

Simple Slopes for Continuous Measured and Latent Variable Interactions

Simple slopes (sometimes “conditional effects”) are used to probe the nature of a significant interaction. They examine the relationships between X and Y for particular values of Z , the moderator. Although other values can be used, the values most commonly used for the moderator are -1 standard deviation below the mean, the mean, and +1 standard deviation above the mean. See the handout “Simple Slopes” from my multiple regression course, <http://web.pdx.edu/~newsomj/mvclass> and Aiken and West (1991) and Cohen, Cohen, West, and Aiken (2003) for more details.

Data from this project come from a recent manuscript coauthored with Emily Denning, Ben Shaw, Kristin August, and Scott Strath on social relationships and physical activity (Newsom et al., 2022). The interactions tested below examine the interaction between physical activity-related emotional support (`emo`) and personal norms that value physical activity (`persnorm`) as predictors of intention to engage in physical activity (`intent`). Only Mplus is illustrated for the plots because `lavaan` does not have simple slope plotting functions (although similar constraints to obtain simple slope values are illustrated below).

Continuous Measured Variable Interaction with Simple Slopes Example Mplus

Although this interaction is not significant, I estimated and plotted the simple slopes to illustrate the process. Normally, if the interaction is not significant, simple slopes are not computed. Other examples can be found in Muthén, Muthén, and Asparouhov (2016).

```
title: Continuous measured variable interaction;
data: file is norms12.dat;

variable: names are female norms subj pdesc pinj sdesc sinj intention champs
          q110 q111 q113 q114 q115 q116 q117 q118 q120 q121 q122 q103 q104r q106 q107 q108
          q123 q124 q125 q126 q130 q131 q132 q133 q137 q138 q139 q140 q151 q152 q153 q154
          marstat married widowed educ race nonwhite income incomead age educ2;

missing are all (-99);

usevariables = q103 q104r q106 q107 q108
              persnorm emo emoxnorm;

define:
  pinj = mean (q115 q116);
  pdesc = mean (q113 q114);
  subj = mean(q110 q111);
  persnorm = mean (pinj pdesc subj);
  emo = mean (q123 q124 q125 q126);
  center persnorm emo (grandmean);
  emoxnorm = emo*persnorm;

!random estimation and integration needed for latent interactions;
!straight ml recommended by Cham et al. 2012, 2017;
analysis: type=general; estimator=mlr;

model:
  intent by q103 q104r q106 q107 q108;

!main effects
  intent on emo (b1);
  intent on persnorm (b2);
  intent on emoxnorm (b3);
  persnorm (pers);

Model constraint:

!SIMPLE SLOPES COMPUTATIONS;
! persnorm mean is 4.692 obtained from prior analysis (var=1.493, SD=1.222);

!declare new names for W values and simple slopes;
NEW(LOW_W MED_W HIGH_W SIMP_LO SIMP_MED SIMP_HI);

!simple slope equations;
LOW_W = 4.692 - 1*(sqrt(pers)) ; !-1 SD below mean of W;
```

```

MED_W = 4.692 ; ! mean of W;
HIGH_W = 4.692 + 1*(sqrt(pers)); ! +1 SD below mean of W;

! Now calc simple slopes for each value of W;
SIMP_LO = b1 + b3*LOW_W;
SIMP_MED = b1 + b3*MED_W;
SIMP_HI = b1 + b3*HIGH_W;

! Use loop plot to plot slopes of X on Y for low, med, high values of W
! NOTE - values from -3 to 3 in LOOP() statement since
! X is factor with mean set at default of 0
! From user guide on loop function: "The LOOP option names
! the variable that will be plotted on the x-axis, gives
! the numbers that are the lower and upper values of the variable, and the
! incremental value of the variable to be used in the computations;
PLOT(LOMOD MEDMOD HIMOD);
LOOP(XVAL,-13,13,1);
LOMOD = (b1 + b3*LOW_W)*XVAL;
MEDMOD = (b1 + b3*MED_W)*XVAL;
HIMOD = (b1 + b3*HIGH_W)*XVAL;

PLOT:
TYPE = plot2;

output: stdyx stand sampstat tech4;

```

Continuous measured variable interaction;

SUMMARY OF ANALYSIS

Number of groups	1
Number of observations	216
Number of dependent variables	5
Number of independent variables	3
Number of continuous latent variables	1
Estimator	MLR

THE MODEL ESTIMATION TERMINATED NORMALLY

MODEL FIT INFORMATION

Number of Free Parameters 20

Loglikelihood

H0 Value	-1430.162
H0 Scaling Correction Factor for MLR	3.1808
H1 Value	-1384.886
H1 Scaling Correction Factor for MLR	2.3642

Information Criteria

Akaike (AIC)	2900.323
Bayesian (BIC)	2967.829
Sample-Size Adjusted BIC (n* = (n + 2) / 24)	2904.452

Chi-Square Test of Model Fit

Value	60.180*
Degrees of Freedom	19
P-Value	0.0000
Scaling Correction Factor for MLR	1.5047

* 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	0.100	
90 Percent C.I.	0.072	0.129
Probability RMSEA <= .05	0.002	

CFI/TLI

CFI	0.830
TLI	0.776

Chi-Square Test of Model Fit for the Baseline Model

Value	267.094
Degrees of Freedom	25
P-Value	0.0000

SRMR (Standardized Root Mean Square Residual)

Value	0.116
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MODEL RESULTS

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
INTENT BY				
Q103	1.000	0.000	999.000	999.000
Q104R	0.486	0.125	3.893	0.000
Q106	1.076	0.123	8.730	0.000
Q107	1.169	0.125	9.386	0.000
Q108	0.665	0.101	6.613	0.000
INTENT ON				
EMO	0.106	0.045	2.348	0.019
PERSNORM	0.245	0.080	3.074	0.002
EMOXNORM	-0.055	0.047	-1.159	0.246
Means				
PERSNORM	0.000	0.074	0.000	1.000
Intercepts				
Q103	4.391	0.064	68.380	0.000
Q104R	4.746	0.043	110.859	0.000
Q106	4.533	0.065	69.606	0.000
Q107	4.483	0.072	62.294	0.000
Q108	4.069	0.065	62.680	0.000
Variances				
PERSNORM	1.186	0.177	6.697	0.000
Residual Variances				
Q103	0.340	0.082	4.127	0.000
Q104R	0.322	0.087	3.694	0.000
Q106	0.158	0.090	1.762	0.078
Q107	0.193	0.093	2.083	0.037
Q108	0.701	0.082	8.551	0.000
INTENT	0.443	0.103	4.296	0.000
New/Additional Parameters				
LOW_W	3.603	0.081	44.305	0.000
MED_W	4.692	0.000	0.000	1.000
HIGH_W	5.781	0.081	71.092	0.000
SIMP_LO	-0.092	0.154	-0.597	0.550
SIMP_MED	-0.152	0.205	-0.740	0.460
SIMP_HI	-0.212	0.257	-0.823	0.410

STANDARDIZED MODEL RESULTS

STDYX Standardization

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
INTENT BY				
Q103	0.784	0.061	12.784	0.000

Q104R	0.534	0.108	4.933	0.000
Q106	0.894	0.059	15.096	0.000
Q107	0.891	0.050	17.728	0.000
Q108	0.505	0.071	7.130	0.000

INTENT ON				
EMO	0.200	0.091	2.185	0.029
PERSNORM	0.362	0.089	4.073	0.000
EMOXNORM	-0.122	0.104	-1.176	0.240

Means				
PERSNORM	0.000	0.068	0.000	1.000

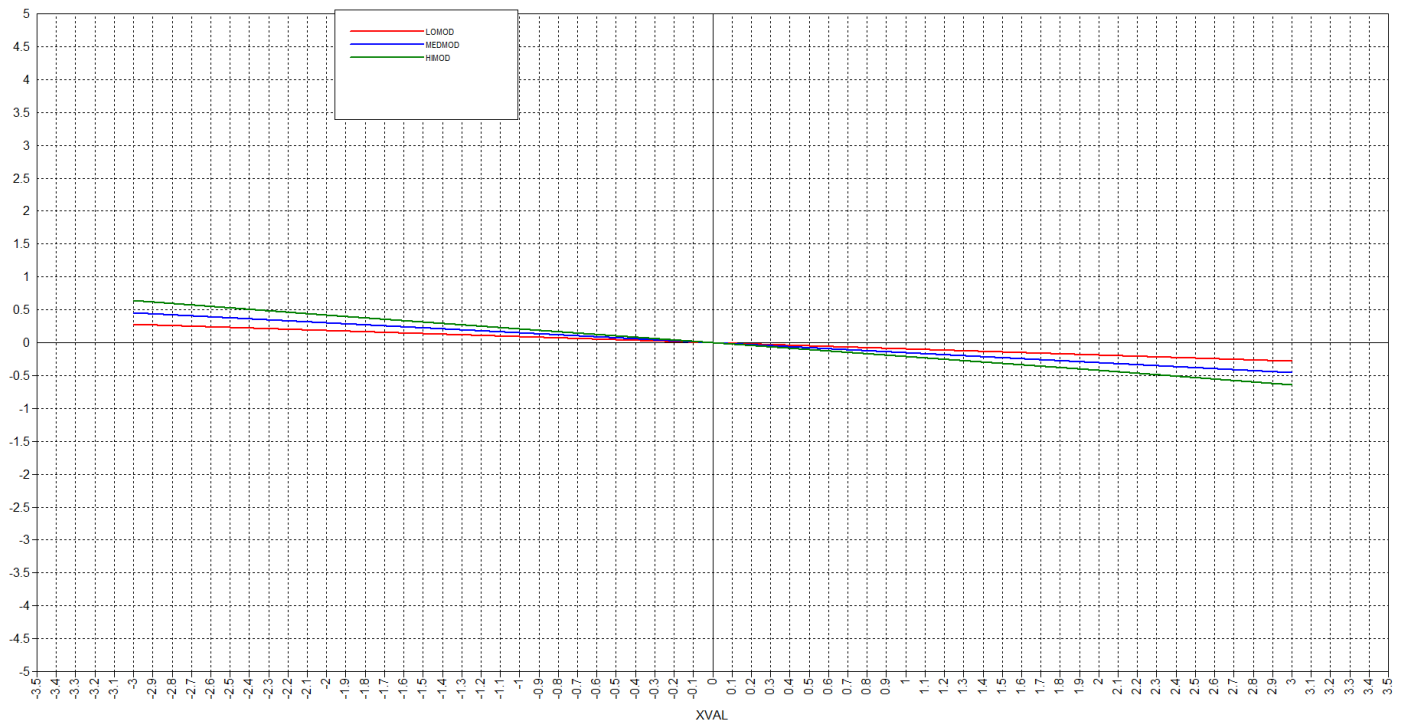
Intercepts				
Q103	4.676	0.376	12.429	0.000
Q104R	7.077	0.894	7.919	0.000
Q106	5.115	0.523	9.785	0.000
Q107	4.638	0.440	10.539	0.000
Q108	4.194	0.262	15.981	0.000

Variances				
PERSNORM	1.000	0.000	999.000	999.000

Residual Variances				
Q103	0.385	0.096	4.009	0.000
Q104R	0.715	0.116	6.189	0.000
Q106	0.201	0.106	1.904	0.057
Q107	0.207	0.089	2.313	0.021
Q108	0.745	0.071	10.426	0.000
INTENT	0.817	0.070	11.590	0.000

R-SQUARE				
Observed				
Variable	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
Q103	0.615	0.096	6.392	0.000
Q104R	0.285	0.116	2.466	0.014
Q106	0.799	0.106	7.548	0.000
Q107	0.793	0.089	8.864	0.000
Q108	0.255	0.071	3.565	0.000

Latent				
Variable	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
INTENT	0.183	0.070	2.601	0.009



lavaan

Note: Using the mimic = "Mplus" option on the sem function fixes a discrepancy in how the scaling correction factor is computed

```
> #create measured variables for interaction
> library(tidyverse)
> mydata$emo<-rowMeans(mydata[, c("q123", "q124", "q125","q126")], na.rm=T)
> mydata$persnorm<-rowMeans(mydata[, c("q115", "q116", "q113","q114","q110","q111")], na.rm=T)
>
> #center predictors
> #mydata$emo <- mydata$emo - mean(mydata$emo)
> #mydata$persnorm <- mydata$persnorm - mean(mydata$persnorm)
> library(QuantPsyc)
> mydata$emo = meanCenter(mydata$emo)
> mydata$persnorm = meanCenter(mydata$persnorm)
> mydata$emoxnorm = mydata$emo*mydata$persnorm
> #be sure to check that centering worked by looking at descriptives
>
>
> #to match Mplus which had N=216, listwise for vars used
> mydata = mydata[complete.cases(mydata[,c("emo", "persnorm")]),]
> #mydata = mydata[complete.cases(mydata[,c("q103", "q104r", "q106", "q107", "q108")]),]
>
> library(lavaan)
> model = '
+   intent =~ q103 + q104r + q106 + q107 + q108
+   intent ~ b1*emo + b2*persnorm + b3*emoxnorm
+   persnorm~~pers*persnorm
+
+ #constraints for simple slopes
+ #NEW(LOW_W MED_W HIGH_W SIMP_LO SIMP_MED SIMP_HI);
+
+ #simple slope equations;
+ LOW_W := 4.692 - 1*(sqrt(pers)); #-1 SD below mean of W;
+ MED_W := 4.692 ; # mean of W;
+ HIGH_W := 4.692 + 1*(sqrt(pers)); # +1 SD below mean of W;
+
+ # Now calc simple slopes for each value of w;
+ SIMP_LO := b1 + b3*LOW_W;
+ SIMP_MED := b1 + b3*MED_W;
+ SIMP_HI := b1 + b3*HIGH_W;
+
+ '
>
> #Below, MLR is used to request Yuan-Bentler scaled chi-square and SEs
> #robust standard errors and scaled chi-square
> fit = sem(model, data = mydata, fixed.x=FALSE, mimic = "mplus", estimator="mlr")
> summary(fit,fit.measures=TRUE, rsquare=TRUE, standardized=TRUE)
lavaan 0.6.15 ended normally after 41 iterations
```

Estimator	ML
Optimization method	NLMINB
Number of model parameters	25
Number of observations	216
Number of missing patterns	7

Model Test User Model:	Standard	Scaled
Test Statistic	90.471	60.035
Degrees of freedom	19	19
P-value (Chi-square)	0.000	0.000
Scaling correction factor		1.507
Yuan-Bentler correction (Mplus variant)		

Model Test Baseline Model:	Standard	Scaled
Test statistic	669.592	269.090
Degrees of freedom	27	27
P-value	0.000	0.000
Scaling correction factor		2.488

User Model versus Baseline Model:	Standard	Scaled
Comparative Fit Index (CFI)	0.889	0.830
Tucker-Lewis Index (TLI)	0.842	0.759
Robust Comparative Fit Index (CFI)		0.904
Robust Tucker-Lewis Index (TLI)		0.864

Loglikelihood and Information Criteria:

Loglikelihood user model (H0)	-2220.187	-2220.187
Scaling correction factor for the MLR correction		2.910
Loglikelihood unrestricted model (H1)	-2174.952	-2174.952
Scaling correction factor for the MLR correction		2.304
Akaike (AIC)	4490.374	4490.374
Bayesian (BIC)	4574.756	4574.756
Sample-size adjusted Bayesian (SABIC)	4495.535	4495.535

Root Mean Square Error of Approximation:

RMSEA	0.132	0.100
90 Percent confidence interval - lower	0.105	0.077
90 Percent confidence interval - upper	0.160	0.124
P-value H ₀ : RMSEA ≤ 0.050	0.000	0.000
P-value H ₀ : RMSEA ≥ 0.080	0.999	0.927
Robust RMSEA		0.121
90 Percent confidence interval - lower		0.086
90 Percent confidence interval - upper		0.158
P-value H ₀ : Robust RMSEA ≤ 0.050		0.001
P-value H ₀ : Robust RMSEA ≥ 0.080		0.970

Standardized Root Mean Square Residual:

SRMR	0.109	0.109
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Parameter Estimates:

Standard errors	Sandwich
Information bread	Observed
Observed information based on	Hessian

Latent Variables:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
intent =~						
q103	1.000				0.736	0.784
q104r	0.486	0.125	3.893	0.000	0.358	0.534
q106	1.076	0.123	8.734	0.000	0.792	0.894
q107	1.169	0.125	9.389	0.000	0.861	0.891
q108	0.665	0.101	6.614	0.000	0.490	0.505

Regressions:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
intent ~						
emo (b1)	0.105	0.045	2.345	0.019	0.143	0.199
persnorm (b2)	0.245	0.080	3.072	0.002	0.332	0.362
emoxnorm (b3)	-0.055	0.047	-1.160	0.246	-0.075	-0.122

Covariances:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
emo ~~						
emoxnorm	0.108	0.221	0.486	0.627	0.108	0.047

Intercepts:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
.q103	4.392	0.064	68.447	0.000	4.392	4.676
.q104r	4.746	0.043	110.975	0.000	4.746	7.077
.q106	4.534	0.065	69.661	0.000	4.534	5.116
.q107	4.484	0.072	62.351	0.000	4.484	4.639
.q108	4.069	0.065	62.681	0.000	4.069	4.194
emo	-0.000	0.095	-0.000	1.000	-0.000	-0.000
persnorm	-0.003	0.074	-0.039	0.969	-0.003	-0.003
emoxnorm	0.721	0.111	6.492	0.000	0.721	0.442
.intent	0.000				0.000	0.000

Variances:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
persnorm (pers)	1.186	0.177	6.688	0.000	1.186	1.000
.q103	0.340	0.082	4.132	0.000	0.340	0.386
.q104r	0.322	0.087	3.695	0.000	0.322	0.715
.q106	0.158	0.090	1.761	0.078	0.158	0.201
.q107	0.193	0.093	2.083	0.037	0.193	0.207
.q108	0.701	0.082	8.552	0.000	0.701	0.745
.intent	0.443	0.103	4.294	0.000	0.817	0.817
emo	1.938	0.136	14.286	0.000	1.938	1.000
emoxnorm	2.666	0.537	4.962	0.000	2.666	1.000

R-Square:

	Estimate
q103	0.614
q104r	0.285
q106	0.799

q107	0.793
q108	0.255
intent	0.183

Defined Parameters:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
LOW_W	3.603	0.081	44.262	0.000	3.603	3.692
MED_W	4.692				4.692	4.692
HIGH_W	5.781	0.081	71.013	0.000	5.781	5.692
SIMP_LO	-0.093	0.155	-0.600	0.549	-0.126	-0.251
SIMP_MED	-0.153	0.206	-0.742	0.458	-0.207	-0.373
SIMP_HI	-0.213	0.258	-0.825	0.409	-0.289	-0.495

lavaan does not have the same type of plotting function as Mplus, so plots would need to be generated in R outside of lavaan

Latent Variable Interaction with Simple Slopes Example

The latent variable interaction approach in Mplus is illustrated below. The Mplus `xwith` command is used for implementing the LMS approach to latent variable interactions (Klein & Moosbrugger, 2000). Plotting examples are available from Chris Stride and colleagues at <http://offbeat.group.shef.ac.uk/FIO/mplusmedmod.htm>. Code for this example was developed by Em Trubits (fka Emily Denning).

Some output omitted

```
INPUT INSTRUCTIONS

title:
data: file is norms12.dat;

variable: names are female norms subj pdesc pinj sdesc sinj intention champs
          q110 q111 q113 q114 q115 q116 q117 q118 q120 q121 q122 q103 q104r q106 q107 q108
          q123 q124 q125 q126 q130 q131 q132 q133 q137 q138 q139 q140 q151 q152 q153 q154
          marstat married widowed educ race nonwhite income incomead age educ2;

missing are all (-99);

usevariables = q103 q104r q106 q107 q108
              q123 q124 q125 q126
              pinj pdesc subj;

define:
pinj = mean (q115 q116);
pdesc = mean (q113 q114);
subj = mean(q110 q111);

!random estimation and integration needed for latent interactions;
!straight ml recommended by Cham et al. 2012, 2017;
analysis: type=random; estimator=ml;
          ALGORITHM=INTEGRATION;

model:
!effects coding is used for scaling latent variables used in the interaction,
!labels correspond to model constraint statements for scaling each factor.
!labels start with ly7 because this was adapted from another model;
emo by q123* (ly7)
  q124 (ly8)
  q125 (ly9)
  q126 (ly10);

intent by q103 q104r q106 q107 q108;
persnorm by pinj* (ly11)
  pdesc (ly12)
  subj (ly13);

!measurement intercepts and factor means;
[q123] (t7);
[q124] (t8);
[q125] (t9);
[q126] (t10);
[pinj] (t11);
[pdesc] (t12);
```

```

[subj] (t13);

[persnorm];
emo;
intent;
persnorm (pers);

!main effects
intent on emo (b1);
intent on persnorm (b2);

!latent interaction variable
emoxpersnorm | emo xwith persnorm;
intent on emoxpersnorm (b3);

Model constraint:
ly7 = 4 - ly8 - ly9 - ly10;
ly11 = 3 - ly12 - ly13;
t7 = 0 - t8 - t9 - t10;
t11 = 0 - t12 - t13;

!SIMPLE SLOPES COMPUTATIONS;
! persnorm mean is 4.692 obtained from prior analysis (var=1.493, SD=1.222);

!declare new names for W values and simple slopes;
NEW(LOW_W MED_W HIGH_W SIMP_LO SIMP_MED SIMP_HI);

!simple slope equations;
LOW_W = 4.692 - 1*(sqrt(pers)) ; !-1 SD below mean of W;
MED_W = 4.692 ; ! mean of W;
HIGH_W = 4.692 + 1*(sqrt(pers)); ! +1 SD below mean of W;

! Now calc simple slopes for each value of W;
SIMP_LO = b1 + b3*LOW_W;
SIMP_MED = b1 + b3*MED_W;
SIMP_HI = b1 + b3*HIGH_W;

! Use loop plot to plot slopes of X on Y for low, med, high values of W
! NOTE - values from -3 to 3 in LOOP() statement since
! X is factor with mean set at default of 0
!From user guide on loop function: "The LOOP option names
!the variable that will be plotted on the x-axis, gives
!the numbers that are the lower and upper values of the variable, and the
!incremental value of the variable to be used in the computations;
PLOT(LOMOD MEDMOD HIMOD);
LOOP(XVAL,-13,13,1);
LOMOD = (b1 + b3*LOW_W)*XVAL;
MEDMOD = (b1 + b3*MED_W)*XVAL;
HIMOD = (b1 + b3*HIGH_W)*XVAL;

PLOT:
TYPE = plot2;

output: stdyx stand sampstat tech4;

*** WARNING in PLOT command
Note that only the first 8 characters of variable names are used in plots.
If variable names are not unique within the first 8 characters, problems
may occur.
1 WARNING(S) FOUND IN THE INPUT INSTRUCTIONS

```

SUMMARY OF ANALYSIS

Number of groups	1
Number of observations	217
Number of dependent variables	12
Number of independent variables	0
Number of continuous latent variables	4

SUMMARY OF DATA

Number of missing data patterns 15

MODEL FIT INFORMATION

Number of Free Parameters 39

Loglikelihood

H0 Value -3445.628

Information Criteria

Akaike (AIC) 6969.256
 Bayesian (BIC) 7101.072
 Sample-Size Adjusted BIC 6977.486
 (n* = (n + 2) / 24)

MODEL RESULTS

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
EMO BY				
Q123	0.983	0.044	22.381	0.000
Q124	0.992	0.038	25.991	0.000
Q125	1.064	0.035	30.646	0.000
Q126	0.961	0.044	21.753	0.000
INTENT BY				
Q103	1.000	0.000	999.000	999.000
Q104R	0.479	0.059	8.136	0.000
Q106	1.079	0.073	14.776	0.000
Q107	1.171	0.079	14.852	0.000
Q108	0.670	0.086	7.741	0.000
PERSNORM BY				
PINJ	1.038	0.039	26.685	0.000
PDESC	0.992	0.042	23.912	0.000
SUBJ	0.969	0.048	20.068	0.000
INTENT ON				
EMO	0.613	0.197	3.109	0.002
PERSNORM	0.460	0.090	5.115	0.000
EMOXPERSNO	-0.094	0.034	-2.723	0.006
PERSNORM WITH				
EMO	2.052	0.350	5.861	0.000
Means				
PERSNORM	4.686	0.118	39.821	0.000
Intercepts				
Q103	1.726	0.459	3.757	0.000
Q104R	3.472	0.254	13.673	0.000
Q106	1.655	0.478	3.461	0.001
Q107	1.359	0.518	2.627	0.009
Q108	2.283	0.362	6.312	0.000
Q123	0.723	0.104	6.961	0.000
Q124	0.007	0.089	0.078	0.938
Q125	-0.414	0.081	-5.115	0.000
Q126	-0.315	0.105	-2.996	0.003
PINJ	-0.009	0.212	-0.044	0.965
PDESC	-0.231	0.226	-1.023	0.306
SUBJ	0.241	0.263	0.913	0.361
Variances				
EMO	5.852	0.584	10.018	0.000
PERSNORM	1.499	0.228	6.588	0.000
Residual Variances				
Q103	0.341	0.040	8.571	0.000
Q104R	0.323	0.032	9.973	0.000
Q106	0.158	0.026	6.117	0.000
Q107	0.192	0.030	6.317	0.000

Q108	0.698	0.070	9.979	0.000
Q123	1.059	0.127	8.346	0.000
Q124	0.665	0.092	7.241	0.000
Q125	0.474	0.084	5.653	0.000
Q126	1.099	0.127	8.637	0.000
PINJ	0.186	0.049	3.778	0.000
PDESC	0.416	0.058	7.224	0.000
SUBJ	0.826	0.091	9.038	0.000
INTENT	0.417	0.064	6.554	0.000

New/Additional Parameters

LOW_W	3.468	0.093	37.315	0.000
MED_W	4.692	0.000	*****	0.000
HIGH_W	5.916	0.093	63.668	0.000
SIMP_LO	0.288	0.085	3.387	0.001
SIMP_MED	0.173	0.053	3.266	0.001
SIMP_HI	0.058	0.046	1.275	0.202

STANDARDIZED MODEL RESULTS

STDYX Standardization

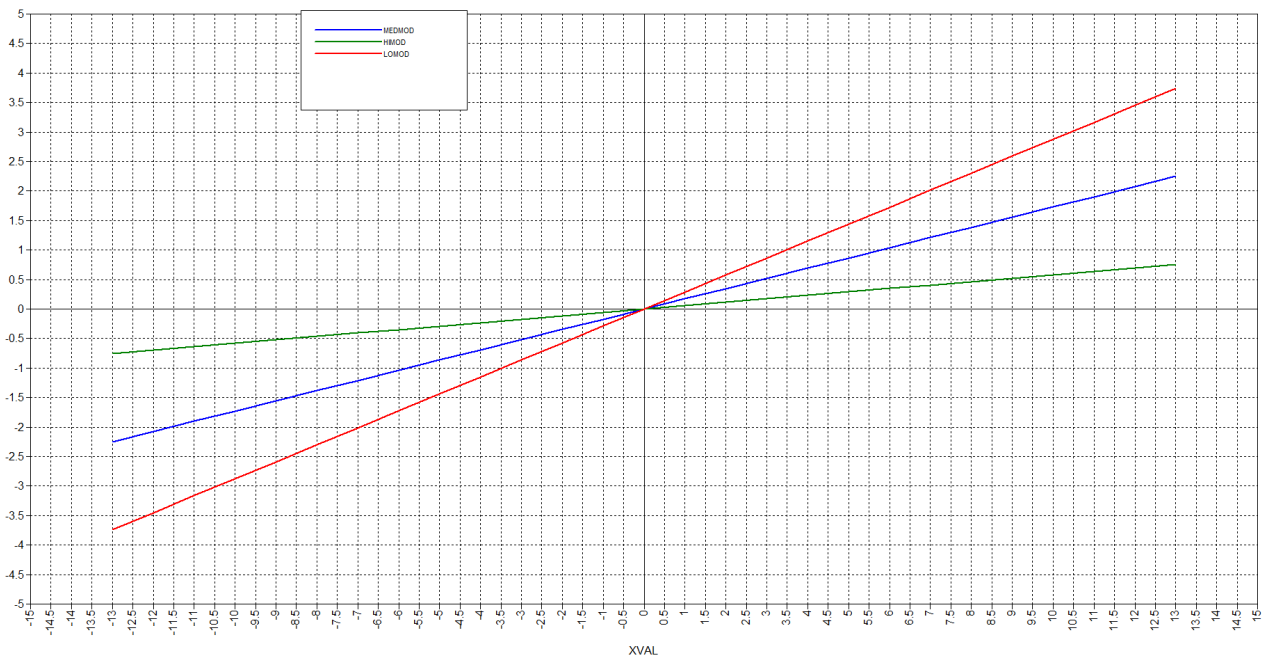
		Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
EMO	BY				
Q123		0.918	0.013	69.320	0.000
Q124		0.947	0.009	99.931	0.000
Q125		0.966	0.007	133.862	0.000
Q126		0.912	0.014	65.603	0.000
INTENT	BY				
Q103		0.894	0.030	29.330	0.000
Q104R		0.700	0.069	10.205	0.000
Q106		0.953	0.015	63.184	0.000
Q107		0.952	0.015	61.967	0.000
Q108		0.682	0.071	9.610	0.000
PERSNORM	BY				
PINJ		0.947	0.016	59.012	0.000
PDESC		0.883	0.023	37.832	0.000
SUBJ		0.794	0.035	22.656	0.000
INTENT	ON				
EMO		1.275	0.260	4.901	0.000
PERSNORM		0.485	0.064	7.605	0.000
EMOXPERTSNO		-0.239	0.060	-3.954	0.000
PERSNORM WITH					
EMO		0.693	0.058	11.847	0.000
Means					
PERSNORM		3.827	0.365	10.475	0.000

R-SQUARE

Observed Variable	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
PINJ	0.897	0.030	29.506	0.000
PDESC	0.780	0.041	18.916	0.000
SUBJ	0.631	0.056	11.328	0.000

Latent Variable	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
INTENT	0.692	0.096	7.205	0.000

The figure shows that the relationship between emotional support and intention to engage in physical activity is stronger when personal norms are low.



Latent Variable Interactions with lavaan

The lavaan package does not have the LMS interaction approach, although see match-paired indicator approach to latent variable interaction (Marsh, Wen, & Hau, 2004) under development in R using the semTools package, the indProd function for computing the indicators, and the probe2WayMC function for computing simple slopes and plotting.

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