

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;
[q103@0]; !setting the measurement intercept to 0;
[intent] (b0); !estimating intercept so this can be used for simples plot;

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

Model constraint:

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

!low, mean, and high values for moderator based on SD for persnorm;
LOW_W = -1.089 ; !-1 SD below mean of W;
```

```

MED_W = 0 ; ! mean of W;
HIGH_W = 1.089; ! +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 -2 to 2 in LOOP() statement since
! approx. range for emo and emo is mean centered
! 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,-2,2,.1);
LOMOD = (b0 + b2*LOW_W) + (b1 + b3*LOW_W)*XVAL;
MEDMOD = b0 + (b1 + b3*MED_W)*XVAL;
HIMOD = (b0 + b2*HIGH_W) + (b1 + b3*HIGH_W)*XVAL;

PLOT:
  TYPE = plot2;

output: stdyx stand sampstat tech4;

```

(Some output omitted)

```

*** WARNING
Data set contains cases with missing on x-variables.
These cases were not included in the analysis.
Number of cases with missing on x-variables: 1
1 WARNING(S) FOUND IN THE INPUT INSTRUCTIONS

```

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

Observed dependent variables

Continuous				
Q103	Q104R	Q106	Q107	Q108

Observed independent variables

PERSNORM	EMO	EMOYNORM
----------	-----	----------

Continuous latent variables

INTENT

Variables with special functions

Centering (GRANDMEAN)
 PERSNORM EMO

Estimator	MLR
Information matrix	OBSERVED
Maximum number of iterations	1000
Convergence criterion	0.500D-04
Maximum number of steepest descent iterations	20
Maximum number of iterations for H1	2000
Convergence criterion for H1	0.100D-03

Input data file(s)
 norms12.dat

Input data format FREE

SUMMARY OF DATA

Number of missing data patterns 7

UNIVARIATE SAMPLE STATISTICS

UNIVARIATE HIGHER-ORDER MOMENT DESCRIPTIVE STATISTICS

Variable/ Sample Size	Mean/ Variance	Skewness/ Kurtosis	Minimum/ Maximum	% with Min/Max	Percentiles 20%/60%	40%/80%	Median
Q103 216.000	4.352 0.922	-1.692 2.627	1.000 5.000	2.78% 58.80%	4.000 5.000	4.000 5.000	5.000
Q104R 215.000	4.726 0.460	-3.093 10.690	1.000 5.000	0.93% 81.40%	5.000 5.000	5.000 5.000	5.000
Q106 209.000	4.483 0.843	-2.287 5.308	1.000 5.000	3.35% 66.03%	4.000 5.000	5.000 5.000	5.000
Q107 211.000	4.436 0.995	-2.131 4.131	1.000 5.000	4.27% 65.88%	4.000 5.000	5.000 5.000	5.000
Q108 213.000	4.042 0.961	-0.952 0.577	1.000 5.000	2.35% 38.97%	3.000 4.000	4.000 5.000	4.000
PERSNORM 216.000	0.000 1.186	-1.032 2.816	-4.368 1.632	1.39% 9.26%	-0.702 0.298	-0.368 0.965	-0.035
EMO 216.000	0.000 1.938	0.353 -0.942	-2.031 2.969	7.41% 3.24%	-1.281 0.219	-0.781 1.219	-0.031
EMOYNORM 216.000	0.721 2.665	0.957 6.742	-7.508 8.873	0.46% 0.46%	-0.136 0.564	0.150 1.755	0.368

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	8.729	0.000
Q107	1.169	0.125	9.384	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	0.000	0.000	999.000	999.000
Q104R	2.611	0.569	4.584	0.000
Q106	-0.190	0.557	-0.342	0.733
Q107	-0.651	0.563	-1.156	0.248
Q108	1.148	0.446	2.575	0.010
INTENT	4.391	0.064	68.380	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	4.295	0.000
New/Additional Parameters				
LOW_W	-1.089	0.000	0.000	1.000
MED_W	0.000	0.000	0.000	1.000
HIGH_W	1.089	0.000	0.000	1.000
SIMP_LO	0.165	0.083	2.003	0.045
SIMP_MED	0.106	0.045	2.348	0.019
SIMP_HI	0.046	0.051	0.907	0.365

QUALITY OF NUMERICAL RESULTS

Condition Number for the Information Matrix (ratio of smallest to largest eigenvalue)	0.410E-04
--	-----------

STANDARDIZED MODEL RESULTS

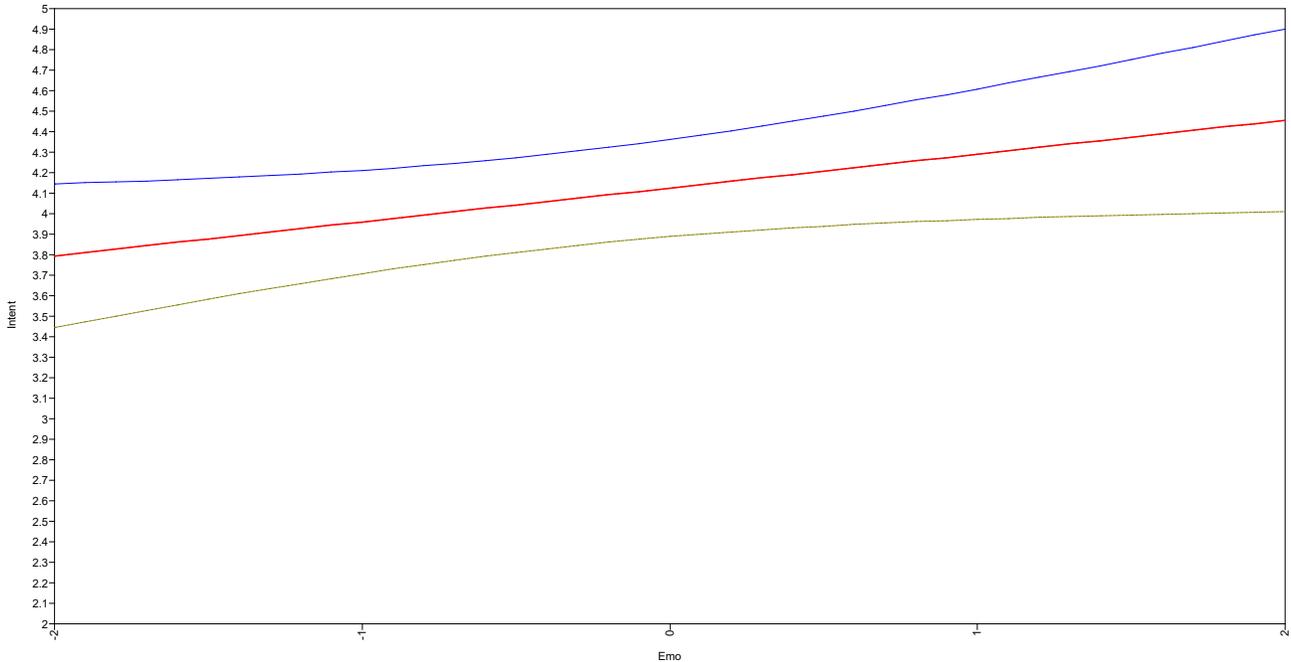
STDYX Standardization

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
INTENT BY				
Q103	0.784	0.061	12.782	0.000
Q104R	0.534	0.108	4.933	0.000
Q106	0.894	0.059	15.097	0.000
Q107	0.891	0.050	17.727	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	0.000	0.000	999.000	999.000
Q104R	3.893	1.138	3.422	0.001
Q106	-0.215	0.625	-0.344	0.731
Q107	-0.673	0.579	-1.164	0.245
Q108	1.183	0.486	2.435	0.015
INTENT	5.965	0.764	7.805	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	6.391	0.000
Q104R	0.285	0.116	2.466	0.014
Q106	0.799	0.106	7.549	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

After the model has completed running, go to the Plot menu and choose View Plots, then choose “Plot one parameter at a time”. Once the plot is produced, the blue graph icon on the menu can be used to change line colors and characteristics. A separate option under the Plot menu Axis Properties can be used to change the range of the Axes and the labels.



Note: dashed green line is low, red dotted line is mean, and solid blue line is high. (legend is not printing for some reason).

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:						
Test Statistic	Standard	Scaled				
Degrees of freedom	90.471	60.035				
P-value (Chi-square)	19	19				
Scaling correction factor	0.000	0.000				
Yuan-Bentler correction (Mplus variant)		1.507				
Model Test Baseline Model:						
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:						
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				
Parameter Estimates:						
Standard errors		Sandwich				
Information bread		Observed				
Observed information based on		Hessian				
Latent variables:						
intent =~	Estimate	Std.Err	z-value	P(> z)	std.lv	std.all
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:						
intent ~	Estimate	Std.Err	z-value	P(> z)	std.lv	std.all
emo (b1)	0.105	0.045	2.345	0.019	0.143	0.199

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
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:						
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
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. You could use regression with lm function and then plot as an approximation.

```
library(ggeffects)
d$intent<-rowMeans(d[, c("q103", "q104r", "q106","q107","q108")], na.rm=T)
fit2 <- lm(intent ~ emo + persnorm + emo * persnorm, data = d)
summary(fit2)
ggpredict(fit2, terms = c("emo[-2:2 by=1.0]", "persnorm")) |> plot()
```

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). The code below does not center the latent variables used in the interaction.¹ 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
```

¹ The effects coding model constraints section could be modified to center the variables by modifying the intercept statements to subtract from the sum of the item means rather than 0.

```

    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 values of W based on factor variance and mean for persnorm factor;
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				

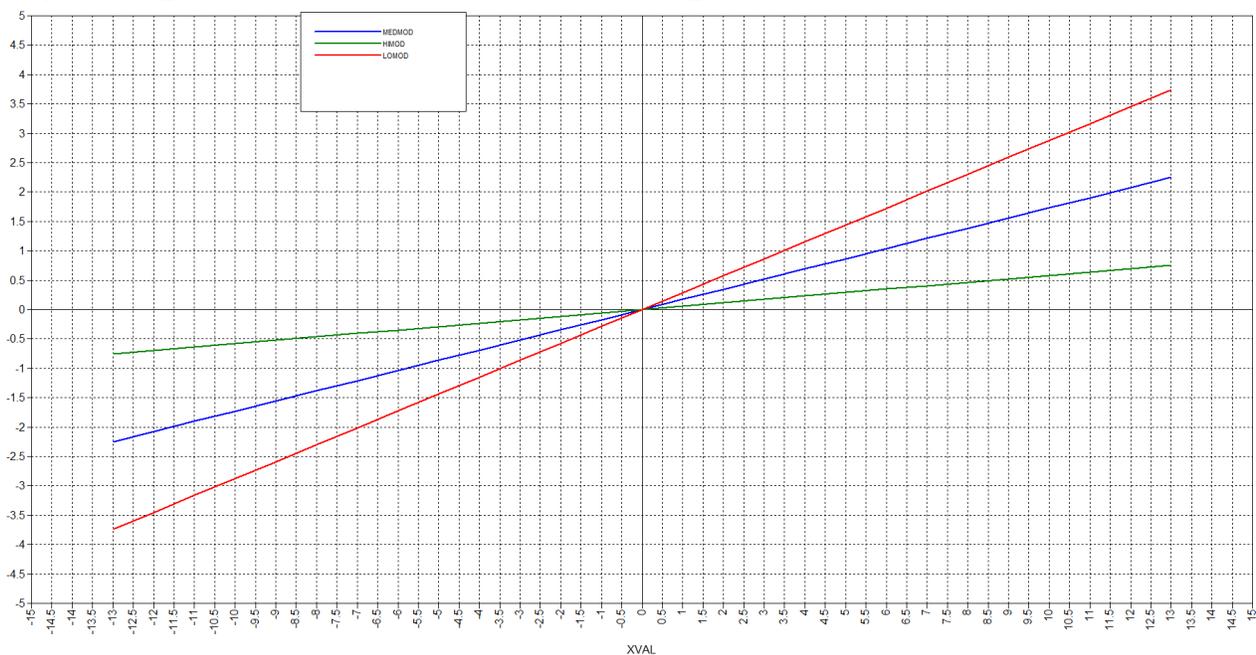
EMO	0.613	0.197	3.109	0.002
PERSNORM	0.460	0.090	5.115	0.000
EMOXPERSONO	-0.094	0.034	-2.723	0.006
PERSNORM WITH				
EMO	2.052	0.350	5.861	0.000
Means				
PERSNORM	4.686	0.118	39.821	0.000
Intercepts				
Q103	1.726	0.459	3.757	0.000
Q104R	3.472	0.254	13.673	0.000
Q106	1.655	0.478	3.461	0.001
Q107	1.359	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
EMOXPERSONO	-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				Two-Tailed
Variable	Estimate	S.E.	Est./S.E.	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
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. I changed several of the axis and line properties.



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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