

Shows up under Wald Test of Parameter Constraints

You can create your own interaction effects:

```
DEFINE:
 cig = citem*cgraph;
 cfg = cfriend*cgraph;
```

Why multi-level?

Dealing with within-subjects and mixed designs

Why multi-level?

Repeated measurements

e.g. participants make 30 decisions

(Partially) within-subjects design

e.g. participants are randomly assigned to 1 of 3 games, and tested once with sound on and once with sound off

Grouped data

e.g. participants perform tasks in groups of 5

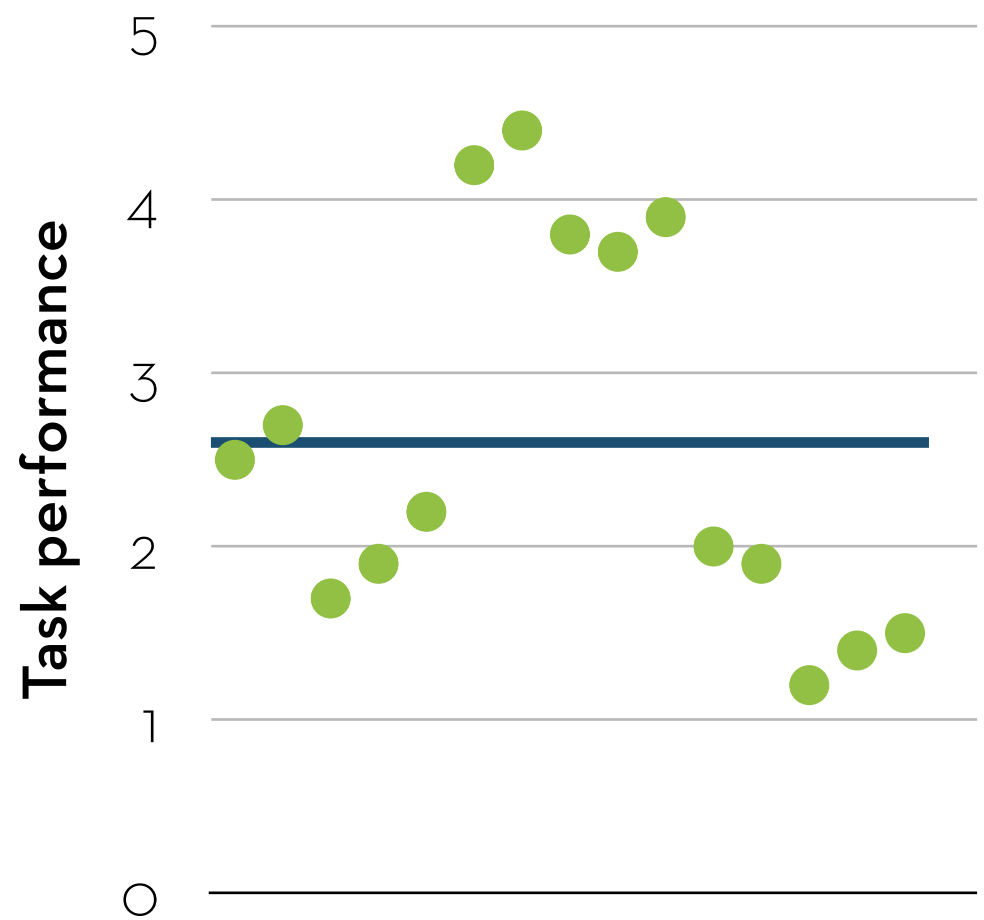
A combination of the above

Correlated errors

Consequence: errors are correlated

- There will be a user-bias (and maybe an task-bias)

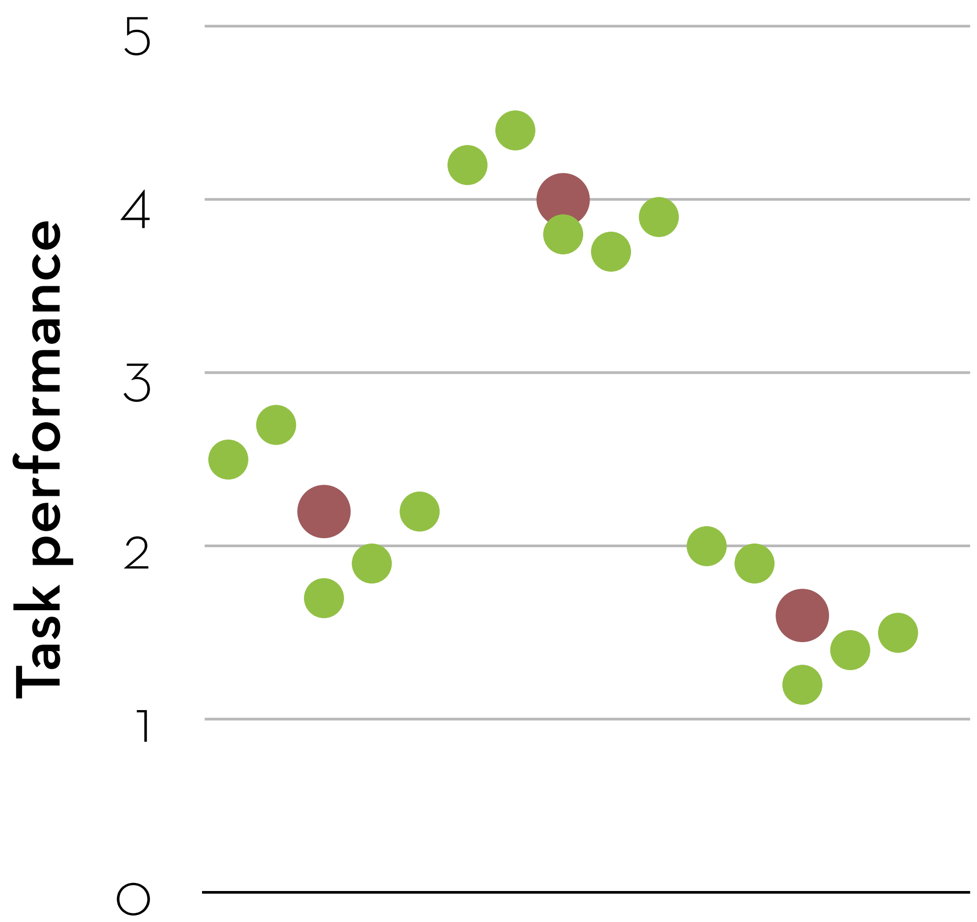
Golden rule: data-points should be **independent**



OK solution

Take the average of the repeated measurements

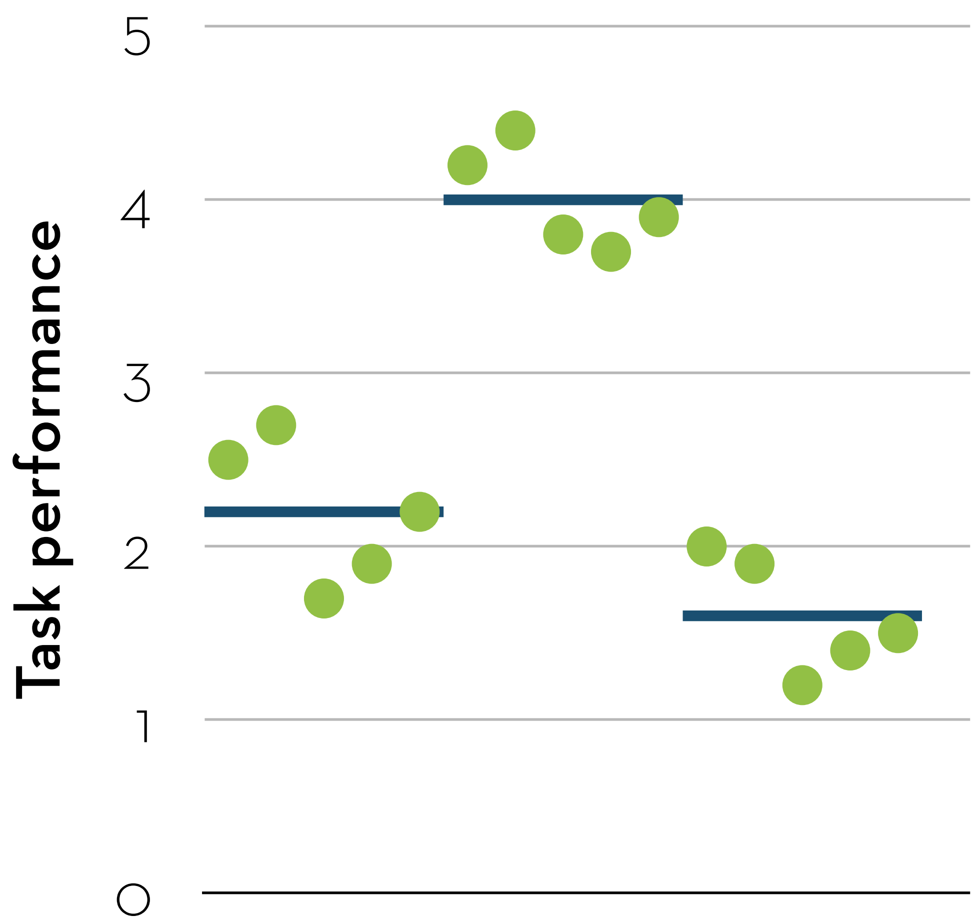
- Reduces the number of observations
- It becomes impossible to make inferences about individual tasks/users/etc.



Good solution

In regression:

- define a random intercept for each user
- impose an error covariance structure
- see "multilevel" of M&E I



In SEM:

- use lavaan.survey (limited)
- use Mplus (better)

Multi-level in R

CFA and SEM

Multi-level in R

Dataset:

Participants rate a number of movies

Participants are randomly assigned to a certain recommendation list length

- 5, 10, 15, 20, or 15 items

Participants get to see three recommendation lists

- low, mid, and high diversification
- In random order

Multi-level in R

Per participant:

- length: length of recommendation list (5, 10, 15, 20, or 25)
- pref1–4: strength of preference (4 items, 7pt scales)
- exp1–4: movie expertise

Multi-level in R

Per list:

divmid, divhigh: dummies for diversification of recommendation list (baseline: low)

chodiff: choice difficulty (single item, 7pt scale)

to: tradeoff difficulty (single item, 7pt scale)

var1–4: perceived recommendation diversity (7pt scales)

acc1–6: perceived recommendation attractiveness

Specifying a CFA

Specify the model:

```
model <- "acc =~ acc1+acc2+acc3+acc4+acc5+acc6
var =~ var1+var2+var3+var4
pref =~ pref1+pref2+pref3+pref4
exp =~ exp1+exp2+exp3+exp4"
```

Run the model:

```
fit <- cfa(model, ordered=names(divR), data=divR, std.lv=T)
```

Get the output:

```
summary(fit, rsquare=T, fit.measures=T)
```

Modification indices:

```
mods <- modindices(fit, power=T)
mods <- mods[grep(“\\*”,mods$decision),]
```

Selected output

```
  Estimator                                         DWLS      Robust
  Minimum Function Test Statistic                487.089     498.526
  Degrees of freedom                                 129         129
  P-value (Chi-square)                             0.000       0.000
  Scaling correction factor                                    1.121
  Shift parameter                                             64.179
    for simple second-order correction (Mplus variant)

User model versus baseline model:

  Comparative Fit Index (CFI)                      0.991       0.978
  Tucker-Lewis Index (TLI)                         0.990       0.974

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

Root Mean Square Error of Approximation:

  RMSEA                                            0.098       0.099
  90 Percent Confidence Interval          0.089  0.107       0.090  0.109
  P-value RMSEA <= 0.05                            0.000       0.000

  Robust RMSEA                                                    NA
  90 Percent Confidence Interval                                  NA     NA
```

Selected output

```
R-Square:
                   Estimate
    acc1              0.834
    acc2              0.677
    acc3              0.945
    acc4              0.696
    acc5              0.891
    acc6              0.593
    var1              0.837
    var2              0.662
    var3              0.557
    var4              0.635
    pref1             0.782
    pref2             0.864
    pref3             0.266
    pref4             0.047
    exp1              0.688
    exp2              0.905
    exp3              0.704
    exp4              0.688
```

Selected output

	lhs	op	rhs	mi	mi.scaled	epc	sepc.all	delta	ncp	power	decision
192	acc	=~	var1	24.165	21.549	0.157	0.157	0.1	9.800	0.879	*epc:m*
194	acc	=~	var3	53.095	47.346	0.232	0.232	0.1	9.878	0.882	*epc:m*
199	acc	=~	pref4	18.791	16.756	0.101	0.101	0.1	18.498	0.990	*epc:m*
205	var	=~	acc2	26.506	23.636	0.171	0.171	0.1	9.093	0.854	*epc:m*
209	var	=~	acc6	14.523	12.950	0.150	0.150	0.1	6.431	0.718	**(m)**
210	var	=~	pref1	3.940	3.513	0.082	0.082	0.1	5.821	0.675	**(m)**
213	var	=~	pref4	13.765	12.274	0.104	0.104	0.1	12.686	0.945	*epc:m*
221	pref	=~	acc4	9.688	8.639	-0.122	-0.122	0.1	6.463	0.720	**(m)**
229	pref	=~	exp2	4.337	3.867	-0.108	-0.108	0.1	3.747	0.490	**(m)**
231	pref	=~	exp4	5.719	5.100	-0.108	-0.108	0.1	4.868	0.597	**(m)**
240	exp	=~	var3	11.609	10.352	0.112	0.112	0.1	9.269	0.861	*epc:m*
242	exp	=~	pref1	5.587	4.982	0.132	0.132	0.1	3.193	0.431	**(m)**
243	exp	=~	pref2	6.881	6.136	0.159	0.159	0.1	2.730	0.379	**(m)**
244	exp	=~	pref3	11.836	10.555	0.128	0.128	0.1	7.244	0.768	*epc:m*
245	exp	=~	pref4	29.025	25.882	0.211	0.211	0.1	6.528	0.724	**(m)**
248	acc1	~~	acc4	16.956	15.120	0.142	0.142	0.1	8.447	0.828	*epc:m*
250	acc1	~~	acc6	15.765	14.058	-0.168	-0.168	0.1	5.558	0.655	**(m)**
253	acc1	~~	var3	13.565	12.096	0.188	0.188	0.1	3.844	0.500	**(m)**
264	acc2	~~	acc4	8.077	7.203	-0.121	-0.121	0.1	5.476	0.648	**(m)**
266	acc2	~~	acc6	19.095	17.027	0.219	0.219	0.1	3.969	0.513	**(m)**
268	acc2	~~	var2	7.373	6.575	-0.123	-0.123	0.1	4.891	0.599	**(m)**
269	acc2	~~	var3	29.199	26.037	-0.268	-0.268	0.1	4.067	0.523	**(m)**
270	acc2	~~	var4	6.273	5.593	0.095	0.095	0.1	6.906	0.748	**(m)**

Multi-level CFA

Install lavaan.survey

Set up the random intercept:

```
divR.design <- svydesign(ids= ~userId, data=divR)
```

Re-run the model with the survey design:

```
fit.multi <- lavaan.survey(fit, divR.design)
```

Get the output:

```
summary(fit.multi, rsquare=T, fit.measures=T)
```

Modification indices:

```
mods <- modindices(fit.multi, power=T)
mods <- mods[grep("\\*",mods$decision),]
```

Selected output

```
  Estimator                                         ML       Robust
  Minimum Function Test Statistic              501.651      263.380
  Degrees of freedom                               129          129
  P-value (Chi-square)                           0.000        0.000
  Scaling correction factor                                   1.905
    for the Satorra-Bentler correction

User model versus baseline model:

  Comparative Fit Index (CFI)                    0.895        0.903
  Tucker-Lewis Index (TLI)                       0.875        0.885

  Robust Comparative Fit Index (CFI)                          0.923
  Robust Tucker-Lewis Index (TLI)                             0.909

Root Mean Square Error of Approximation:

  RMSEA                                          0.100        0.060
  90 Percent Confidence Interval          0.091  0.109        0.052  0.067
  P-value RMSEA <= 0.05                          0.000        0.016

  Robust RMSEA                                                0.083
  90 Percent Confidence Interval                              0.068  0.097
```

Selected output

```
R-Square:
                   Estimate
    acc1              0.825
    acc2              0.667
    acc3              0.918
    acc4              0.494
    acc5              0.857
    acc6              0.333
    var1              0.739
    var2              0.614
    var3              0.562
    var4              0.586
    pref1             0.746
    pref2             0.742
    pref3             0.257
    pref4             0.046
    exp1              0.654
    exp2              0.867
    exp3              0.653
    exp4              0.570
```

Selected output

	lhs	op	rhs	mi	mi.scaled	epc	sepc.all	delta	ncp	power	decision
69	acc	=~	var1	12.639	6.636	0.229	0.158	0.1	2.407	0.342	**(m)**
71	acc	=~	var3	24.447	12.835	0.345	0.240	0.1	2.059	0.300	**(m)**
82	var	=~	acc2	9.295	4.880	0.202	0.126	0.1	2.275	0.326	**(m)**
84	var	=~	acc4	16.264	8.539	-0.331	-0.202	0.1	1.488	0.230	**(m)**
86	var	=~	acc6	11.341	5.955	0.295	0.191	0.1	1.301	0.207	**(m)**
93	var	=~	exp3	4.275	2.245	0.131	0.083	0.1	2.481	0.350	**(m)**
106	pref	=~	exp2	11.565	6.072	-0.238	-0.139	0.1	2.034	0.297	**(m)**
108	pref	=~	exp4	5.978	3.138	-0.178	-0.124	0.1	1.882	0.279	**(m)**
112	exp	=~	acc4	3.858	2.026	-0.148	-0.090	0.1	1.764	0.264	**(m)**
122	exp	=~	pref4	5.501	2.888	0.216	0.161	0.1	1.174	0.192	**(m)**
125	acc1	~~	acc4	6.200	3.255	0.138	0.050	0.1	3.255	0.438	**(m)**
126	acc1	~~	acc5	5.422	2.847	0.098	0.035	0.1	5.654	0.662	**(m)**
138	acc1	~~	exp3	10.174	5.342	0.146	0.055	0.1	4.801	0.591	**(m)**
139	acc1	~~	exp4	6.048	3.175	0.111	0.046	0.1	4.874	0.598	**(m)**
140	acc2	~~	acc3	11.760	6.174	-0.146	-0.053	0.1	5.545	0.654	**(m)**
143	acc2	~~	acc6	5.294	2.779	0.166	0.067	0.1	1.932	0.285	**(m)**
146	acc2	~~	var3	5.870	3.082	-0.141	-0.061	0.1	2.961	0.406	**(m)**
150	acc2	~~	pref3	4.830	2.536	0.128	0.068	0.1	2.938	0.403	**(m)**
152	acc2	~~	exp1	4.999	2.624	0.118	0.050	0.1	3.584	0.473	**(m)**
172	**acc4**	**~~**	**acc6**	**110.831**	**58.189**	**-0.935**	**-0.370**	**0.1**	**1.267**	**0.203**	**(m)**
174	acc4	~~	var2	6.941	3.644	0.178	0.077	0.1	2.200	0.317	**(m)**
184	acc4	~~	exp4	7.039	3.695	0.185	0.078	0.1	2.068	0.301	**(m)**
211	var1	~~	var3	13.731	7.209	0.291	0.139	0.1	1.623	0.247	**(m)**

Trimming

Remove pref4, acc4, and acc6:

```
model <- "acc =~ acc1+acc2+acc3+acc5
var =~ var1+var2+var3+var4
pref =~ pref1+pref2+pref3
exp =~ exp1+exp2+exp3+exp4"
```

Run the model, then rerun it with the survey design:

```
fit <- cfa(model, ordered=names(divR), data=divR, std.lv=T)
fit.multi <- lavaan.survey(fit, divR.design)
```

Get the output and modification indices:

```
summary(fit.multi, rsquare=T, fit.measures=T)
mods <- modindices(fit.multi, power=T)
mods <- mods[grep(“\\*”,mods$decision),]
```

Specifying an SEM

Specify the model:

```
model <- "acc =~ acc1+acc2+acc3+acc5
var =~ var1+var2+var3+var4
pref =~ pref1+pref2+pref3
exp =~ exp1+exp2+exp3+exp4

chodiff ~ to+acc+var+length
to ~ divmid+divhigh+pref
acc ~ var+divmid+divhigh+exp
var ~ divmid+divhigh"
```

Run the model:

```
fit <-sem(model,ordered=names(divR[5:24]),data=divR,std.lv=T)
```

Get the output:

```
summary(fit, rsquare=T, fit.measures=T)
```

Selected output

```
  Estimator                                         DWLS      Robust
  Minimum Function Test Statistic                274.599     265.706
  Degrees of freedom                                 158         158
  P-value (Chi-square)                             0.000       0.000
  Scaling correction factor                                    1.500
  Shift parameter                                             82.594
    for simple second-order correction (Mplus variant)

User model versus baseline model:

  Comparative Fit Index (CFI)                      0.997       0.993
  Tucker-Lewis Index (TLI)                         0.996       0.992

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

Root Mean Square Error of Approximation:

  RMSEA                                            0.050       0.048
  90 Percent Confidence Interval          0.040  0.060       0.038  0.058
  P-value RMSEA <= 0.05                            0.458       0.586

  Robust RMSEA                                                    NA
  90 Percent Confidence Interval                                  NA     NA
```

Selected output

```
Regressions:
                   Estimate  Std.Err  z-value  P(>|z|)
  chodiff ~
    to                0.352    0.045    7.827    0.000
    acc              -0.233    0.045   -5.188    0.000
    var              -0.240    0.054   -4.453    0.000
    length            0.017    0.009    1.979    0.048
  to ~
    divmid           -0.049    0.153   -0.318    0.750
    divhigh          -0.348    0.149   -2.327    0.020
    pref             -0.147    0.059   -2.511    0.012
  acc ~
    var               0.361    0.052    6.985    0.000
    divmid            0.244    0.160    1.524    0.127
    divhigh           0.179    0.159    1.127    0.260
    exp               0.242    0.062    3.897    0.000
  var ~
    divmid            0.320    0.159    2.018    0.044
    divhigh           0.515    0.152    3.389    0.001

Covariances:
                   Estimate  Std.Err  z-value  P(>|z|)
  pref ~~
    exp               0.435    0.045    9.632    0.000
```

note: to and chodiff are not standardized!

Multi-level SEM

Re-run the model with the survey design:

```
fit.multi <- lavaan.survey(fit, divR.design)
```

Get the output:

```
summary(fit.multi, rsquare=T, fit.measures=T)
```

Selected output

```
  Estimator                                         ML       Robust
  Minimum Function Test Statistic              302.464      187.340
  Degrees of freedom                               158          158
  P-value (Chi-square)                           0.000        0.055
  Scaling correction factor                                   1.615
    for the Satorra-Bentler correction

User model versus baseline model:

  Comparative Fit Index (CFI)                    0.953        0.980
  Tucker-Lewis Index (TLI)                       0.945        0.977

  Robust Comparative Fit Index (CFI)                          0.984
  Robust Tucker-Lewis Index (TLI)                             0.981

Root Mean Square Error of Approximation:

  RMSEA                                          0.056        0.025
  90 Percent Confidence Interval          0.046  0.066        0.010  0.036
  P-value RMSEA <= 0.05                          0.145        1.000

  Robust RMSEA                                                0.032
  90 Percent Confidence Interval                                 NA  0.049
```

Selected output

```
Regressions:
                   Estimate  Std.Err  z-value  P(>|z|)
  chodiff ~
    to                0.351    0.079    4.413    0.000
    acc              -0.361    0.127   -2.851    0.004
    var              -0.381    0.129   -2.954    0.003
    length            0.019    0.016    1.181    0.237
  to ~
    divmid           -0.031    0.164   -0.189    0.850
    divhigh          -0.412    0.166   -2.486    0.013
    pref             -0.144    0.112   -1.285    0.199
  acc ~
    var               0.389    0.093    4.164    0.000
    divmid            0.248    0.121    2.045    0.041
    divhigh           0.186    0.137    1.355    0.175
    exp               0.270    0.088    3.074    0.002
  var ~
    divmid            0.364    0.126    2.900    0.004
    divhigh           0.530    0.150    3.522    0.000

Covariances:
                   Estimate  Std.Err  z-value  P(>|z|)
  pref ~~
    exp               0.439    0.108    4.073    0.000
```

Multi-level in R

Downsides:

- Having to run the model twice is awkward
- Items are treated as ratio variables rather than ordinal (this sucks for 5-point scales)
- Advanced tricks with random slopes etc. not possible (more on this next week)

Solution:

Use Mplus, which has native support for multi-level models

Multi-level in Mplus

CFA and SEM

Multi-level in Mplus

Data preparation:

- Remove heading row from divR.csv file, save as divM.csv
- Make a new file in MPlus with the dataset and model definition
- Save file as model.inp
- Run the model, this will create and open model.out
- Inspect model output file

Specifying a CFA

```
DATA: FILE IS divM.csv;
VARIABLE:
 names are userId divmid divhigh length chodiff to
 var1 var2 var3 var4 acc1 acc2 acc3 acc4 acc5 acc6
 pref1 pref2 pref3 pref4 exp1 exp2 exp3 exp4;

 usevariables are var1 var2 var3 var4 acc1 acc2 acc3 acc4 acc5 acc6
 pref1 pref2 pref3 pref4 exp1 exp2 exp3 exp4;

 categorical are all;
 cluster = userId;

ANALYSIS:
 type is complex;

MODEL:
 acc by acc1-acc6;
 var by var1-var4;
 pref by pref1-pref4;
 exp by exp1-exp4;

OUTPUT:
 standardized;
 modindices(all);
```

Selected output

```
Chi-Square Test of Model Fit

          Value                                293.063*
          Degrees of Freedom                       129
          P-Value                               0.0000

RMSEA (Root Mean Square Error Of Approximation)

          Estimate                               0.066
          90 Percent C.I.                        0.056  0.076
          Probability RMSEA <= .05               0.005

CFI/TLI

          CFI                                    0.979
          TLI                                    0.976
```

Selected output

R-SQUARE

Observed Variable	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value	Residual Variance
VAR1	0.855	0.038	22.376	0.000	0.145
VAR2	0.665	0.044	15.036	0.000	0.335
VAR3	0.556	0.044	12.560	0.000	0.444
VAR4	0.627	0.043	14.624	0.000	0.373
ACC1	0.809	0.025	32.693	0.000	0.191
ACC2	0.684	0.037	18.553	0.000	0.316
ACC3	0.923	0.011	82.658	0.000	0.077
ACC4	**0.706**	**0.049**	**14.397**	**0.000**	**0.294**
ACC5	0.917	0.020	45.548	0.000	0.083
ACC6	**0.580**	**0.051**	**11.304**	**0.000**	**0.420**
PREF1	0.782	0.091	8.632	0.000	0.218
PREF2	0.862	0.086	10.028	0.000	0.138
PREF3	0.269	0.081	3.318	0.001	0.731
PREF4	**0.049**	**0.046**	**1.067**	**0.286**	**0.951**
EXP1	0.680	0.065	10.517	0.000	0.320
EXP2	0.901	0.058	15.567	0.000	0.099
EXP3	0.710	0.063	11.331	0.000	0.290
EXP4	0.695	0.077	9.027	0.000	0.305

Selected output

MODEL MODIFICATION INDICES

WITH Statements

VAR1	WITH ACC	14.524	0.128	0.142	0.372
VAR1	WITH VAR	14.566	-0.326	-0.353	-0.926
VAR3	WITH ACC	27.635	0.178	0.198	0.298
VAR3	WITH VAR	27.964	-0.458	-0.496	-0.744
VAR3	WITH VAR2	12.708	0.193	0.193	0.501
ACC2	WITH ACC	18.492	-0.330	-0.367	-0.653
ACC2	WITH VAR	15.597	0.140	0.151	0.269
ACC2	WITH VAR3	14.072	-0.273	-0.273	-0.729
ACC3	WITH ACC2	11.073	-0.115	-0.115	-0.740
ACC4	WITH ACC	20.035	0.370	0.411	0.760
ACC4	WITH VAR	11.487	-0.133	-0.144	-0.265
ACC6	**WITH ACC4**	**45.503**	**-0.300**	**-0.300**	**-0.853**
PREF4	WITH PREF3	15.281	0.430	0.430	0.516

SEM (trimmed)

```
DATA: FILE IS divM.csv;
VARIABLE:
 names are userId divmid divhigh length chodiff to
 var1 var2 var3 var4 acc1 acc2 acc3 acc4 acc5 acc6
 pref1 pref2 pref3 pref4 exp1 exp2 exp3 exp4;

 usevariables are divmid divhigh length chodiff to
 var1 var2 var3 var4 acc1 acc2 acc3 acc5
 pref1 pref2 pref3 exp1 exp2 exp3 exp4;

 categorical are var1-exp4;
 cluster = userId;

ANALYSIS:
 type is complex;

MODEL:
 acc by acc1-acc5;
 var by var1-var4;
 pref by pref1-pref3;
 exp by exp1-exp4;

 chodiff on to acc var length;
 to on divmid divhigh pref;
 acc on var divmid divhigh exp;
 var on divmid divhigh;

OUTPUT: standardized;
```

Selected output

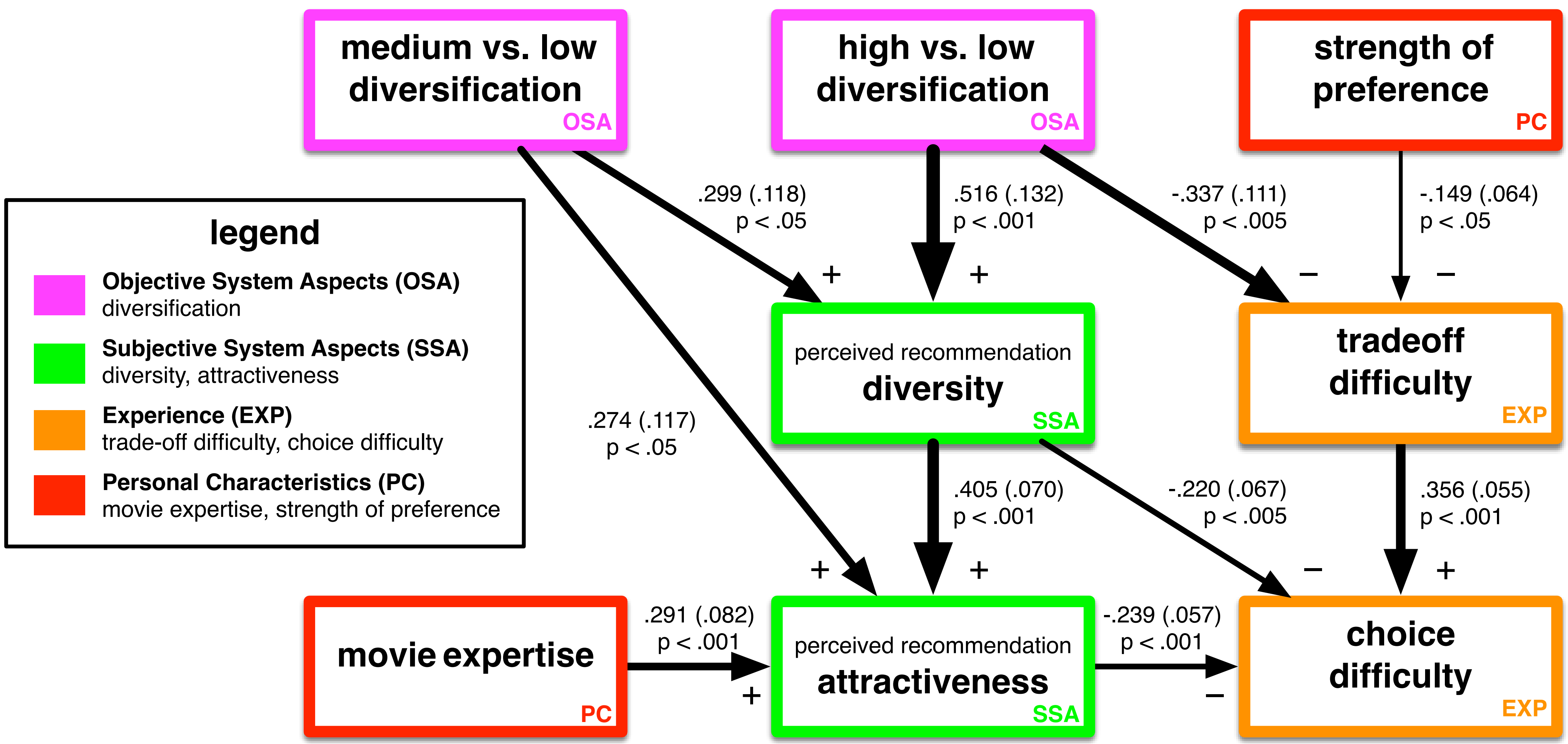
```
Chi-Square Test of Model Fit

          Value                              199.864*
          Degrees of Freedom                     158
          P-Value                             0.0135

*   The chi-square value for MLM, MLMV, MLR, ULSMV, WLSM and WLSMV cannot be
used
    for chi-square difference testing in the regular way.  MLM, MLR and WLSM
    chi-square difference testing is described on the Mplus website.  MLMV,
WLSMV,
    and ULSMV difference testing is done using the DIFFTEST option.

RMSEA (Root Mean Square Error Of Approximation)

          Estimate                             0.030
          90 Percent C.I.                      0.015  0.042
          Probability RMSEA <= .05             0.998

CFI/TLI

          CFI                                  0.995
          TLI                                  0.994
```

Selected output

ACC ON				
VAR	0.336	0.052	6.436	0.000
EXP	0.218	0.069	3.159	0.002
ACC ON				
DIVMID	0.217	0.106	2.056	0.040
DIVHIGH	0.157	0.116	1.349	0.177
VAR ON				
DIVMID	0.311	0.115	2.700	0.007
DIVHIGH	0.504	0.126	3.991	0.000
CHODIFF ON				
ACC	-0.274	0.069	-3.944	0.000
VAR	-0.206	0.063	-3.255	0.001
TO ON				
PREF	-0.148	0.069	-2.139	0.032
CHODIFF ON				
TO	0.365	0.069	5.254	0.000
LENGTH	**0.014**	**0.011**	**1.322**	**0.186**
TO ON				
DIVMID	-0.047	0.116	-0.408	0.683
DIVHIGH	-0.314	0.110	-2.844	0.004

note: using STDY standardization… why?

Final model



medium vs. low diversification
OSA
high vs. low diversification
OSA
strength of preference
PC
legend
Objective System Aspects (OSA)
diversification
Subjective System Aspects (SSA)
diversity, attractiveness
Experience (EXP)
trade-off difficulty, choice difficulty
Personal Characteristics (PC)
movie expertise, strength of preference
.299 (.118)
p < .05
+
.516 (.132)
p < .001
+
-.337 (.111)
p < .005
−
-.149 (.064)
p < .05
−
perceived recommendation
diversity
SSA
tradeoff difficulty
EXP
.274 (.117)
p < .05
+
.405 (.070)
p < .001
+
-.220 (.067)
p < .005
−
.356 (.055)
p < .001
+
movie expertise
PC
.291 (.082)
p < .001
+
perceived recommendation
attractiveness
SSA
-.239 (.057)
p < .001
−
choice difficulty
EXP

Total effects? Easy!

```
MODEL INDIRECT:
 acc IND divmid;
 acc IND divhigh;
 chodiff IND divmid;
 chodiff IND divhigh;
```

"It is the mark of a truly intelligent person to be moved by statistics."

T H A N K S !

George Bernard Shaw