MIX{WILD}

Mixed Model Analysis With Intensive Longitudinal Data

New Horizons in Statistical Modeling of Intraindividual Variability with Intensive Longitudinal Data

SBM 2023 Pre-Conference Workshop

Genevieve F. Dunton, PhD, University of Southern California
Donald Hedeker, PhD, University of Chicago
Wei-Lin Wang, PhD, University of Southern California

Speakers

- Genevieve F. Dunton, PhD, University of Southern California
- Donald Hedeker, PhD, University of Chicago
- Wei-Lin Wang, PhD, University of Southern California

Workshop Agenda

- 11:00-11:15am Introduction–Overview, Agenda, How to download (Dunton)
- 11:15-11:30am Conceptual Overview and Research Applications (Dunton)
- 11:30-12:00pm Statistical Modeling of Within-Subject Variances (Hedeker)
- 12:00-12:10pm Short Break
- 12:10-12:50pm MixWILD Demonstration and usage (Wang)
- 12:50-1:00pm Closing/Q&A (Dunton, Hedeker, Wang)

MixWILD for Windows

How to Download MixWILD

MixWILD for Mac

- Please visit: https://reach-lab.github.io/MixWildGUI/

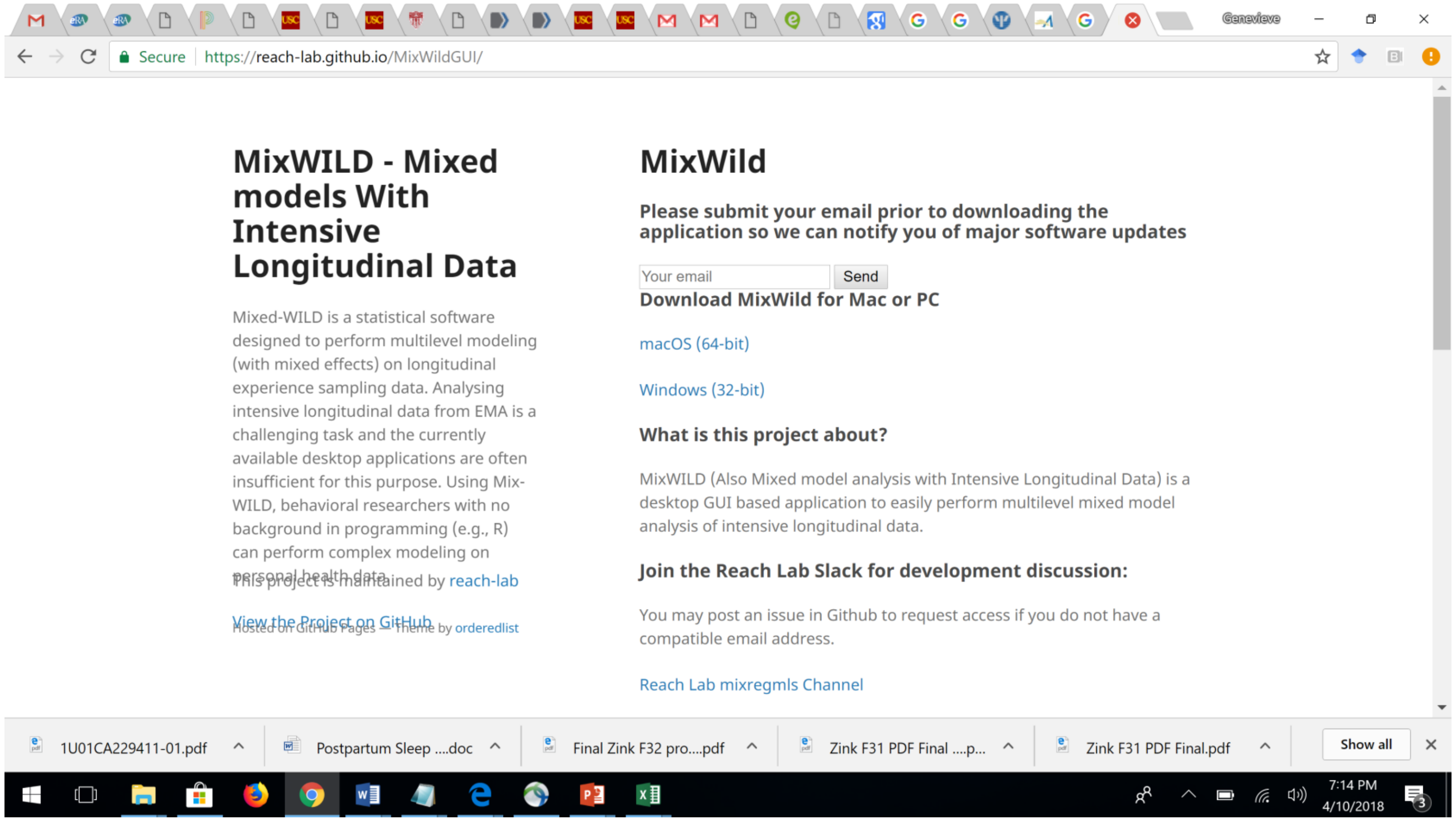
- Please submit your email prior to downloading the application in the web page so we can notify you of major software updates.

- Click on macOS or Windows to download the program.

- Select your directory to save the program.

When finished downloading, double-click on the MixWILD icon and follow the instructions to complete installation.

MixWILD GitHub Page



- Software download
- User guide
- Cheat sheets
- Example datasets
- Video tutorial
- Published papers
- User discussion board

MixWILD: Conceptual Overview and Research Applications

Genevieve F. Dunton, PhD, MPH
University of Southern California

Why use MixWILD?

Repeated Occurrence Health Behaviors (e.g., phy. act., healthy eating)

- High frequency (e.g., daily or multiple times per day)
- Time-varying explanatory factors (e.g., context, self-control)

Limited Occurrence Health Behaviors (e.g., vaccinations, diagnostic tests)

- Low frequency (e.g., annually)
- Time-invariant explanatory factors (e.g., access to health care)

Methodological Weaknesses in Health Behavior Research

- Behaviors measured <u>infrequently</u> using retrospective or summary measures

- Measures capture <u>usual</u> level of behavior or determinants on a typical week or month

- Not conducive to testing factors that <u>vary frequently over micro-timescales</u> (e.g., min, hours)

Dunton, G. F. (2017). Ecological momentary assessment in physical activity research. Exercise and Sport Sciences Reviews, 45(1), 48.

Intensive Longitudinal Data (ILD)

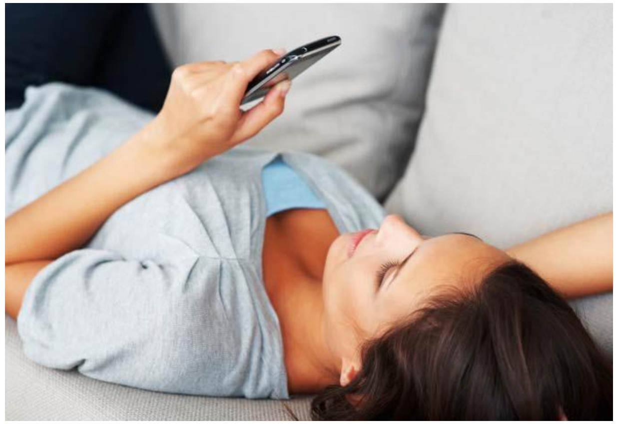
- High-frequency and high-density repeated measures data
- Collected over a micro-timescale (e.g., seconds, minutes, hours, days)

- Real-world settings

Types of ILD from mobile and sensor devices: self-report (EMA), body movement, biological responses, geographic location, phone/app use, social interactions, and communication patterns.

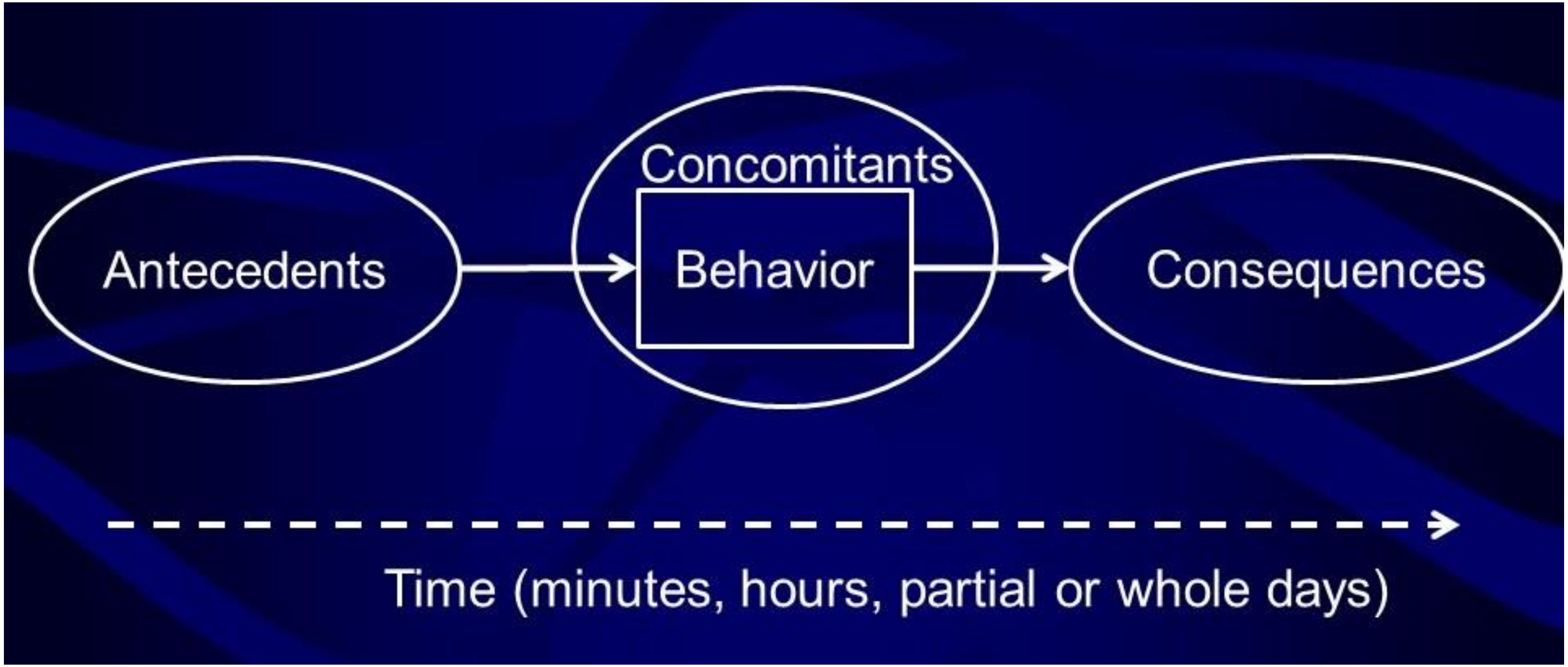
Ecological Momentary Assessment (EMA)

- **Ecological**
  - Real-world environments & experiences
  - Provides ecological validity
- **Momentary**
  - Real-time assessment
  - Avoids recall bias
- **Assessment**
  - Self-report (subjective)
  - Multiple repeated measures



Stone & Shiffman, 1994

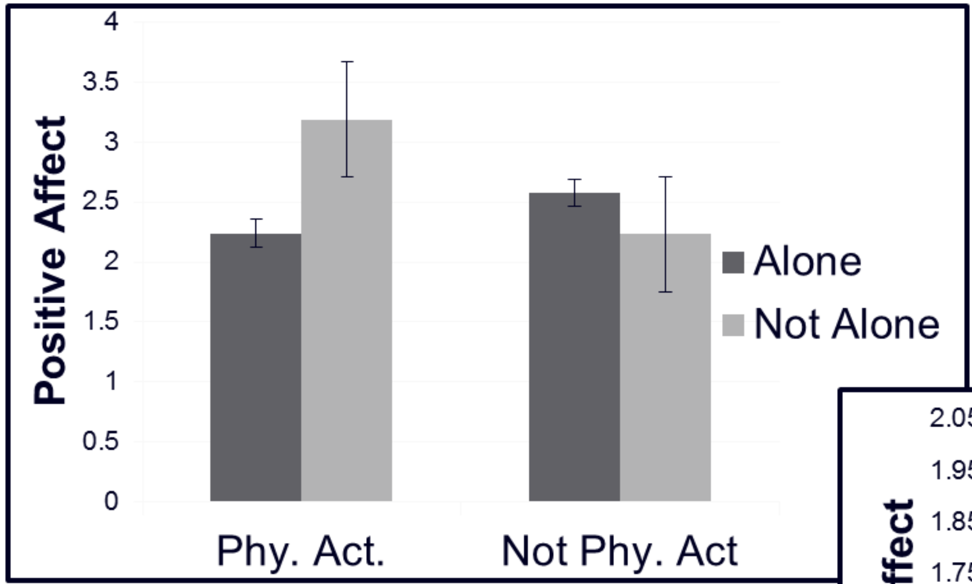
Common Use of ILD: Examining Momentary Within-Subject Effects of Time-Varying Variables on Health Behaviors

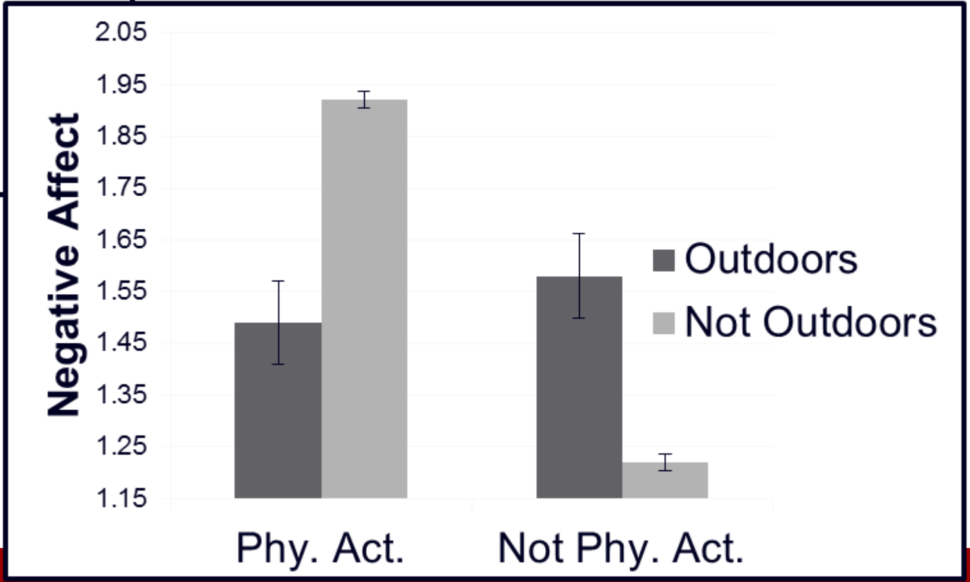


Dunton, G. F. (2017). Ecological Momentary Assessment in physical activity research. Exercise and Sports Sciences Reviews, 45(1), 48-54.

Common Use of ILD: Examining Momentary Within-Subject Effects of Time-Varying Variables on Health Behaviors

Contextual Influences on Affective Response During Physical Activity





Measured through 12 days of EMA

Dunton, G. F., Liao, Y., Intille, S., Huh, J, Leventhal, A. M. (2015). Momentary assessment of contextual influences on affective response during physical activity. Health Psychology, 34(12), 1145-1153.

Less Common Use of ILD: Examining Aggregated Intraindividual Effects of Within-Subject Effects of Time-Varying Variables on Health Behaviors

1. Intraindividual means (i.e., random location effect)
   How happy is a subject, on average, across occasions?

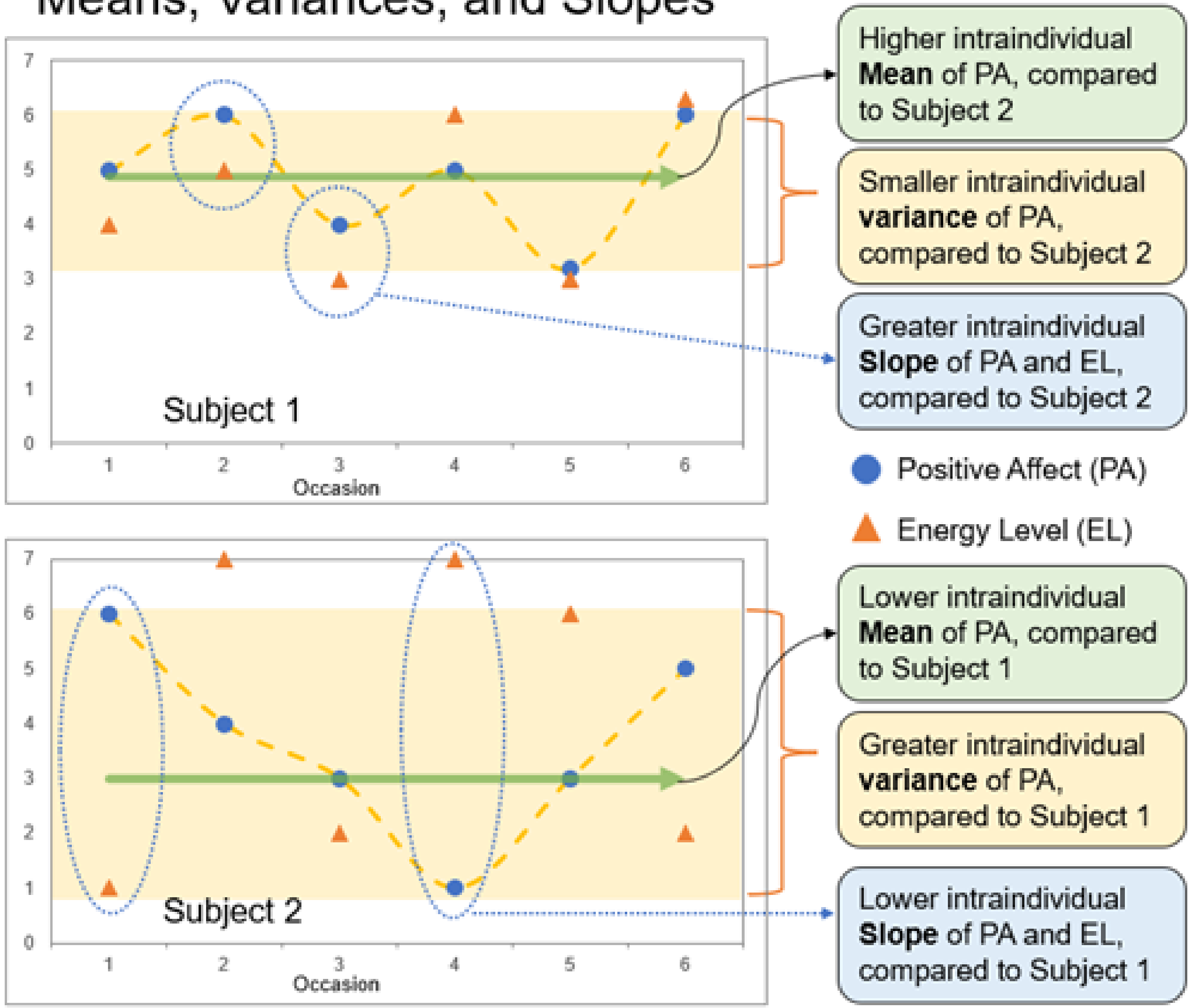
2. Intraindividual variances (i.e., random scale effect)
   How erratic is a subject's mood across occasions?

3. Intraindividual slopes (i.e., random slope effect)
   How strongly is a subject's mood related to activity across occasions?

Dzubur, E., Ponnada, A., Nordgren, R., Yang, C. H., Intille, S., Dunton, G., & Hedeker, D. (2020). MixWILD: A program for examining the effects of variance and slope of time-varying variables in intensive longitudinal data. *Behavior Research Methods*, *52*, 1403-1427.

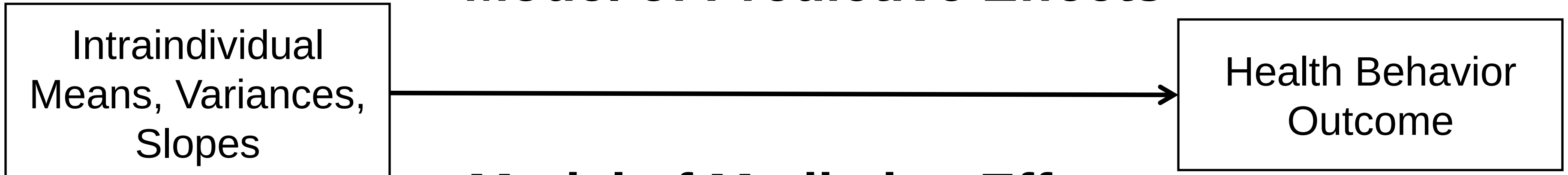
ILD Can Examine Aggregated Intraindividual Effects of Time-Varying Variables on Health Behaviors

Figure 1-2: Conceptual Graphs of Intraindividual Means, Variances, and Slopes



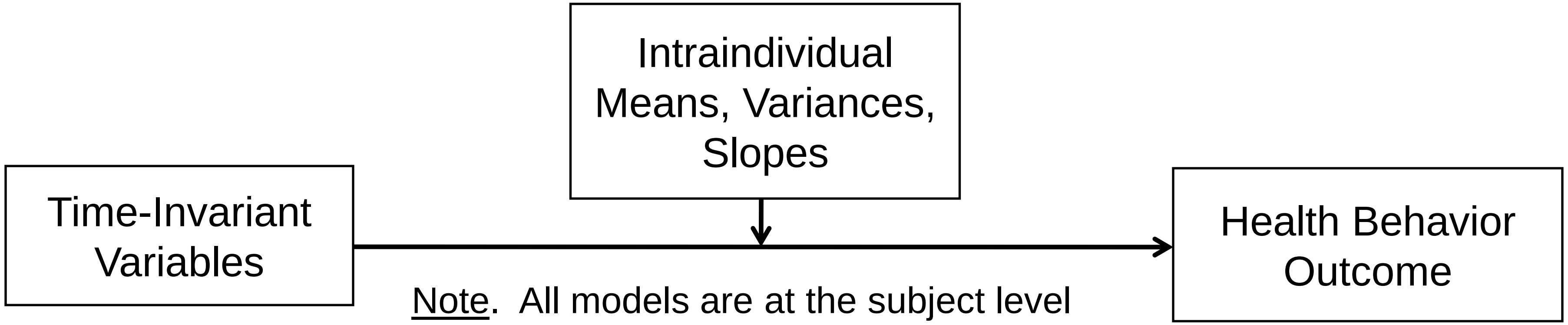
ILD Can Examine Aggregated Intraindividual Effects of Time-Varying Variables on Health Behaviors

Model of Predictive Effects



Model of Mediation Effects

Model of Moderation Effects



<u>Note</u>. All models are at the subject level

ILD Can Examine Aggregated Intraindividual Effects of Time-Varying Variables on Health Behaviors

Model of Predictive Effects

Intraindividual Variances → Health Behavior Outcome

Note. All models are at the subject level

Intraindividual Variance Predicting a Subject-Level Health Behavior Outcome

Individuals with greater variability in feelings of energy have lower odds of meeting physical activity guidelines

Table 4
Subject-Level Regression Models predicting Odds of Meeting Physical Activity Guidelines (Logistic) and Sedentary Time (Linear).

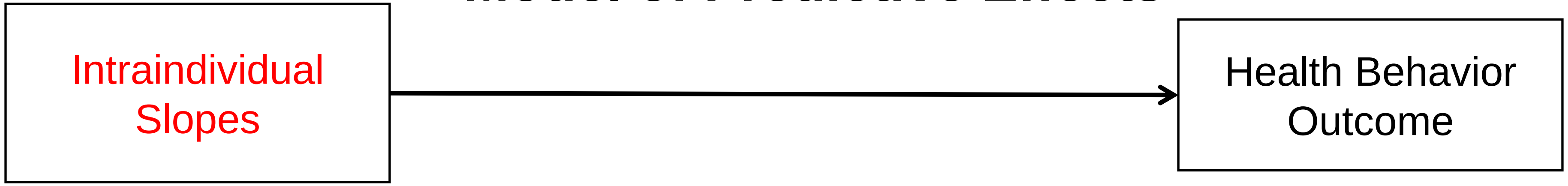
	Predicting Odds of Meeting Physical Activity Guidelines Estimate (Standard Error)	Predicting Minutes of Sedentary Time per Valid Hour of Wear Estimate (Standard Error)
Positive Affect		
Intercept	0.58 (0.32)	33.74** (0.68)
Mean level of Positive Affect	0.09 (0.10)	0.33 (0.31)
Variability in Positive Affect	0.07 (0.09)	0.16 (0.23)
Sex (Female)	−0.92** (0.21)	1.04* (0.41)
Age	0.01 (0.01)	0.11** (0.01)
Feelings of Energy		
Intercept	0.51 (0.55)	34.93** (1.03)
Mean level of Feelings of Energy	−0.09 (0.18)	−0.26 (0.30)
Variability in Feelings of Energy	−0.43* (0.21)	0.15 (0.37)
Sex (Female)	−1.13** (0.36)	1.40* (0.58)
Age	−0.01 (0.01)	0.07** (0.02)

Note. Model using positive affect data are based on 617 participants. Model using feelings of energy data are based on 245 participants. For logistic regression models predicting odds of meeting physical activity guidelines, logit (i.e., log odds) estimates are displayed. $*p < 0.05$. $**p < 0.01$.

Maher JP, Dzubur E, Nordgren R, et al. Do fluctuations in positive affective and physical feeling states predict physical activity and sedentary time? *Psychology of Sport and Exercise.* 2018..

ILD Can Examine Aggregated Intraindividual Effects of Time-Varying Variables on Health Behaviors

Model of Predictive Effects

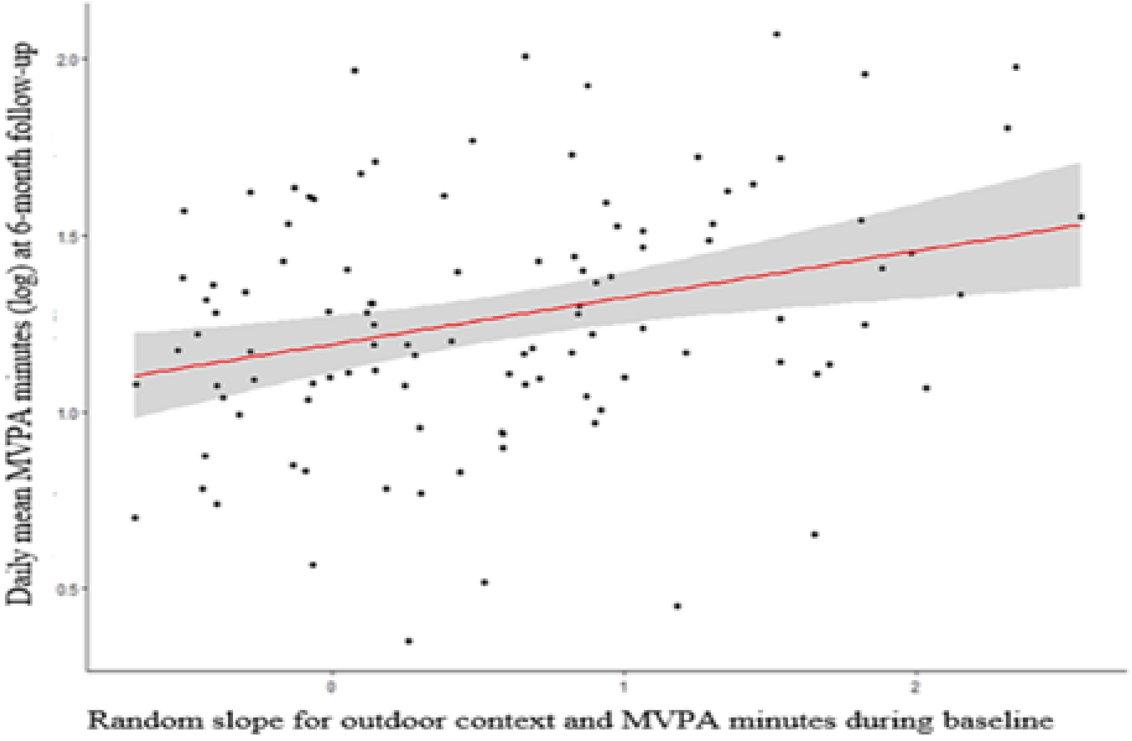


Note. All models are at the subject level

Intraindividual Slope Predicting a Subject-Level Outcome

Intraindividual slope = momentary association between context and MVPA

Figure 6: Intraindividual Slope (i.e., Momentary Association of Outdoor Context and MVPA) Predicting Adults' MVPA Six Months Later

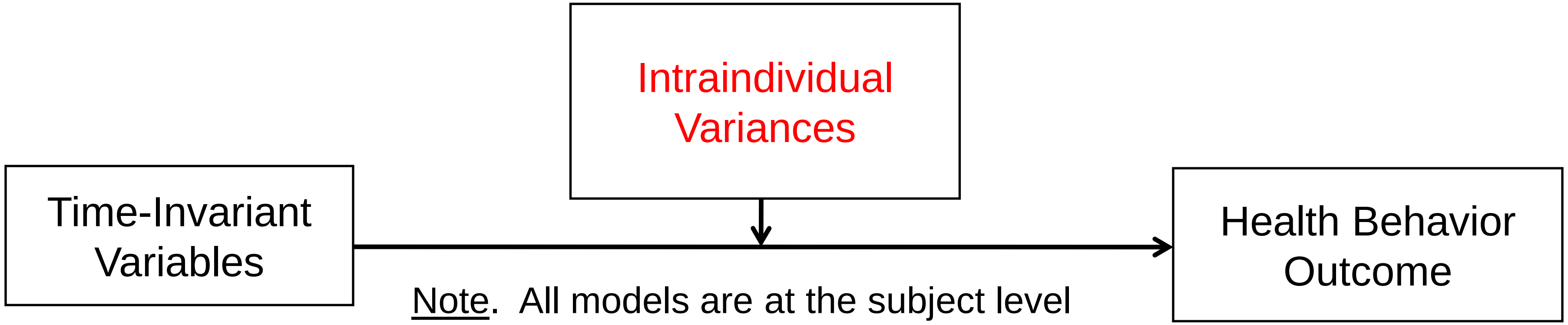


Participants, who had more momentary MVPA when outdoors (vs. indoors) during baseline (i.e., higher intraindividual lope), had higher daily MVPA six months later

Maher, J. P., Ra, C. K., Leventhal, A. M., Hedeker, D., Huh, J., Chou, C. P., & Dunton, G. F. (2018). Mean level of positive affect moderates associations between volatility in positive affect, mental health, and alcohol consumption among mothers. *Journal of Abnormal Psychology*, *127*(7), 639.

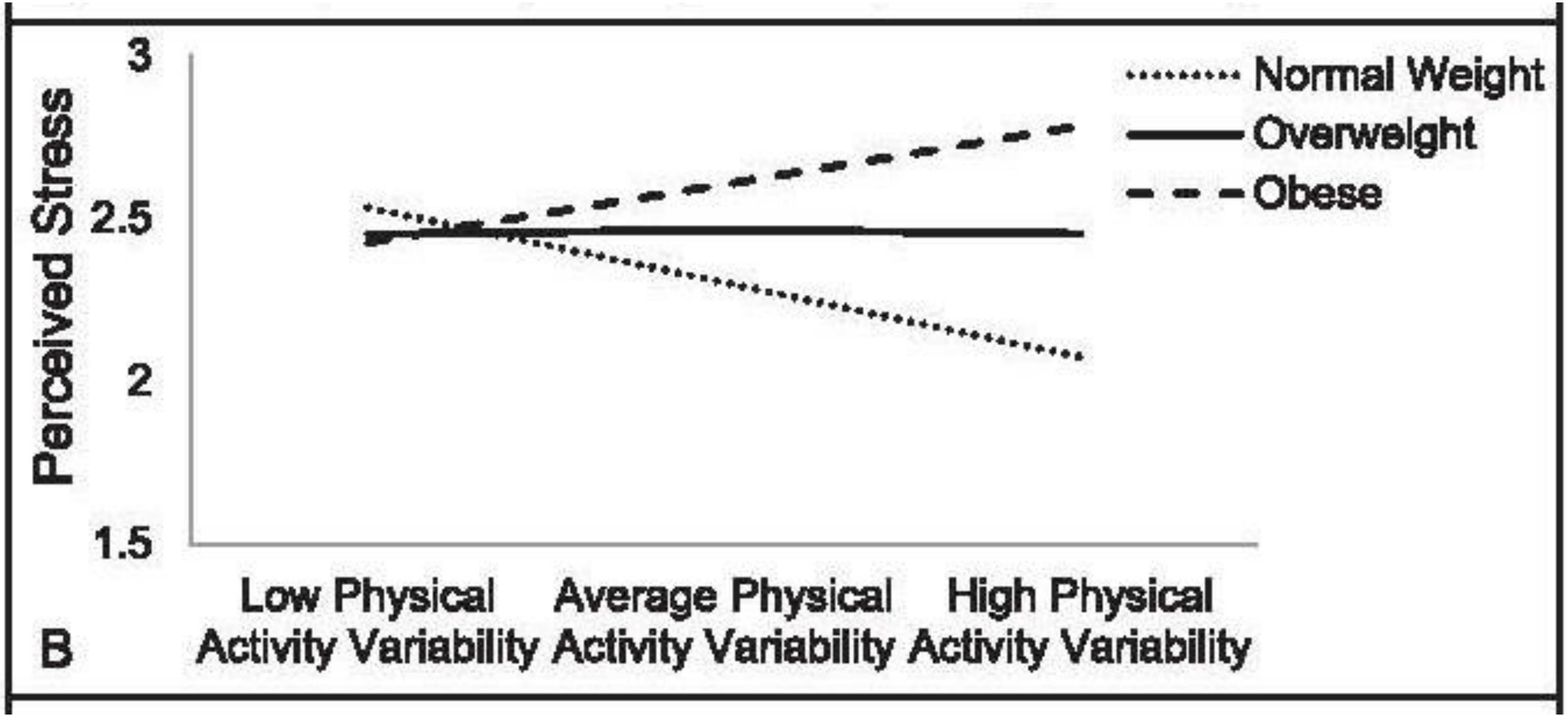
ILD Can Examine Aggregated Intraindividual Effects of Time-Varying Variables on Health Behaviors

Model of Moderation Effects



Note. All models are at the subject level

Intraindividual Variance Moderating the Effect of a Subject-Level Factor on a Subject-Level Outcome

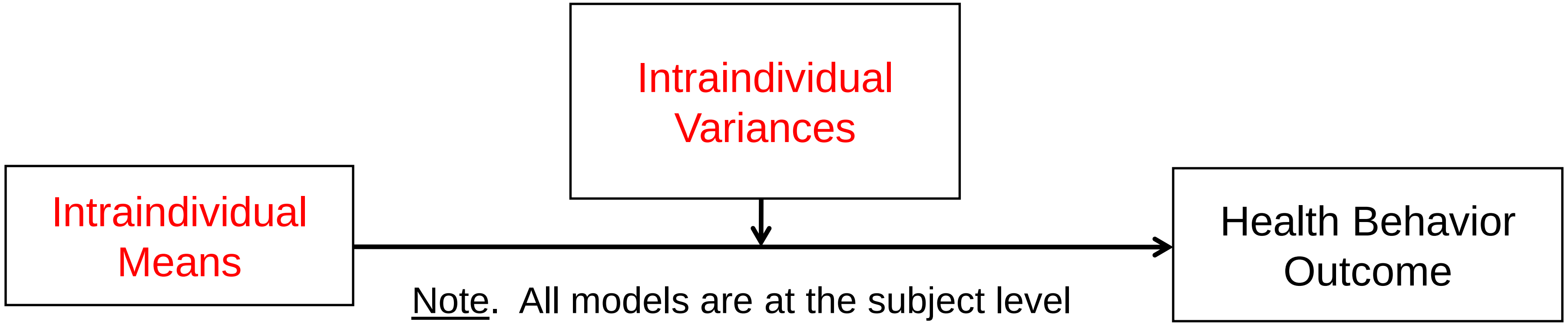


Individuals with obesity have higher levels of perceived stress, but only for those with high day-to-day variability in physical activity

Maher JP, Huh J, Intille S, Hedeker D, Dunton GF. Greater variability in daily physical activity is associated with poorer mental health profiles among obese adults. *Mental Health and Physical Activity.* 2018;14:74-81.

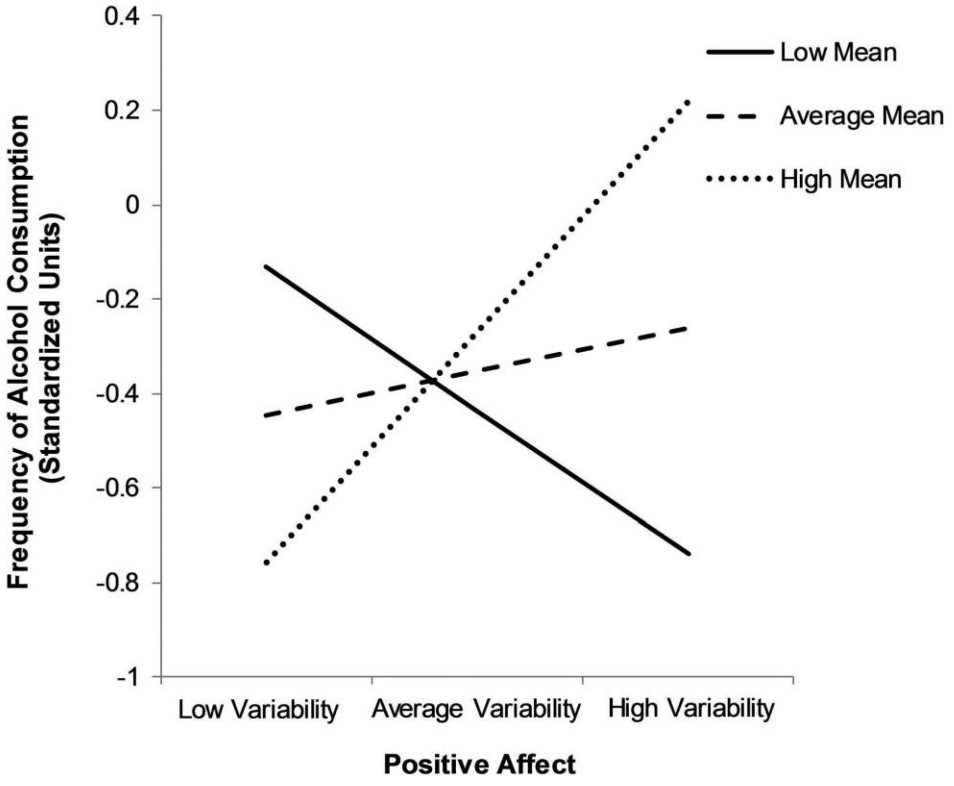
ILD Can Examine Aggregated Intraindividual Effects of Time-Varying Variables on Health Behaviors

Model of Moderation Effects



Note. All models are at the subject level

Intraindividual Variance Moderating the Effect of a Intraindividual Mean on a Subject-Level Outcome



Individuals with low mean positive affect have higher alcohol consumption, but only for those with low variability in positive affect

Maher, J. P., Ra, C. K., Leventhal, A. M., Hedeker, D., Huh, J., Chou, C. P., & Dunton, G. F. (2018). Mean level of positive affect moderates associations between volatility in positive affect, mental health, and alcohol consumption among mothers. *Journal of Abnormal Psychology*, *127*(7), 639.

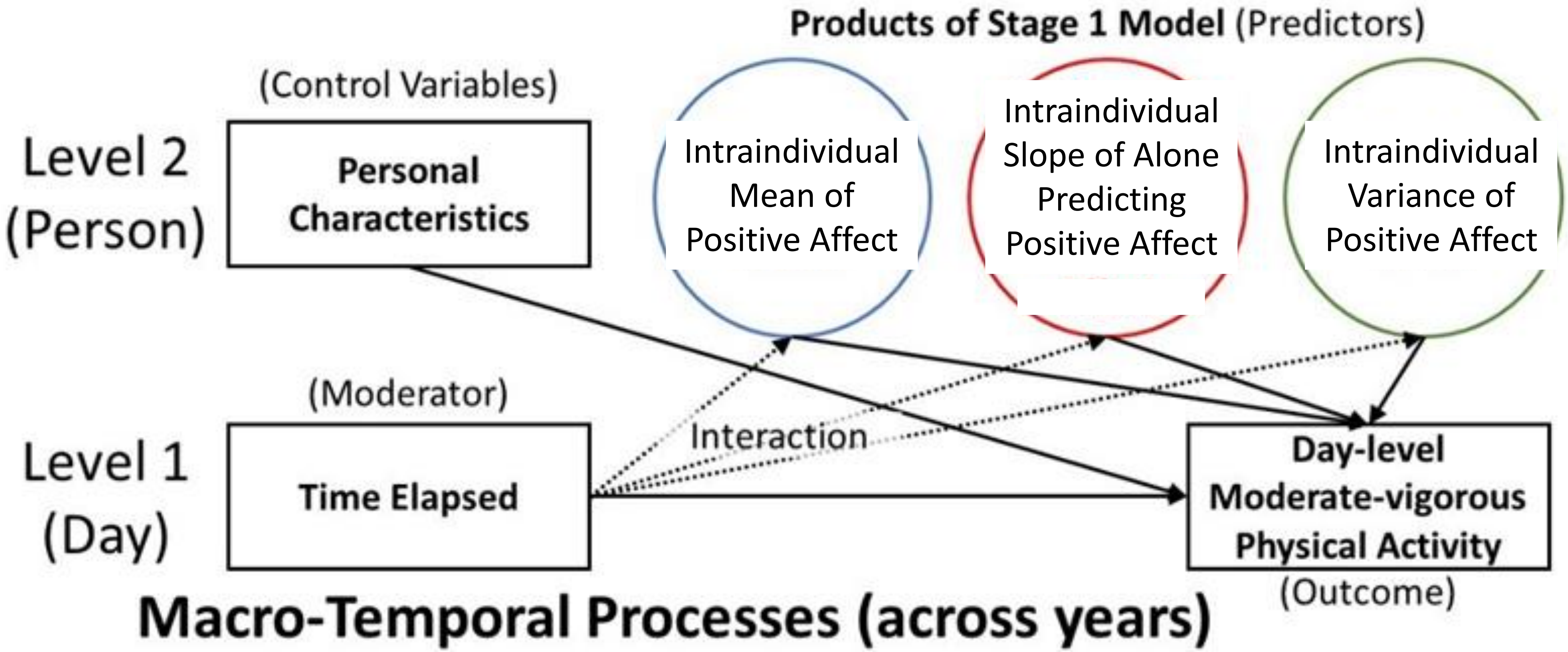
ILD Can Examine Aggregated Intraindividual Effects of Time-Varying Variables on Health Behaviors

Model of Predictive Effects

Intraindividual Means, Variances, Slopes → Change in Health Behavior Outcome Over time

Note. Outcome is no longer at the subject level

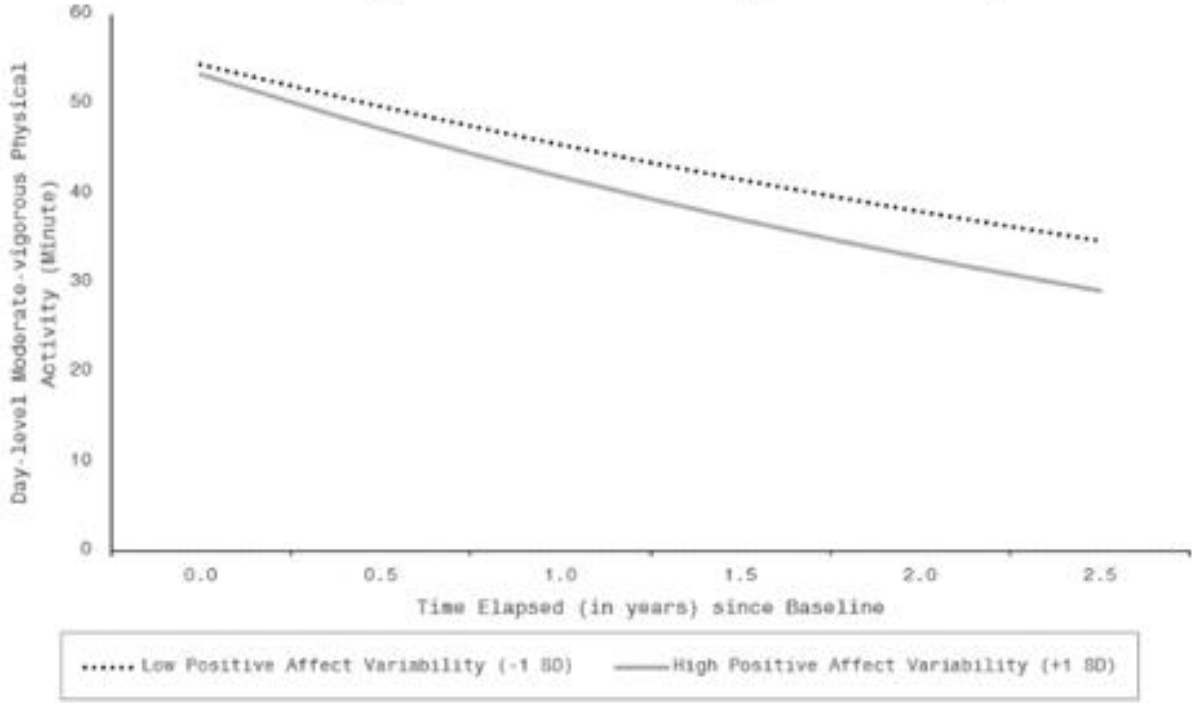
Intraindividual Means, Variances, and Slopes Predicting Change in an Outcome over Time



Dunton, G. F., Wang, W. L., Intille, S. S., Dzubur, E., Ponnada, A., & Hedeker, D. (2022). How acute affect dynamics impact longitudinal changes in physical activity among children. *Journal of Behavioral Medicine*, *45*(3), 451-460.

Intraindividual Variance Predicting Change in an Outcome over Time

Figure 4: Time Elapsed (in years) Since Baseline × Intraindividual Scale (i.e., Positive Affect Variability) Interaction Predicting Children's Day-level MVPA



Children who had greater intraindividual variance in positive affect had a faster rates of decline in physical across three years

Dunton, G. F., Wang, W. L., Intille, S. S., Dzubur, E., Ponnada, A., & Hedeker, D. (2022). How acute affect dynamics impact longitudinal changes in physical activity among children. *Journal of Behavioral Medicine*, *45*(3), 451-460.

ILD Can Examine Aggregated Intraindividual Effects of Time-Varying Variables on Health Behaviors

Model of Predictive Effects

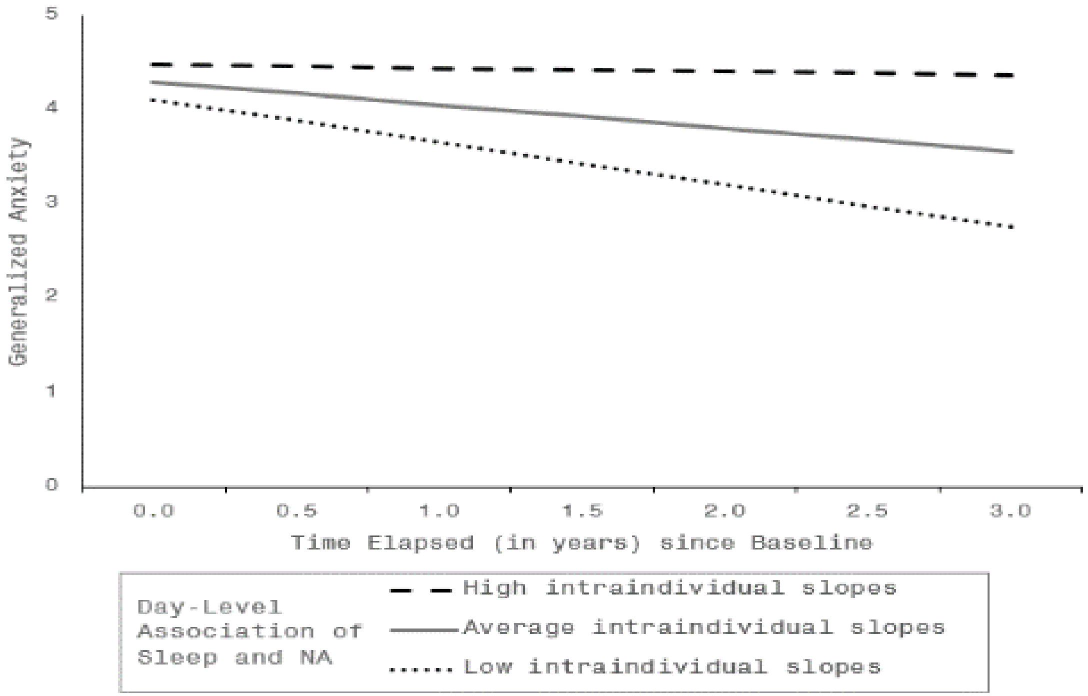
Intraindividual Slopes → Change in Health Behavior Outcome Over time

Note. Outcome is no longer at the subject level

Intraindividual Slope Predicting Change in an Outcome over Time

Intraindividual slope = day-level association between negative affect and sleep

Figure 5: Time Elapsed (in years) Since Baseline x Intraindividual Slope (i.e., Day-Level Association of Sleep and NA) Interaction Predicting Children's Generalized Anxiety



Children who needed to sleep more on nights following days with higher negative affect had a slower rate of decline in generalized anxiety across three years

Wang, W-L., Hedeker, D., Mason, T. B., Dzubur, E., Intille, S., Ponnada, A., Naya, C.H., O'Connor, S. G., Dunton, G. F., Daily Coupling of Negative Affect and Sleep Predict Longitudinal Changes in Children's Mental Health: An Ecological Momentary Assessment Study. Society for Behavioral Medicine Annual Meeting. April,2021

Overview of MixWILD

- <u>First Stage Model</u>- estimates intraindividual means, variances, and slopes as random effects in mixed-effects location scale multilevel model

- <u>Second Stage Model</u>- uses random means, variances, and slopes from first stage as predictors of a subject-level or time-varying outcome in a single or multilevel linear or logistic regression model

MIX{WILD}
Mixed Model Analysis With Intensive Longitudinal Data

Dzubur, E., Ponnada, A., Nordgren, R., Yang, C. H., Intille, S., Dunton, G., & Hedeker, D. (2020). MixWILD: A program for examining the effects of variance and slope of time-varying variables in intensive longitudinal data. *Behavior Research Methods*, *52*, 1403-1427.

Other 2023 SBM Presentations Using MixWILD

Do et al. Investigating day-level associations between affective variability and physical activity using Ecological Momentary Assessment.
Symposium on Friday April 28, 2023 at 9:00 AM

Yang et al. The mean level, between-person differences, and within-person variability of older adults' daily sleep quality and duration.
Paper Session 34 on Friday April 28, 2023 at 1:00 PM

Wang et al. Associations of smartphone usage with average day-level and day-to-day variability of mood in emerging adults
Poster Session E on Sat. April 29, 2023 at 11:00 AM

Acknowledgments

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Aaron Coleman (Fitabase)

Hailey Persinger (Fitabase)

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USC REACH Lab website: http://reach.usc.edu/

Twitter: @GenevieveDunton

REACH

A Brief Introduction to the Mixed-Effects Location Scale (MELS) Model

Don Hedeker
Department of Public Health Sciences
University of Chicago

https://voices.uchicago.edu/hedeker/

Supported by National Cancer Institute grant R01 CA240713 (Hedeker & Dunton)

Ecological Momentary Assessment (EMA) data

experience sampling and diary methods, intensive longitudinal data

- Subjects provide frequent reports on events and experiences of their daily lives (*e.g.*, 30-40 responses per subject collected over the course of a week or so)

- electronic diaries: cell phones, palm pilots, personal digital assistants (PDAs), interactive voice response (IVR) systems, actigraphs, web-based

- Capture particulars of experience in a way not possible with more traditional designs
  e.g., allow investigation of phenomena as they happen over time

- Reports could be time-based, following a fixed-schedule, randomly triggered, event-triggered

Data are rich and offer many modeling possibilities!

- person- and occasion-level effects on occasion-level responses
  $\Rightarrow$ potential influence of context and/or environment
  e.g., subject response might vary when alone vs with others

- data are inherently multilevel
  - occasions (level-1) within subjects (level-2)
  - occasions (level-1) within days (level-2) within subjects (level-3)
  - occasions (level-1) within waves (level-2) within subjects (level-3)

- References for mixed model analysis of EMA data
  - Schwartz, J.E. & Stone, A. (2007). The analysis of real-time momentary data: A practical guide. In: A.A. Stone, S.S. Shiffman, A. Atienza, and L. Nebeling, editors, *The science of real-time data capture: Self-report in health research*. Oxford, England: Oxford University Press, p. 76-113.
  - Walls, T.A., Jung, H., & Schwartz, J.E. (2006). Multilevel models for intensive longitudinal data. In: Walls, T.A. and Schafer, J.L., editors, *Models for intensive longitudinal data*. New York: Oxford University Press, p. 3-37

Learning Objectives

- Using mixed-effects location scale (MELS) models, examine why subjects differ in mean level *as well as variability*
  - Between-subjects variance
    e.g., subject heterogeneity can vary by gender, age, or context
    * modeling of between-subjects variance in terms of covariates
    * inclusion of random subject intercepts and slopes
  - Within-subjects variance
    e.g., subject inconsistency can vary by gender, age, or context
    * modeling of within-subjects variance in terms of covariates, including random subject scale

- MixWILD freeware program example

Carroll (2003) Variances are not always nuisance parameters, *Biometrics*.

Mixed-Effects Location Scale Models for EMA data

- Hedeker, Mermelstein, & Demirtas (2008). An application of a mixed-effects location scale model for analysis of Ecological Momentary Assessment (EMA) data. *Biometrics, 64*, 627-634.
- Hedeker, D., Mermelstein, R.J., & Demirtas, H. (2012). Modeling between- and within-subject variance in EMA data using mixed-effects location scale models. *Statistics in Medicine, 31* 3328-3336.

Multilevel (mixed-effects regression) model for measurement y of subject i ($i = 1, 2, \ldots, N$) on occasion j ($j = 1, 2, \ldots, n_i$)

$$y_{ij} \; = \; \boldsymbol{x}'_{ij}\boldsymbol{\beta} + \upsilon_i + \epsilon_{ij}$$

$\boldsymbol{x}_{ij} = p \times 1$ vector of regressors (including a column of ones)

$\boldsymbol{\beta} = p \times 1$ vector of regression coefficients

$\upsilon_i \sim N(0, \sigma^2_\upsilon)$ BS variance; how homogeneous/heterogeneous are subjects?

$\epsilon_{ij} \sim N(0, \sigma^2_\epsilon)$ WS variance; how consistent/erratic are the data within subjects?

Model with no covariates: $y_{ij} = \beta_0 + \upsilon_i + \epsilon_{ij}$

- υ_i is subject's mean (deviation from β_0)
  - if subjects are alike, $\upsilon_i \approx 0$ and σ^2_υ will approach 0
  - if subjects are different, $\upsilon_i \neq 0$ and σ^2_υ will increase from 0

  $\Rightarrow$ magnitude of σ^2_υ indicates how different subjects are from each other (homogeneity/heterogeneity)

- ϵ_{ij} is subject i's error at time j (deviations from their mean)
  - if subjects are all well-fit, $\epsilon_{ij} \approx 0$ and σ^2_ϵ will approach 0
  - if subjects are not well-fit, $\epsilon_{ij} \neq 0$ and σ^2_ϵ will increase from 0

  $\Rightarrow$ magnitude of σ^2_ϵ indicates how data vary within subjects (consistency/erraticism)

Log-linear models for variances

$$\text{BS variance} \quad \sigma^2_{\upsilon_{ij}} = \exp(\boldsymbol{u}'_{ij}\boldsymbol{\alpha}) \quad \text{or} \quad \log(\sigma^2_{\upsilon_{ij}}) = \boldsymbol{u}'_{ij}\boldsymbol{\alpha}$$

$$\text{WS variance} \quad \sigma^2_{\epsilon_{ij}} = \exp(\boldsymbol{w}'_{ij}\boldsymbol{\tau}) \quad \text{or} \quad \log(\sigma^2_{\epsilon_{ij}}) = \boldsymbol{w}'_{ij}\boldsymbol{\tau}$$

- $\boldsymbol{u}_{ij}$ and $\boldsymbol{w}_{ij}$ include covariates (and $\mathbf{1}$)
- subscripts i and j on variances indicate that these change depending on covariates $\boldsymbol{u}_{ij}$ and $\boldsymbol{w}_{ij}$ (and their coefficients)
- exp function ensures a positive multiplicative factor, and so resulting variances are positive

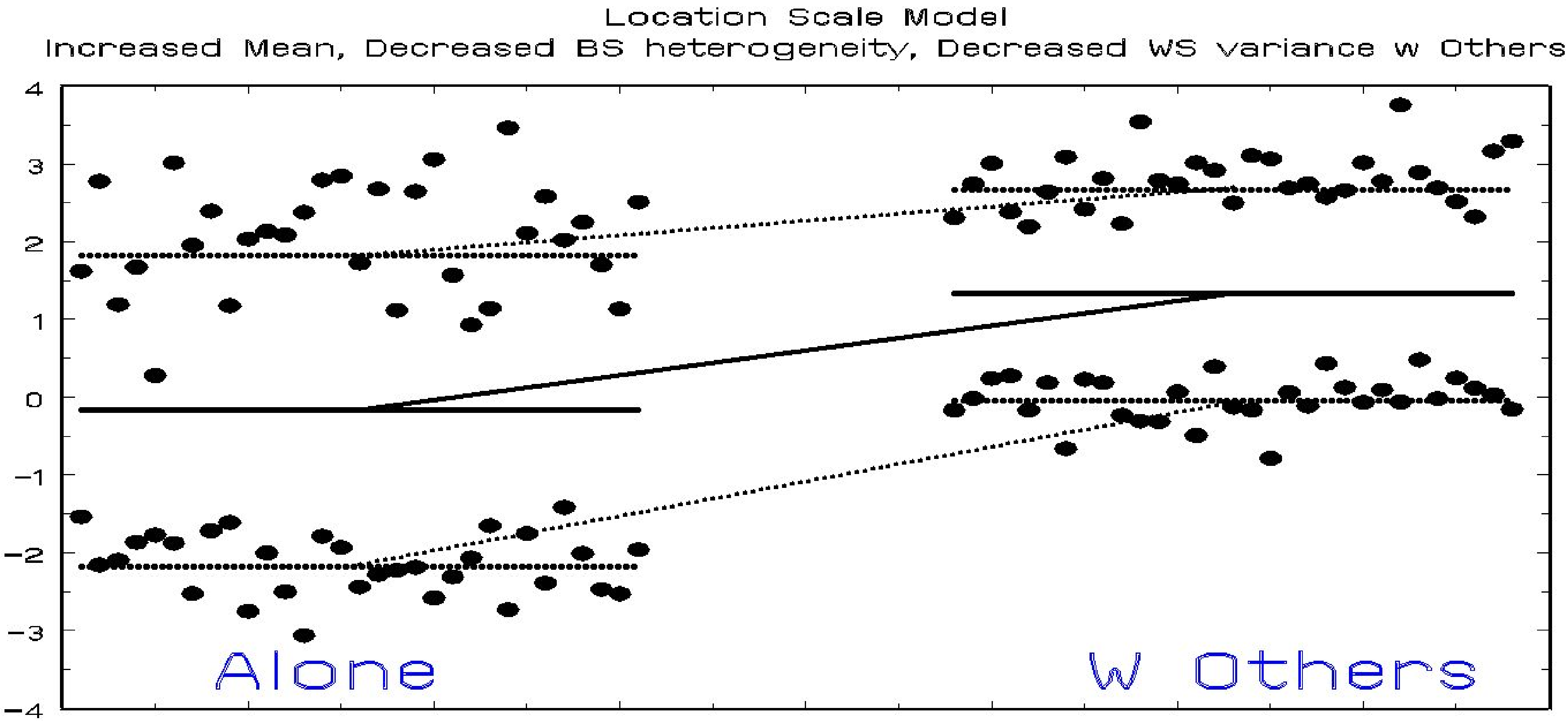
How can WS variables influence BS variance?

$$\sigma^2_{\upsilon_{ij}} = \exp(\boldsymbol{u}'_{ij}\boldsymbol{\alpha})$$

- Do rainy days and Mondays get everyone down?
- Is Tuesday just as bad as Stormy Monday for all?
- Are all kids happy on the last day of school?

Example: strong positive effect of being alone on BS variance of positive and negative mood

$\Rightarrow$ being alone increases subject heterogeneity (or, subjects report more similar mood when with others)



- Means are increased with others
- Subjects are more similar to each other when with others (BS var)
- Within-subject data are more consistent with others (WS var)

WS variance varies across subjects

$$\sigma^2_{\epsilon_{ij}} = \exp(\boldsymbol{w}'_{ij}\boldsymbol{\tau} + \omega_i) \quad \text{where} \quad \omega_i \sim N(0, \sigma^2_\omega)$$

$$\log(\sigma^2_{\epsilon_{ij}}) = \boldsymbol{w}'_{ij}\boldsymbol{\tau} + \omega_i$$

- ω_i are log-normal subject-specific perturbations of WS variance
- ω_i are "scale" random effects - how does a subject differ in terms of the variation in their data
- υ_i are "location" random effects - how does a subject differ in terms of the mean of their data

Multilevel model of WS variance

$$\log(\sigma^2_{\epsilon_{ij}}) \;=\; \boldsymbol{w}'_{ij}\boldsymbol{\tau} + \omega_i$$

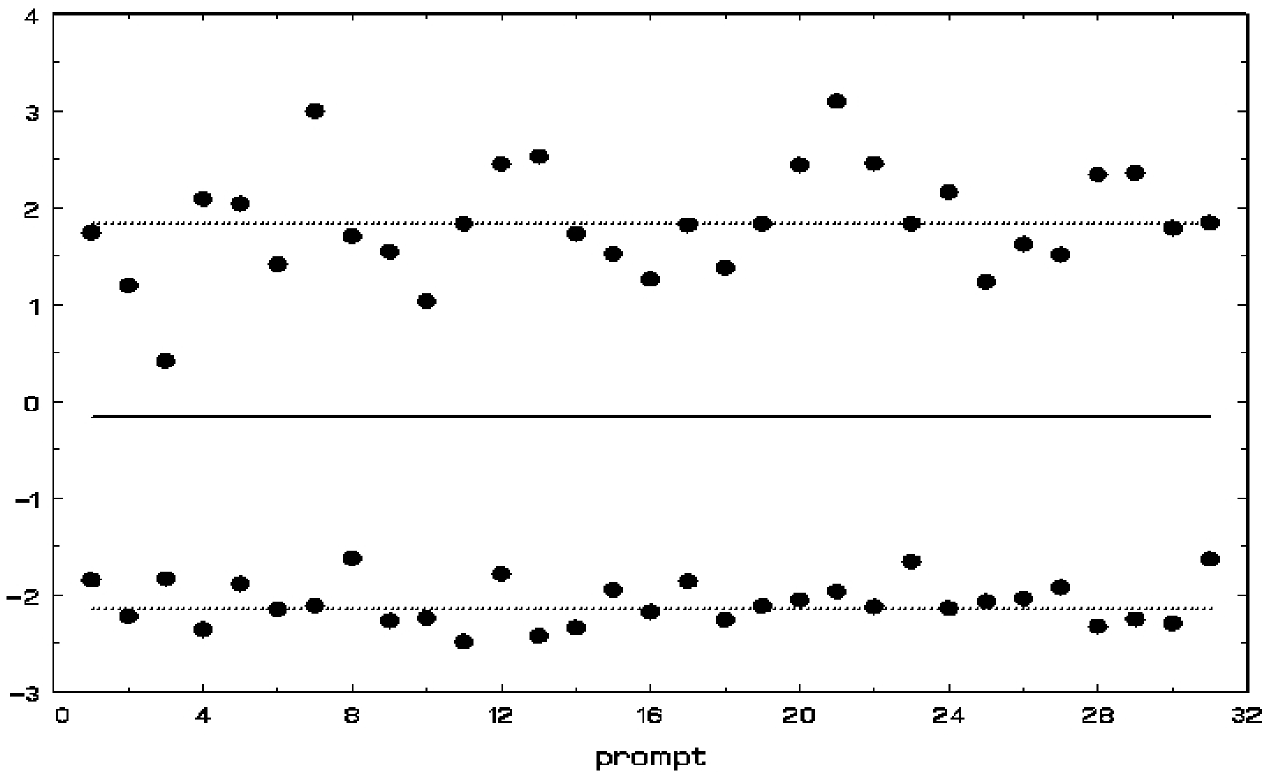
Why not use some summary statistic per subject (say, calculated subject standard deviation S_{y_i}) in a second-stage model?

$$S_{y_i} = \boldsymbol{x}'_i\boldsymbol{\beta} + \epsilon_i$$

latter approach

- treats all standard deviations as if they are equally precise (but some might be based on 2 prompts or 40 prompts)
- does not recognize that these are estimated quantities (underestimation of sources of variation)
- does not allow occasion-varying predictors

$\Rightarrow$ We use multilevel models for mean response, why not for variance?



Model allows covariates to influence

- mean: level of solid line
- BS variance: dispersion of dotted lines
- WS variance: dispersion of points

additional random subject effects on: mean and WS variance

MixWILD: Mixed-effects models With Intensive Longitudinal Data

Dzubur, E., Ponnada, A., Nordgren, R., Yang, C.-H., Intille, S., Dunton, G., & Hedeker, D. (2020). MixWILD: A program for examining the effects of variance and slope of time-varying variables in intensive longitudinal data. *Behavior Research Methods*, 52:1403–1427.

https://reach-lab.github.io/MixWildGUI

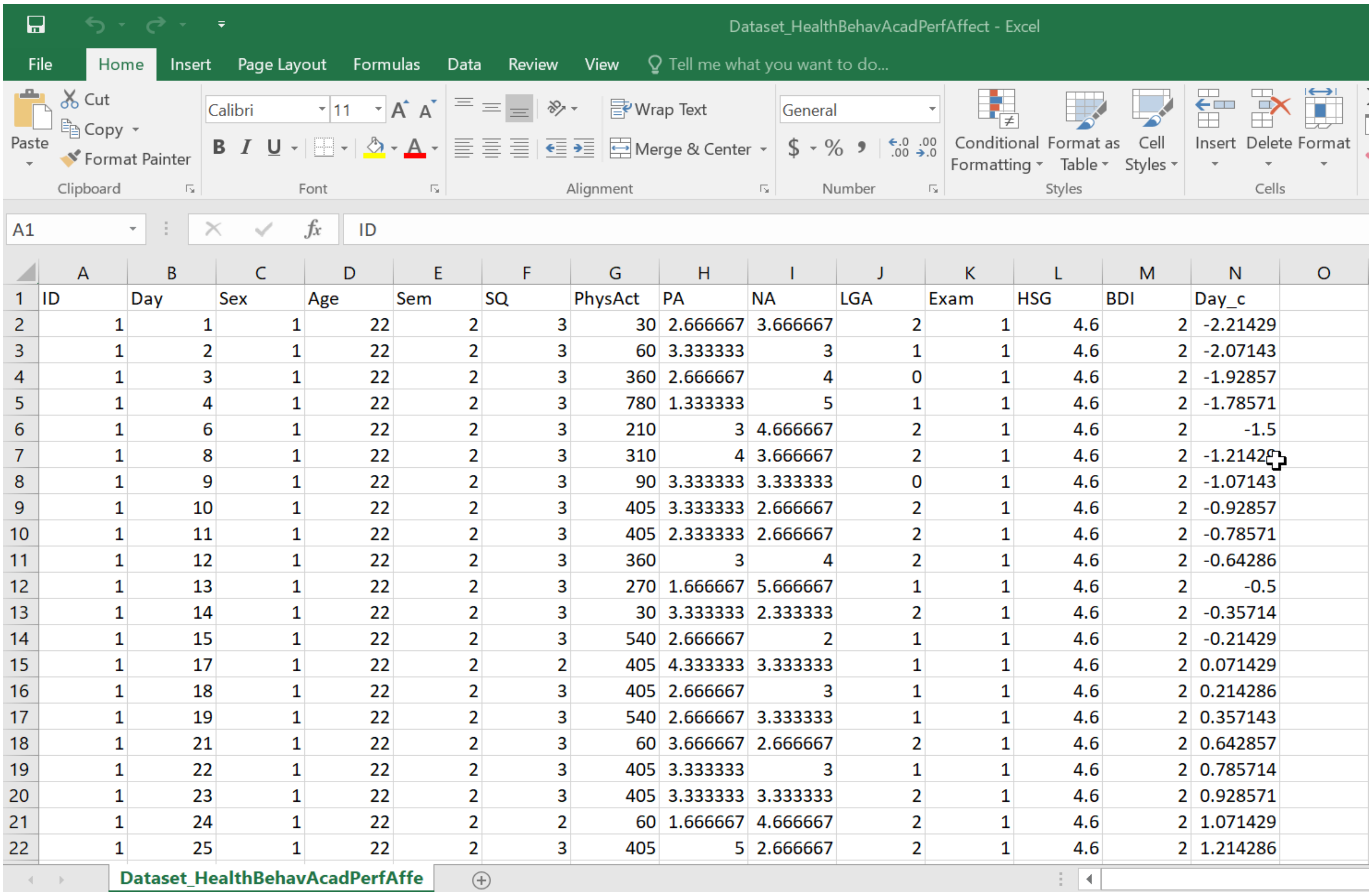
Example: a MELS model using MixWILD

Data are from: https://dataverse.harvard.edu/dataverse/harvard

"How health behaviors relate to academic performance via affect: An intensive longitudinal study" by Flueckiger L, Lieb R, Meyer AH, Mata J

ID	Subject number
Day	Survey day
Sex	Participants' sex
Age	Participants' age
Sem	Semester: Number of semesters studied
SQ	Sleep quality 1 (very bad) to 4 (very good)
PhysAct	Physical activity: Number of minutes engaged in mild, moderate and strenuous exercise weighted by metabolic equivalents and then summed to produce a total daily leisure activity score
PA	Positive affect 1 (not at all) to 7 (extremely)
NA	Negative affect 1 (not at all) to 7 (extremely)
LGA	Learning goal achievement 0 (not at all) to 4 (completely)
Exam	Examination success 0 (fail) 1 (pass)
HSG	High school grades 1 (lowest grade) to 6 (highest grade)
BDI	Beck Depression Inventory 1(not) 2 (mild to moderate) 3 (clinically relevant symptoms)
Added variable:	
Day_c	centered and scaled version of day (-2.2143 to 2.2143; 1 unit = 1 week)
-99	**Missing value**

Dataset_HealthBehavAcadPerfAffect.csv



	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	ID	Day	Sex	Age	Sem	SQ	PhysAct	PA	NA	LGA	Exam	HSG	BDI	Day_c
2	1	1	1	22	2	3	30	2.666667	3.666667	2	1	4.6	2	-2.21429
3	1	2	1	22	2	3	60	3.333333	3	1	1	4.6	2	-2.07143
4	1	3	1	22	2	3	360	2.666667	4	0	1	4.6	2	-1.92857
5	1	4	1	22	2	3	780	1.333333	5	1	1	4.6	2	-1.78571
6	1	6	1	22	2	3	210	3	4.666667	2	1	4.6	2	-1.5
7	1	8	1	22	2	3	310	4	3.666667	2	1	4.6	2	-1.2142[illegible]
8	1	9	1	22	2	3	90	3.333333	3.333333	0	1	4.6	2	-1.07143
9	1	10	1	22	2	3	405	3.333333	2.666667	2	1	4.6	2	-0.92857
10	1	11	1	22	2	3	405	2.333333	2.666667	2	1	4.6	2	-0.78571
11	1	12	1	22	2	3	360	3	4	2	1	4.6	2	-0.64286
12	1	13	1	22	2	3	270	1.666667	5.666667	1	1	4.6	2	-0.5
13	1	14	1	22	2	3	30	3.333333	2.333333	2	1	4.6	2	-0.35714
14	1	15	1	22	2	3	540	2.666667	2	1	1	4.6	2	-0.21429
15	1	17	1	22	2	2	405	4.333333	3.333333	1	1	4.6	2	0.071429
16	1	18	1	22	2	3	405	2.666667	3	1	1	4.6	2	0.214286
17	1	19	1	22	2	3	540	2.666667	3.333333	1	1	4.6	2	0.357143
18	1	21	1	22	2	3	60	3.666667	2.666667	2	1	4.6	2	0.642857
19	1	22	1	22	2	3	405	3.333333	3	1	1	4.6	2	0.785714
20	1	23	1	22	2	3	405	3.333333	3.333333	2	1	4.6	2	0.928571
21	1	24	1	22	2	2	60	1.666667	4.666667	2	1	4.6	2	1.071429
22	1	25	1	22	2	3	405	5	2.666667	2	1	4.6	2	1.214286

MELS model of PA

outcome: PA (positive affect)
regressor: Day_c (centered and scaled version of day)

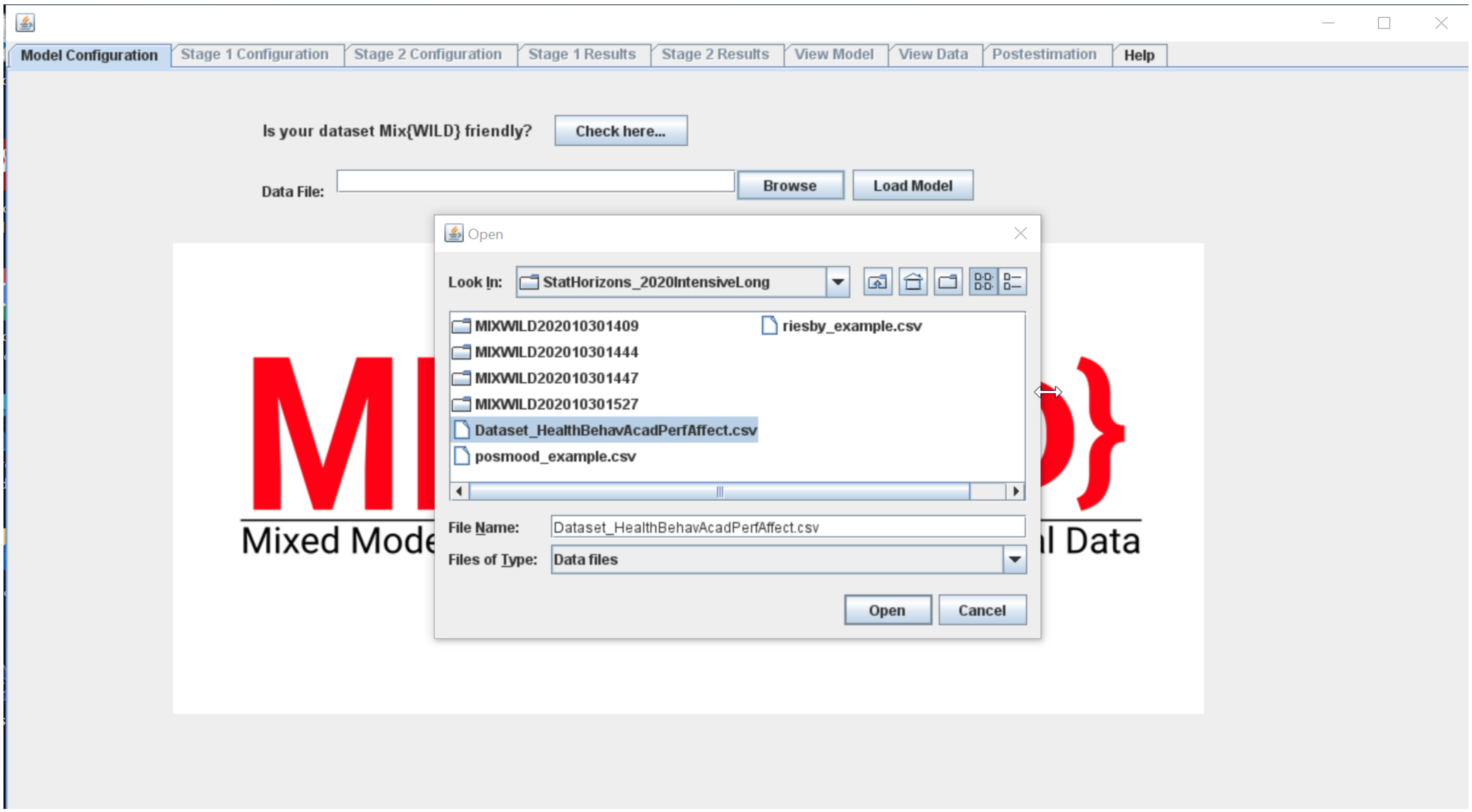
$$PA_{ij} = \beta_0 + \beta_1 Day\_c_{ij} + \upsilon_i + \epsilon_{ij}$$

$$\sigma^2_{\upsilon_{ij}} = \exp(\alpha_0 + \alpha_1 Day\_c_{ij})$$

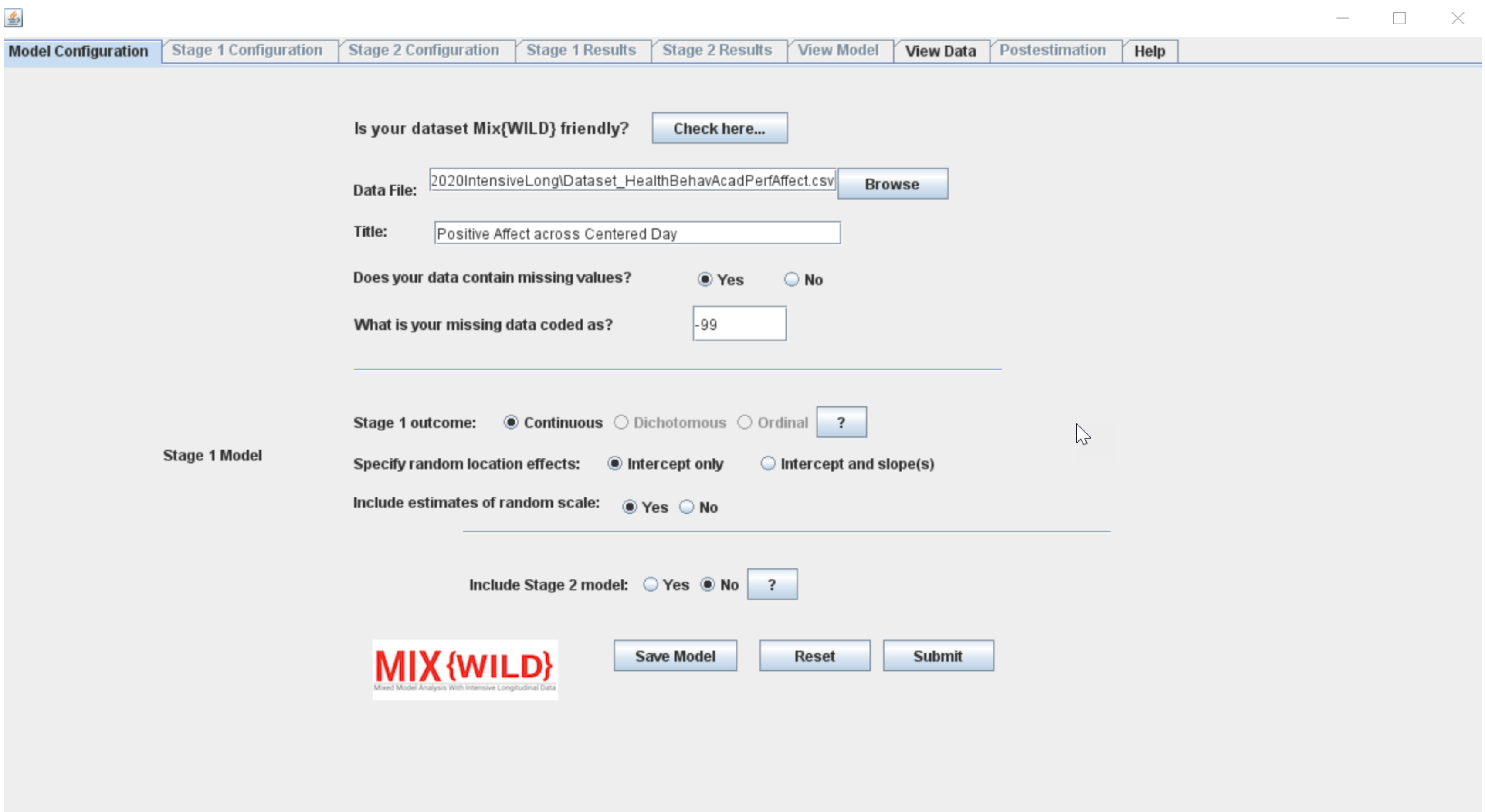
$$\sigma^2_{\epsilon_{ij}} = \exp(\tau_0 + \tau_1 Day\_c_{ij} + \tau_\upsilon \upsilon_i + \omega_i)$$

Here, υ_i is the random subject location effect, and ω_i is the random subject scale effect, both normally distributed

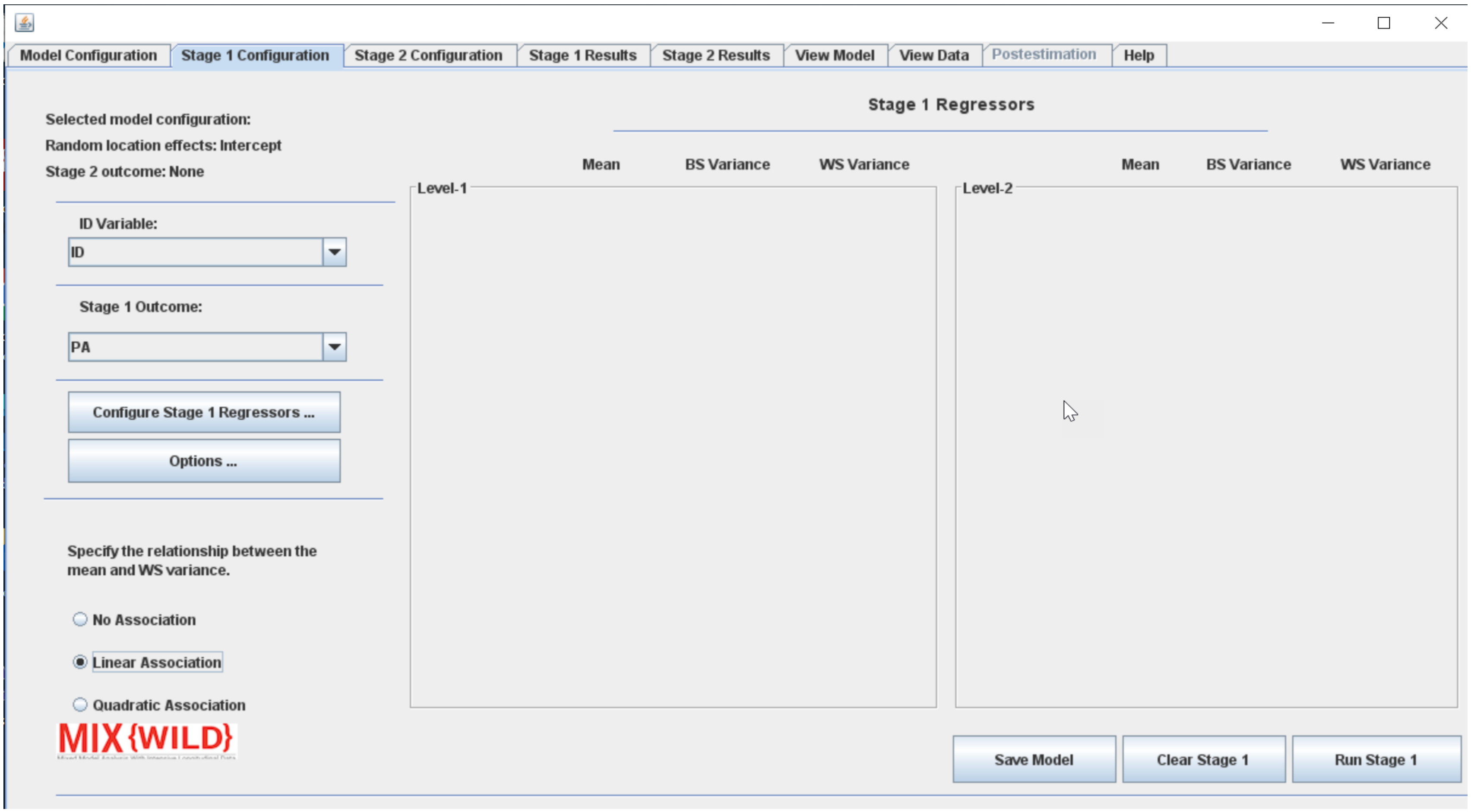
Browse for Dataset_HealthBehavAcadPerfAffect.csv



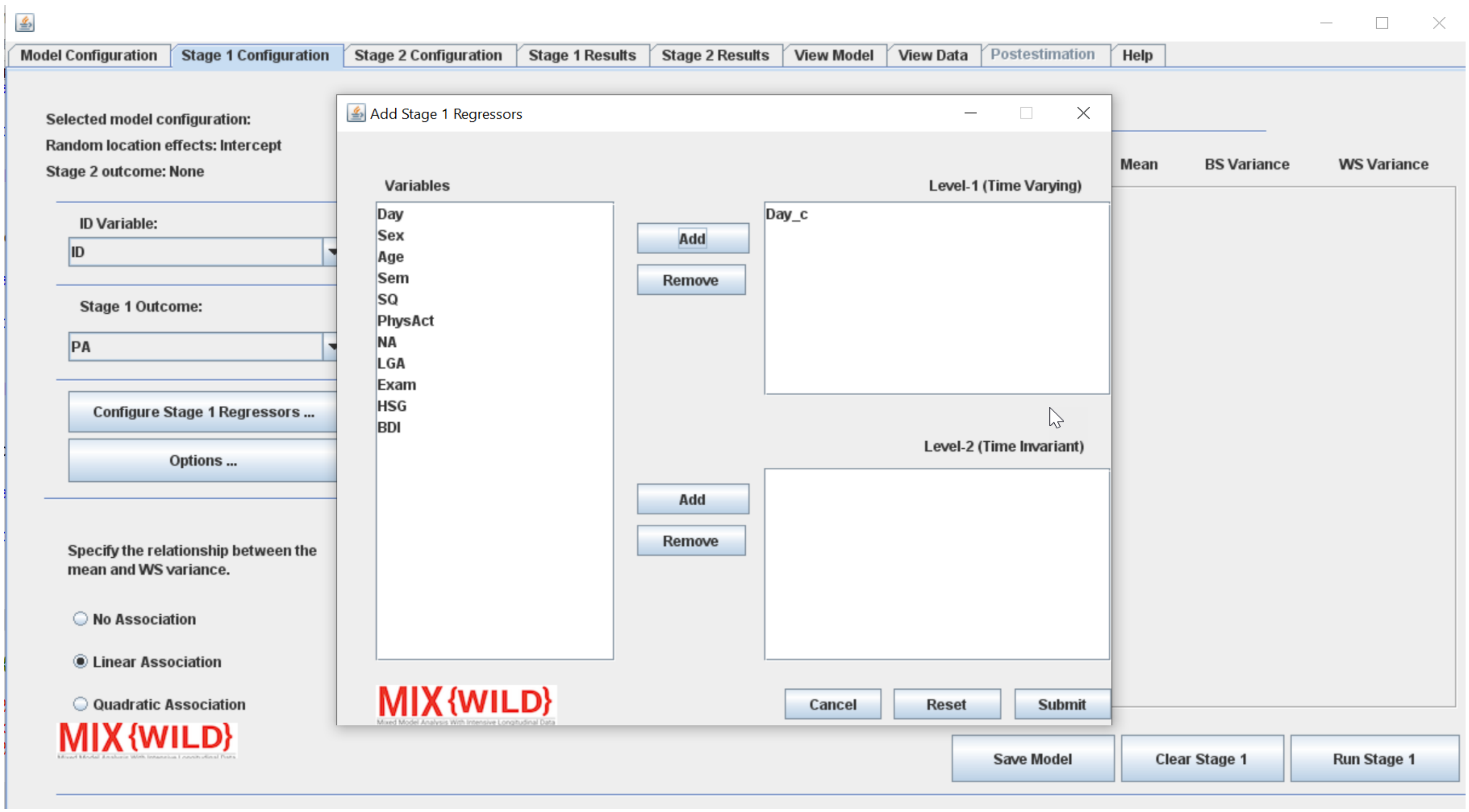
Provide a title and make selections, the click on Submit

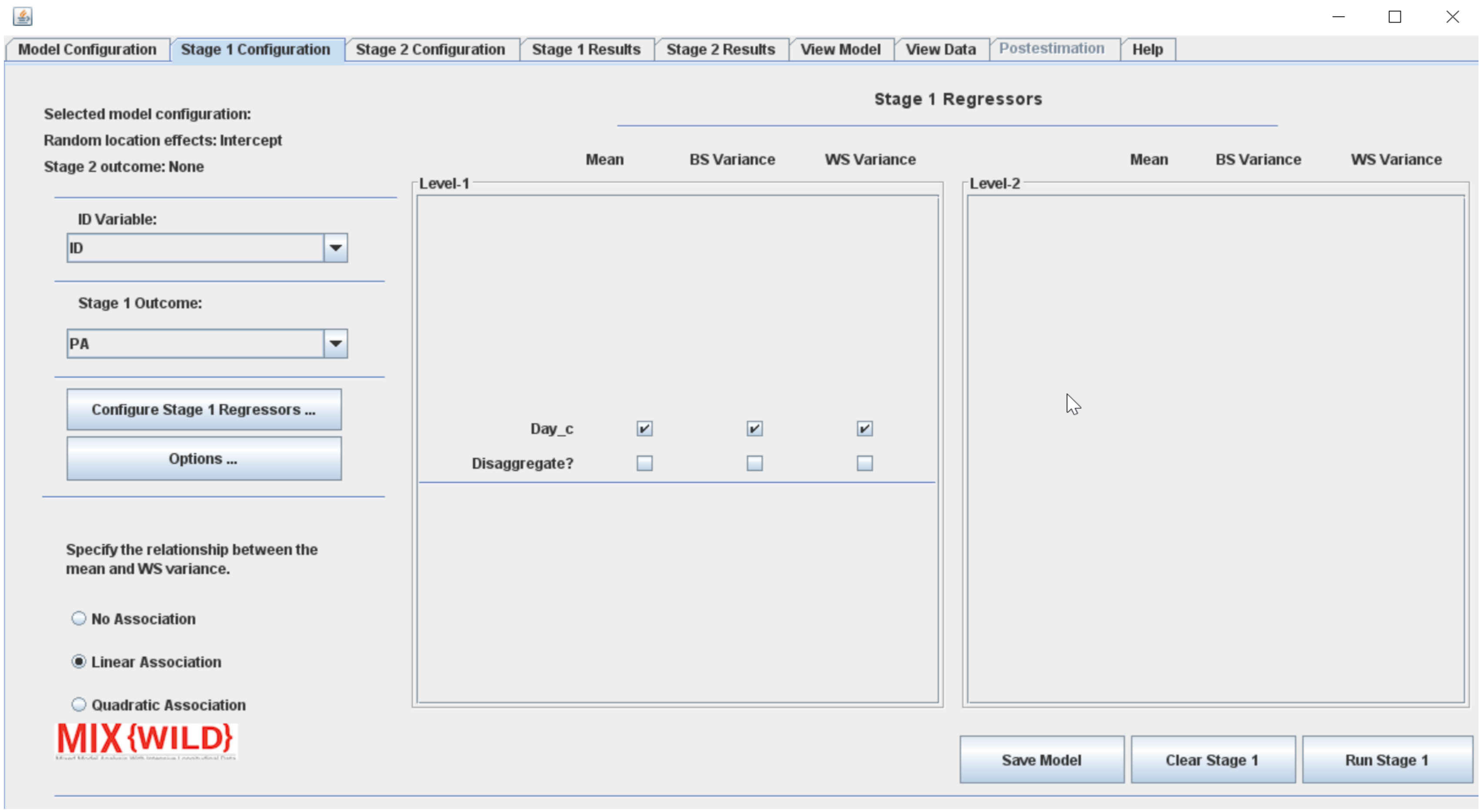


Select PA as the Stage 1 Outcome, select linear association



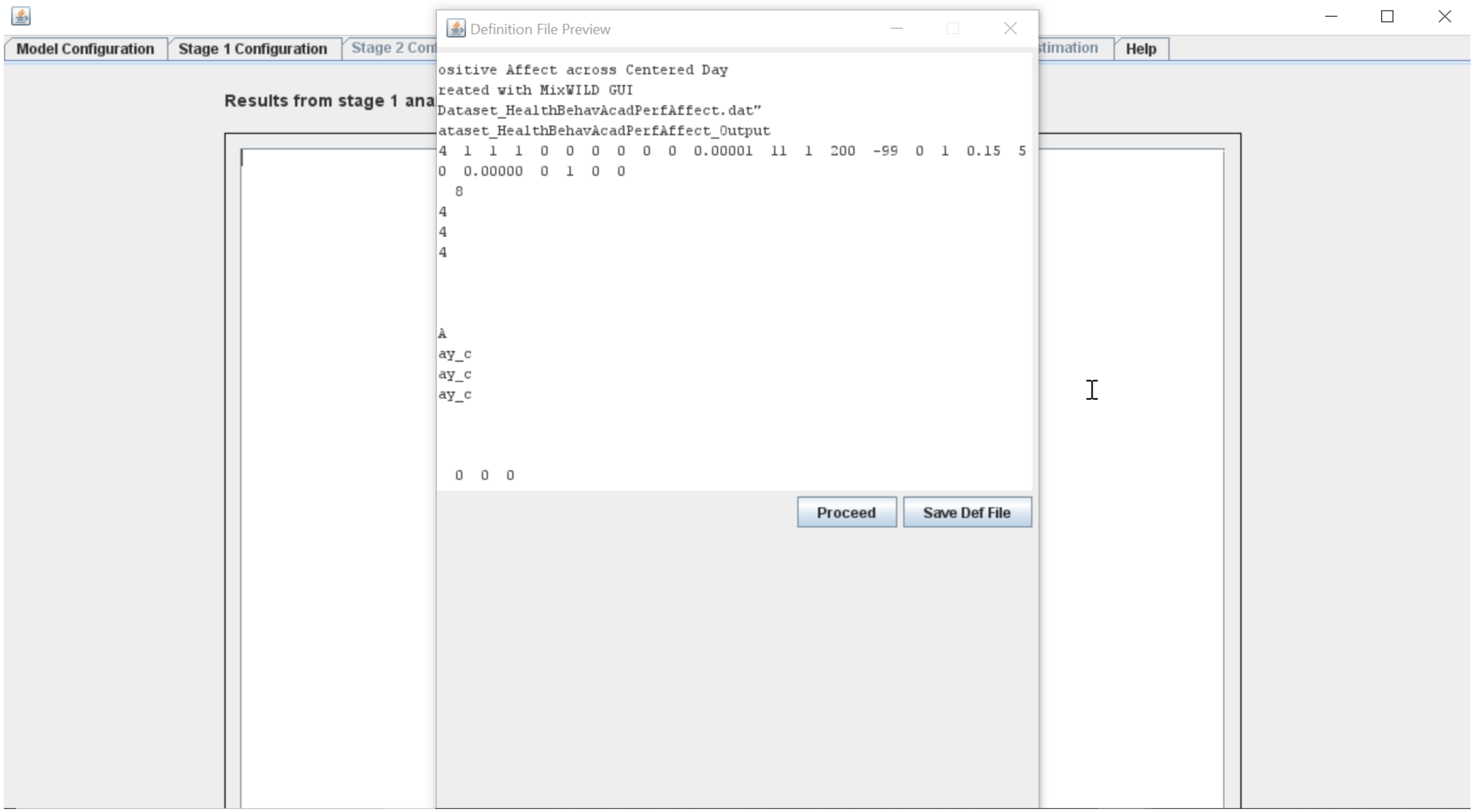
Select Day_c as PA as a time-varying predictor, click Submit





Add Day_c to the mean, BS variance, and WS variance models; click on Run Stage 1

DEF file is created, click on Proceed



```
MIXREGLS: Mixed-effects Location Scale Model with BS and WS variance models

------------------------------
mixREGLS.DEF specifications
------------------------------
 Positive Affect across Centered Day
 Created with MixWILD GUI

 data and output files:
 Dataset_HealthBehavAcadPerfAffect_Output
 Dataset_HealthBehavAcadPerfAffect_Output_1.out_1.out

 CONVERGENCE CRITERION =  0.00001000
 RIDGEIN    =   0.1500
 NQ         =   11
 QUADRATURE =    1 (0=non-adaptive, 1=adaptive)
 MAXIT      =  200


------------
Descriptives
------------

 Number of level-1 observations =     2109

 Number of level-2 clusters     =       72
```

```
Number of level-1 observations for each level-2 cluster
    27    32    32    32    32    31    31    32    32    30    20    32    32
    31    30    32    31    32    27    32    29    32    32    31    32    26
    22    29    27    32    32    32    27    32    32     8    17    32    32
    30    20    32    32    30    28    32    32    32    29    32    32    32
    28    30    32    32    31    32    32    32    32    11    26    30    32
    31    32    19    30    16    30    32

Dependent variable
                                 mean         min         max     std dev
------------------------------------------------------------------------
PA                             4.1841      1.0000      7.0000      1.6107

Mean model covariates
                                 mean         min         max     std dev
------------------------------------------------------------------------
Intercept                      1.0000      1.0000      1.0000      0.0000
Day_c                          0.0160     -2.2143      2.2143      1.3061

BS variance model covariates
                                 mean         min         max     std dev
------------------------------------------------------------------------
Intercept                      1.0000      1.0000      1.0000      0.0000
Day_c                          0.0160     -2.2143      2.2143      1.3061

WS variance model covariates
                                 mean         min         max     std dev
------------------------------------------------------------------------
Intercept                      1.0000      1.0000      1.0000      0.0000
Day_c                          0.0160     -2.2143      2.2143      1.3061
```

```
------------------------
Model WITH RANDOM Scale
------------------------
==> BAD NR ITERATION     9 with NEW ridge =   0.4500

 Total  Iterations =  15
 Final Ridge value = 0.0

 Log Likelihood                 =    -3099.477
 Akaike's Information Criterion =    -3107.477
 Schwarz's Bayesian Criterion   =    -3116.583

 ==> multiplied by -2
 Log Likelihood                 =     6198.953
 Akaike's Information Criterion =     6214.953
 Schwarz's Bayesian Criterion   =     6233.167


Variable                         Estimate    AsymStdError         z-value         p-value
-------------------------    ------------    ------------    ------------    ------------
BETA (regression coefficients)
Intercept                         4.13067         0.14192        29.10653         0.00000
Day_c                            -0.10365         0.01829        -5.66789         0.00000
ALPHA (BS variance parameters: log-linear model)
Intercept                         0.33310         0.17051         1.95351         0.05076
Day_c                             0.11952         0.01981         6.03332         0.00000
TAU (WS variance parameters: log-linear model)
Intercept                        -0.09005         0.10237        -0.87967         0.37904
Day_c                             0.13537         0.02615         5.17739         0.00000
Random scale standard deviation
```

```
Std Dev                              0.73614        0.07047        10.44576         0.00000
Random location (mean) effect on WS variance
Loc  Eff                            -0.36749        0.09955        -3.69164         0.00022


BS variance ratios and 95% CIs
------------------------------

Variable                               Ratio          Lower           Upper
-------------------------    ------------    ------------    ------------
ALPHA (BS variance parameters: log-linear model)
Intercept                            1.39529        0.99890         1.94898
Day_c                                1.12695        1.08404         1.17157


WS variance ratios and 95% CIs
------------------------------

Variable                               Ratio          Lower           Upper
-------------------------    ------------    ------------    ------------
TAU (WS variance parameters: log-linear model)
Intercept                            0.91388        0.74774         1.11694
Day_c                                1.14496        1.08776         1.20516
Random location (mean) effect on WS variance
Location Effect                      0.69247        0.56972         0.84166

Random scale standard deviation
Std Dev                              2.08785        1.81850         2.39710
```

Interpretation of Results: Model with RANDOM scale

- Using the centered and scaled version Day_c, the intercepts represent the average across days and the slopes for day represent change per week.
- Mean model: the mean PA is estimated to be a bit over 4, and the slope is negative and significant ($\hat{\beta} = -0.10365, p = 0.00001$). PA decreases by approximately one-tenth of a point per week.
- BS variance model: this is a log-linear model, so in addition to the estimates from the log-linear model, the program provides exponentiated estimates as well. From these, the BS variance is estimated to be 1.39529 with a 95% confidence interval of 0.99890 to 1.94898. The effect of Day_c is positive and significant ($\hat{\alpha} = 0.11952, p = 0.00001$). The exponentiated slope is 1.12695 with a 95% confidence interval of 1.08404 to 1.17157. The exponeniated slope represents a variance ratio (ratio of BS variance comparing values one week apart, for example the BS variance at week 2 divided by the BS variance at week 1). From the estimate of 1.13, we can conclude that the BS variance increases by a factor of 13% per week; thus, subjects become more heterogeneous over time.
- WS variance model: this is also a log-linear model, so in addition to the estimates from the log-linear model, the program provides exponentiated estimates. From these, the WS variance is estimated to be 0.91388 with a 95% confidence interval of 0.74774 to 1.11694. The effect of Day_c is positive and significant ($\hat{\tau} = 0.13537, p = 0.00001$). The exponentiated slope is 1.14496 with a 95% confidence interval of 1.08776 to 1.20516. The exponeniated slope represents a variance ratio (ratio of WS variance comparing values one week apart, for example the WS variance at week 2 divided by the WS variance at week 1). From the estimate of 1.15, we can conclude that the WS variance increases by a factor of 15% per week; thus, subjects exhibit more erraticism (less consistency) over time.
- The standard deviation of the random scale effect is estimated to be 0.73614, and this is a highly significant effect. Thus, subjects vary considerably in terms of how consistent/erratic they are in their PA reports. The relationship between the random location and scale effects is negative and significant ($\hat{\tau} = -0.36749, p = 0.00022$) indicating that subjects with higher average PA are also more consistent, and subjects with lower average PA are more erratic.

MELS summary (Stage 1)

- Mixed models (aka multilevel or hierarchical linear models) useful for analysis of intensive longitudinal data.
- Intensive longitudinal data and the mixed-effects location scale model allow one to consider modeling of the between-subjects and within-subjects variances in terms of covariates.
  - What subject and/or contextual variables associated with subject homogeneity/heterogeneity?
  - What subject and/or contextual variables associated with within-subject consistency/erraticism?
- Model and software can also allow for multiple random subject effects of location (intercept and slope).
- Random effects can be considered as predictors of stage-2 subject-level outcomes (continuous, binary, ordinal, nominal, count) using plausible values replications.

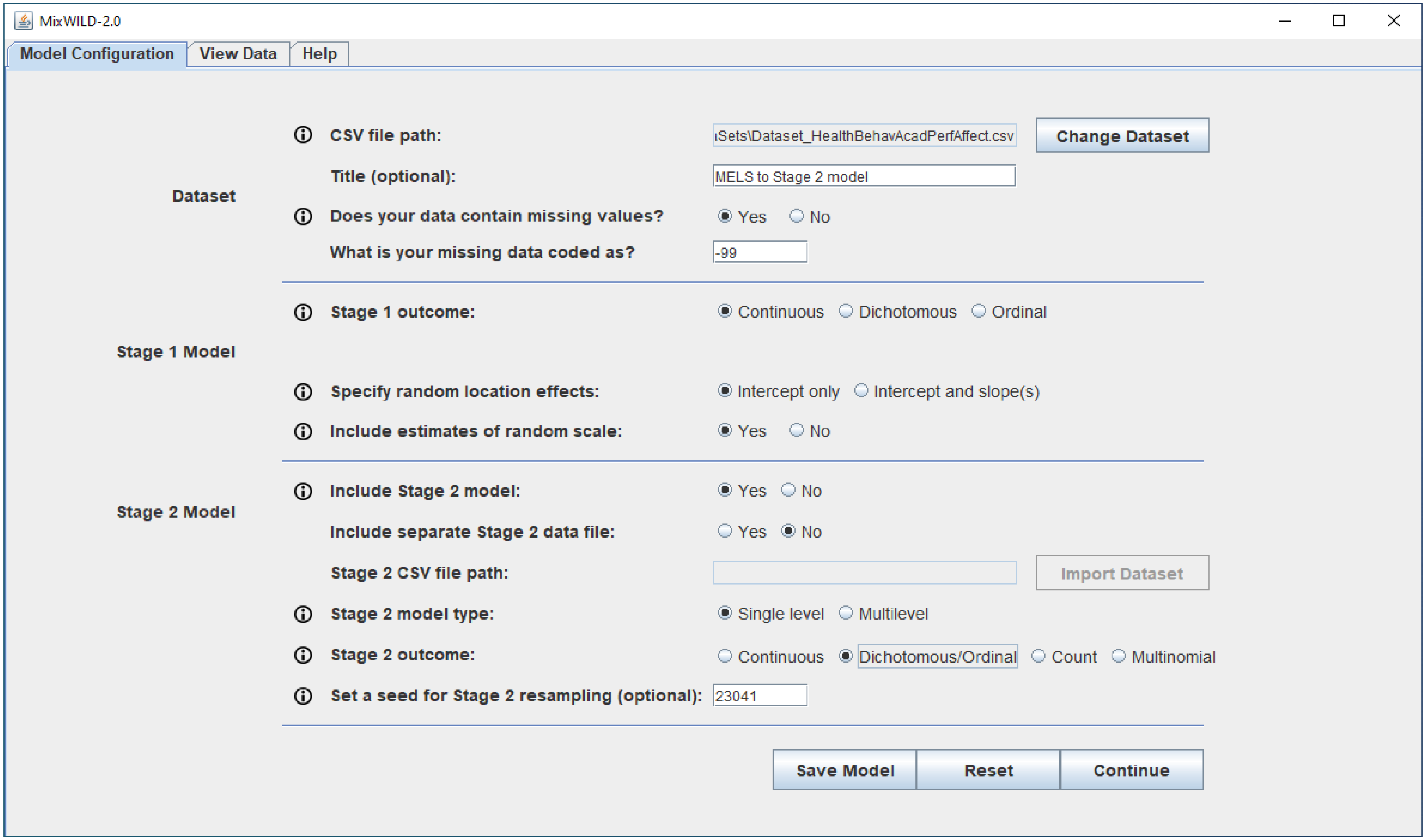
Stage 2 analysis (optional, but hopefully useful)

Stage 1 random subject effect estimates (e.g., intercept $\hat{\upsilon}_{0i}$, slope $\hat{\upsilon}_{1i}$, scale $\hat{\omega}_i$) and other subject-level variables $\boldsymbol{x}_i$ can be used as regressors and interaction terms to predict a Stage 2 subject-level outcome y_i

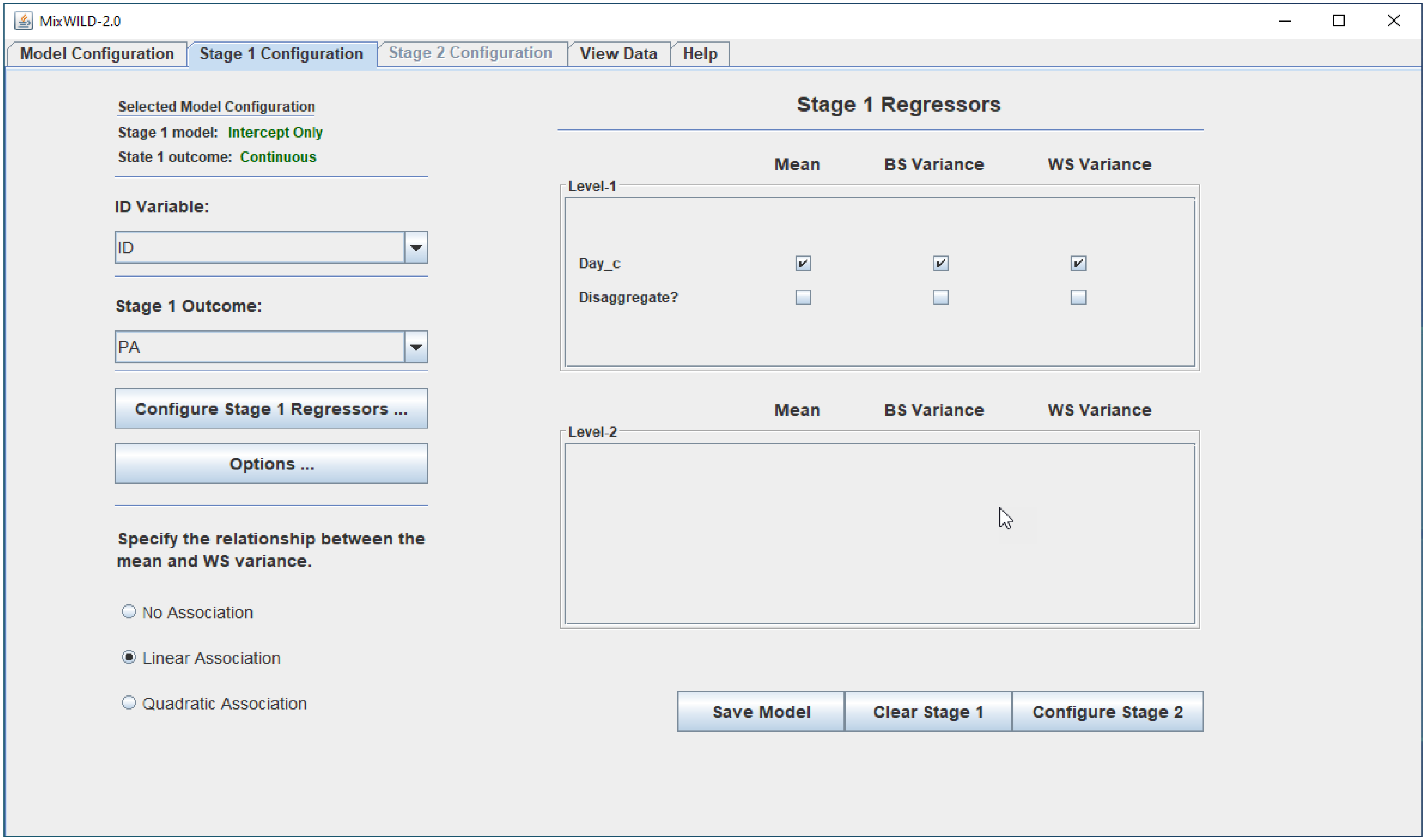
- Multiple regression for continuous subject-level outcome
$$y_i = \beta_0 + \beta_1 \hat{\upsilon}_{0i} + \beta_2 \hat{\upsilon}_{1i} + \beta_3 \hat{\omega}_i + \boldsymbol{x}_i' \boldsymbol{\beta} + \varepsilon_i$$
- Logistic regression for binary/ordinal/nominal subject-level outcome; Poisson regression for subject-level count outcome
- Multilevel (random-intercept) Stage 2 model is also possible

Since the random subject effects are estimates with estimated uncertainty, "plausible value" replications of the the random effects are performed (Mislevy, 1991, *Psychometrika*); akin to multiple imputation for missing values.

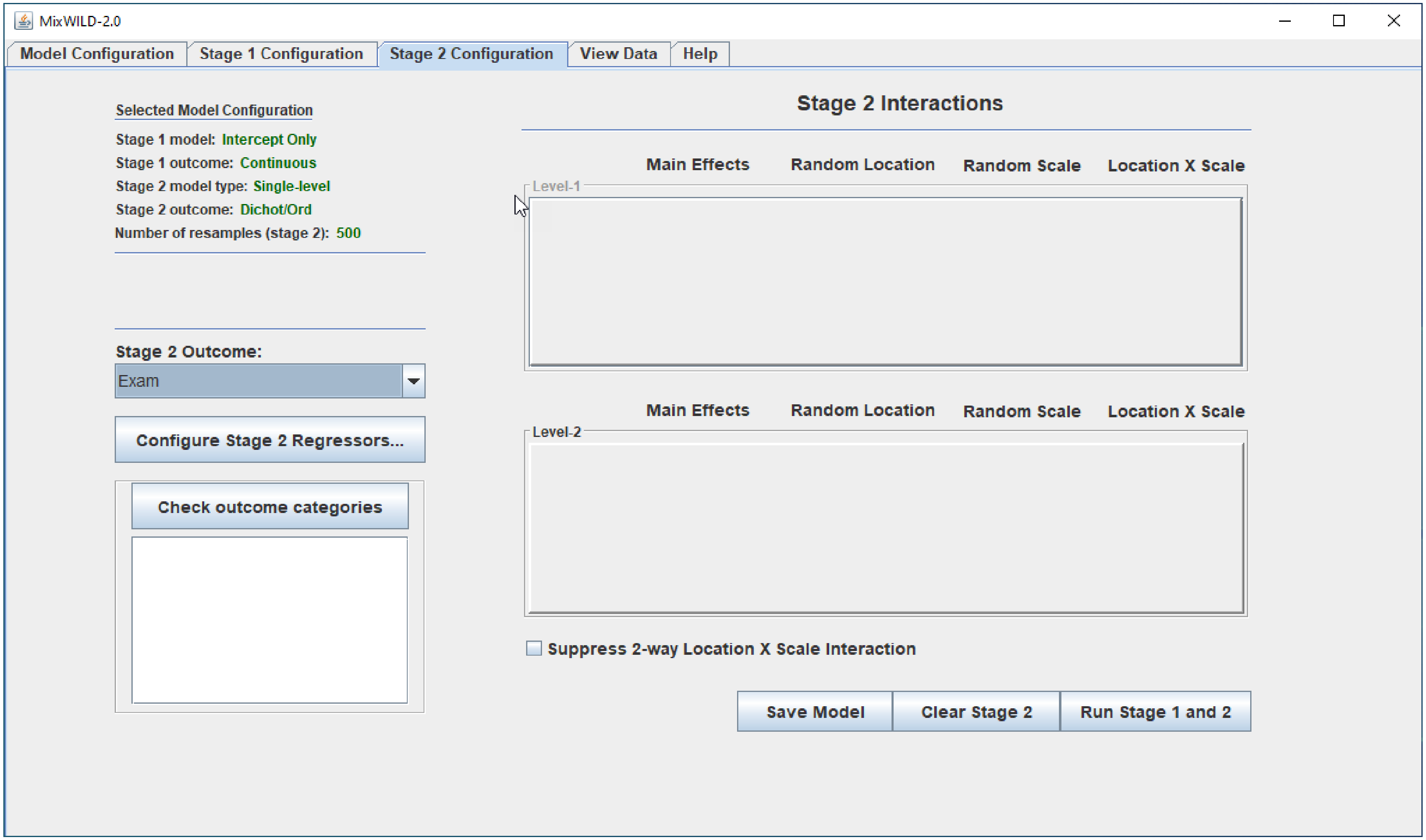
Yes Include Stage 2 model, no separate data file, single level, dichotomous outcome



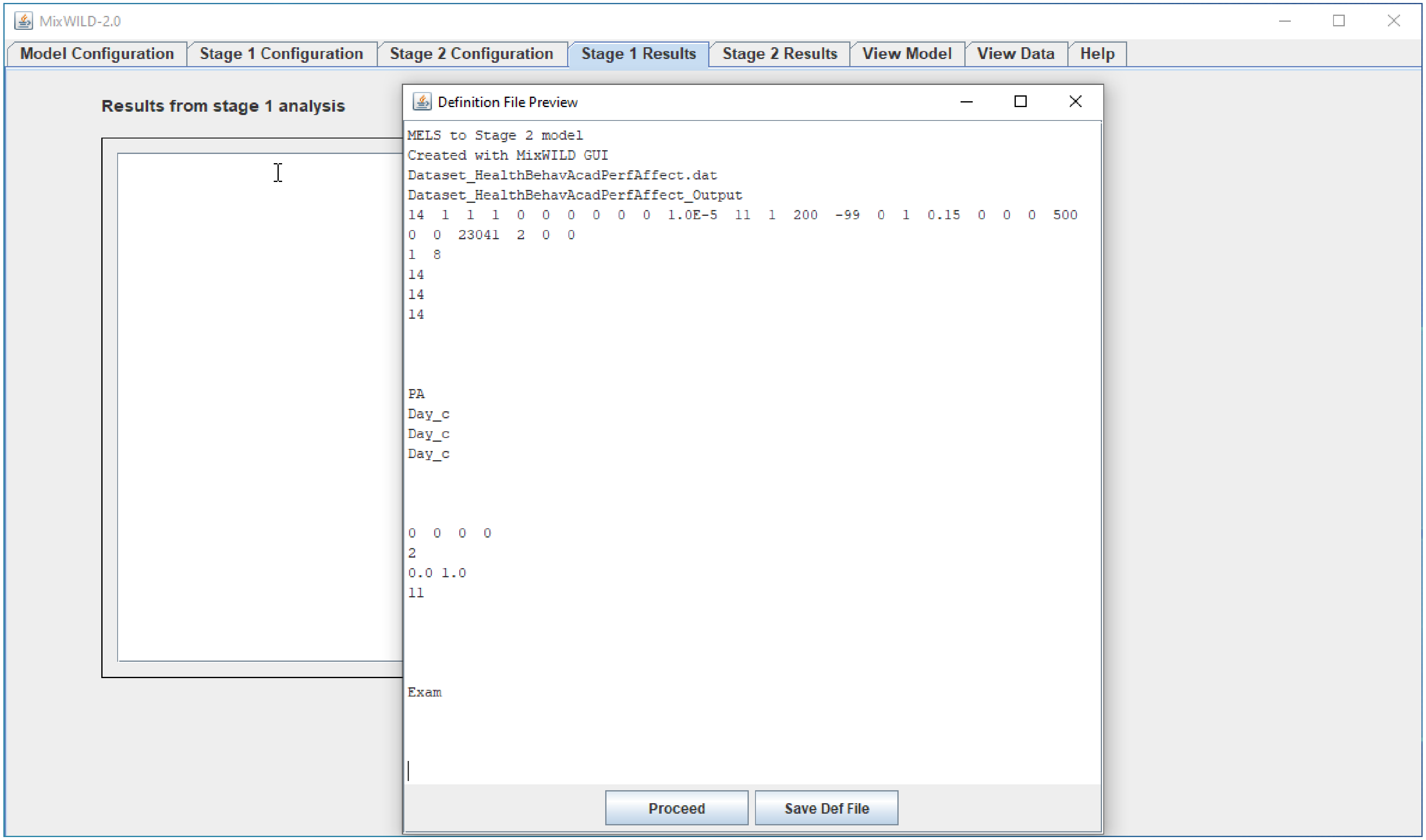
All as before; click on Configure Stage 2



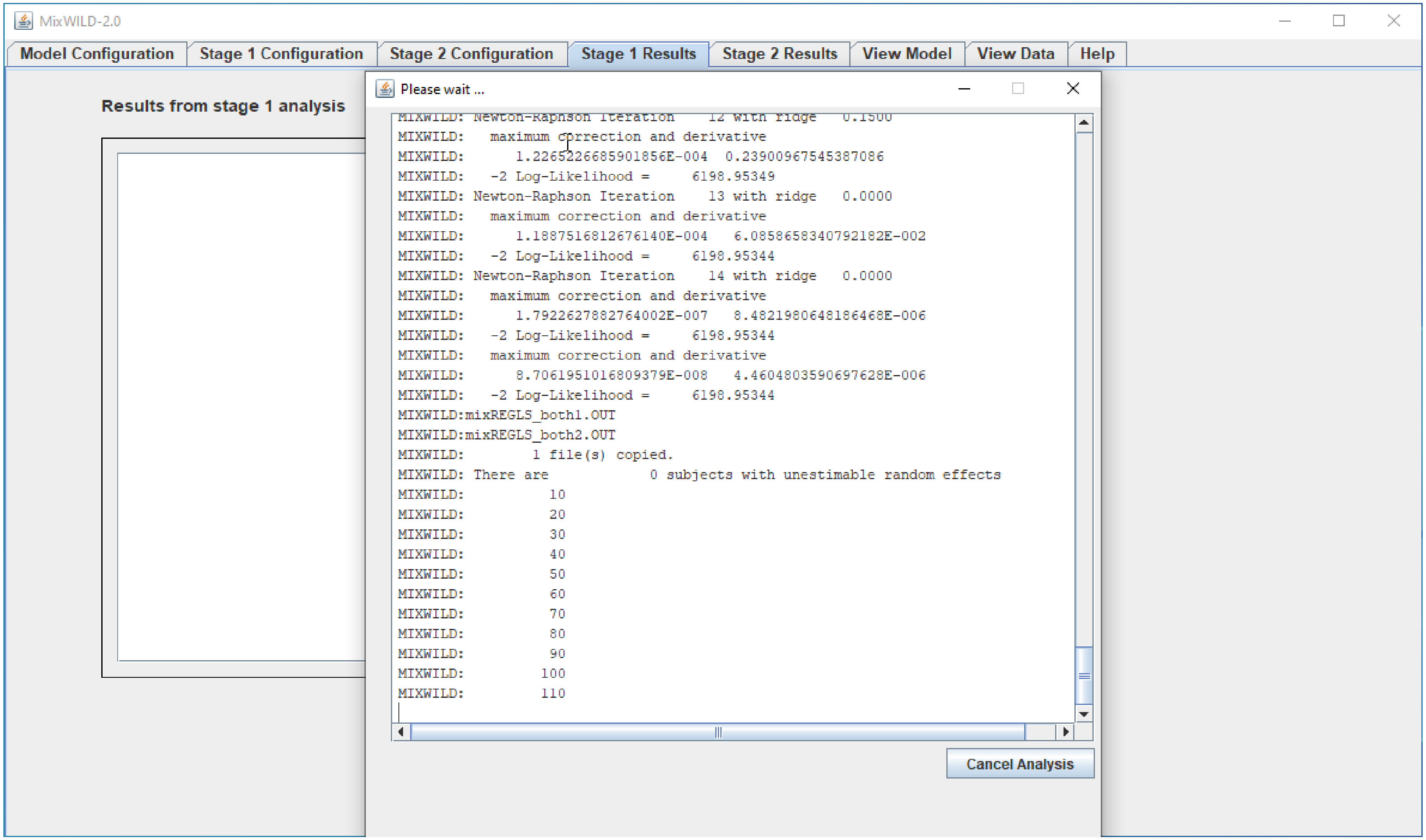
Select Exam as Stage 2 Outcome; Run Stage 1 and 2



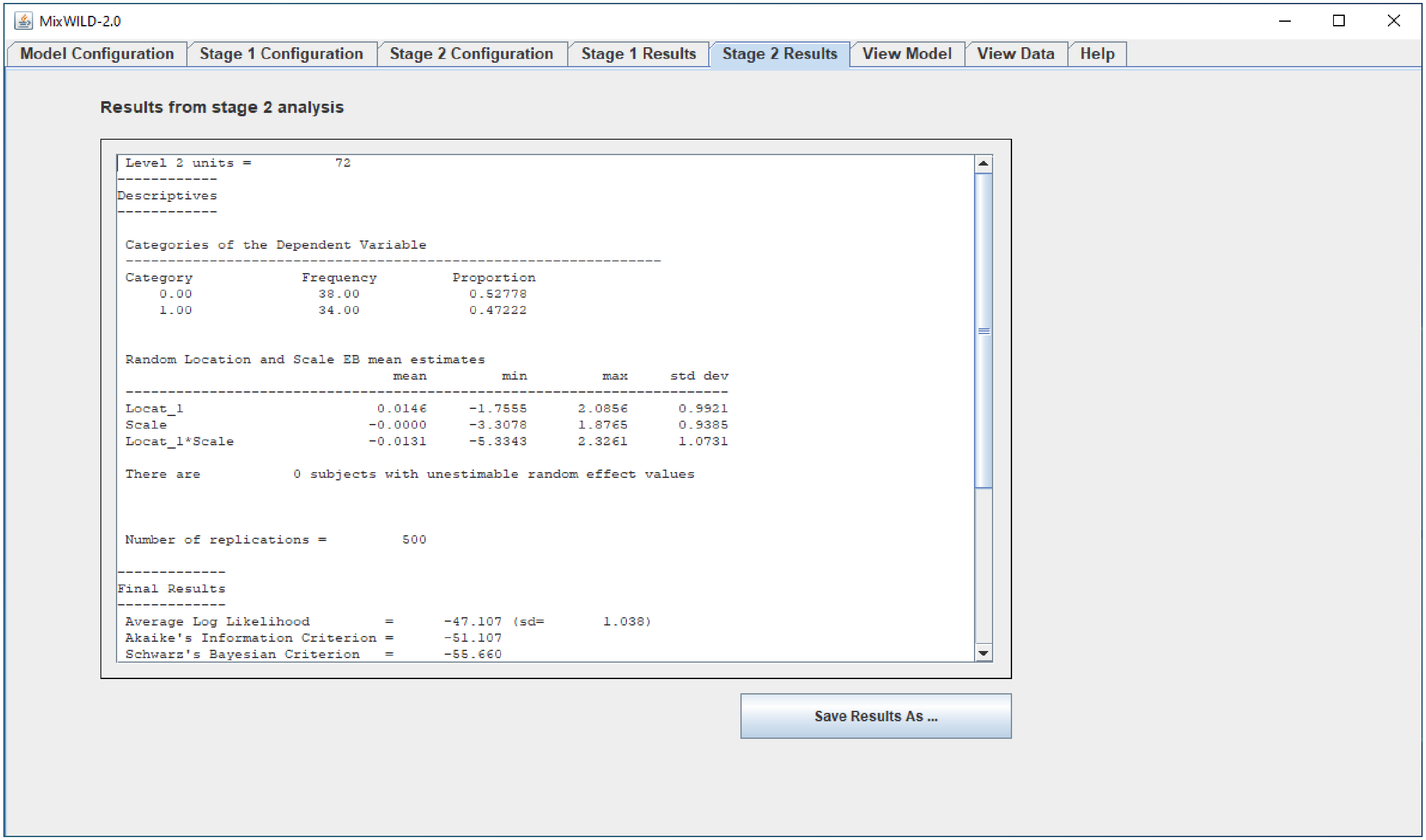
Click on Proceed



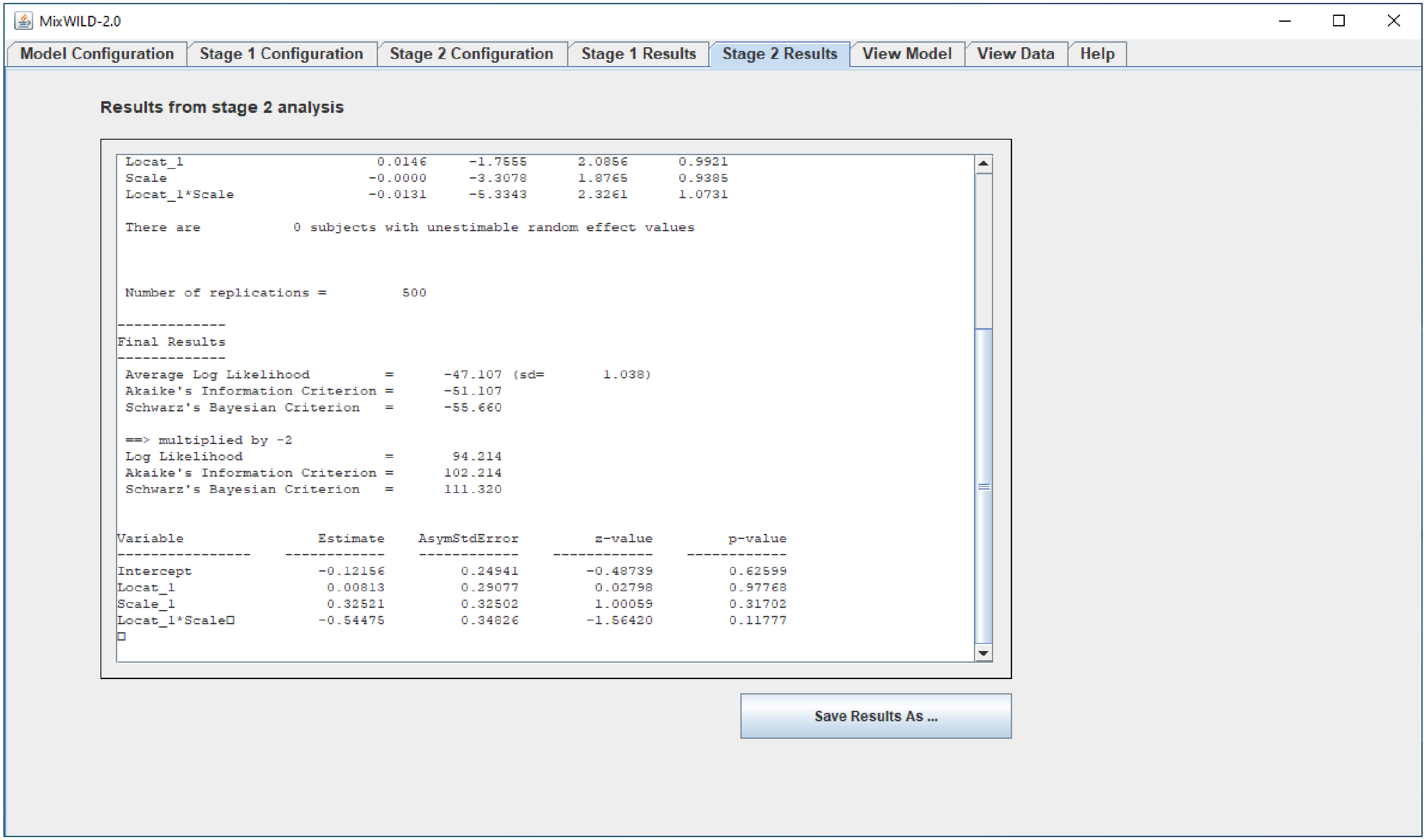
After completing Stage 1, it performs 500 logistic regressions



Stage 2 Results: descriptive statistics



Stage 2 Results: no significant effects on exam success



MELS Model References - some are available at https://voices.uchicago.edu/hedeker

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And there are many more articles without me ☺

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Running Mixed-Effects Location Scale (MELS) Models on MixWILD

Wei-Lin Wang

2023.04.26 @ SBM Workshop

Supported by National Cancer Institute grant R01CA240713 (Hedeker & Dunton)

Learning Objects

- Understand what MixWILD is and why we need MixWILD
- Learn the basic settings of MixWILD software
- Utilize MixWILD to build your own models to address your research questions and interpret results
  – Stage 1 model
  – Two-stage model approach (Stage 1 & Stage 2 Models)
  – Try your own model (Optional)
- Learn some handy ways of MixWILD troubleshooting

What is MixWILD?

What is MixWILD

- Mixed model analysis With Intensive Longitudinal Data (MixWILD)
- It is a standalone and user-friendly statistical software program, using a Java platform for Windows and Mac.
- The software consists of a front-end GUI (i.e., view and controller) and backend data processing (i.e., model).

What can MixWILD do

- MixWILD allows one to examine the effects of subject-level parameters (intercept, slope(s), and scale) comprised of time-varying variables on a subject-level outcome or an outcome nested within time or clusters.

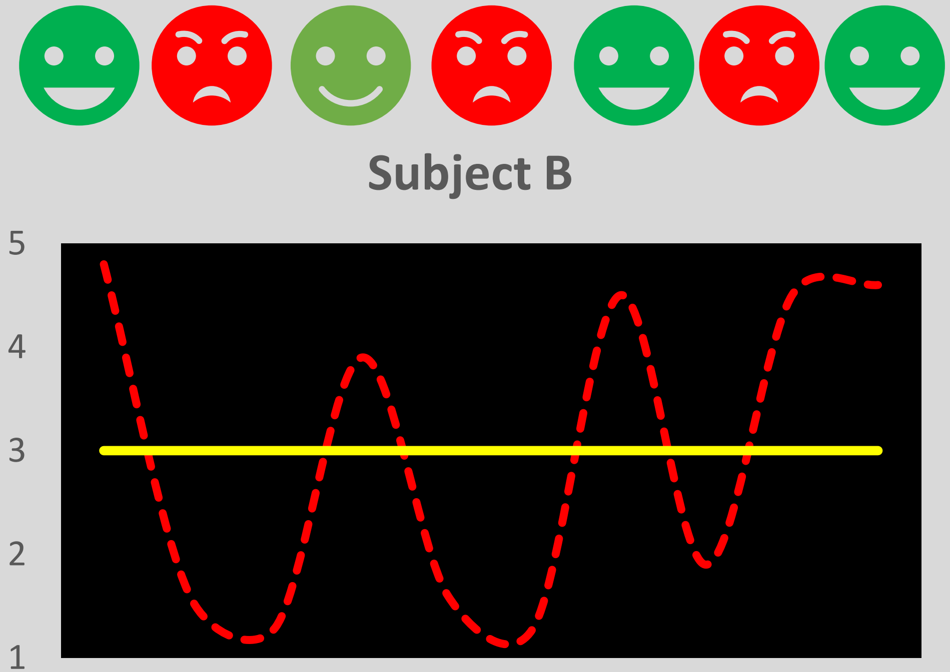
- This is specifically in the context of studies using intensive sampling methods, such as ecological momentary assessment (EMA).

Why do we need MixWILD?

Novel Stat Project

Novel Statistical Models for EMA Studies of Physical Activity
1R01HL121330 & R01CA240713
(Dunton and Hedeker, PIs)

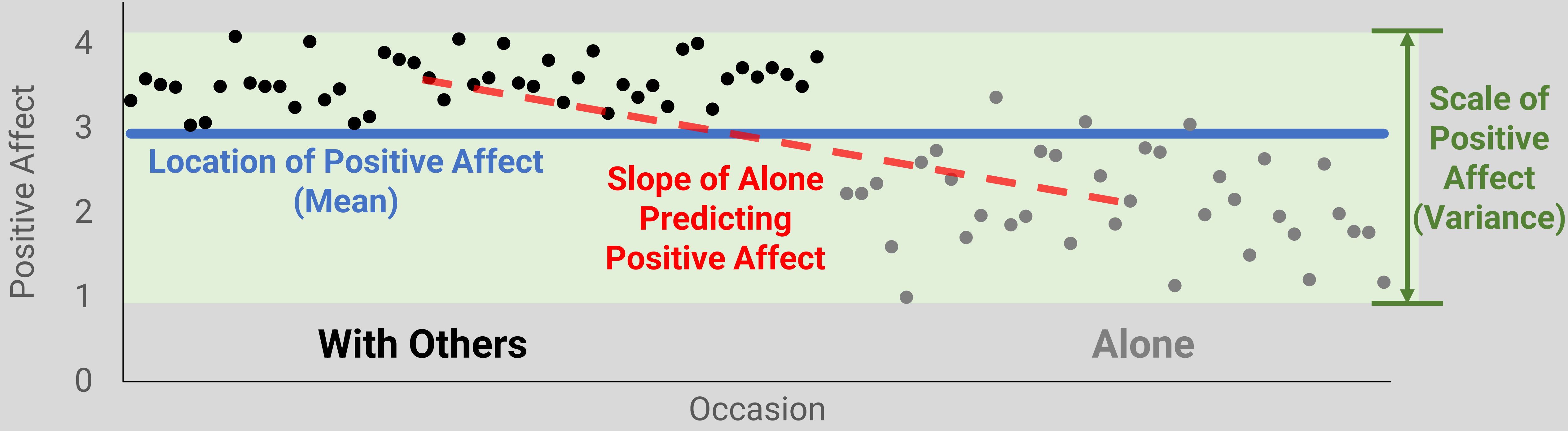
MixWILD is a handy and free standalone application to run Mixed-effects location and scale models.



Mean = 3

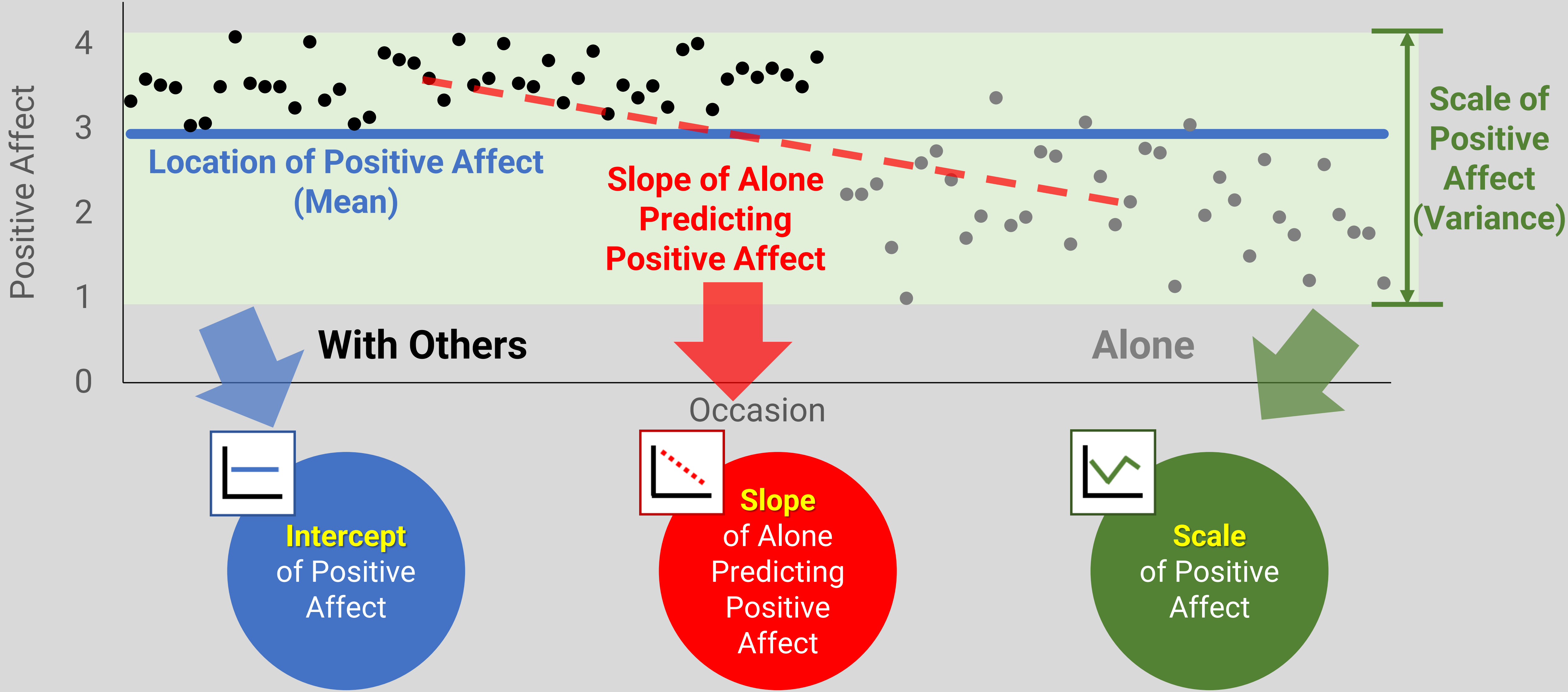
MixWILD (Stage 1 Model)

- Go above and beyond the effects of mean!



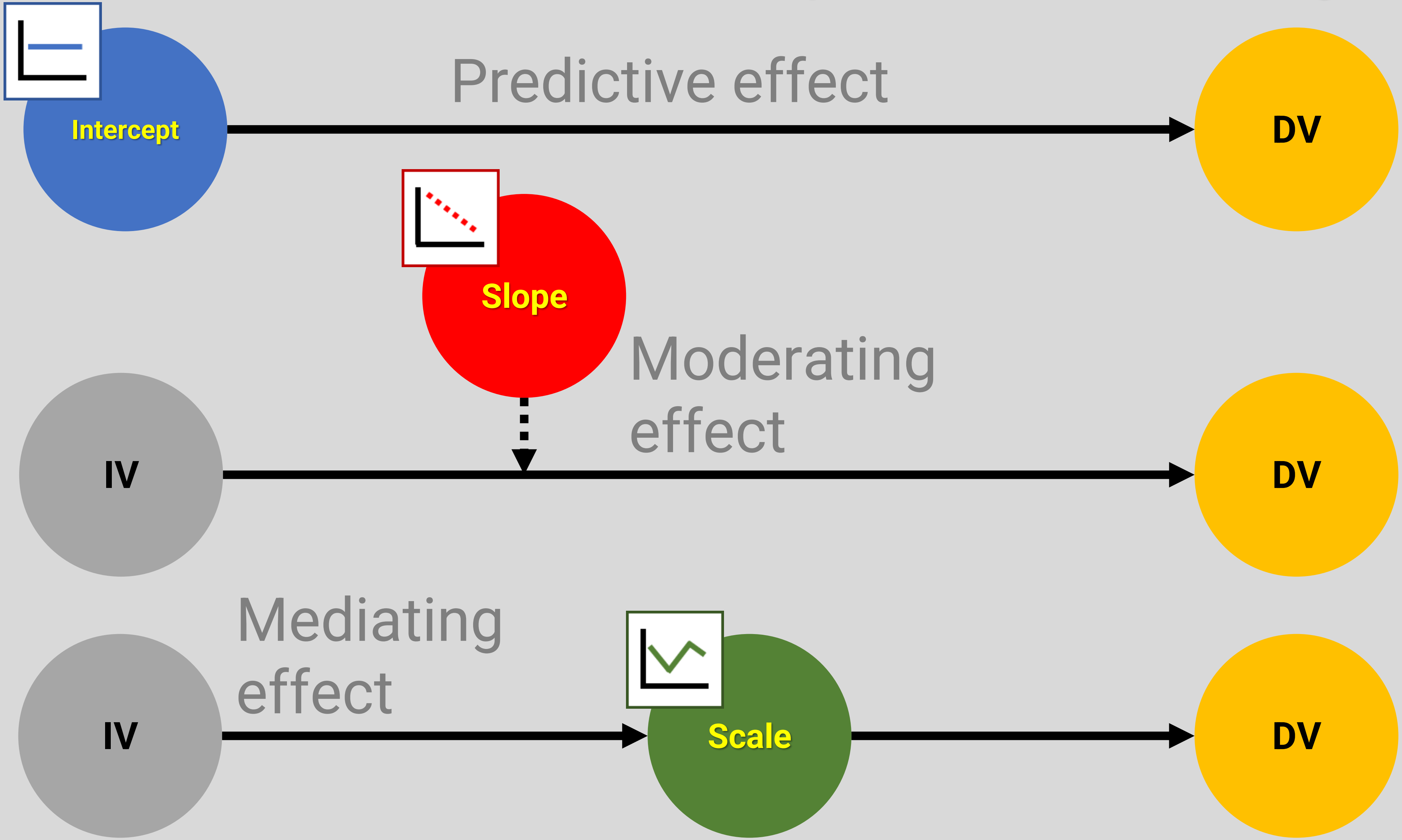
MixWILD (Stage 2 Model)

- Extract the estimated random effects as regressors.



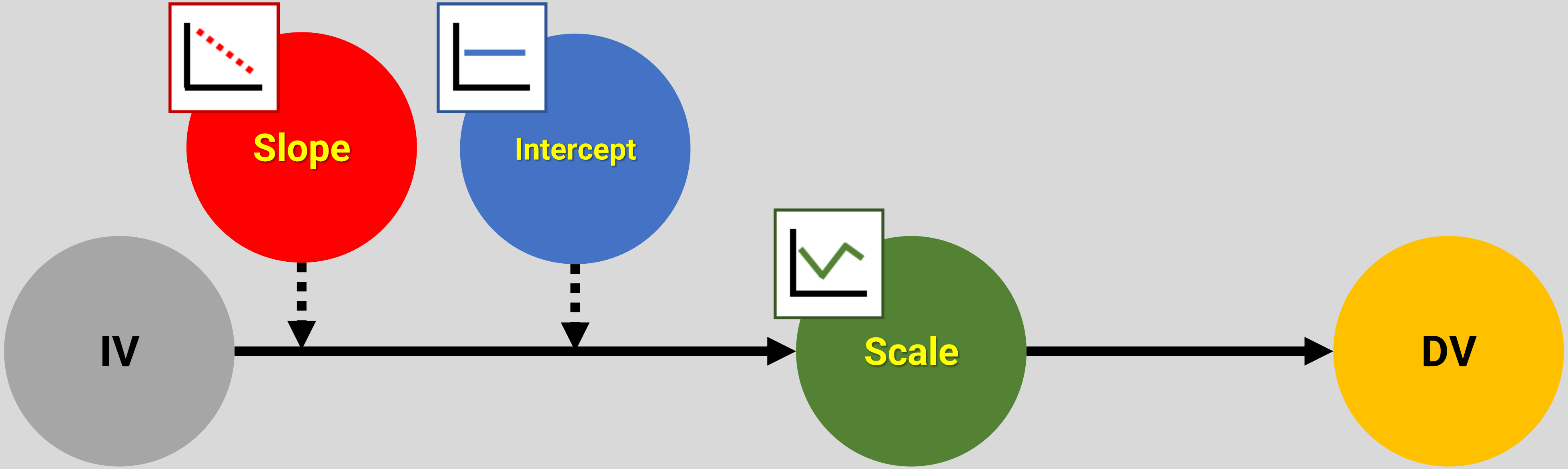
MixWILD (Stage 2 Model)

- Test if the random effects can predict DV in Stage 2



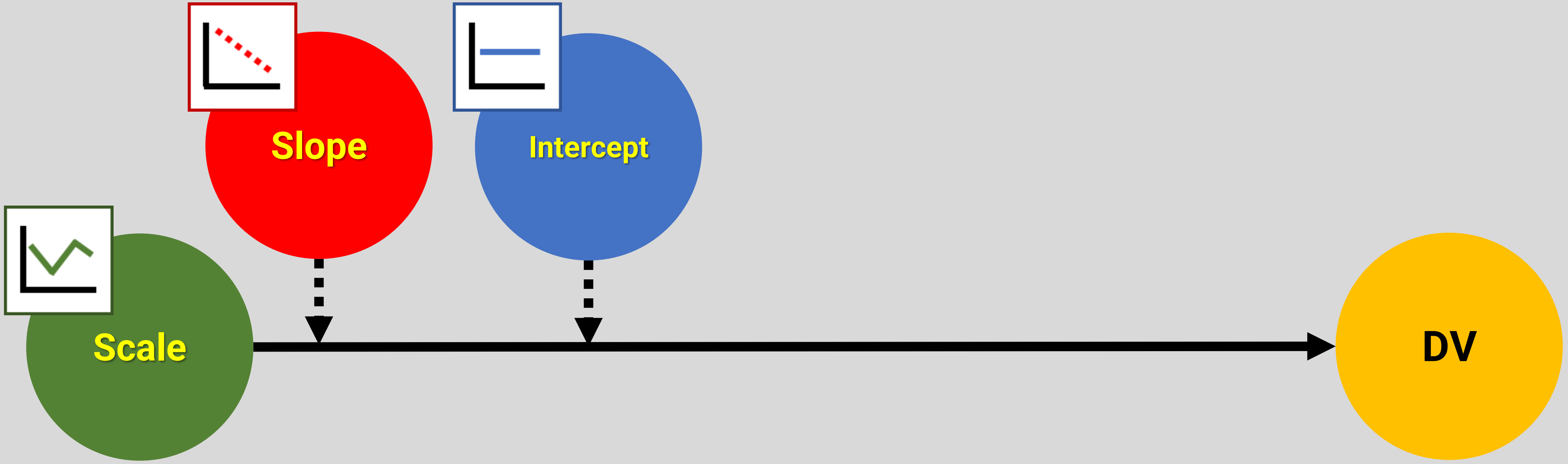
MixWILD (Stage 2 Model)

- Design your model and test associations (Use multiple random effects in the same model)



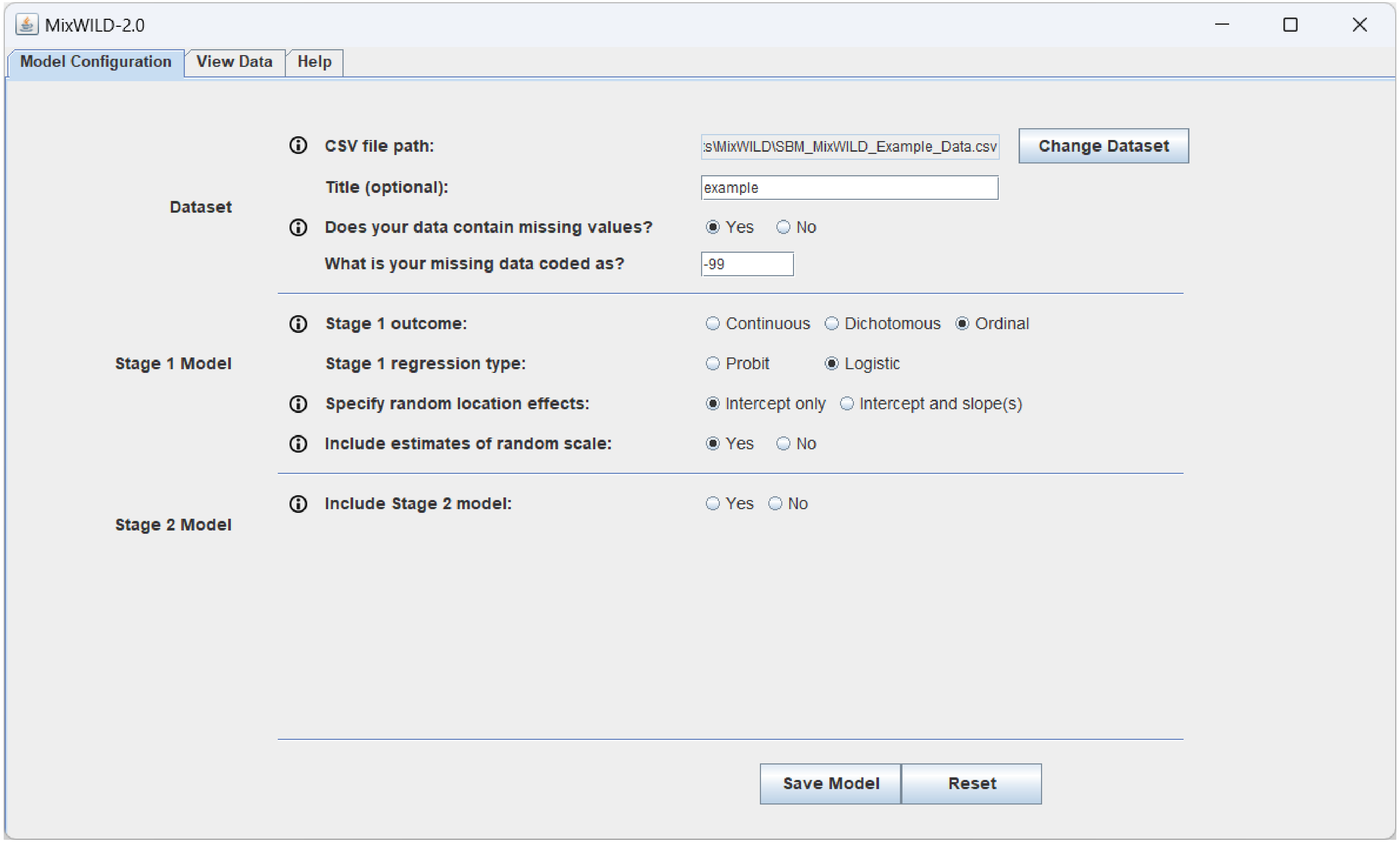
MixWILD (Stage 2 Model)

- Design your model and test associations
  (Even with interactions among random effects!!!)



Basic Settings

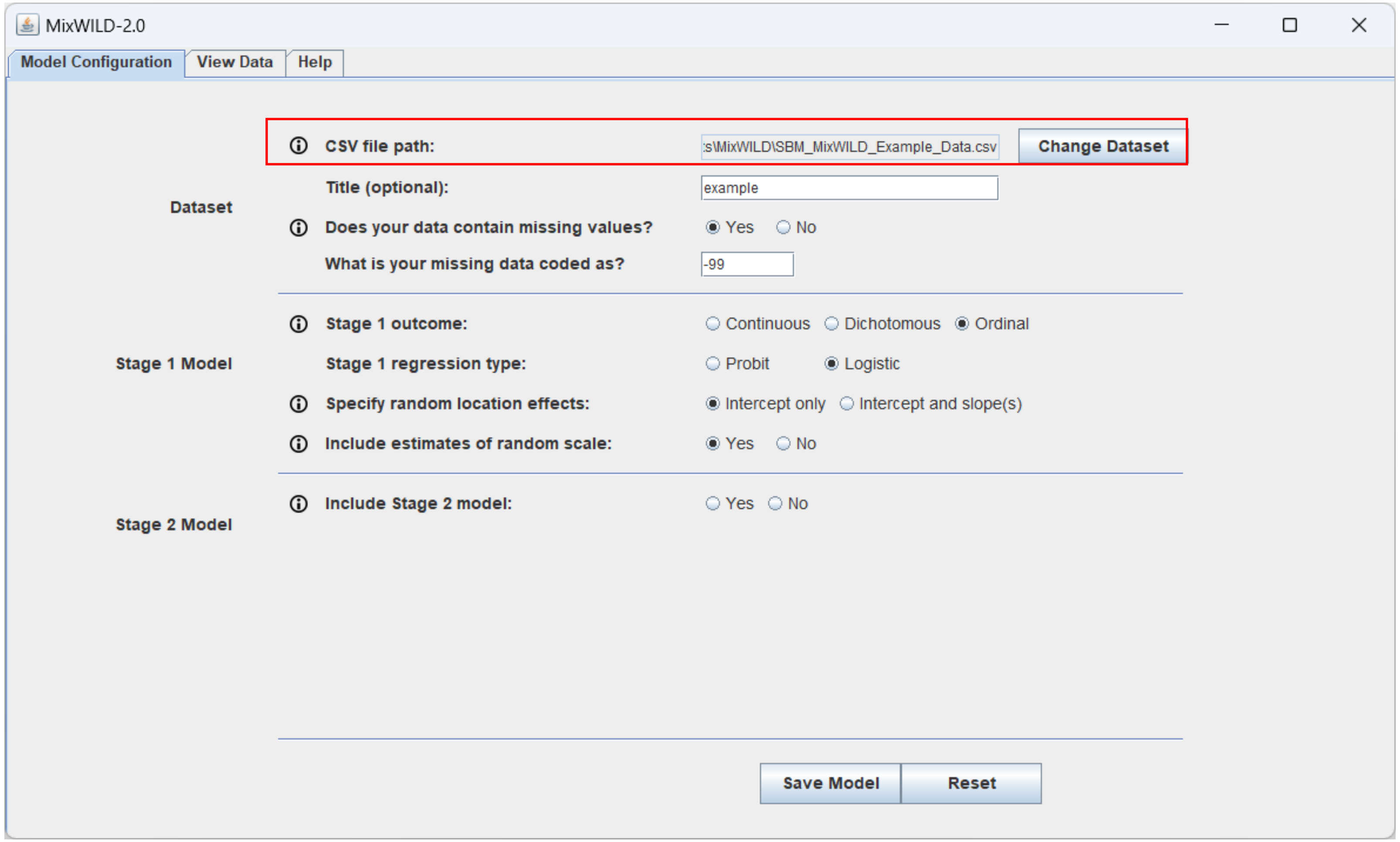
Basic Settings



Basic Settings

Open a new .CSV file

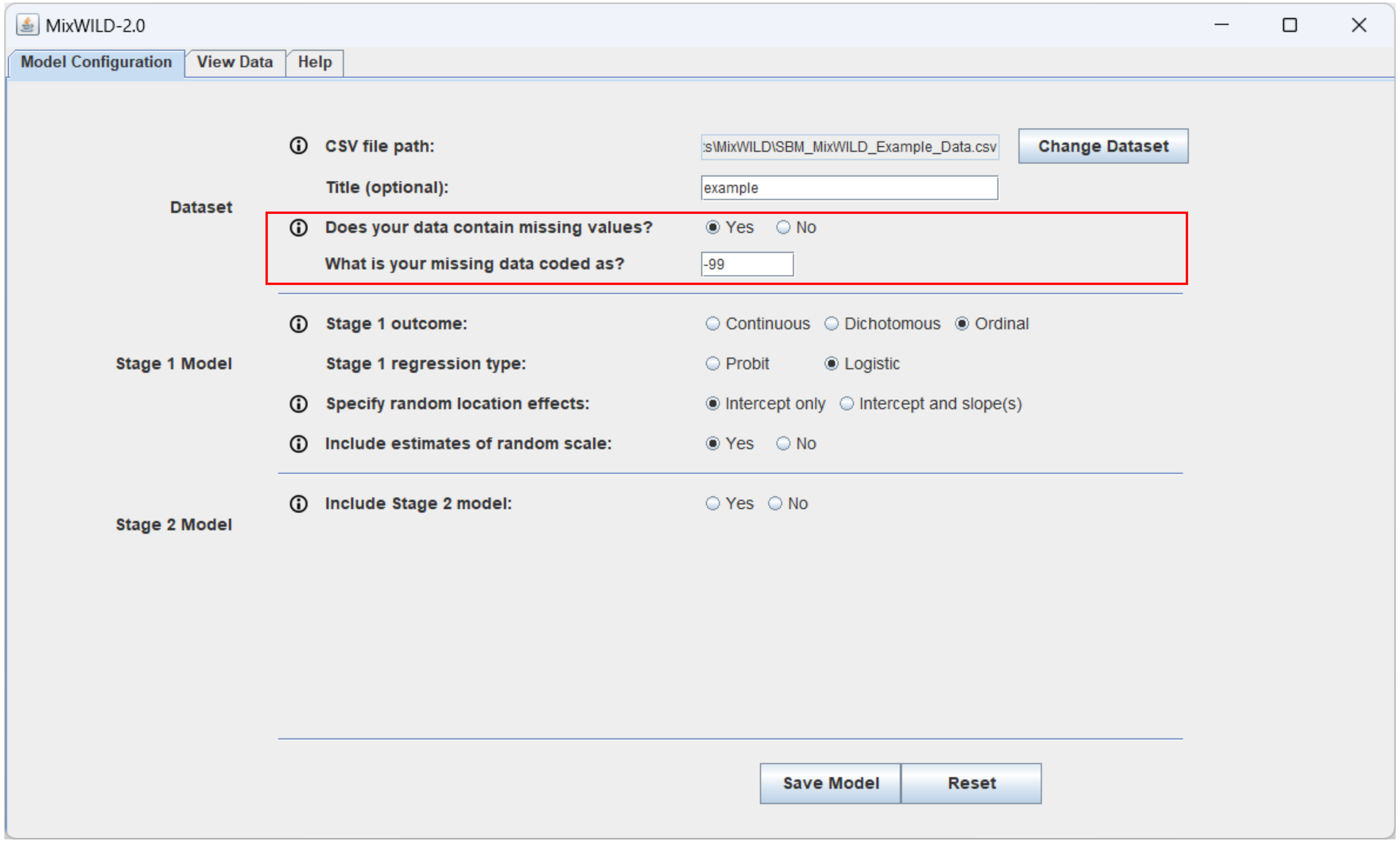
Load the file from your local address. Folder name **CANNOT** have **any blank SPACES**



Basic Settings

Format missing value
Click on missing values if there are any in your dataset; specify the missing value code in the box.

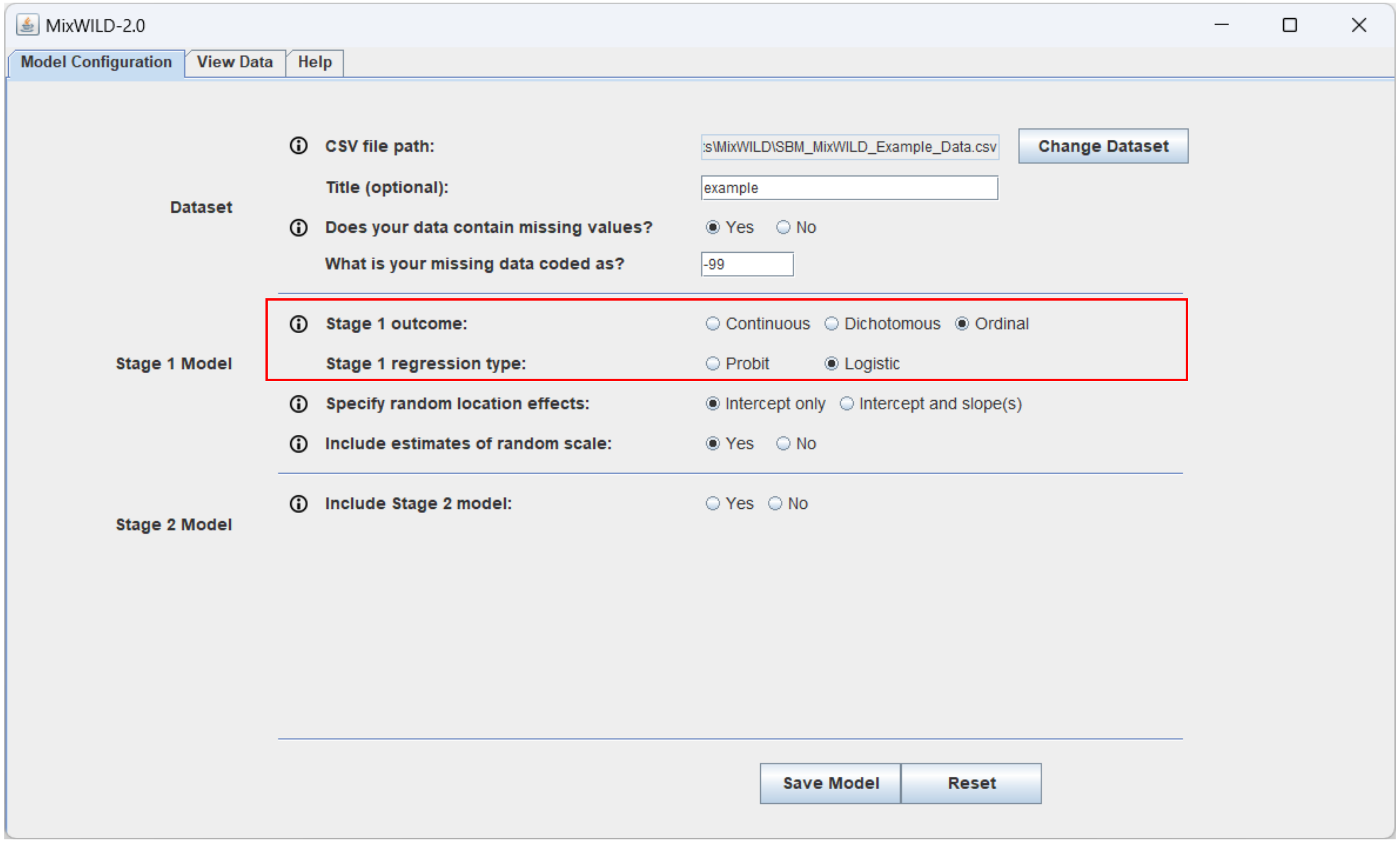
Example: Missing = -99



Basic Settings

Select Stage 1 outcome
Select **Continuous**, **Dichotomous**, or **Ordinal** for Stage 1 outcome.
- **Continuous:** Weight;
- **Dichotomous:** Yes or No;
- **Ordinal:** Preference level

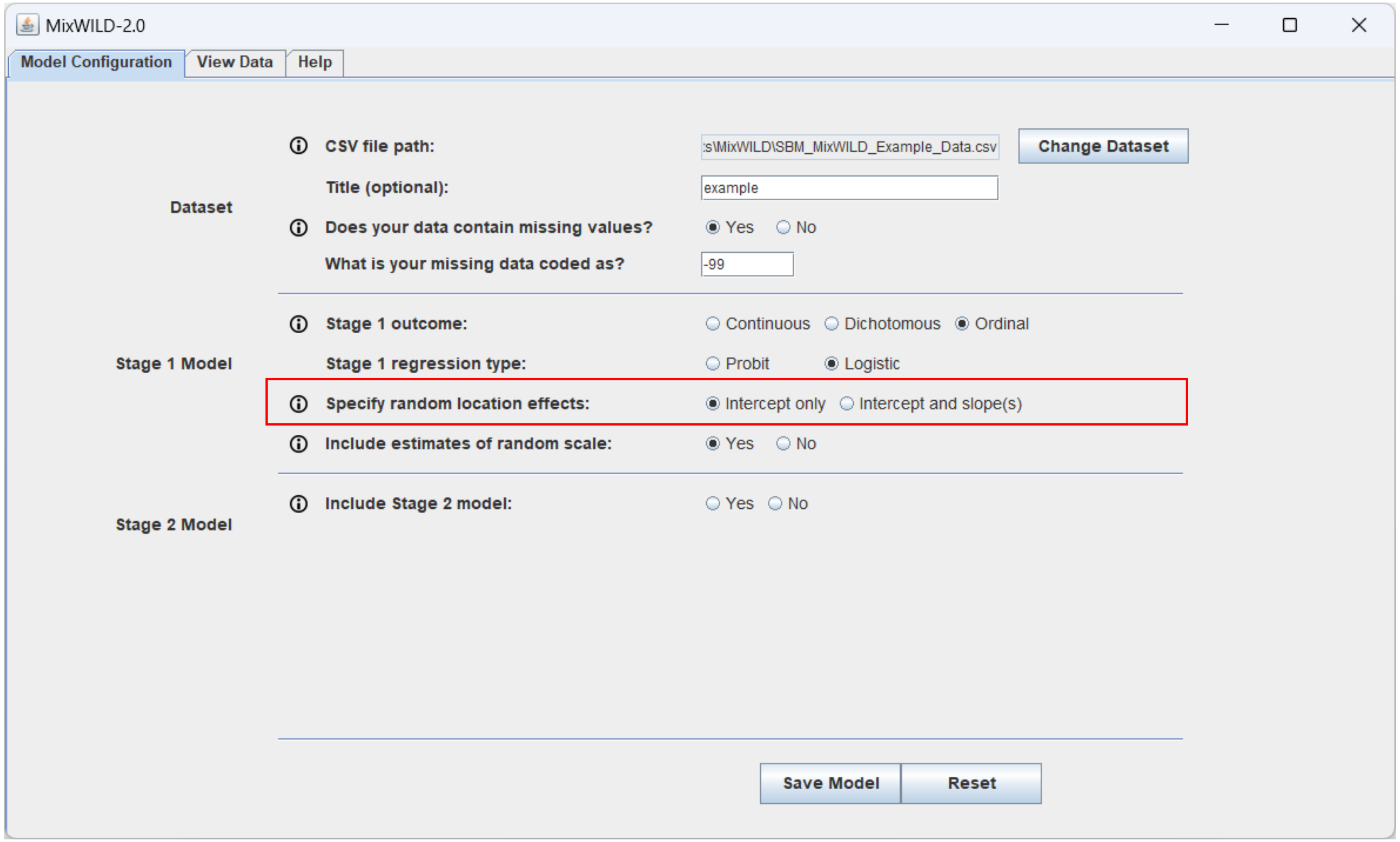
Choose between **Probit** or **Logistic** model if your Stage 1 outcome is **Dichotomous/Ordinal**.



Basic Settings

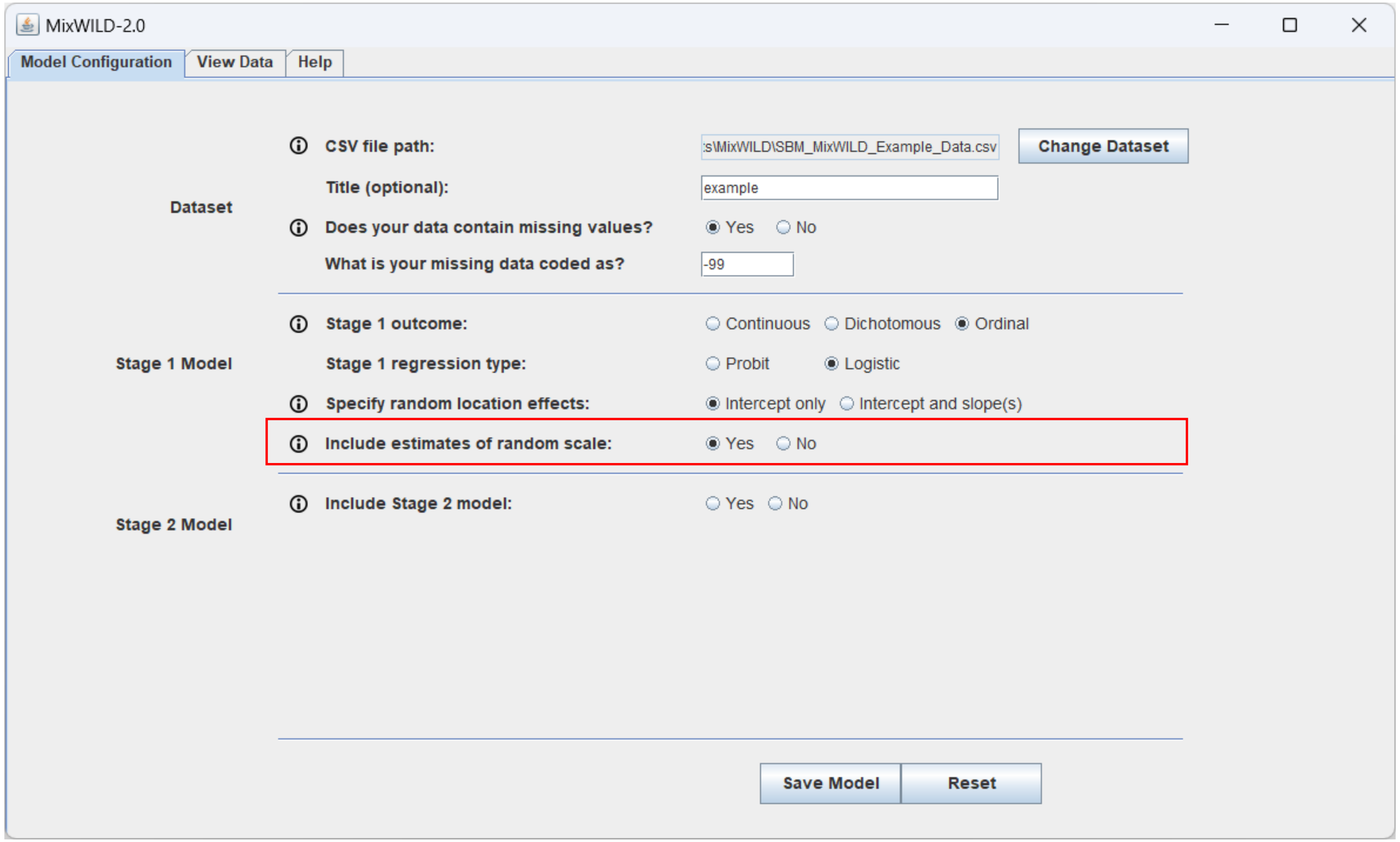
Specify random location
Select **"Intercept only"** and the model includes a random subject intercept.

Select **"Intercept and slope(s)"** and the model includes a random subject intercept and random slope(s).



Basic Settings

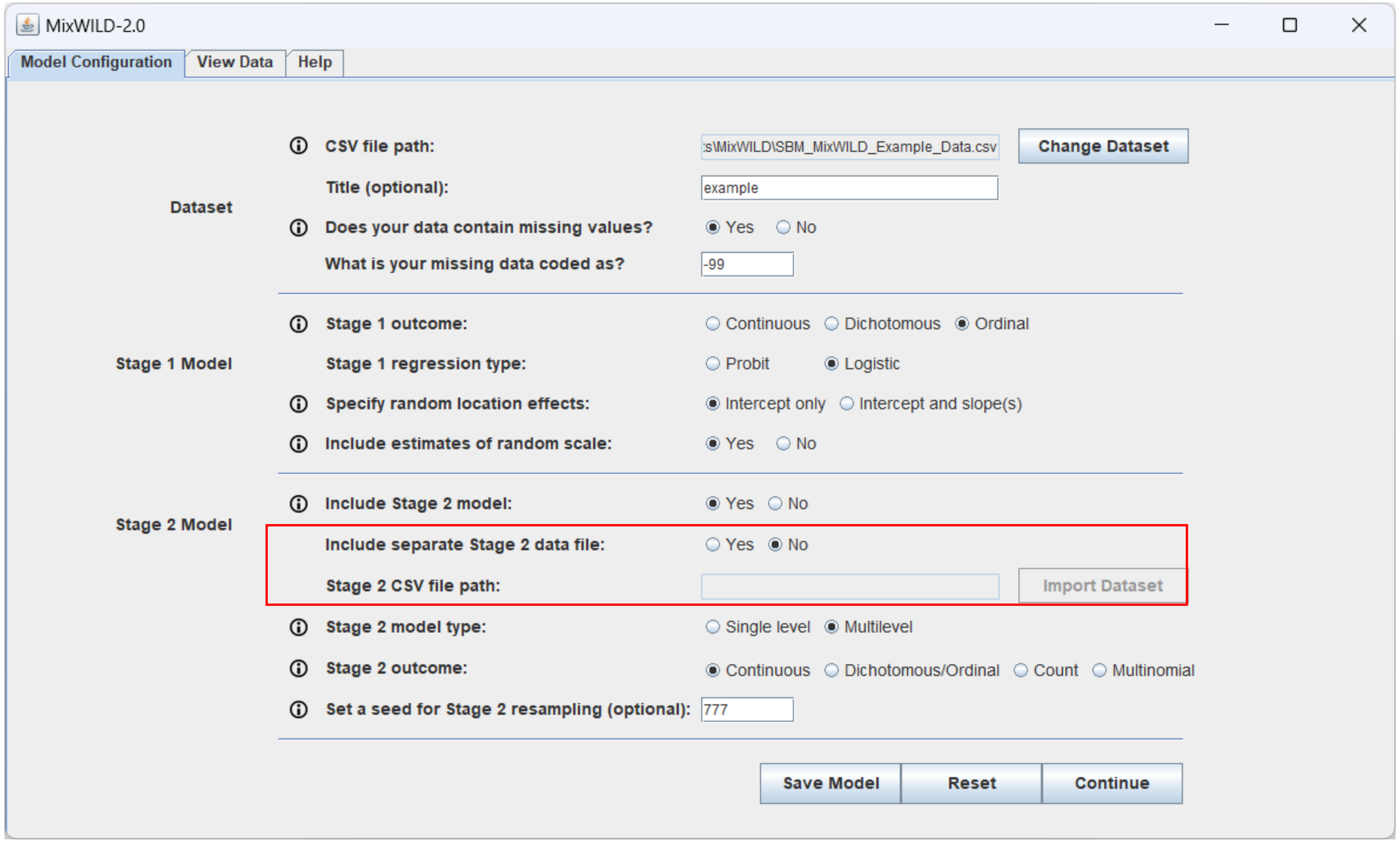
Select random scale
Select **“Yes”** if the model includes **random subject scale** (allowing subjects to have individual within-subject variance effects); otherwise **“No”**.



Basic Settings

Select separate Stage 2 data Select “**Yes**” when your stage 2 data file is separate (need **ID** to link with stage 1).

Import Dataset for stage 2 separate data.



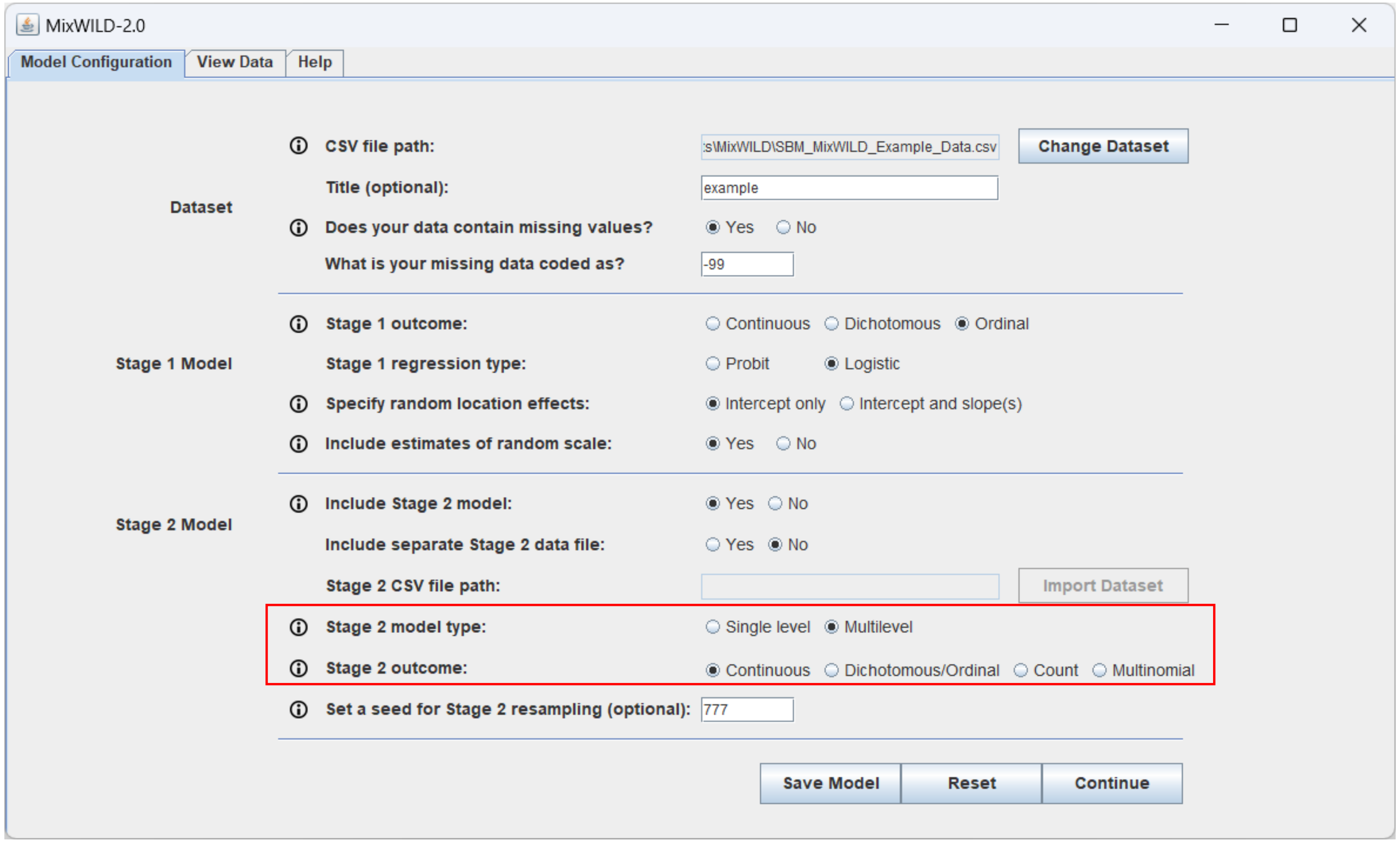
Basic Settings

Select stage 2 model

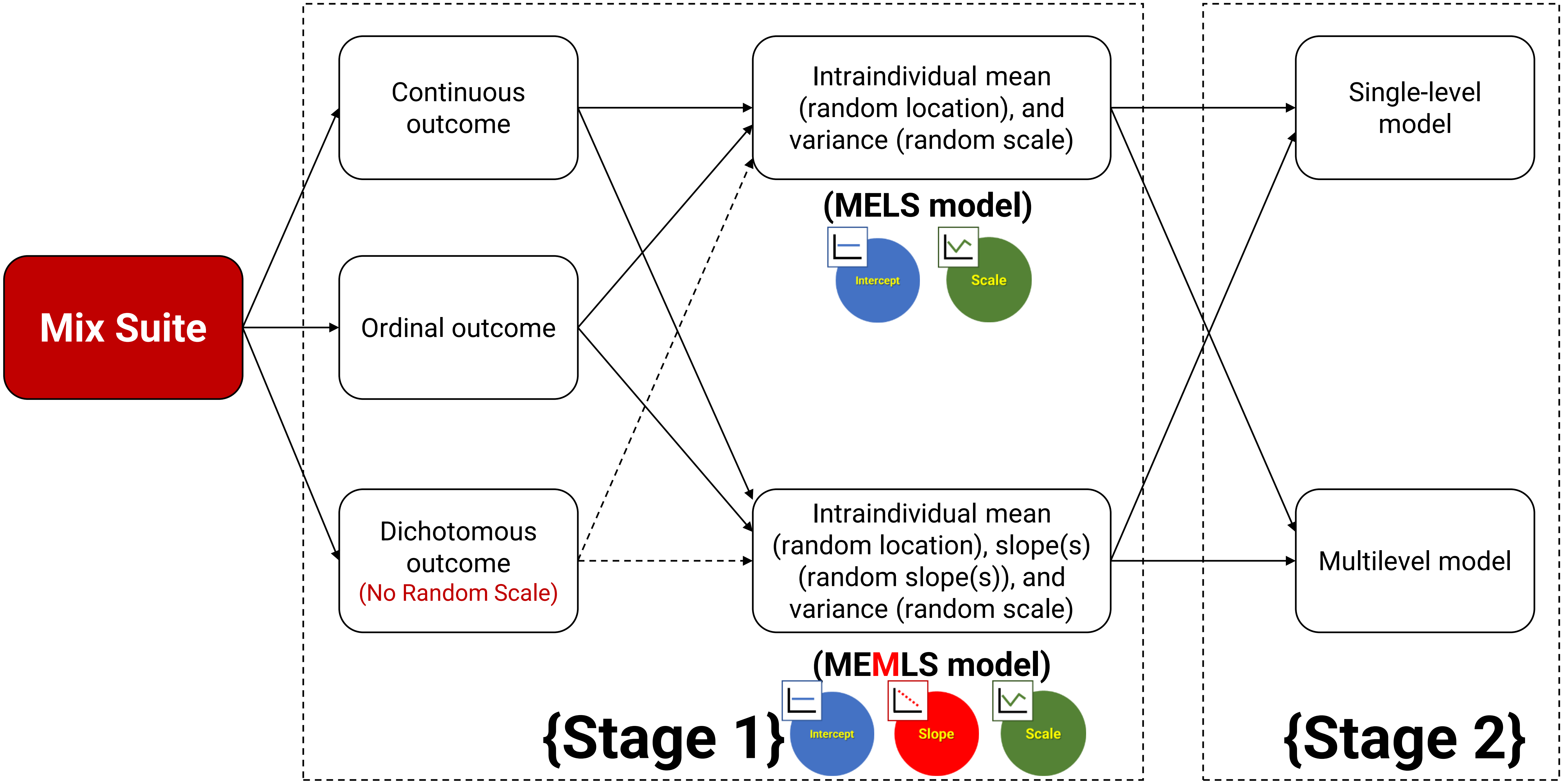
The stage-2 outcome can be single- or multilevel.

Select stage 2 outcome

- **Continuous:** Weight;
- **Dichotomous:** Yes or No;
- **Count:** Times of having snacks/exercise per day
- **Nominal:** Types of physical activities



Basic Settings



Exercise

Data

Variable	Level	Description
ID	2	Subject number (1 to 82)
Day_C	1	Centered and scaled version of day (-2.21 to 2.21; 1 unit = 1 week); day-level
Sex_F	2	Dummy coded sex (0=M; 1=F)
Age_C	2	Participants' age, centered age (-6 to 28, mean=0, sd=9.15) Original scale is from 17 to 51 yrs.
Sem	2	Semester: Number of semesters studied (subject-level variable; 1 to 10, mean = 2.93, sd=1.89)
Exam	2	Examination success (0=fail, 1=pass); subject-level variable
HSG	2	High school grades 1 (lowest grade) to 6 (highest grade) Subject-level variable; (3.4 to 5.6; mean=4.68, sd=0.45)
HSG_Rank	2	Ranked version of HSG (good for stage-2 subject-level count outcome); subject-level variable
BDI	2	Beck Depression Inventory 1(not) 2 (mild to moderate) 3 (clinically relevant symptoms); subject-level variable
SQ	1	Sleep quality 1 (very bad) to 4 (very good) (day-level variable; mean = 3)
PhysAct	1	Physical activity: Number of minutes engaged in mild, moderate and strenuous exercise weighted by metabolic equivalents and then summed to produce a total daily leisure activity score (day-level variable; 0 to 3960, sd=413.68)
PhysAct_LN	1	Physical activity (Log term) (day-level variable; mean=3.92, sd=4.85)
PA	1	Positive affect 1 (not at all) to 7 (extremely); day-level
PA_D	1	Positive affect (Dichotomous) (Coded as 1 when PA > 4)
PA_Ord	1	Rounded version of PA (good for stage-1 ordinal outcome); day-level
NA	1	Negative affect 1 (not at all) to 7 (extremely); day-level
NA_D	1	Negative affect 1 (not at all) to 7 (extremely); day-level (Dichotomous) (Coded as 1 when NA > 4)
NA_Mean	2	Average negative affect per subject; subject-level variable (mean=2.65; sd=0.98)
LGA	1	Learning goal achievement 0 (not at all) to 4 (completely); day-level variable

Missing value = -99

Data are from: https://dataverse.harvard.edu/dataverse/harvard
“How health behaviors relate to academic performance via aect: An intensive longitudinal study" by Flueckiger L, Lieb R, Meyer AH, Mata J

Research Question 1(Q1)

{Stage 1 Model}

Does the number of days in the study influence one's positive affect (PA)?

Research Question 1(Q1)

{Stage 1 Model}

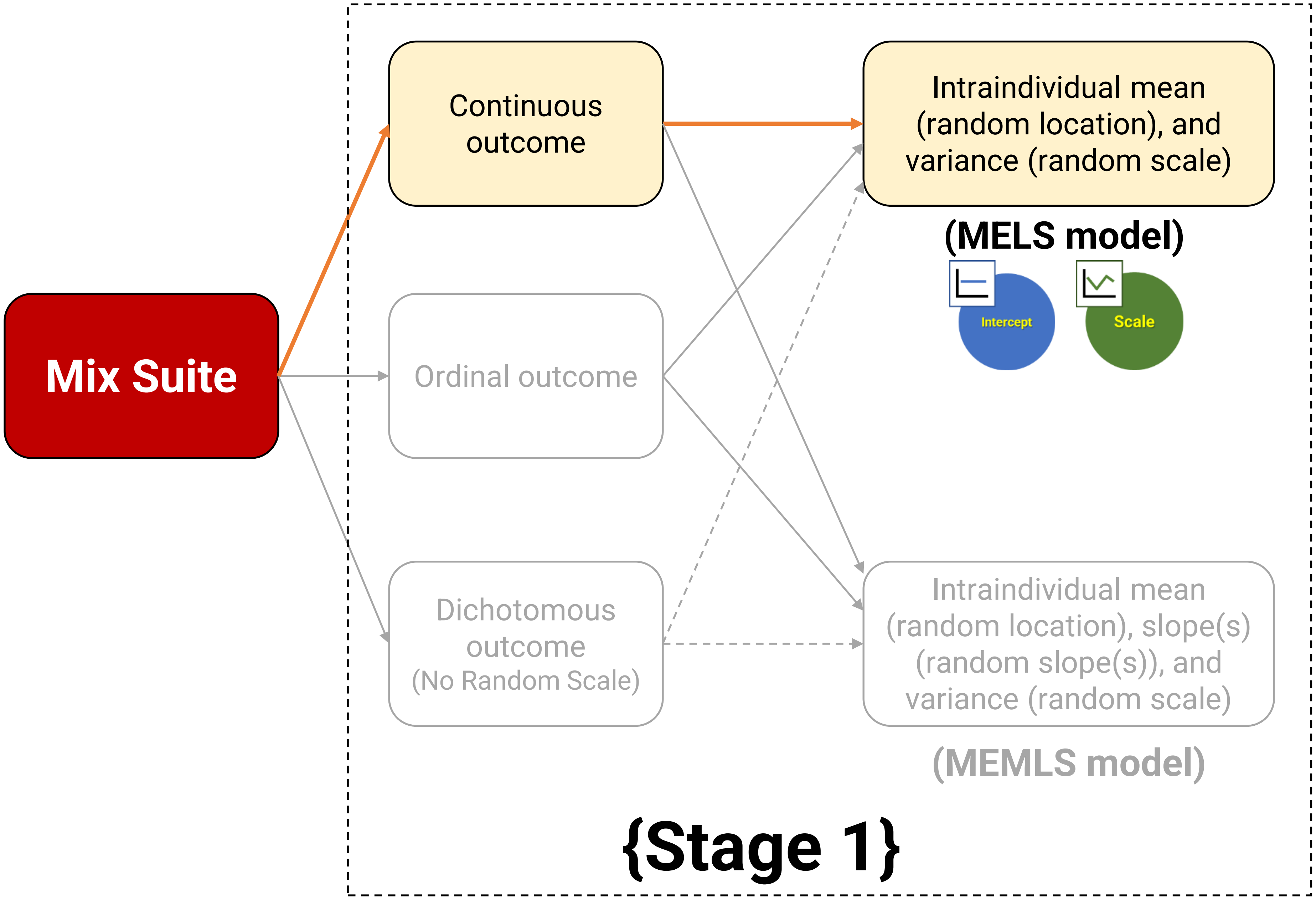
Does the number of days in the survey influence one's positive affect (PA)?

- (Mean model) Does positive affect change across days?

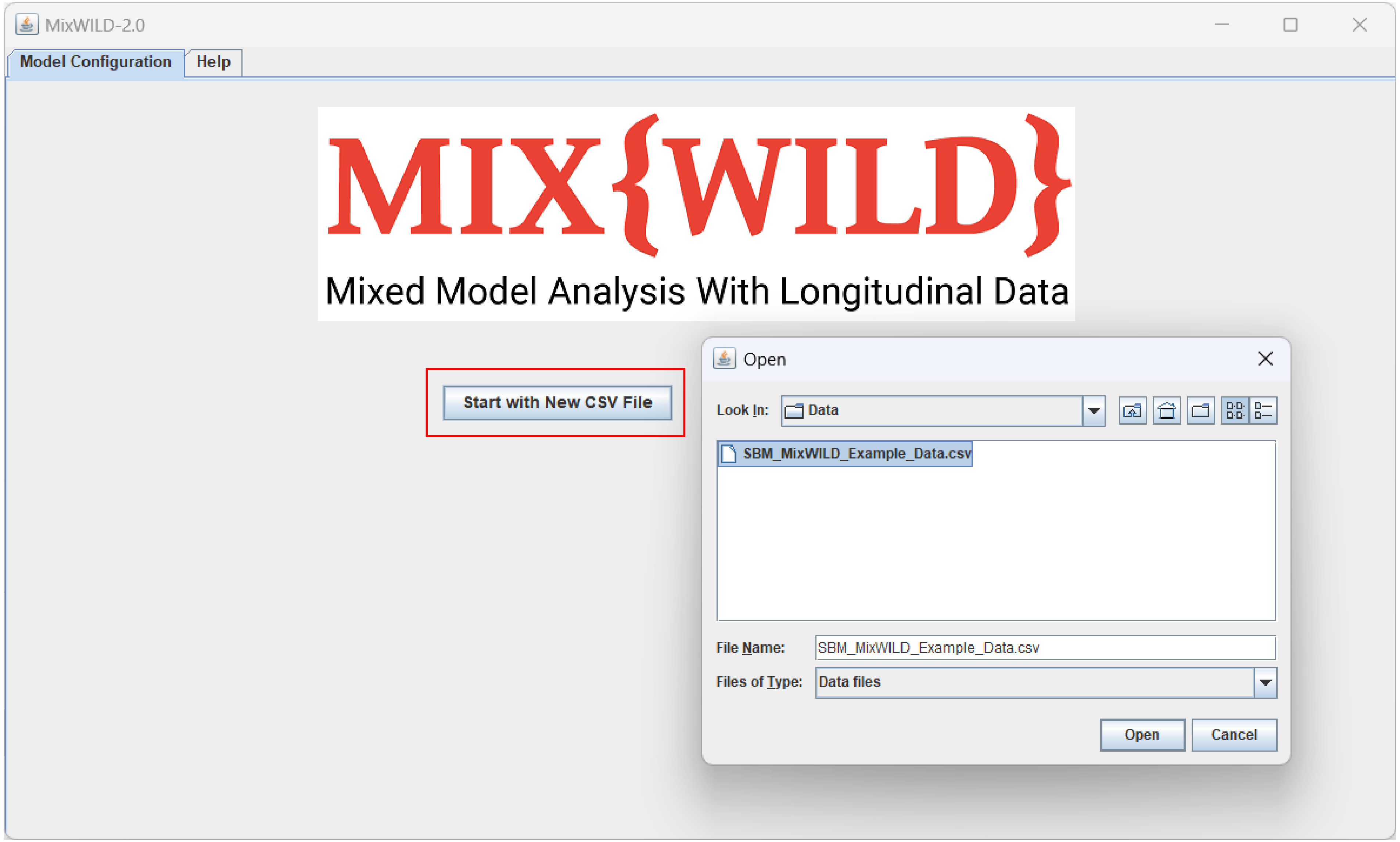
- (BSV model) Does the sample become more heterogeneous in PA as day passes?

- (WSV model) Do a subject's PA become more erratic as day passes?

Q1:Does the number of days in the study influence one's positive affect (PA)?

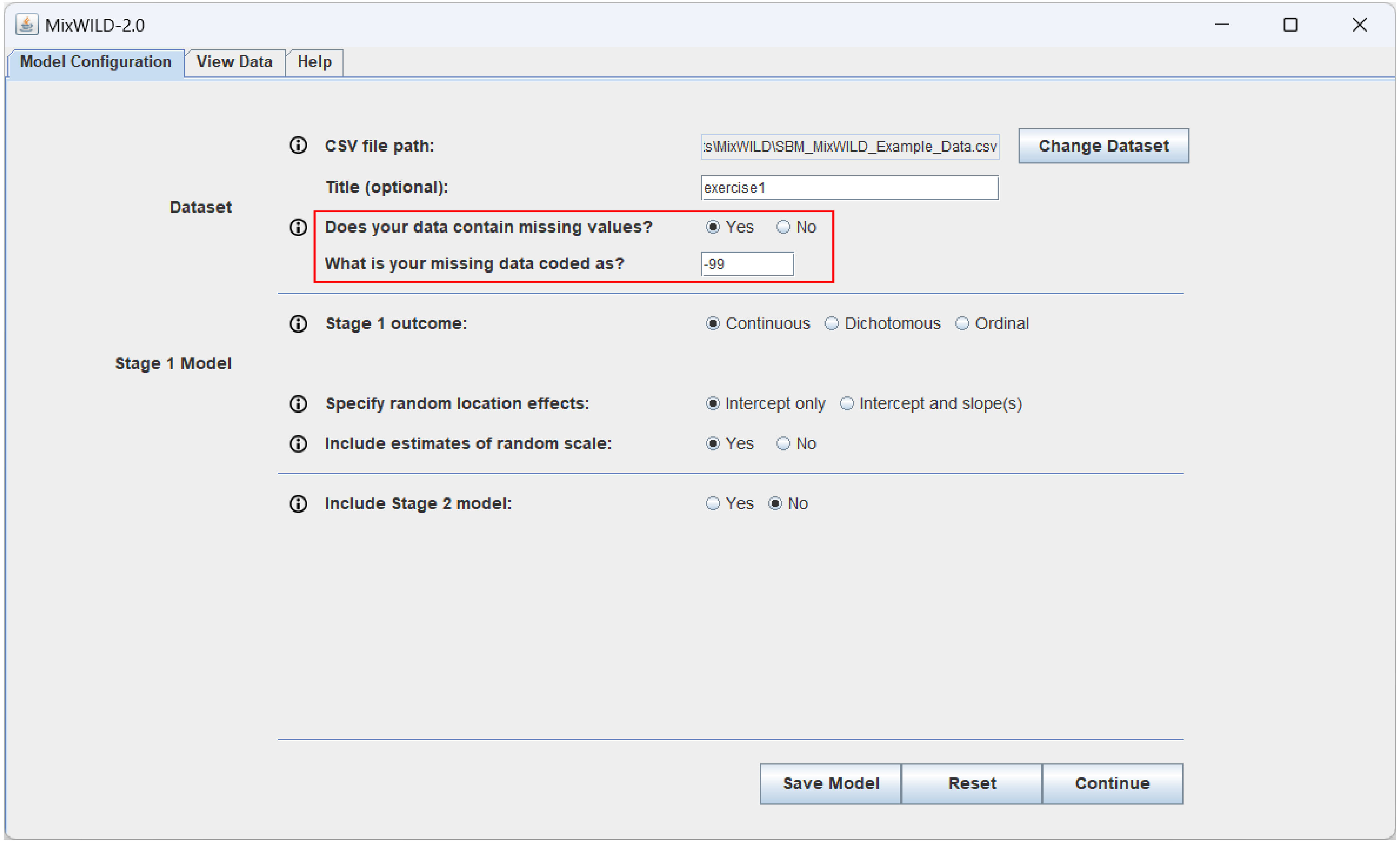


Q1:Does the number of days in the study influence one's positive affect (PA)?



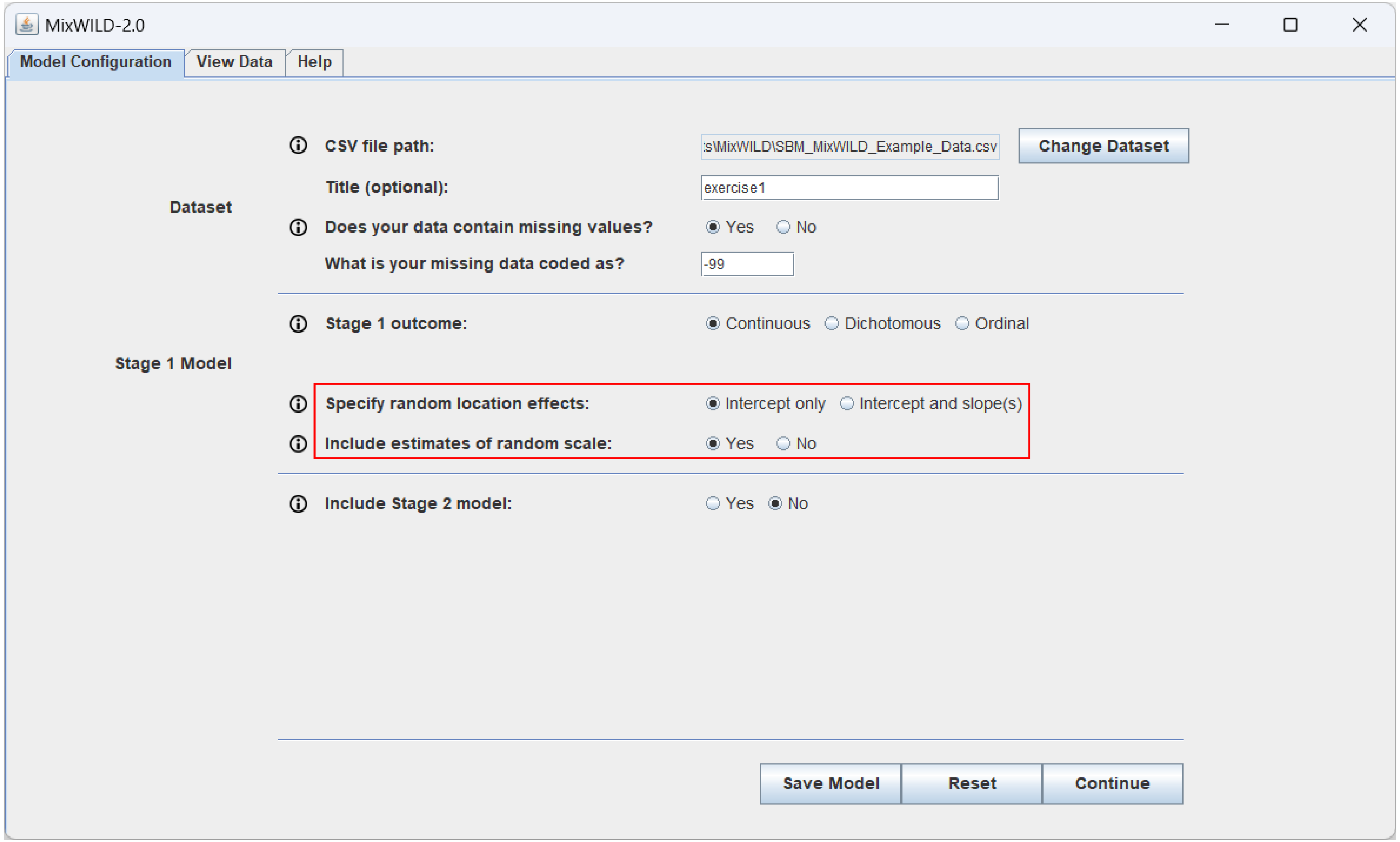
Start with "New CSV File" and locate the MixWILD example dataset

Q1:Does the number of days in the study influence one's positive affect (PA)?



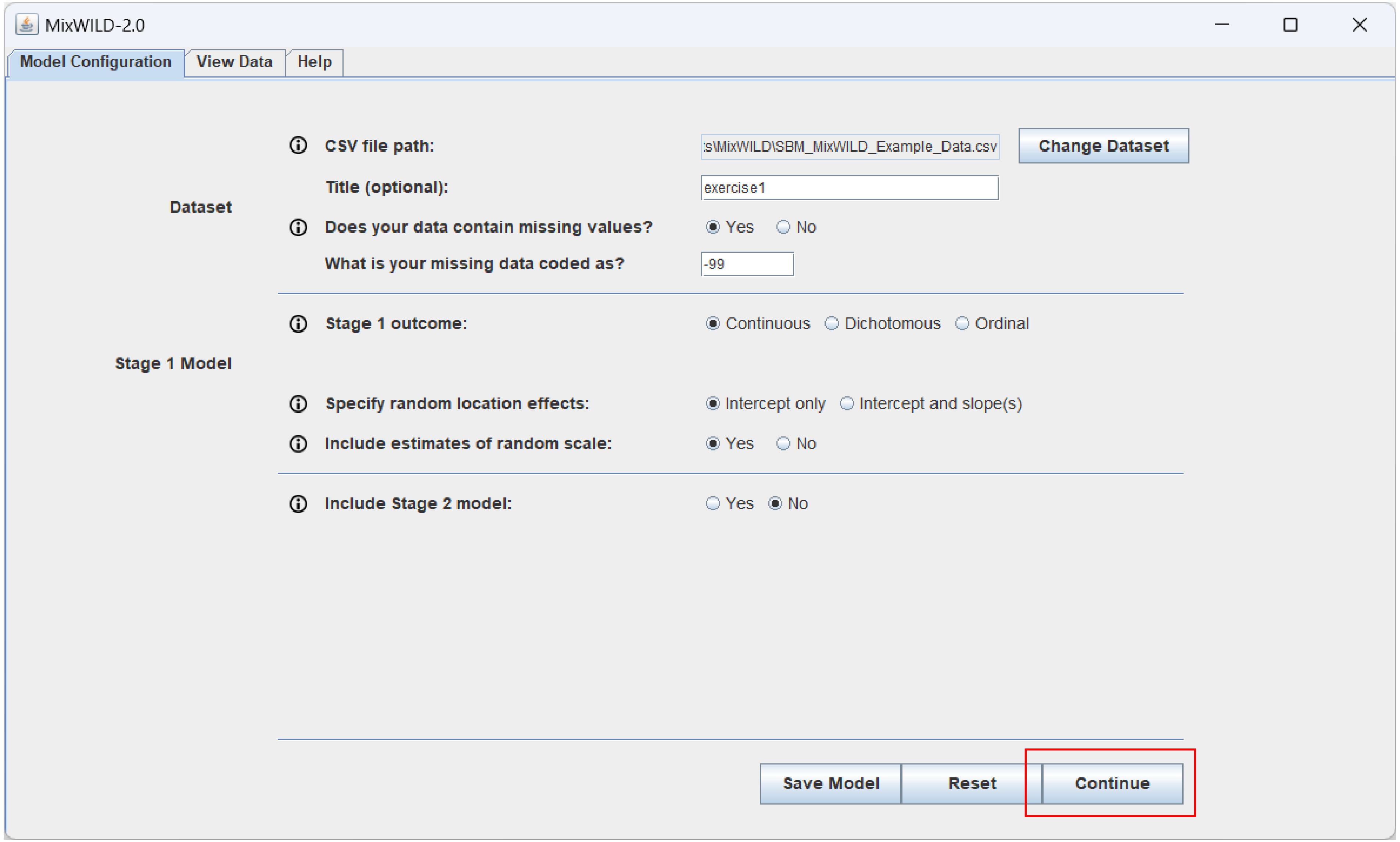
Provide a title and make selections (Don't forget set up missing value)

Q1:Does the number of days in the study influence one's positive affect (PA)?



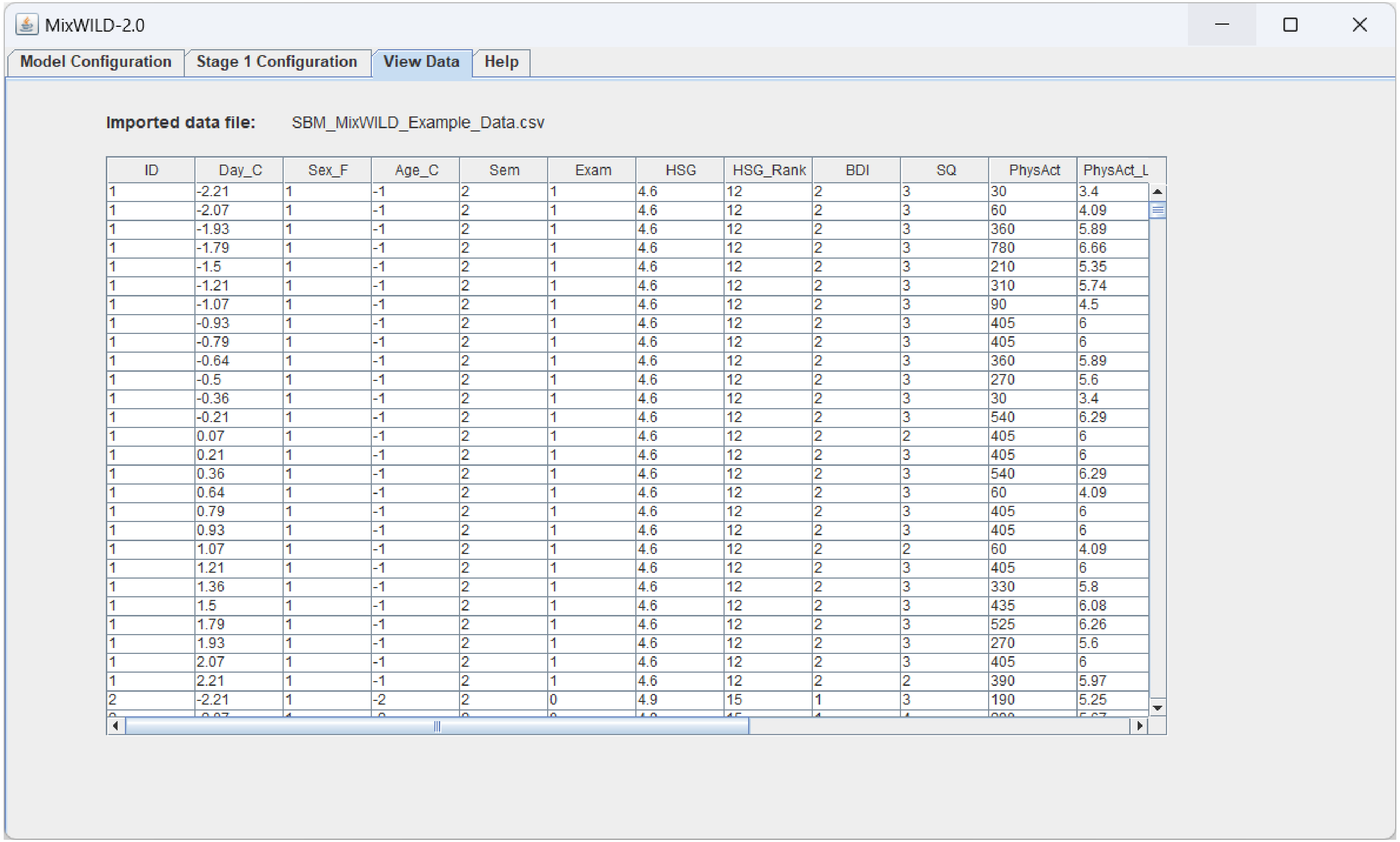
Specify random effects (Select "Intercept only" and include "Random scale")

Q1:Does the number of days in the study influence one's positive affect (PA)?



Select "Continue" to enter the next page

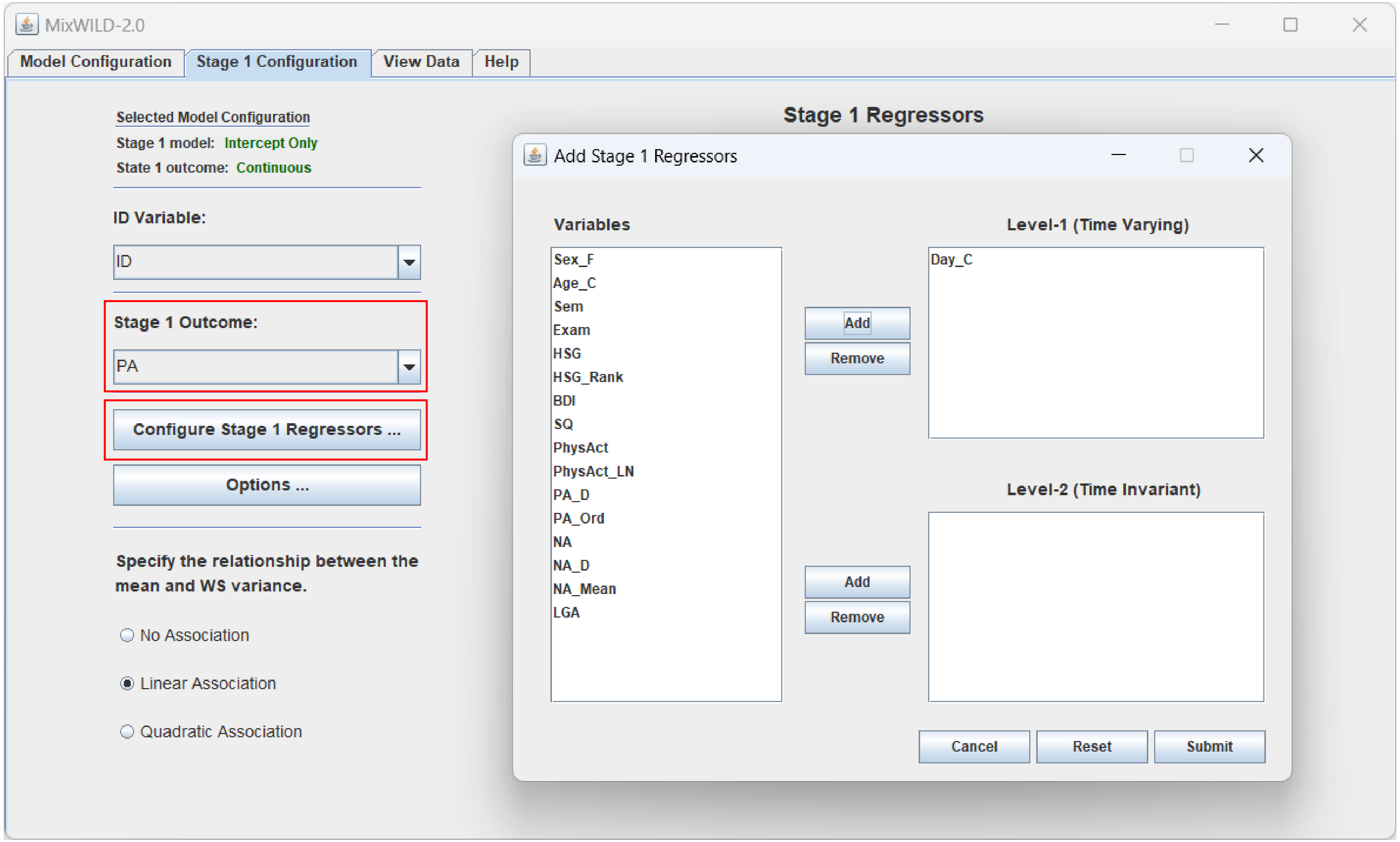
Q1:Does the number of days in the study influence one's positive affect (PA)?



ID	Day_C	Sex_F	Age_C	Sem	Exam	HSG	HSG_Rank	BDI	SQ	PhysAct	PhysAct_L
1	-2.21	1	-1	2	1	4.6	12	2	3	30	3.4
1	-2.07	1	-1	2	1	4.6	12	2	3	60	4.09
1	-1.93	1	-1	2	1	4.6	12	2	3	360	5.89
1	-1.79	1	-1	2	1	4.6	12	2	3	780	6.66
1	-1.5	1	-1	2	1	4.6	12	2	3	210	5.35
1	-1.21	1	-1	2	1	4.6	12	2	3	310	5.74
1	-1.07	1	-1	2	1	4.6	12	2	3	90	4.5
1	-0.93	1	-1	2	1	4.6	12	2	3	405	6
1	-0.79	1	-1	2	1	4.6	12	2	3	405	6
1	-0.64	1	-1	2	1	4.6	12	2	3	360	5.89
1	-0.5	1	-1	2	1	4.6	12	2	3	270	5.6
1	-0.36	1	-1	2	1	4.6	12	2	3	30	3.4
1	-0.21	1	-1	2	1	4.6	12	2	3	540	6.29
1	0.07	1	-1	2	1	4.6	12	2	2	405	6
1	0.21	1	-1	2	1	4.6	12	2	3	405	6
1	0.36	1	-1	2	1	4.6	12	2	3	540	6.29
1	0.64	1	-1	2	1	4.6	12	2	3	60	4.09
1	0.79	1	-1	2	1	4.6	12	2	3	405	6
1	0.93	1	-1	2	1	4.6	12	2	3	405	6
1	1.07	1	-1	2	1	4.6	12	2	2	60	4.09
1	1.21	1	-1	2	1	4.6	12	2	3	405	6
1	1.36	1	-1	2	1	4.6	12	2	3	330	5.8
1	1.5	1	-1	2	1	4.6	12	2	3	435	6.08
1	1.79	1	-1	2	1	4.6	12	2	3	525	6.26
1	1.93	1	-1	2	1	4.6	12	2	3	270	5.6
1	2.07	1	-1	2	1	4.6	12	2	3	405	6
1	2.21	1	-1	2	1	4.6	12	2	2	390	5.97
2	-2.21	1	-2	2	0	4.9	15	1	3	190	5.25

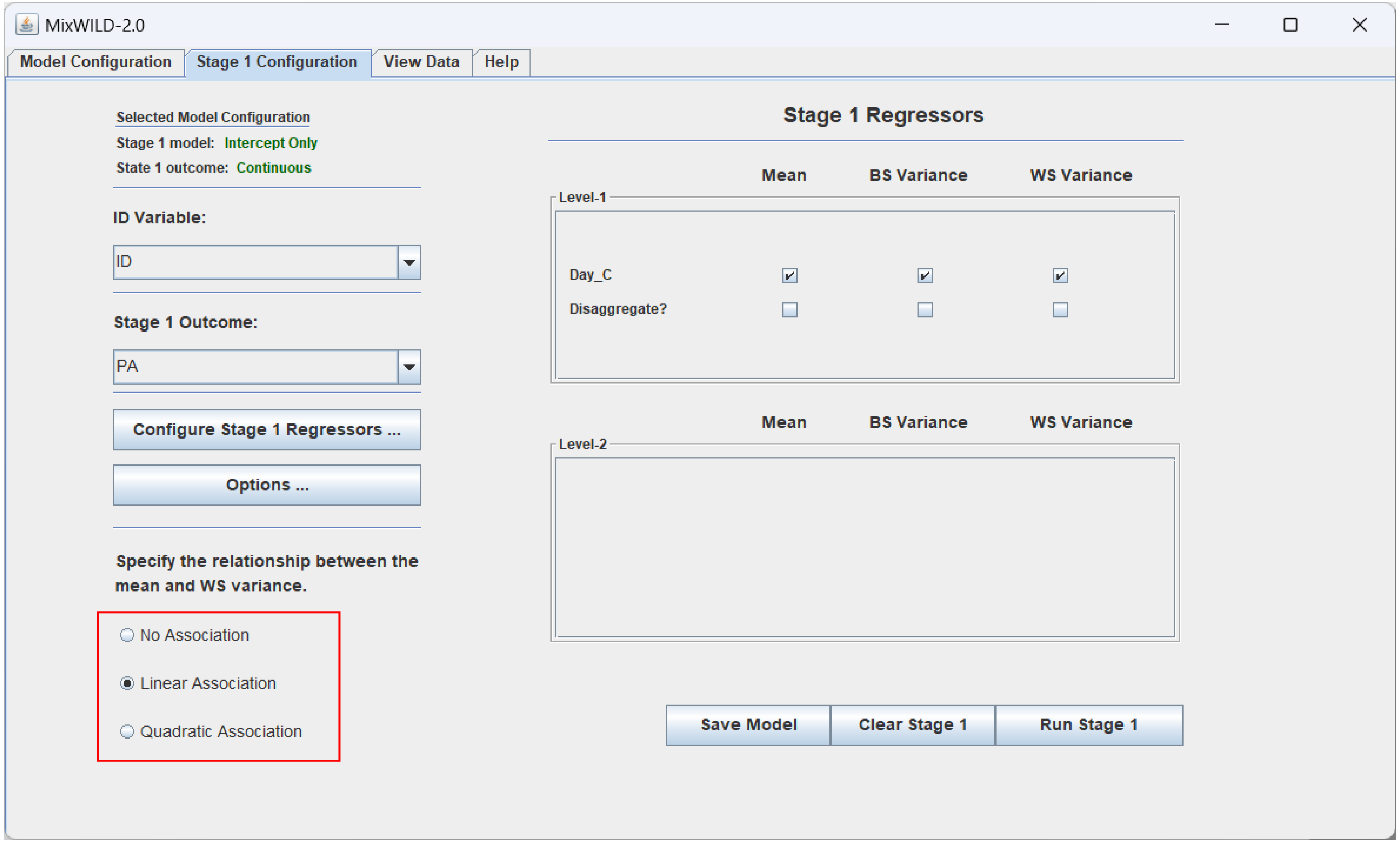
Review your data in "View Data" page

Q1:Does the number of days in the study influence one's positive affect (PA)?



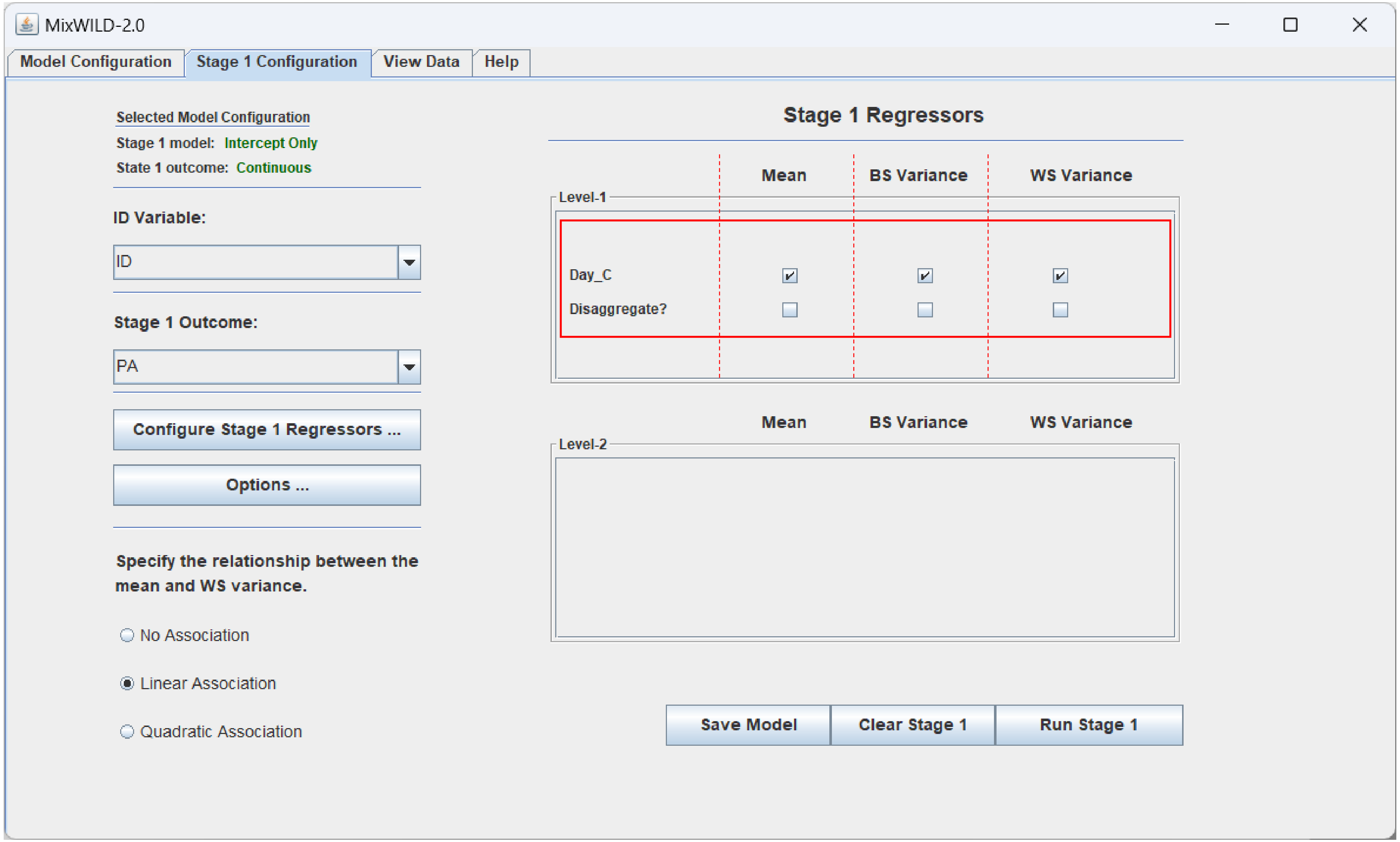
Select "PA" as the Stage 1 Outcome and "Day_C" as a time-varying predictor

Q1:Does the number of days in the study influence one's positive affect (PA)?



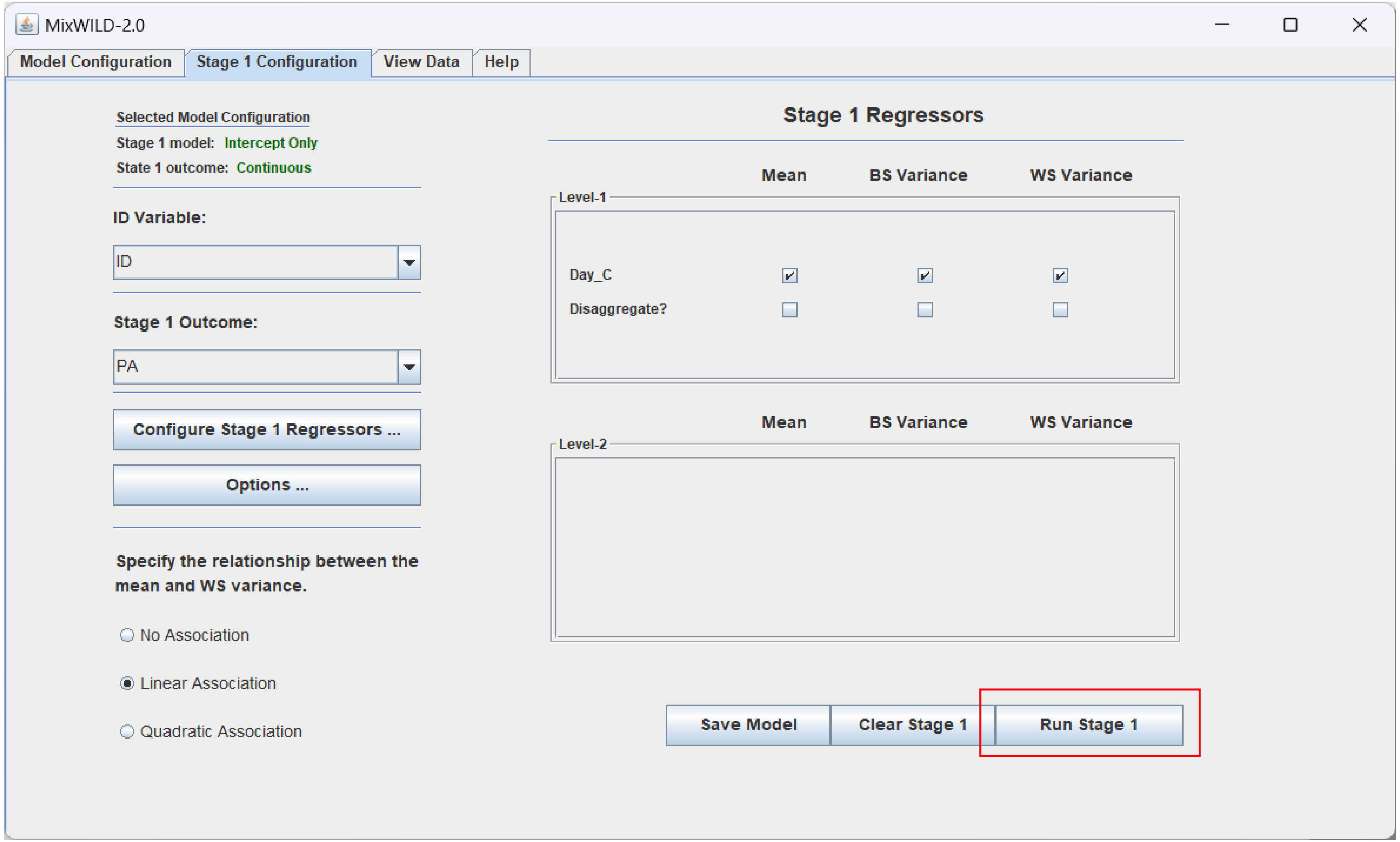
Specify the relationship between the mean and WS variance, select "Linear"

Q1:Does the number of days in the study influence one's positive affect (PA)?



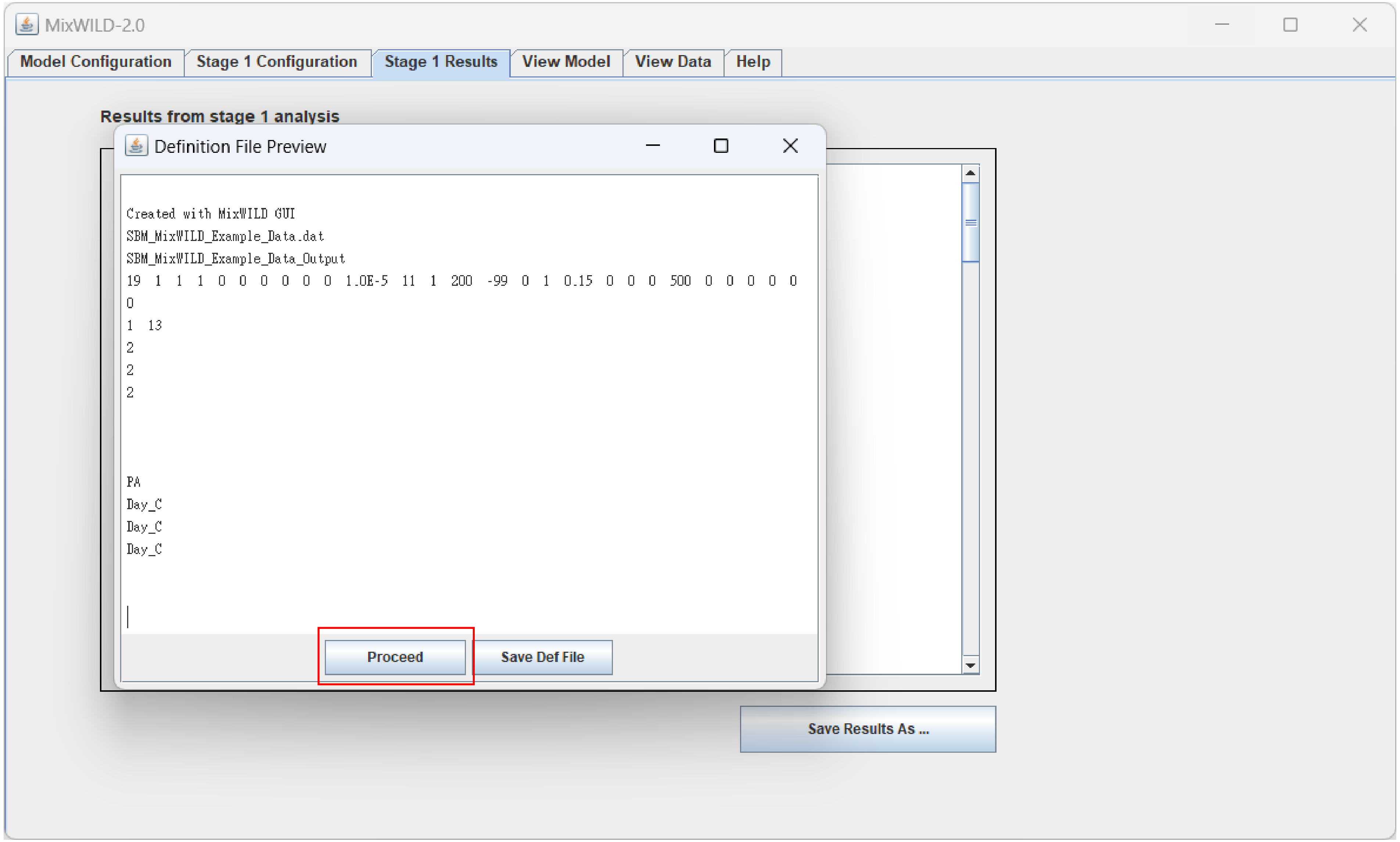
Specify the regressors in Stage 1 Models (Mean, BSV, and WSV)

Q1:Does the number of days in the study influence one’s positive affect (PA)?



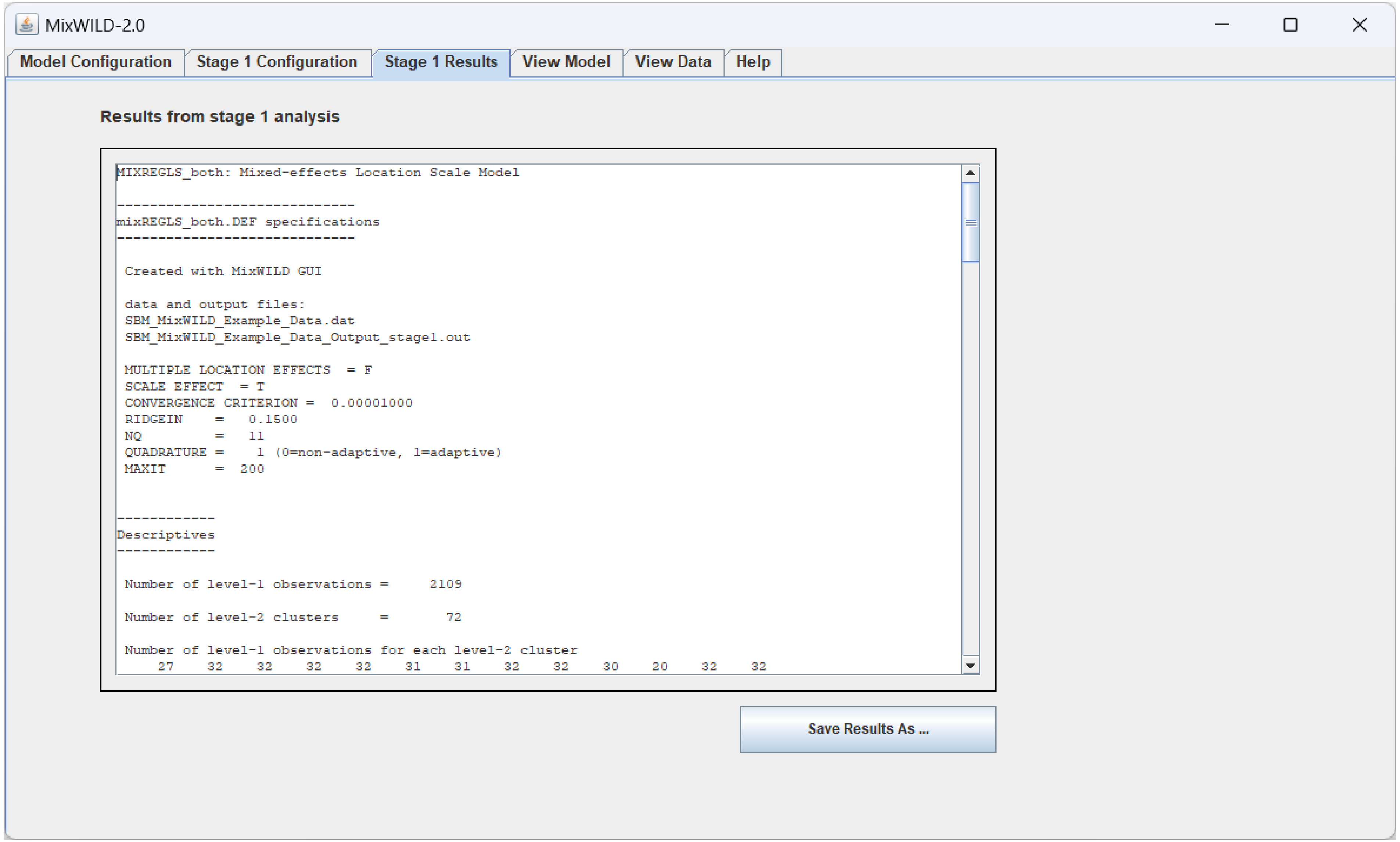
Click on “Run Stage 1”

Q1:Does the number of days in the study influence one's positive affect (PA)?



Click on "Proceed" and it will run the model automatically

Q1:Does the number of days in the study influence one's positive affect (PA)?



Check the Stage 1 Results

Q1:Does the number of days in the study influence one's positive affect (PA)?

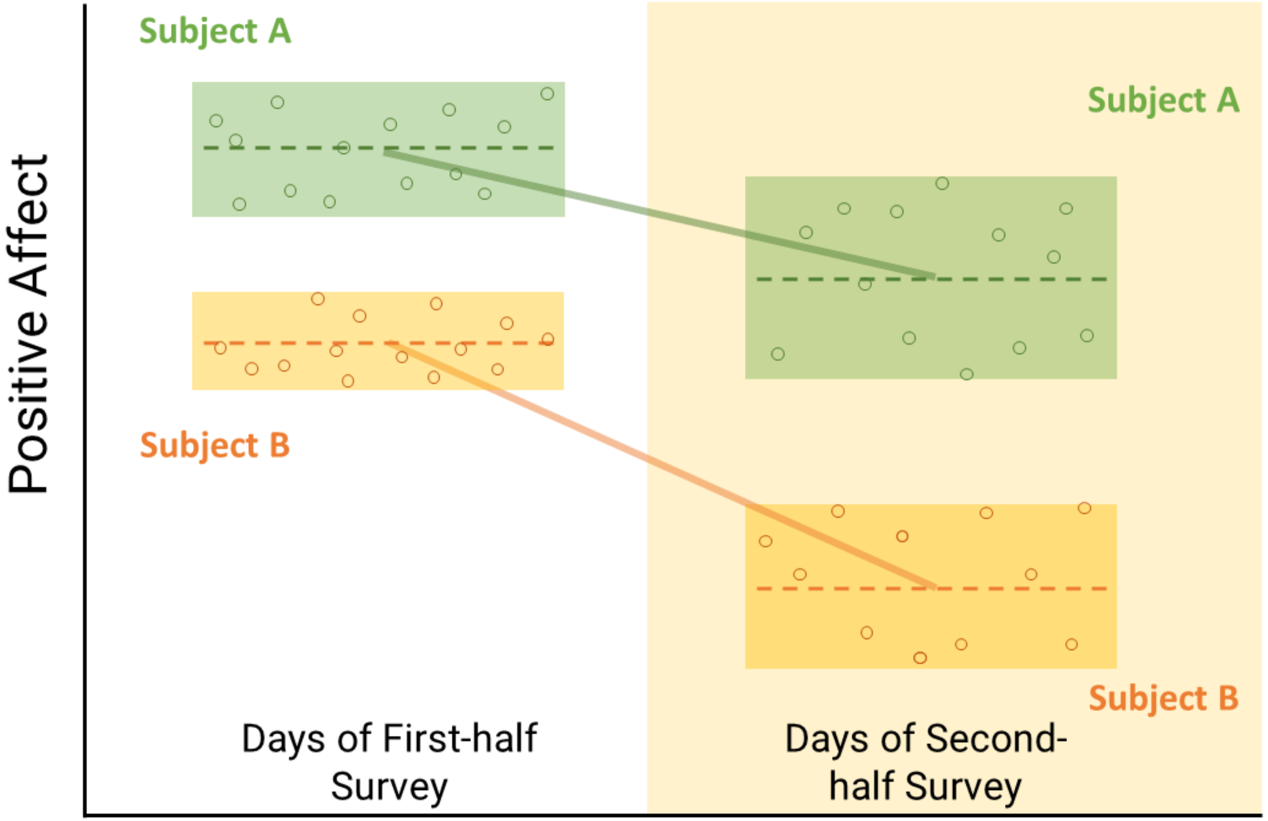
Variable	Estimate	AsymStdError	z-value	p-value
BETA (regression coefficients)				
intercept	4.13072	0.14192	29.10578	0.00000
Day_C	-0.10383	0.01829	-5.67717	0.00000
ALPHA (BS variance parameters: log-linear model)				
intercept	0.33320	0.17051	1.95409	0.05069
Day_C	0.11952	0.01981	6.03246	0.00000
TAU (WS variance parameters: log-linear model)				
intercept	-0.09010	0.10237	-0.88010	0.37881
Day_C	0.13547	0.02616	5.17843	0.00000
Random scale standard deviation				
Std Dev	0.73612	0.07047	10.44548	0.00000
Random location (mean) effect on WS variance				
Loc Eff	-0.36756	0.09955	-3.69233	0.00022

Mean model (BETA): the mean PA is estimated to be a bit over 4, and the slope is negative and significant (beta $= -0.10383$; $p < 0.001$). PA decreases by approximately one-tenth of a point per week.

Q1:Does the number of days in the study influence one's positive affect (PA)?

(Mean model) Does positive affect change across days?

– the slope is negative and significant, and it shows PA decreases over time.



Q1:Does the number of days in the study influence one's positive affect (PA)?

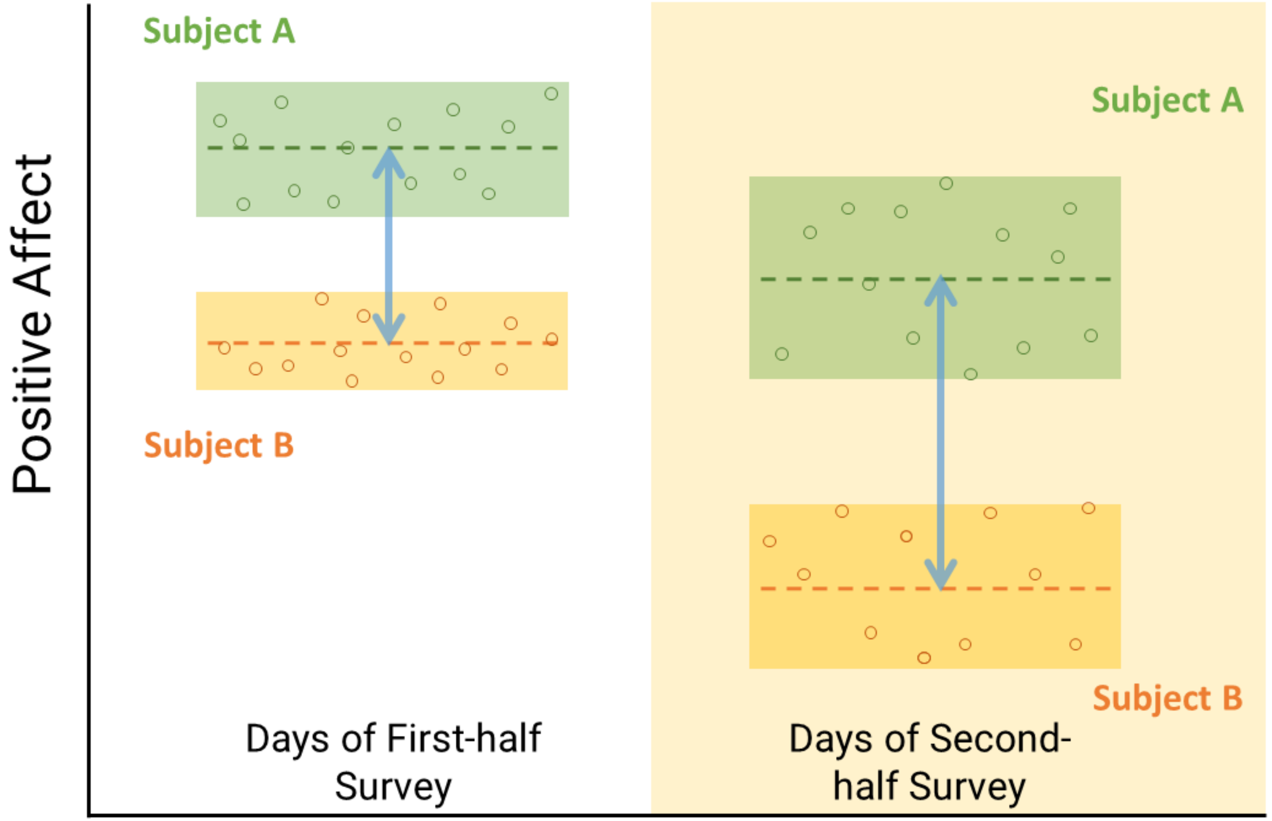
Variable	Estimate	AsymStdError	z-value	p-value
BETA (regression coefficients)				
intercept	4.13072	0.14192	29.10578	0.00000
Day_C	-0.10383	0.01829	-5.67717	0.00000
ALPHA (BS variance parameters: log-linear model)				
intercept	0.33320	0.17051	1.95409	0.05069
Day_C	0.11952	0.01981	6.03246	0.00000
TAU (WS variance parameters: log-linear model)				
intercept	-0.09010	0.10237	-0.88010	0.37881
Day_C	0.13547	0.02616	5.17843	0.00000
Random scale standard deviation				
Std Dev	0.73612	0.07047	10.44548	0.00000
Random location (mean) effect on WS variance				
Loc Eff	-0.36756	0.09955	-3.69233	0.00022

BS variance model (ALPHA): the effect of Day_C is positive and significant (alpha = 0.11952; $p < 0.001$). The exponentiated slope is 1.12696. From the estimate of 1.13, we can conclude that the BS variance increases by a factor of 13% per week; thus, subjects become more heterogeneous over time.

Q1:Does the number of days in the study influence one's positive affect (PA)?

(BSV model) Does the sample become more heterogeneous in PA as day passes?

– The effect of Day_C is positive and significant, and it indicates that subjects become more heterogeneous over time.



Q1:Does the number of days in the study influence one's positive affect (PA)?

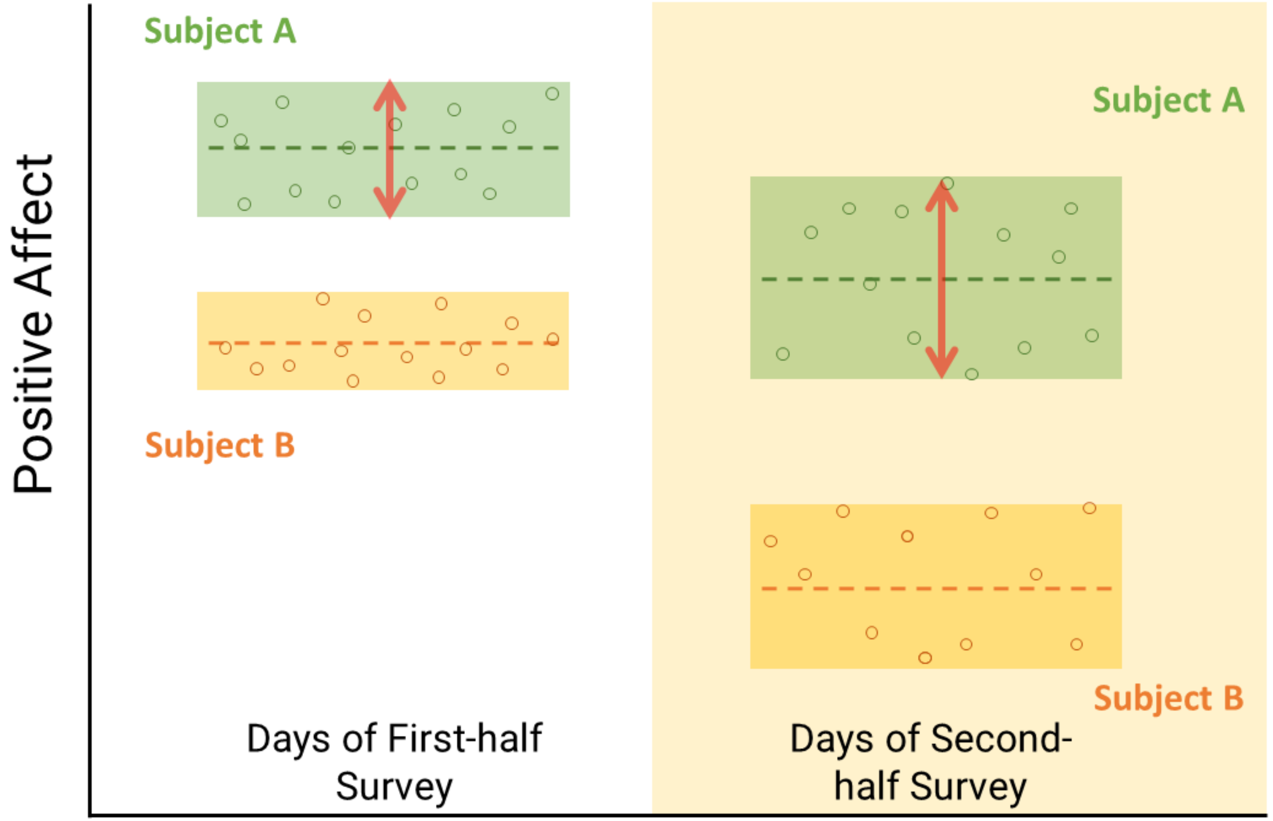
Variable	Estimate	AsymStdError	z-value	p-value
BETA (regression coefficients)				
intercept	4.13072	0.14192	29.10578	0.00000
Day_C	-0.10383	0.01829	-5.67717	0.00000
ALPHA (BS variance parameters: log-linear model)				
intercept	0.33320	0.17051	1.95409	0.05069
Day_C	0.11952	0.01981	6.03246	0.00000
TAU (WS variance parameters: log-linear model)				
intercept	-0.09010	0.10237	-0.88010	0.37881
Day_C	0.13547	0.02616	5.17843	0.00000
Random scale standard deviation				
Std Dev	0.73612	0.07047	10.44548	0.00000
Random location (mean) effect on WS variance				
Loc Eff	-0.36756	0.09955	-3.69233	0.00022

WS variance model (TAU): the effect of Day_C is positive and significant (tau = 0.13547; $p < 0.001$). The exponentiated slope is 1.14507. From the estimate of 1.15, we can conclude that the WS variance increases by a factor of 15% per week; thus, subjects exhibit more erraticism (less consistency) over time.

Q1:Does the number of days in the study influence one's positive affect (PA)?

(WSV model) Do a subject's PA become more erratic as day passes?

– The effect of Day_C is positive and significant, and it suggests subjects exhibit more erraticism (less consistency) over time.

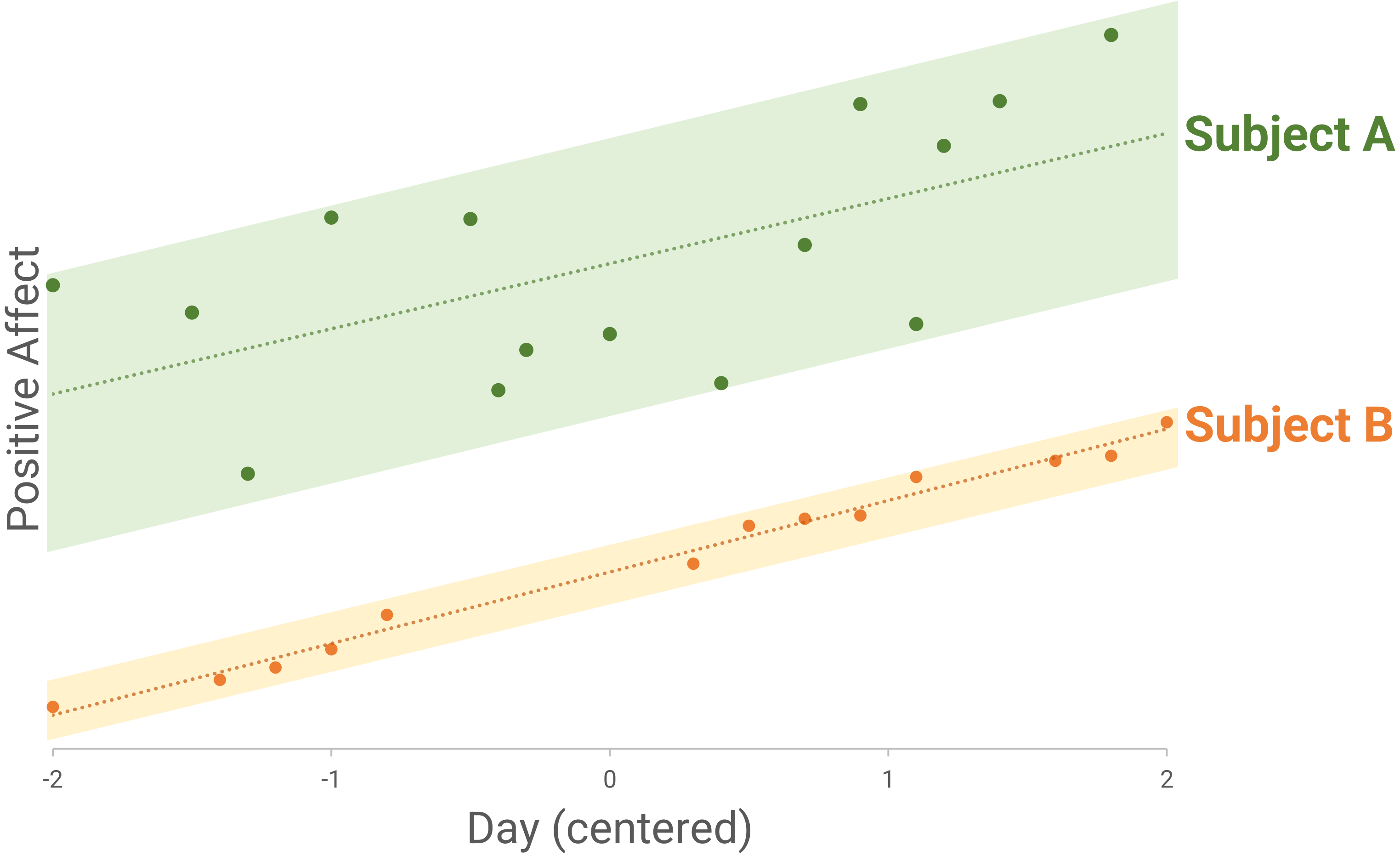


Q1:Does the number of days in the study influence one's positive affect (PA)?

Variable	Estimate	AsymStdError	z-value	p-value
BETA (regression coefficients)				
intercept	4.13072	0.14192	29.10578	0.00000
Day_C	-0.10383	0.01829	-5.67717	0.00000
ALPHA (BS variance parameters: log-linear model)				
intercept	0.33320	0.17051	1.95409	0.05069
Day_C	0.11952	0.01981	6.03246	0.00000
TAU (WS variance parameters: log-linear model)				
intercept	-0.09010	0.10237	-0.88010	0.37881
Day_C	0.13547	0.02616	5.17843	0.00000
Random scale standard deviation				
Std Dev	0.73612	0.07047	10.44548	0.00000
Random location (mean) effect on WS variance				
Loc Eff	-0.36756	0.09955	-3.69233	0.00022

The standard deviation of the random scale effect is estimated to be 0.73614, and this is a highly significant effect. Thus, subjects vary considerably in terms of how consistent/erratic they are in their PA reports.

Q1:Does the number of days in the study influence one's positive affect (PA)?



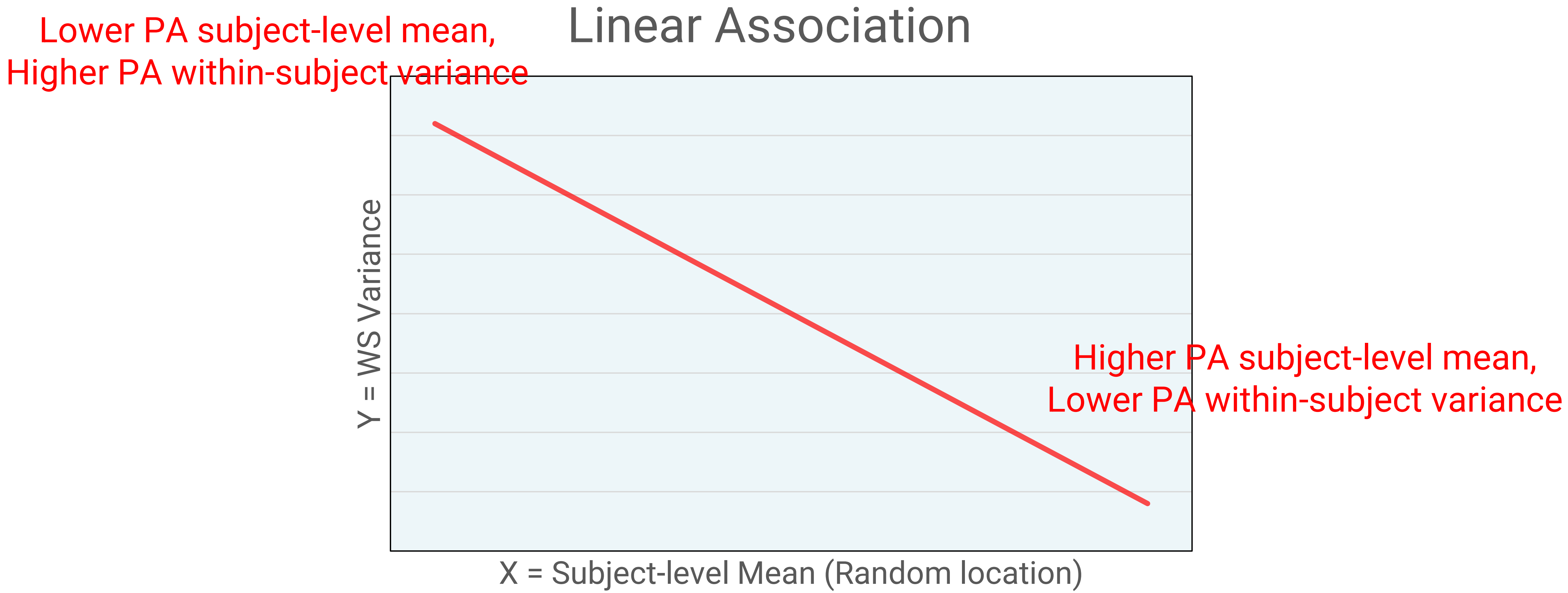
The standard deviation of the random scale effect is estimated to be 0.73614, and this is a highly significant effect. Thus, subjects vary considerably in terms of how consistent/erratic they are in their PA reports.

Q1:Does the number of days in the study influence one's positive affect (PA)?

Variable	Estimate	AsymStdError	z-value	p-value
BETA (regression coefficients)				
intercept	4.13072	0.14192	29.10578	0.00000
Day_C	-0.10383	0.01829	-5.67717	0.00000
ALPHA (BS variance parameters: log-linear model)				
intercept	0.33320	0.17051	1.95409	0.05069
Day_C	0.11952	0.01981	6.03246	0.00000
TAU (WS variance parameters: log-linear model)				
intercept	-0.09010	0.10237	-0.88010	0.37881
Day_C	0.13547	0.02616	5.17843	0.00000
Random scale standard deviation				
Std Dev	0.73612	0.07047	10.44548	0.00000
Random location (mean) effect on WS variance				
Loc Eff	-0.36756	0.09955	-3.69233	0.00022

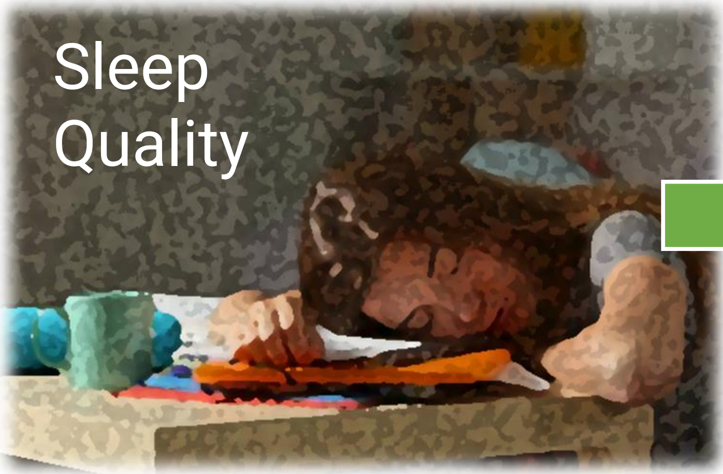
The relationship between the random location and scale effects is negative and significant indicating that subjects with higher average PA are also more consistent, and subjects with lower average PA are more erratic (also could be ceiling/cap effect).

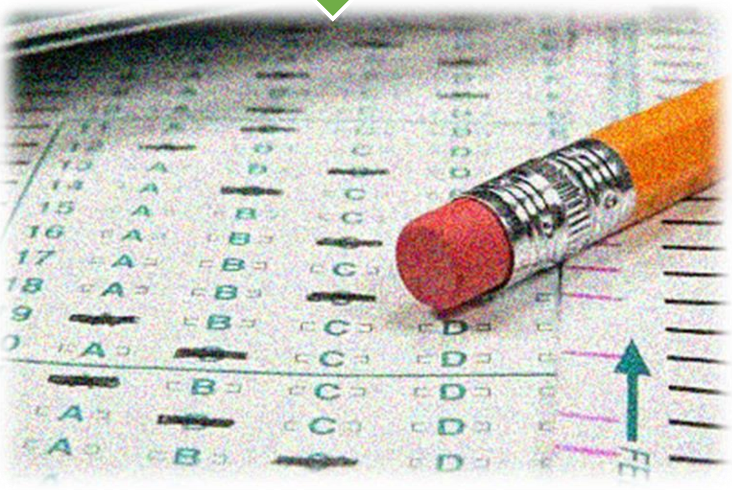
Q1:Does the number of days in the study influence one's positive affect (PA)?



The relationship between the random location and scale effects is negative and significant indicating that subjects with higher average PA are also more consistent, and subjects with lower average PA are more erratic (also could be ceiling/cap effect).

Research Question 2 (Q2)





- Does day-to-day sleep quality influence one's day-to-day learning goal achievement (LGA)?

  {Stage 1 Model}

- Does subject's mean level of- or intraindividual variance in LGA influence one's chance of passing exam?

  {Stage 2 Model}

Research Question 2 (Q2)

{Stage 1 Model}

Does sleep quality (SQ) influence one's learning goal achievement (LGA)?

- (Mean model) Does a subject have a higher LGA on days with higher SQ?

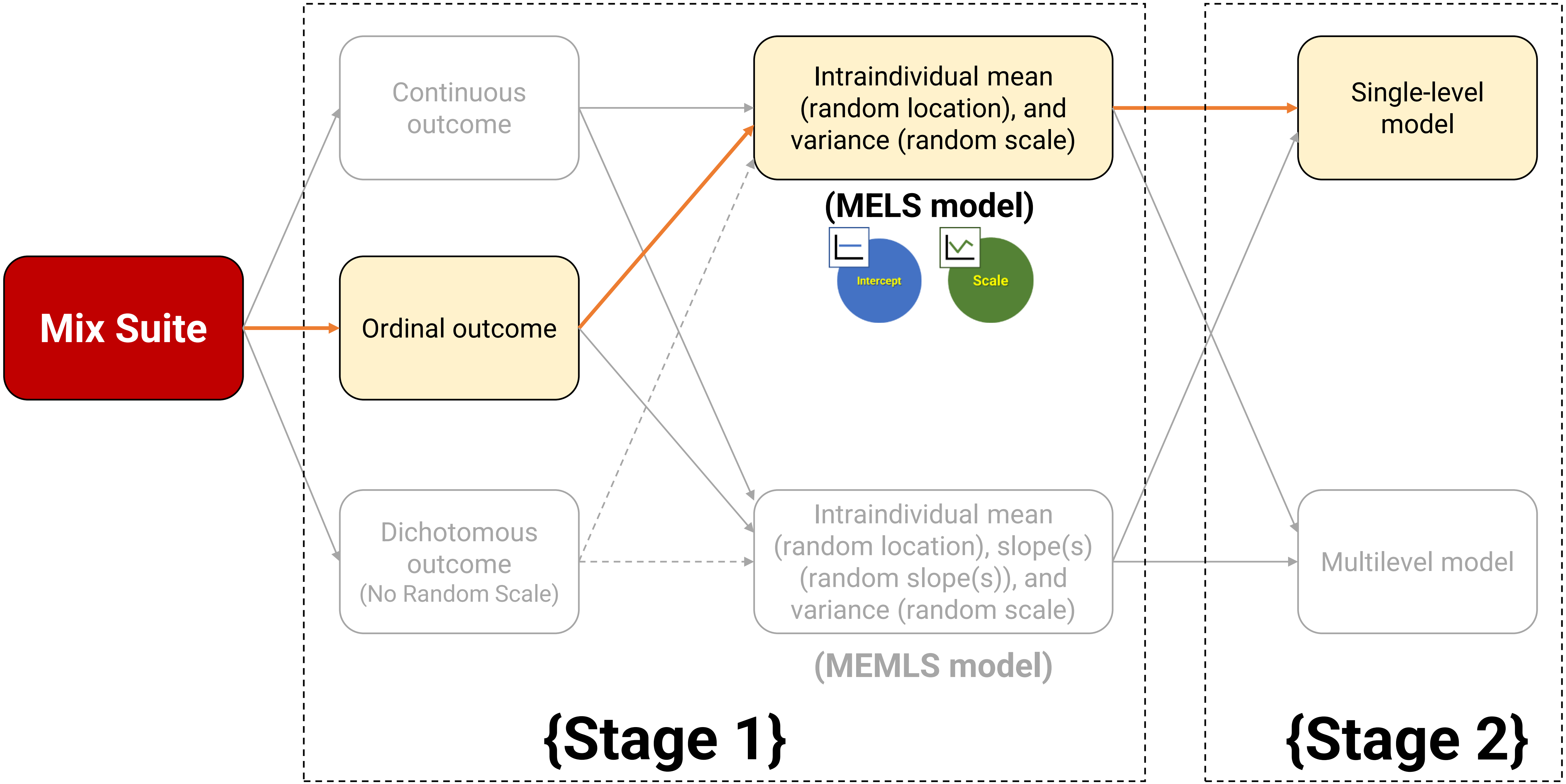
- (BSV model) Does the sample become more homogeneous in LGA on days with higher SQ?

- (WSV model) Does a subject's LGA become more consistent on days with higher SQ?

{Stage 2 Model}

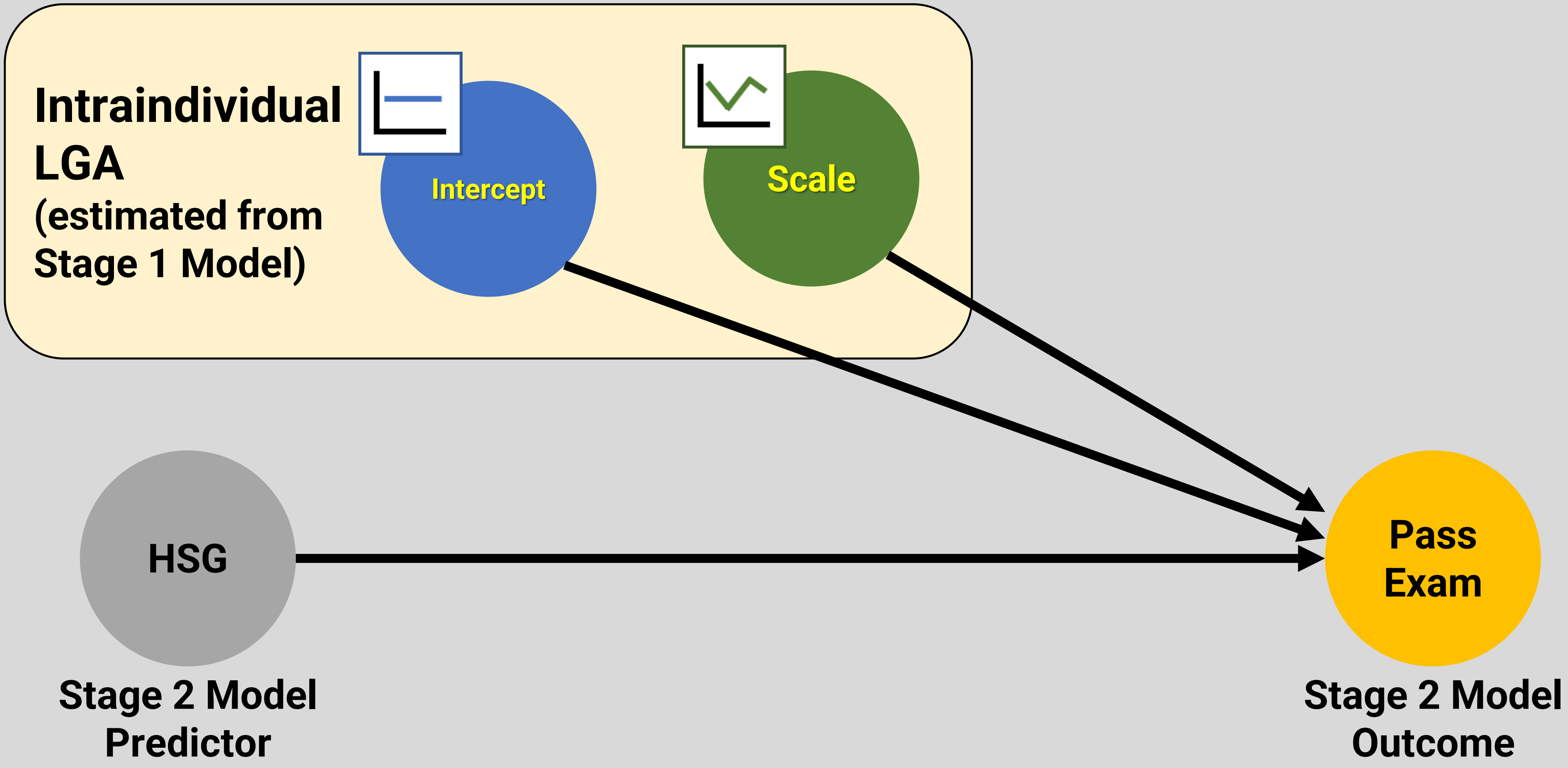
Does subject's mean level of- or intraindividual variance in LGA influence one's chance of passing exam? (Subject-level Model)

Q2: (Stage 2) Does subject's mean level of- or intraindividual variance in LGA influence one's chance of passing exam?

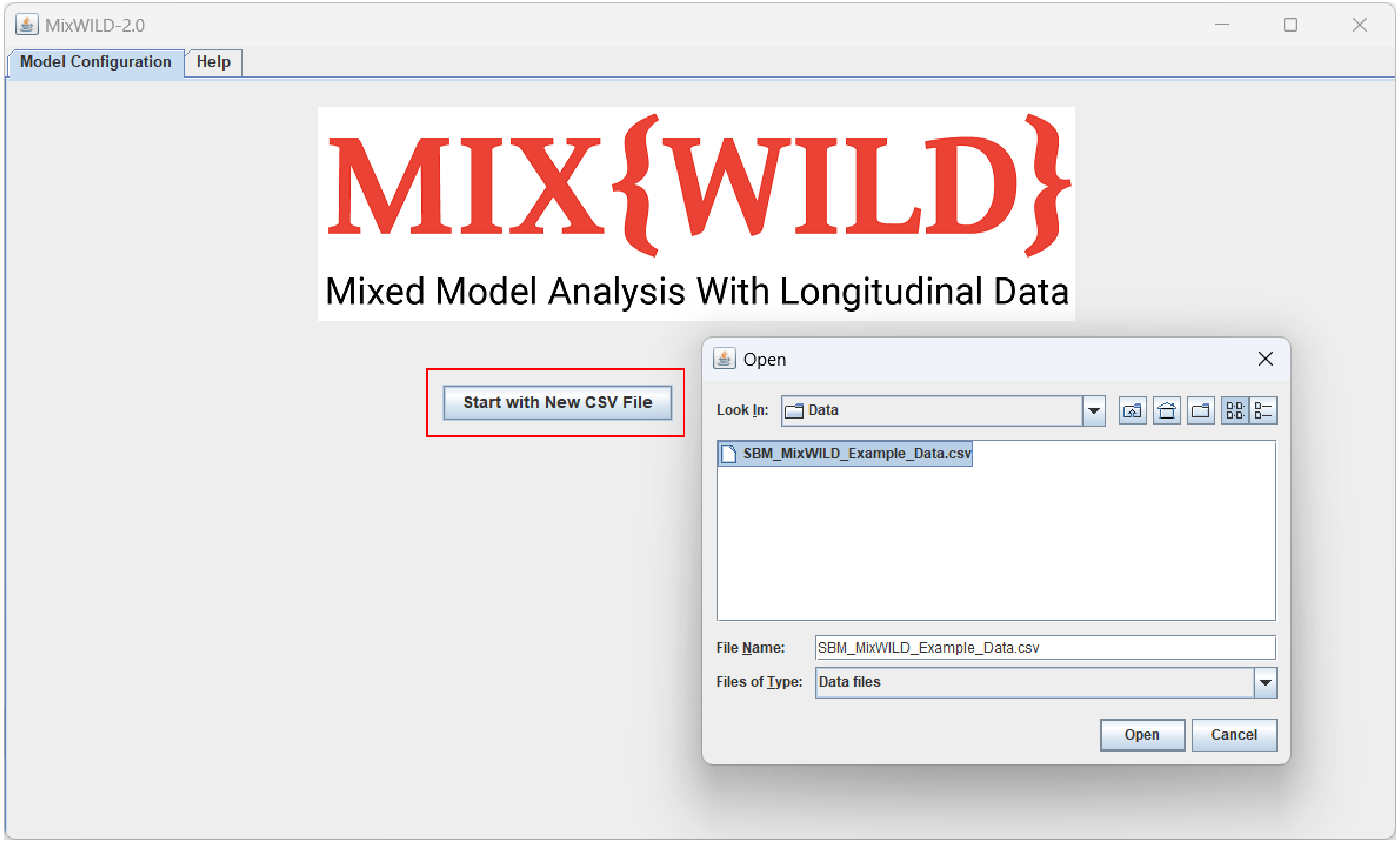


MixWILD (Stage 2 Model)

- Use mean level of- and variance in LGA to predict exam results (Single-level model)

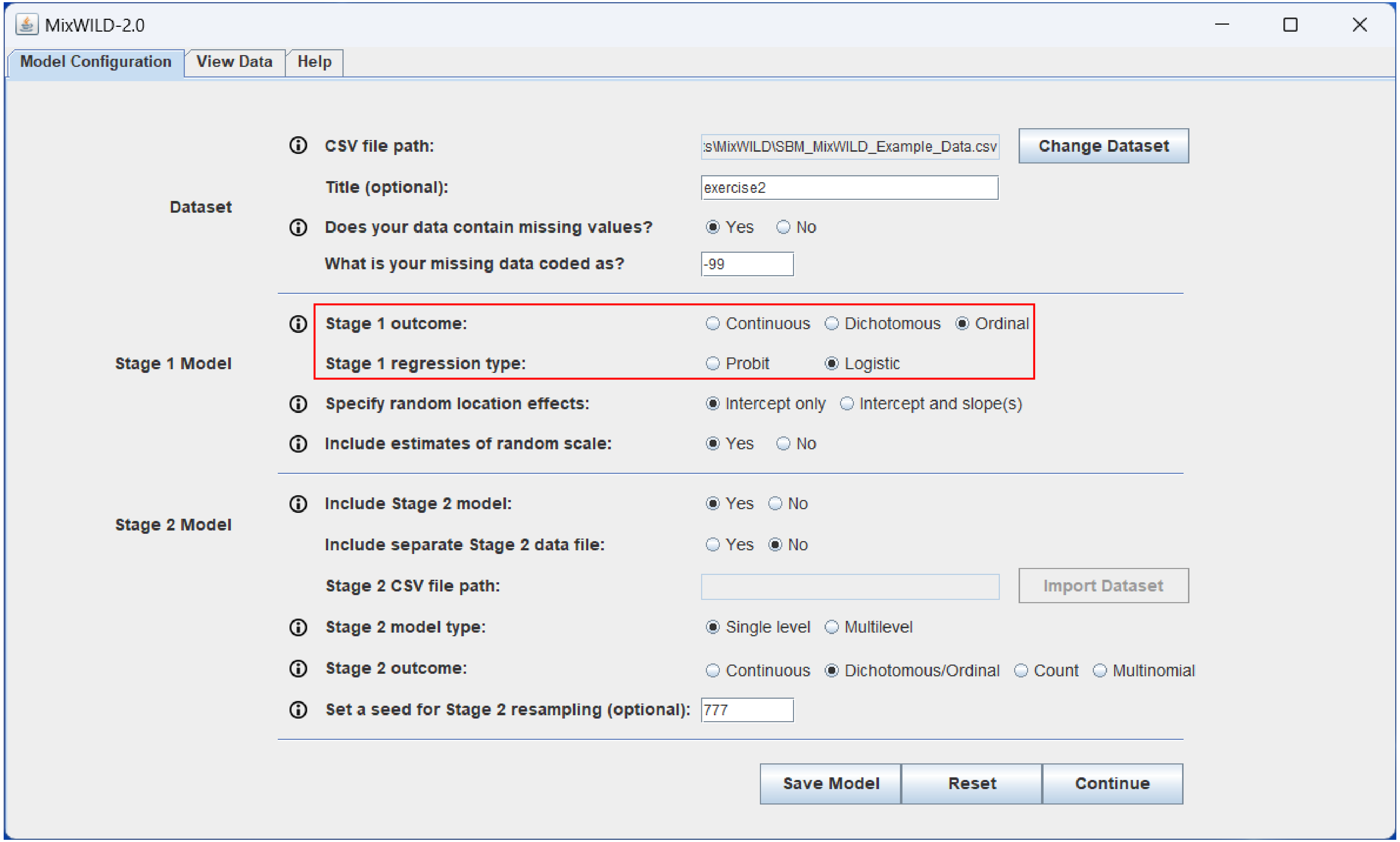


Research Question 2 (Q2)



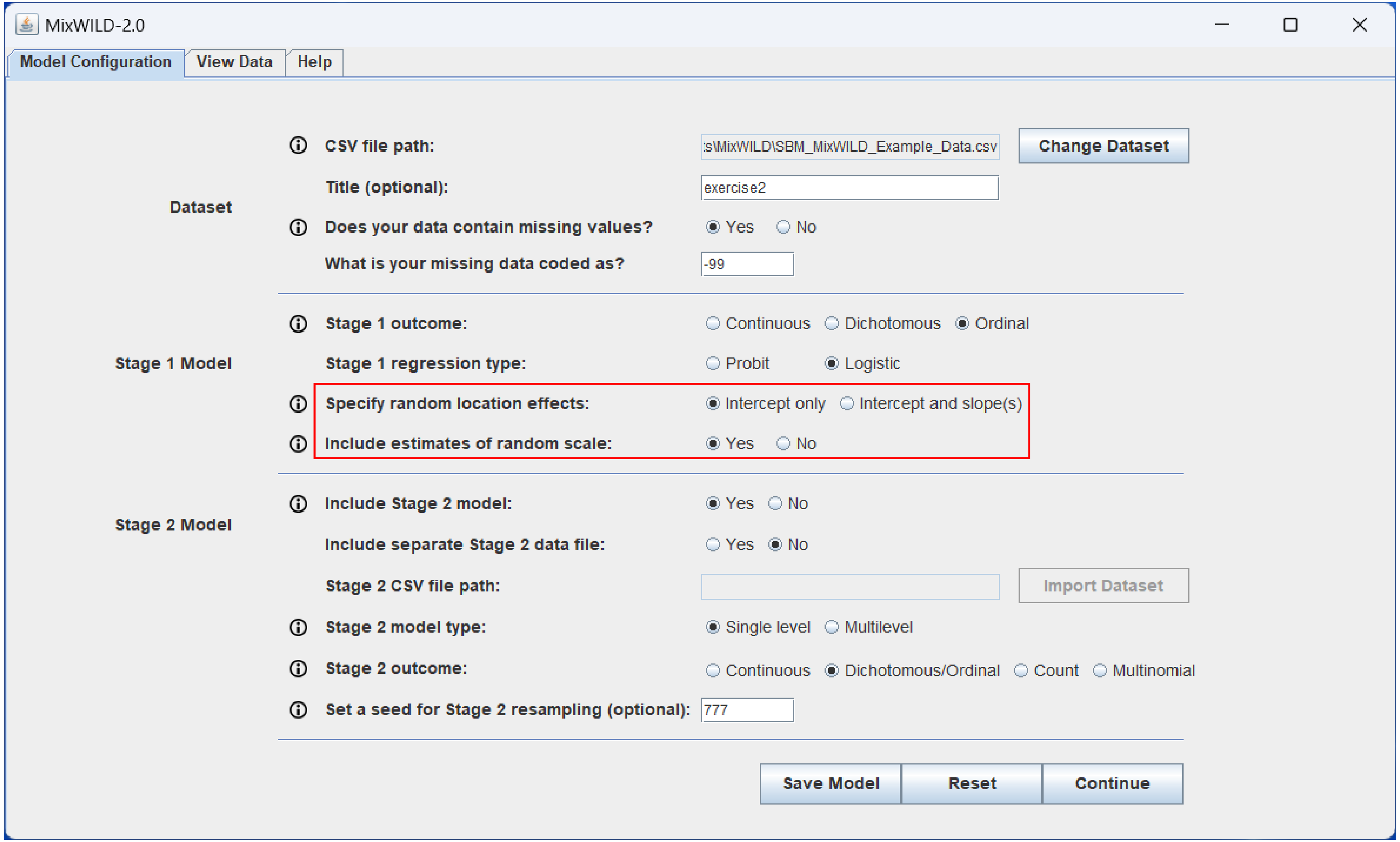
Start with "New CSV File" and locate the MixWILD example dataset

Q2: (Stage 1) Does sleep quality (SQ) influence one's learning goal achievement (LGA)?



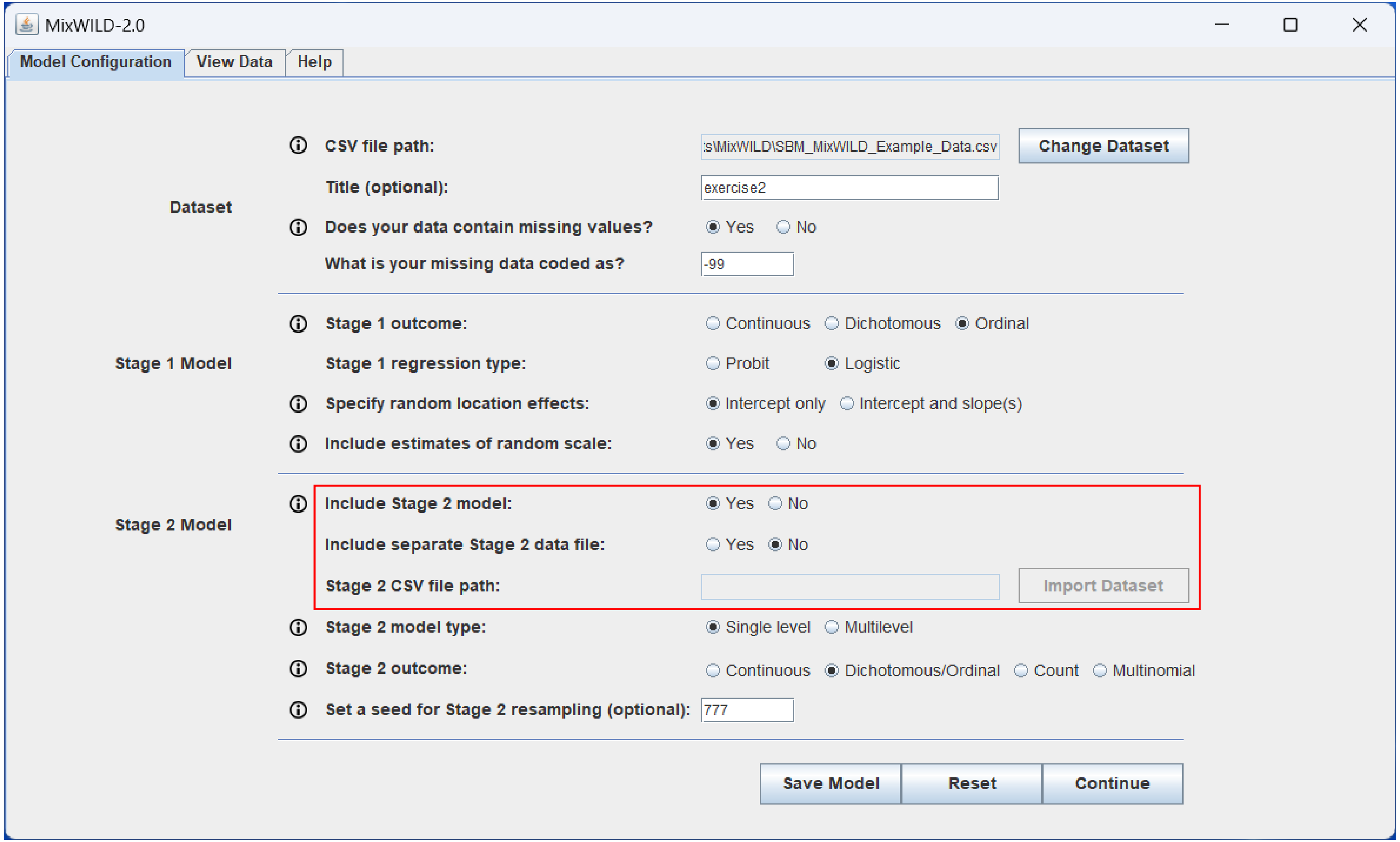
Select Stage 1 outcome "Ordinal" (Outcome = "Learning goal achievement")

Q2: (Stage 1) Does sleep quality (SQ) influence one's learning goal achievement (LGA)?



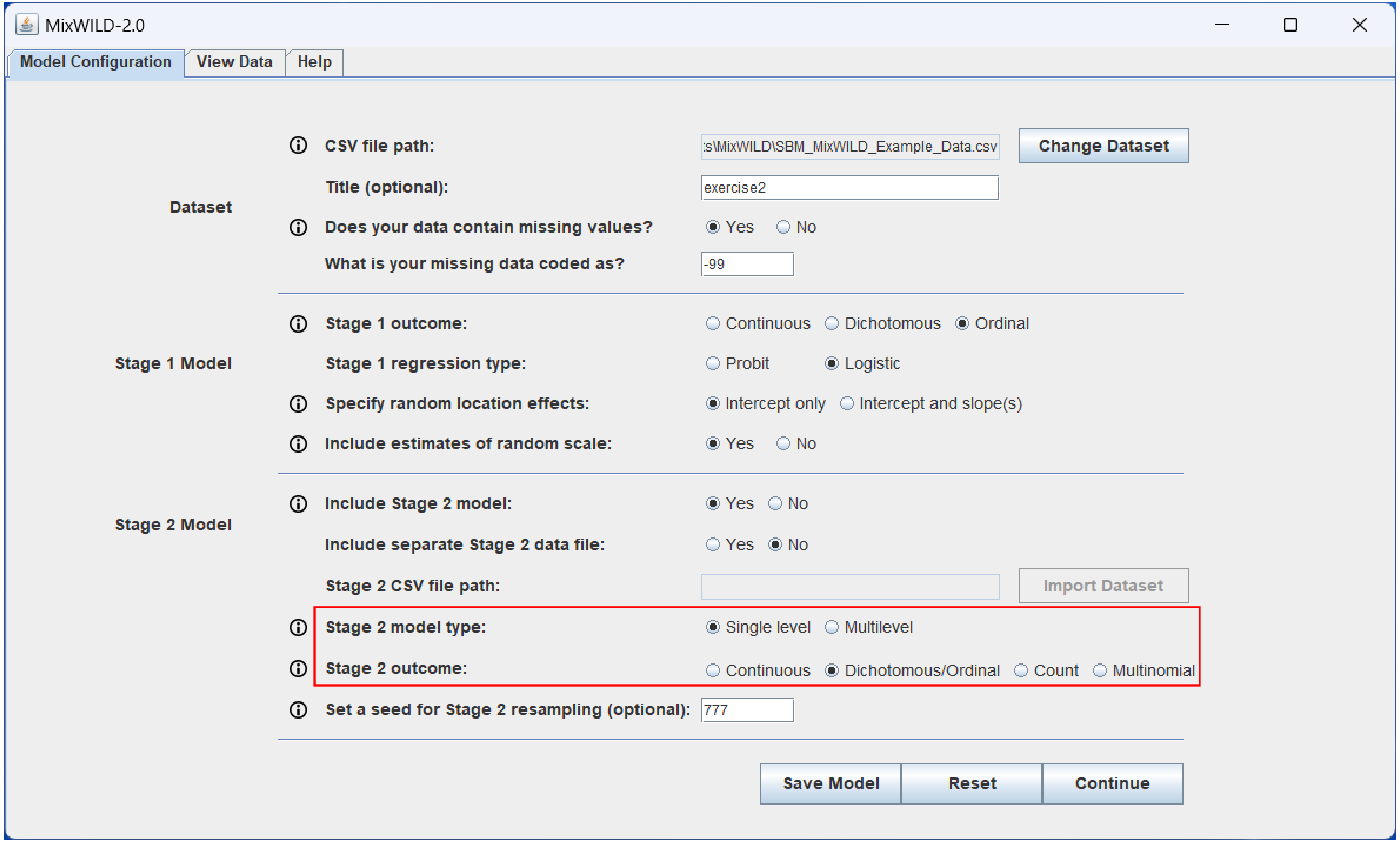
Specify random effects (Select "Intercept only" and include "Random scale")

Q2: (Stage 2) Does subject's mean level of- or intraindividual variance in LGA influence one's chance of passing exam?



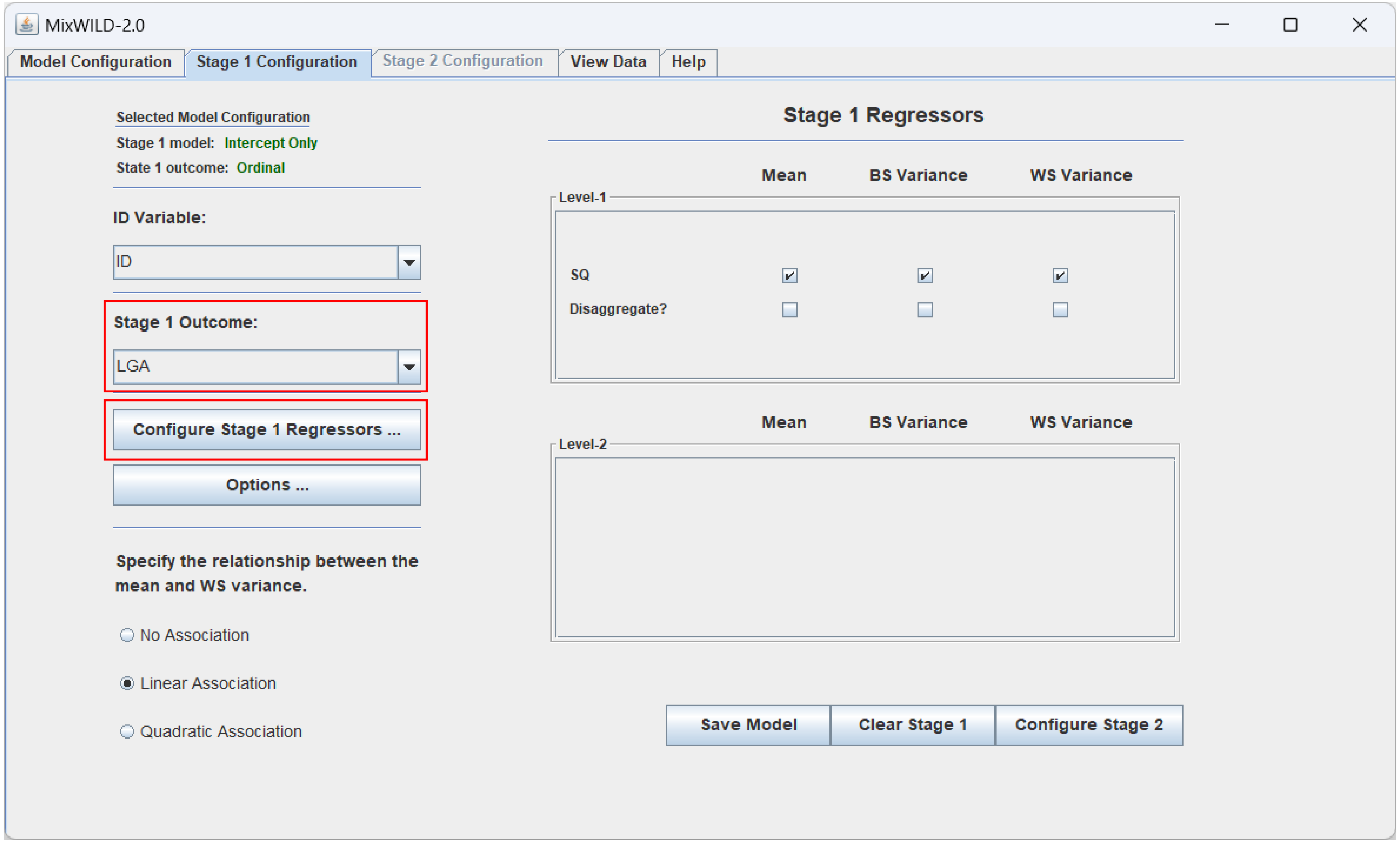
Select Stage 2 Model and locate the Stage 2 data in your folder

Q2: (Stage 2) Does subject's mean level of- or intraindividual variance in LGA influence one's chance of passing exam?



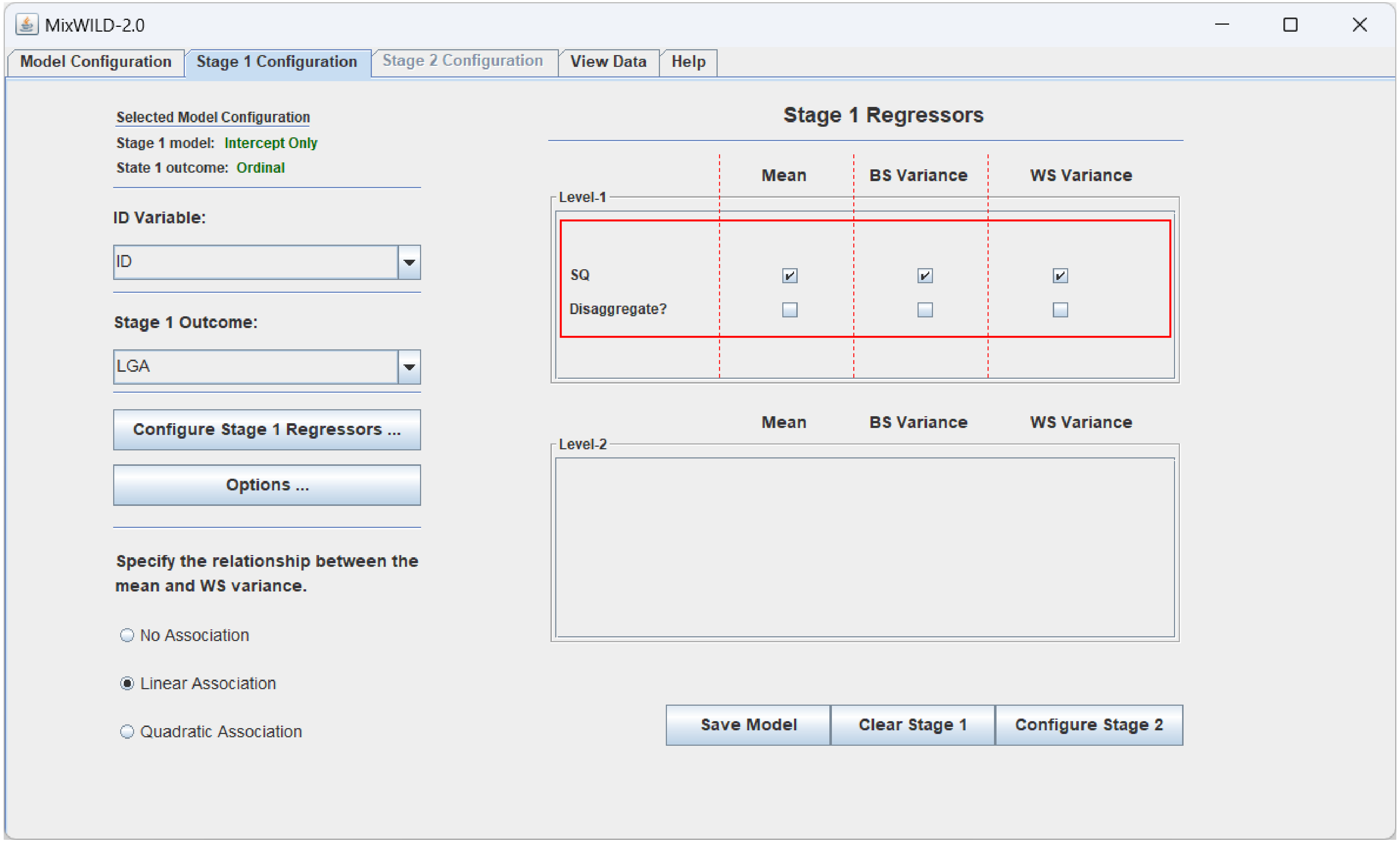
Specify Stage 2 model type ("Single level"); Outcome ("Exam" 1 = Pass; 0 = Fail)

Q2: (Stage 1) Does sleep quality (SQ) influence one's learning goal achievement (LGA)?



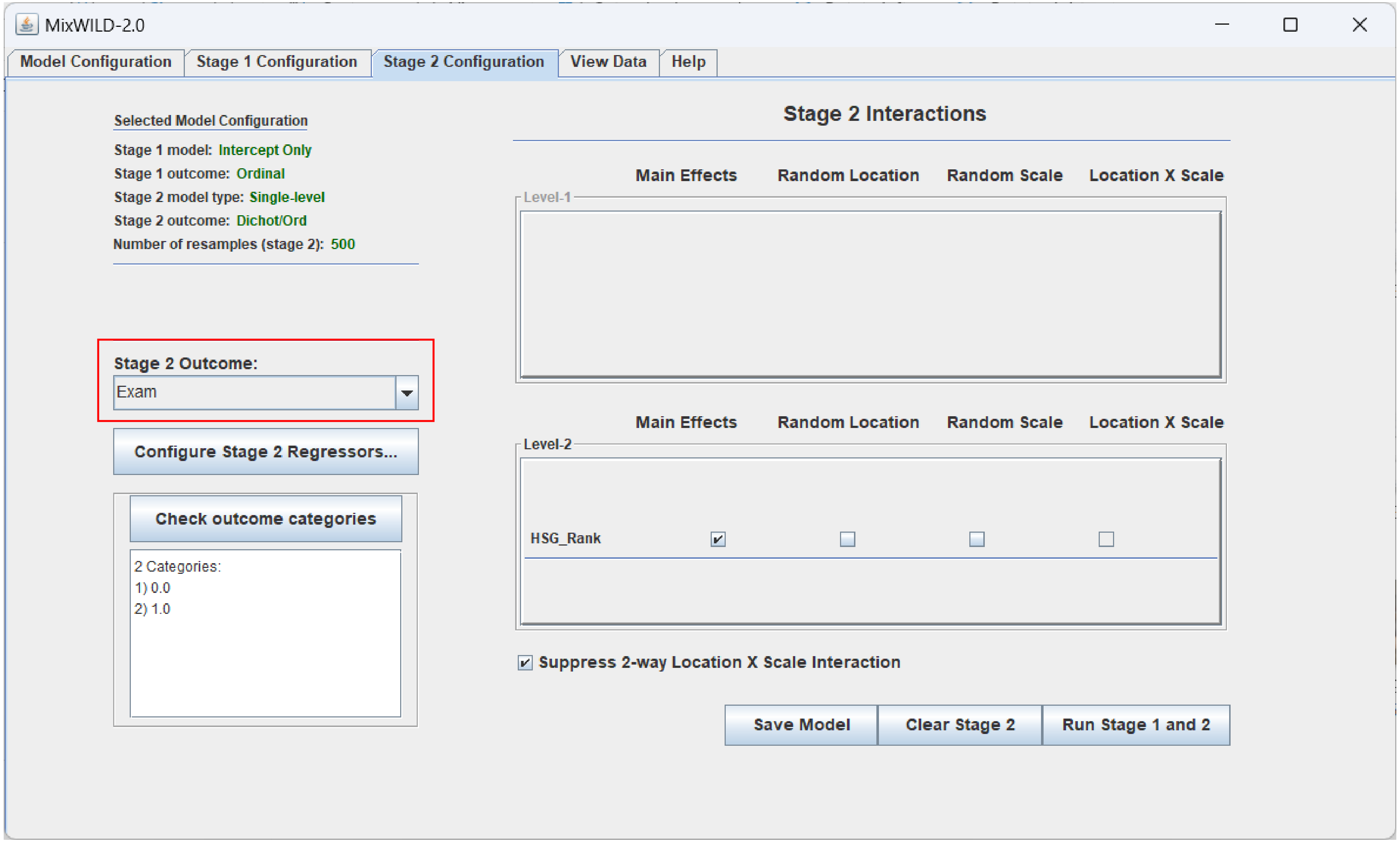
Select "LGA" as the Stage 1 outcome and "SQ" as a time-varying predictor

Q2: (Stage 1) Does sleep quality (SQ) influence one's learning goal achievement (LGA)?



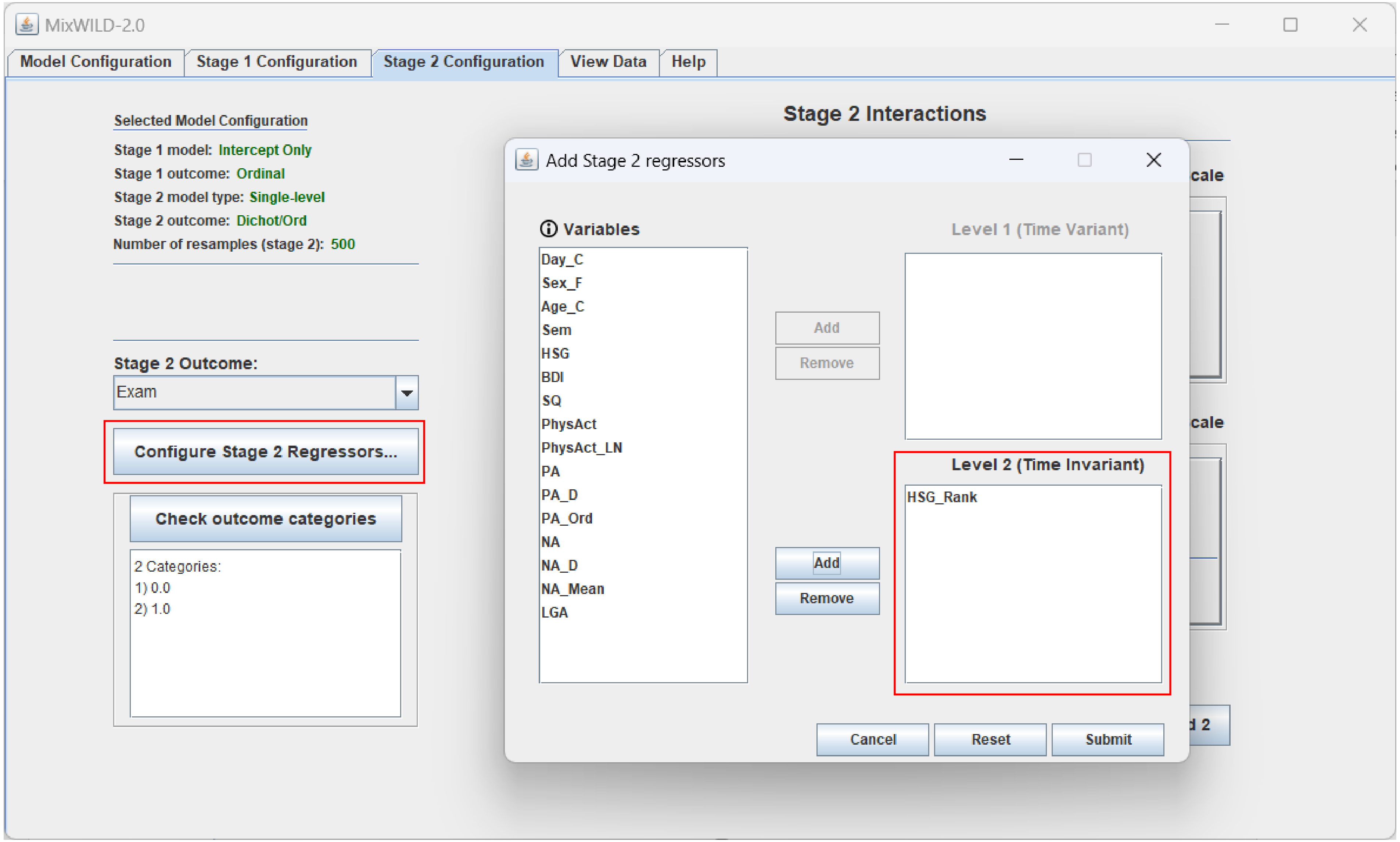
Specify the regressors in Stage 1 Models and click on "Configure Stage 2"

Q2: (Stage 2) Does subject's mean level of- or intraindividual variance in LGA influence one's chance of passing exam?



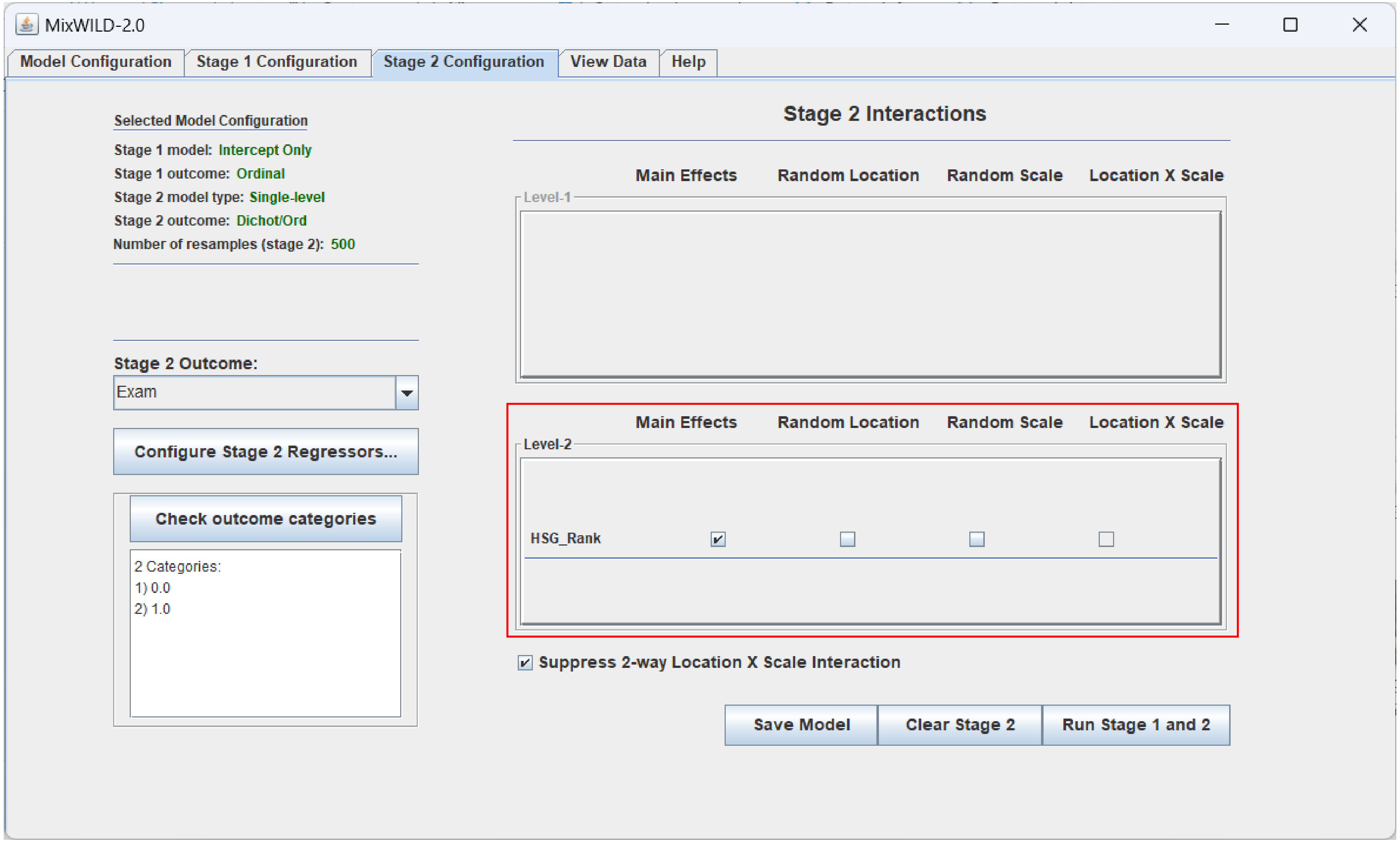
Select "Exam" as Stage 2 Outcome; Check the outcome

Q2: (Stage 2) Does subject's mean level of- or intraindividual variance in LGA influence one's chance of passing exam?



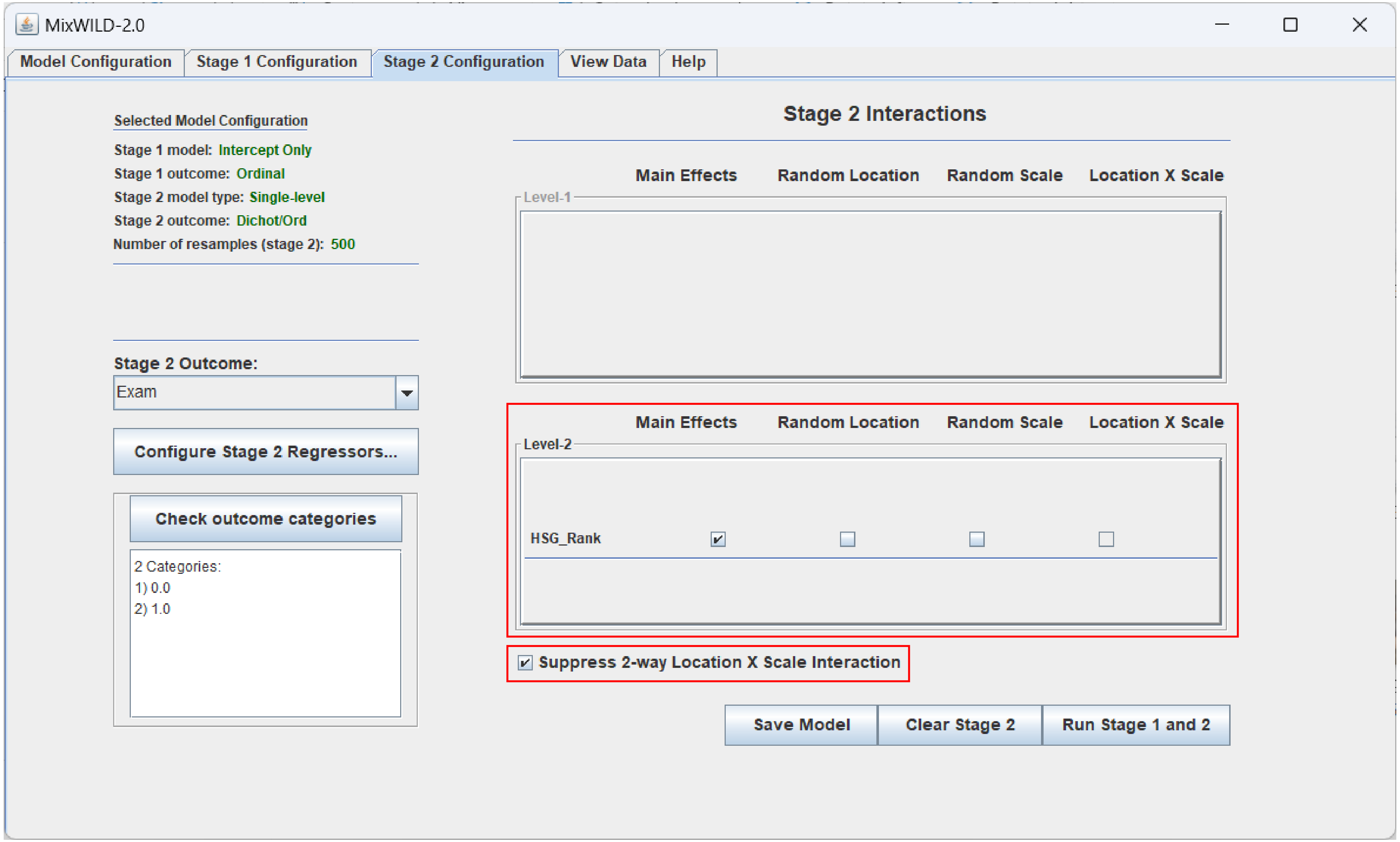
Click on "Configure Stage 2 Regressors to select "HSG_Rank" as covariate"

Q2: (Stage 2) Does subject's mean level of- or intraindividual variance in LGA influence one's chance of passing exam?



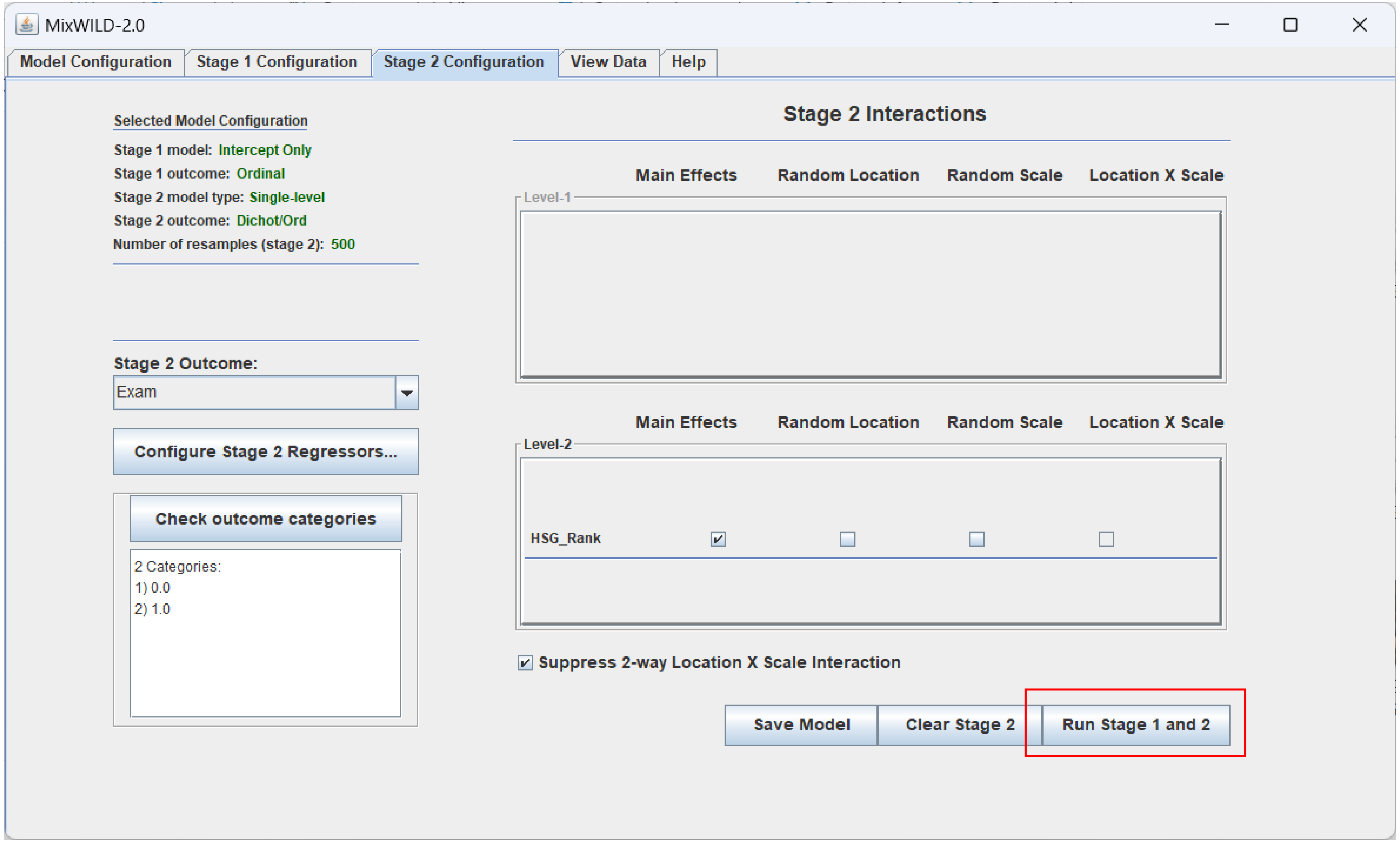
Specify the regressor in the single-level model (Check "Main Effects")

Q2: (Stage 2) Does subject's mean level of- or intraindividual variance in LGA influence one's chance of passing exam?



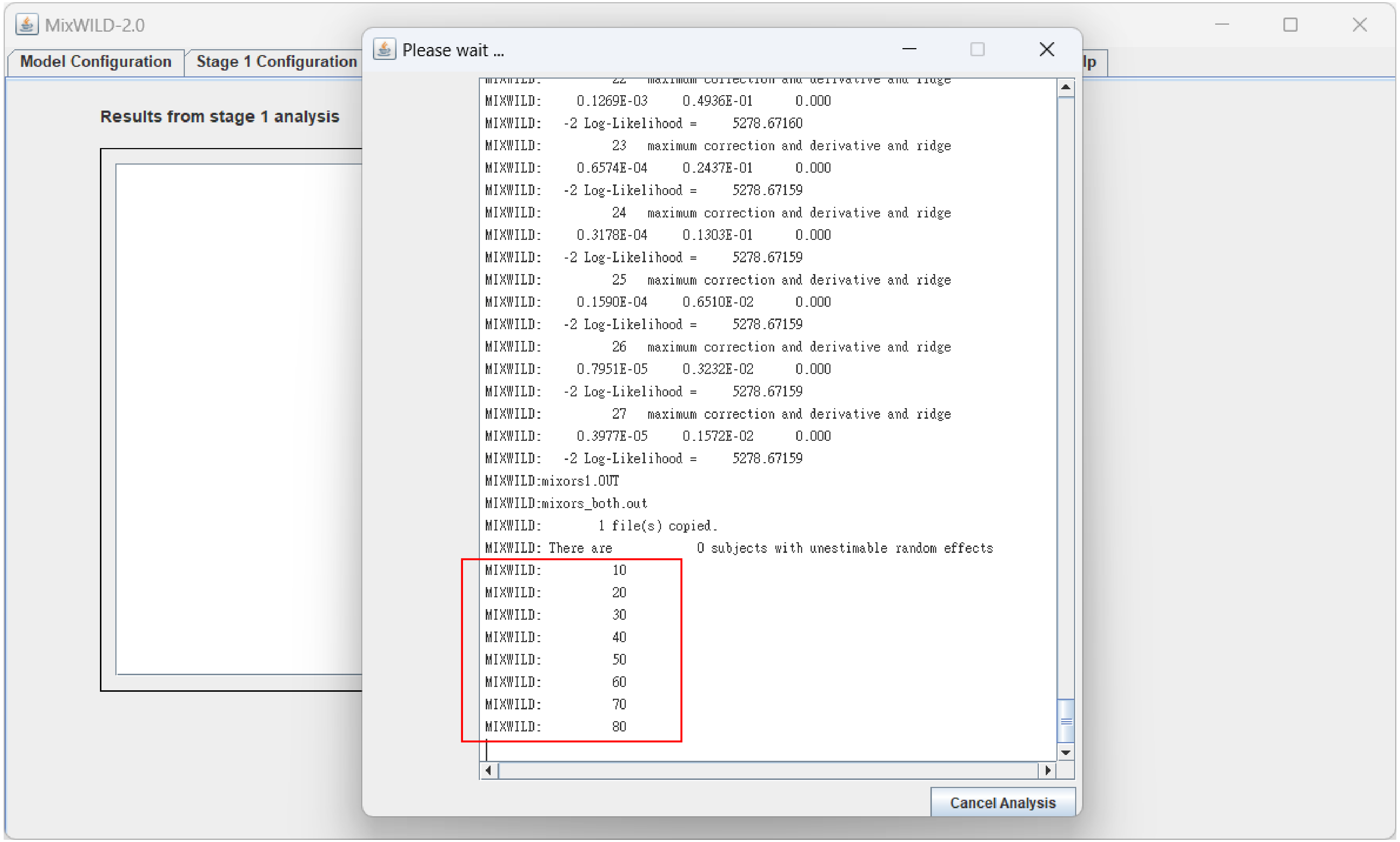
Please note random location and scale estimates are **default** regressors

Q2: (Stage 2) Does subject's mean level of- or intraindividual variance in LGA influence one's chance of passing exam?



Run Stage 1 and 2

Q2: (Stage 2) Does subject's mean level of- or intraindividual variance in LGA influence one's chance of passing exam?



After completing Stage 1, it performs 500 logistic regressions

Q2: (Stage 1) Does sleep quality (SQ) influence one's learning goal achievement (LGA)?

Variable	Estimate	AsymStdError	z-value	p-value
BETA (regression coefficients)				
SQ	0.22590	0.05959	3.79082	0.00015
ALPHA (BS variance parameters: log-linear model)				
Intercept	0.25980	0.42487	0.61147	0.54089
SQ	0.00193	0.10377	0.01858	0.98518
TAU (WS variance parameters: log-linear model)				
SQ	-0.03627	0.03271	-1.10881	0.26751
Thresholds (for identification)				
1	-2.11209	0.30704	-6.87893	0.00000
2	-0.60166	0.22607	-2.66143	0.00778
3	1.11348	0.25694	4.33365	0.00001
4	3.41990	0.44740	7.64389	0.00000
Random location effects on WS variance (log-linear model)				
Linear	0.10151	0.05563	1.82469	0.06805
Random scale standard deviation				
Std Dev	0.31285	0.03770	8.29837	0.00000

Mean model (BETA): the slope of sleep quality (SQ) is positive and significant (beta = 0.22590; $p < 0.001$). On average, a subject has a higher learning goal achievement (LGA) on days with higher SQ.

Q2: (Stage 2) Does subject's mean level of- or intraindividual variance in LGA influence one's chance of passing exam?

```
 Number of replications =         500

-------------
Final Results
-------------
 Average Log Likelihood         =      -42.094 (sd=       0.762)
 Akaike's Information Criterion =      -46.094
 Schwarz's Bayesian Criterion   =      -50.647

 ==> multiplied by -2
 Log Likelihood                 =       84.188
 Akaike's Information Criterion =       92.188
 Schwarz's Bayesian Criterion   =      101.295
```

Variable	Estimate	AsymStdError	z-value	p-value
Intercept	-2.33488	0.91741	-2.54509	0.01092
HSG_Rank	0.17185	0.06764	2.54081	0.01106
Locat_1	0.65342	0.31175	2.09596	0.03609
Scale_1	0.01781	0.31544	0.05646	0.95498

Subject's high school grades (HSG_Rank) is positive and significant. For every one unit increase in student's HSG_Rank, the odds of being more likely to pass exam is multiplied 1.19 times (exp(0.17185) = 1.19).

Q2: (Stage 2) Does subject's mean level of- or intraindividual variance in LGA influence one's chance of passing exam?

```
 Number of replications =        500

-------------
Final Results
-------------
 Average Log Likelihood        =      -42.094 (sd=       0.762)
 Akaike's Information Criterion =     -46.094
 Schwarz's Bayesian Criterion   =     -50.647

 ==> multiplied by -2
 Log Likelihood                =       84.188
 Akaike's Information Criterion =      92.188
 Schwarz's Bayesian Criterion   =     101.295
```

Variable	Estimate	AsymStdError	z-value	p-value
Intercept	-2.33488	0.91741	-2.54509	0.01092
HSG Rank	0.17185	0.06764	2.54081	0.01106
Locat_1	0.65342	0.31175	2.09596	0.03609
Scale_1	0.01781	0.31544	0.05646	0.95498

Subject-level random location effect: the random location (subject's mean level) of learning goal achievement (LGA) is positive and significant. For every one unit increase in student's LGA, the odds of being more likely to pass exam is multiplied 1.92 times (exp(0.65342) = 1.92).

Q2: (Stage 2) Does subject's mean level of- or intraindividual variance in LGA influence one's chance of passing exam?

```
 Number of replications =         500

-------------
Final Results
-------------
 Average Log Likelihood         =       -42.094 (sd=       0.762)
 Akaike's Information Criterion =       -46.094
 Schwarz's Bayesian Criterion   =       -50.647

 ==> multiplied by -2
 Log Likelihood                 =        84.188
 Akaike's Information Criterion =        92.188
 Schwarz's Bayesian Criterion   =       101.295


Variable               Estimate    AsymStdError      z-value        p-value
----------------    ------------   ------------   ------------   ------------
Intercept              -2.33488         0.91741       -2.54509        0.01092
HSG_Rank                0.17185         0.06764        2.54081        0.01106
Locat_1                 0.65342         0.31175        2.09596        0.03609
Scale_1                 0.01781         0.31544        0.05646        0.95498
```

Subject-level random scale effect: the random scale (intraindividual variance) of learning goal achievement (LGA) is not significantly associated with the odds of being more likely to pass exam.

Research Question 2b (Q2b) *Interaction Effects*

{Stage 1 Model}

Does sleep quality (SQ) influence one's learning goal achievement (LGA)?

- (Mean model) Does a subject have a higher LGA on days with higher SQ?

- (BSV model) Does the sample become more homogeneous in LGA on days with higher SQ?

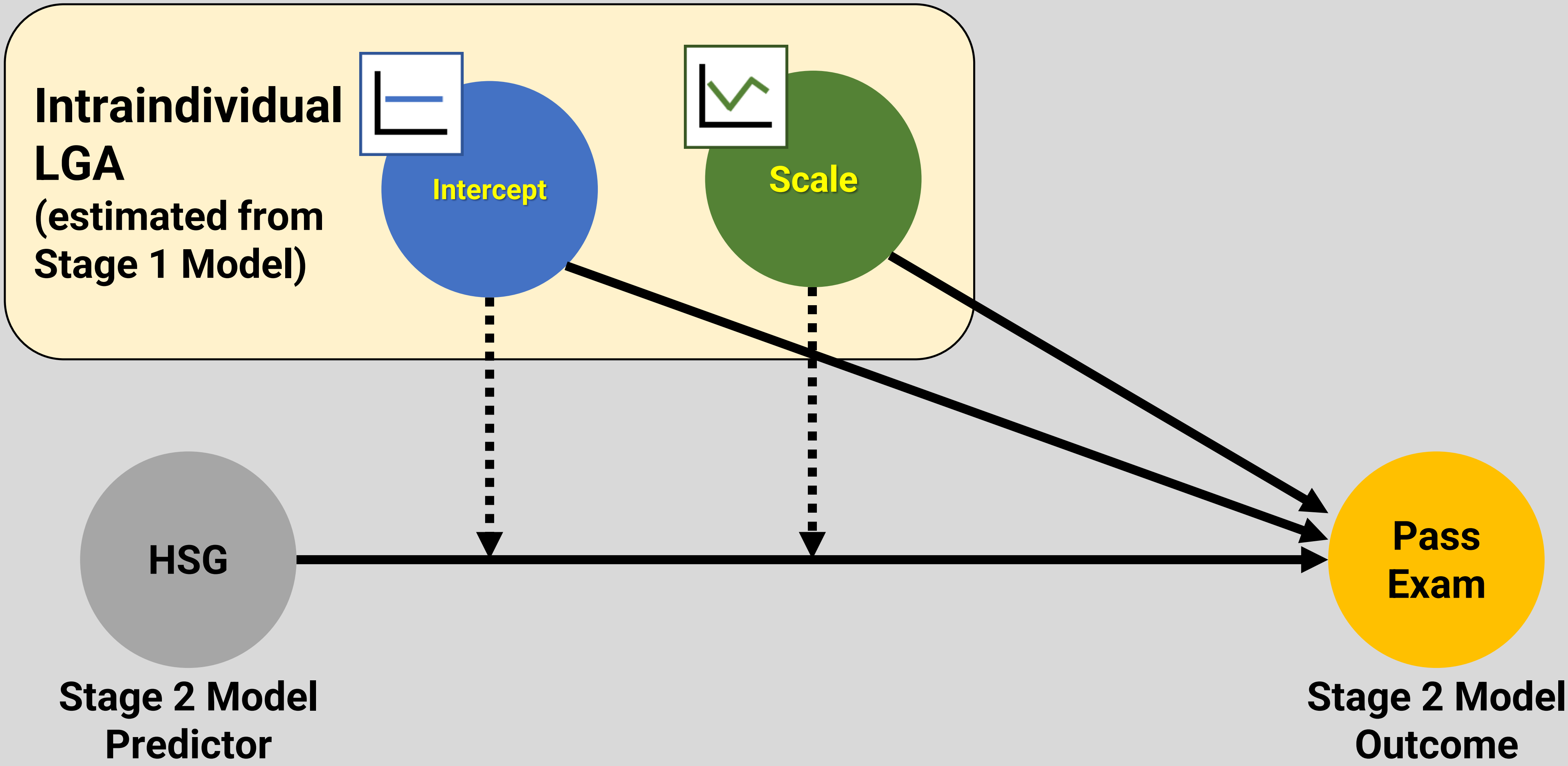
- (WSV model) Does a subject's LGA become more consistent on days with higher SQ?

{Stage 2 Model}

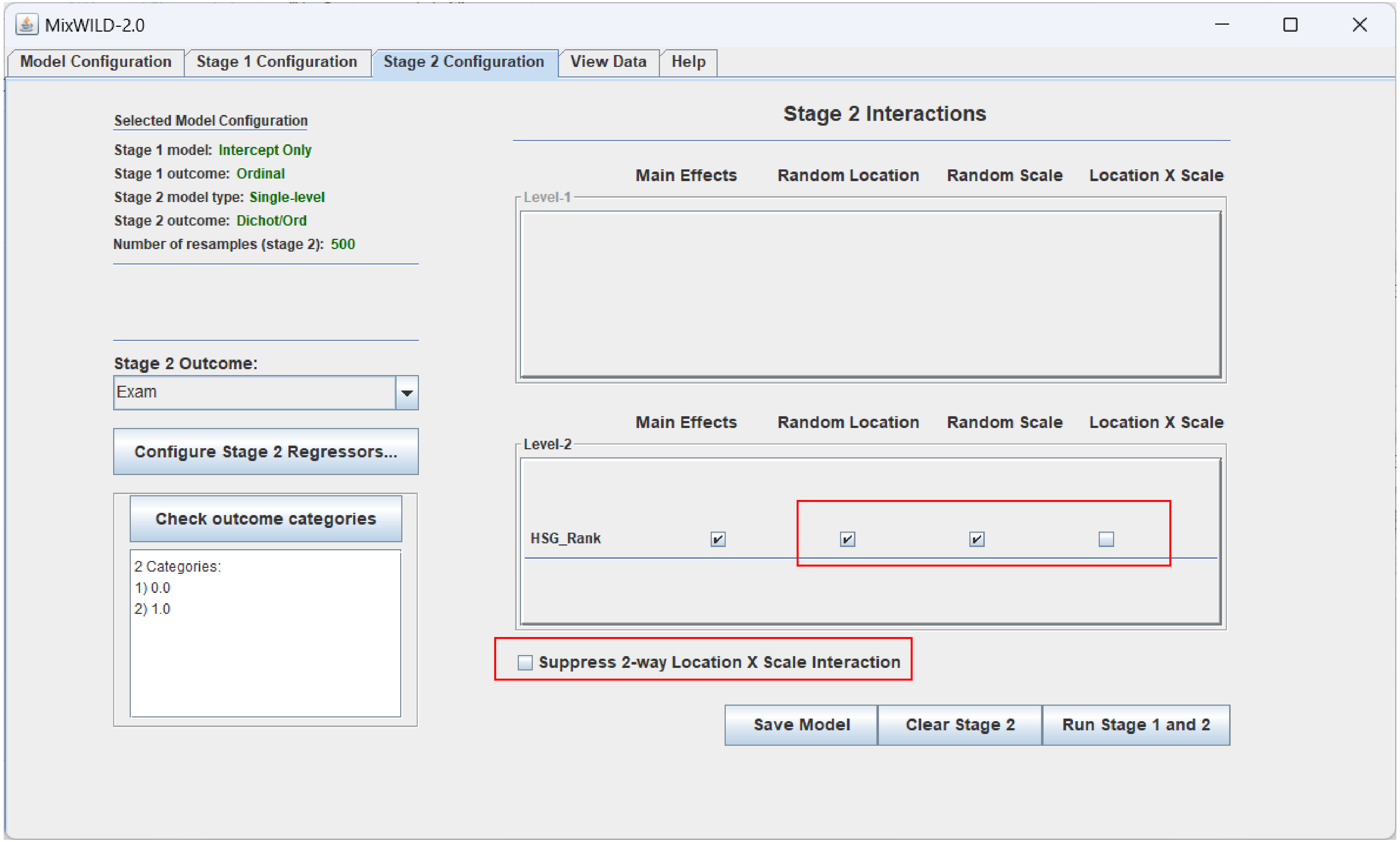
Does subject's mean level of-, or intraindividual variance in LGA, or **interaction effects** influence one's chance of passing exam? (Subject-level Model)

MixWILD (Stage 2 Model)

- Use mean level of-, variance in LGA, or the interaction effects to predict exam results



Q2b: (Stage 2) Does subject's mean level of- or intraindividual variance in LGA, or interaction effects influence one's chance of passing exam?



Try interaction effects and uncheck "Suppress 2-way Location x Scale"

Q2b: (Stage 2) Does subject's mean level of- or intraindividual variance in LGA, or interaction effects influence one's chance of passing exam?

```
 Number of replications =          500

-------------
Final Results
-------------
 Average Log Likelihood          =      -41.213 (sd=       1.042)
 Akaike's Information Criterion =      -48.213
 Schwarz's Bayesian Criterion    =      -56.181

 ==> multiplied by -2
 Log Likelihood                  =       82.425
 Akaike's Information Criterion =       96.425
 Schwarz's Bayesian Criterion    =      112.362
```

Variable	Estimate	AsymStdError	z-value	p-value
Intercept	-2.49042	1.00474	-2.47867	0.01319
HSG_Rank	0.18321	0.07466	2.45385	0.01413
Locat_1	0.17765	1.11884	0.15878	0.87384
Locat_1*HSG_Rank	0.04033	0.08421	0.47885	0.63204
Scale_1	-0.16927	1.36956	-0.12359	0.90164
Scale_1*HSG_Rank	0.01372	0.10099	0.13582	0.89197
Locat_1*Scale	0.21538	0.35947	0.59917	0.54906

Research Question 2c (Q2c) *Random Slope*

{Stage 1 Model}

Does sleep quality (SQ) influence one's learning goal achievement (LGA)?

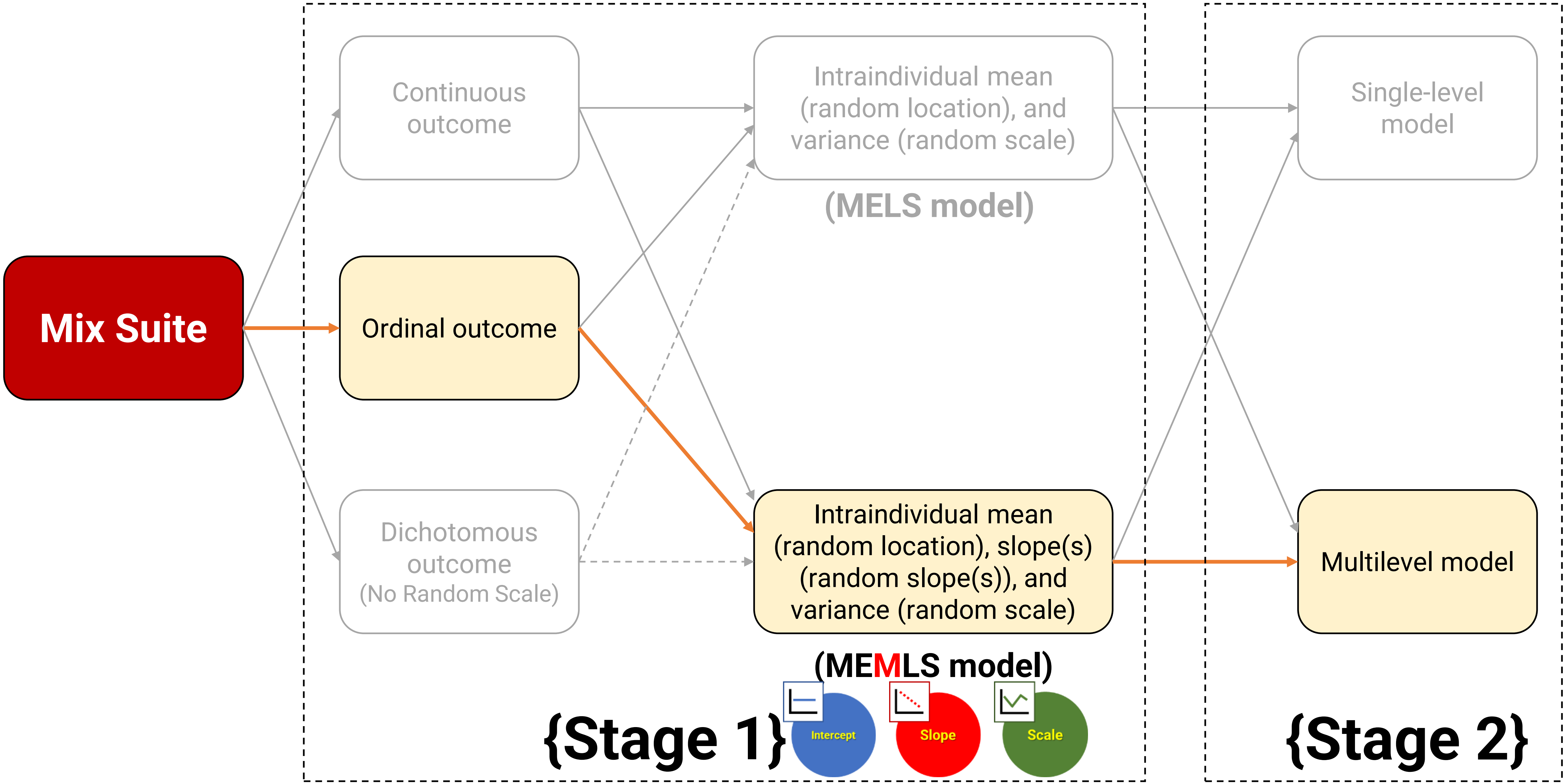
- (Mean model) Does a subject have a higher LGA on days with higher SQ? **Is the association between LGA and SQ different across subjects?**

- (WSV model) Does a subject's LGA become more consistent on days with higher SQ?

{Stage 2 Model}

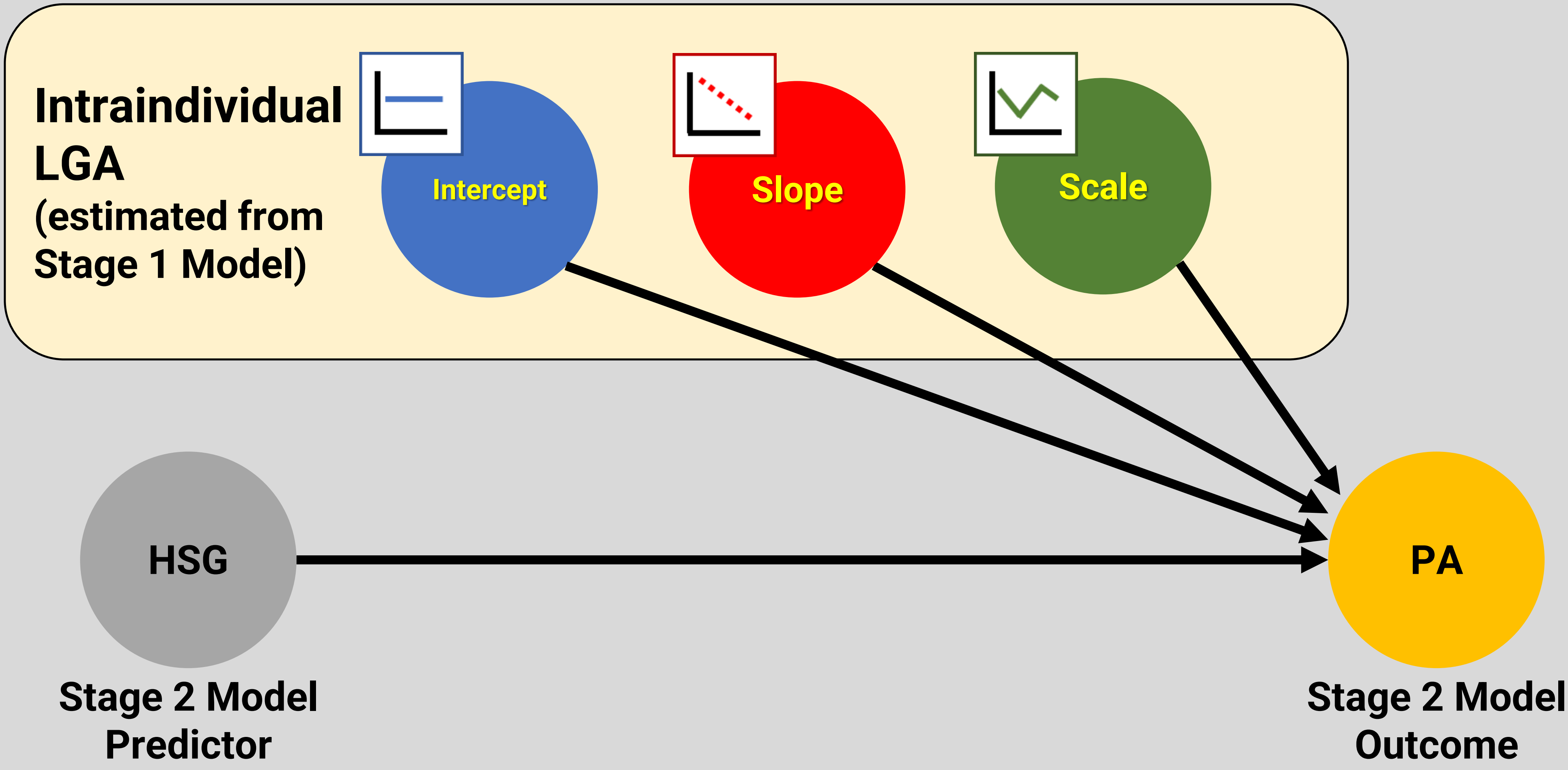
Does subject's mean level of-, or intraindividual variance in LGA, or **random-subject slope of SQ predicting LGA** influence one's daily positive affect? (Multilevel model, Level 1: Day; Level 2: Subject)

Q2c: (Stage 2) Does subject's mean level of-, or intraindividual variance in LGA, or random-subject slope of SQ predicting LGA influence one's daily positive affect?

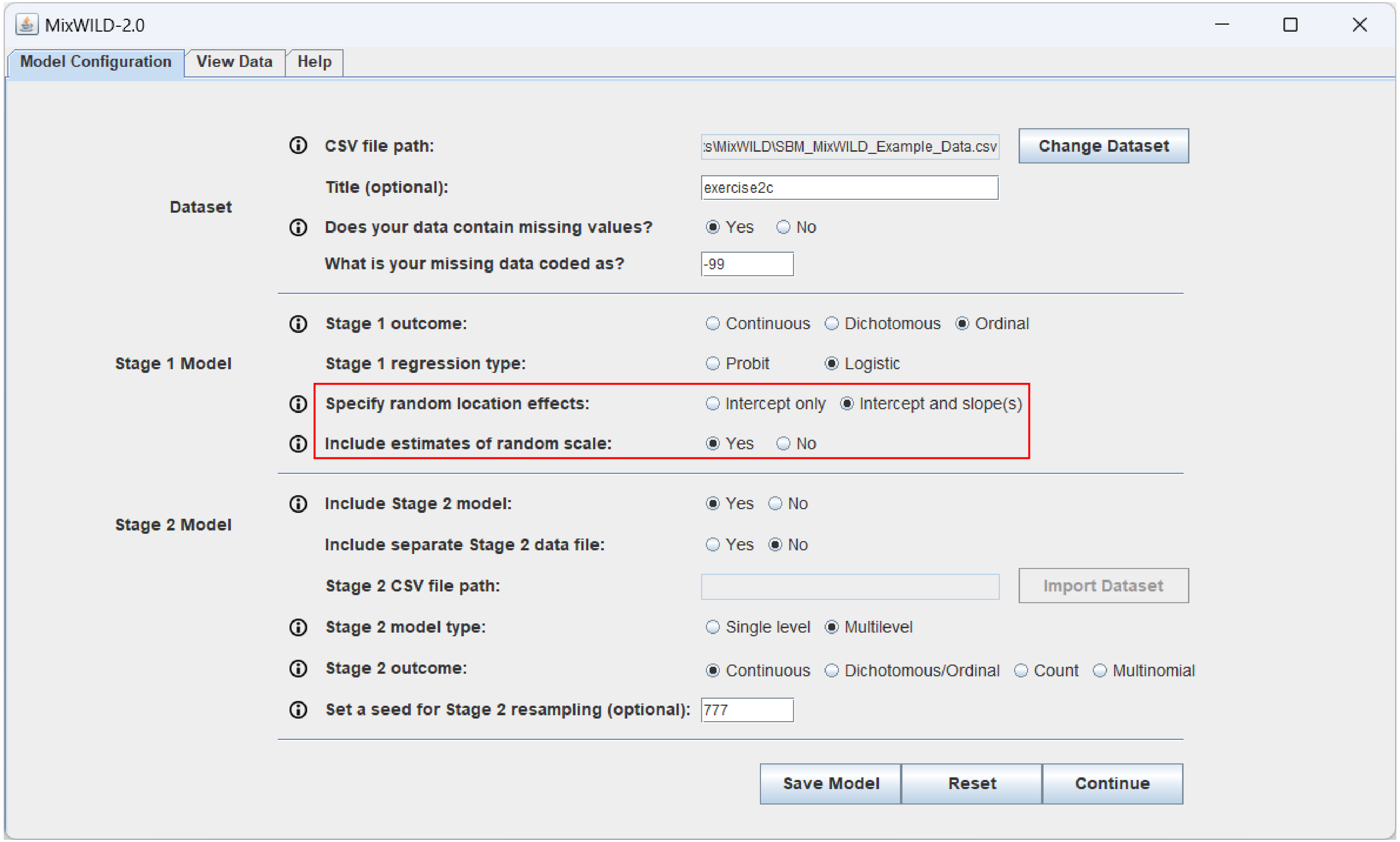


MixWILD (Stage 2 Model)

- Use mean level of-, slope of and variance in LGA to predict positive affect

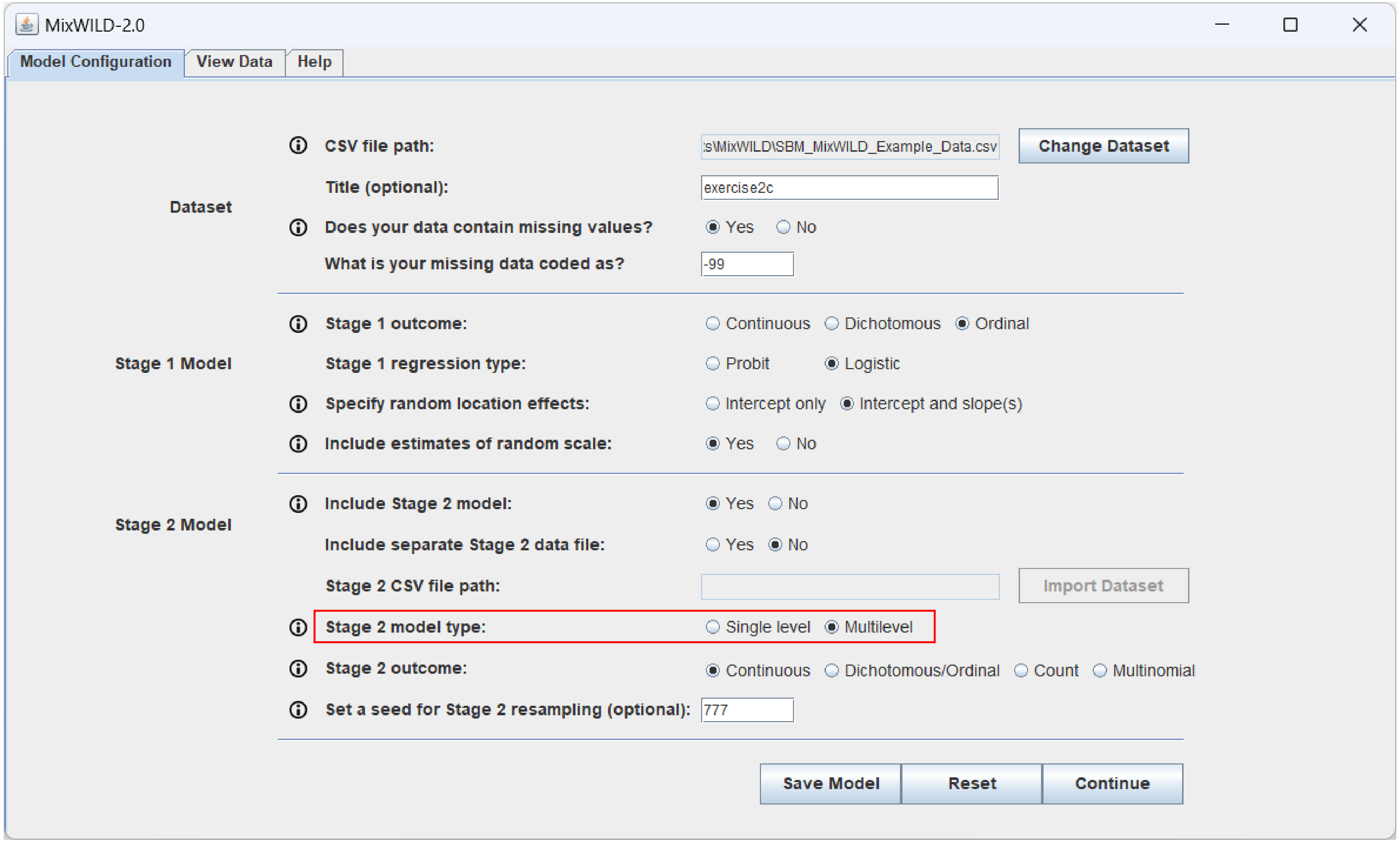


Q2c: (Stage 1) Does sleep quality (SQ) influence one's learning goal achievement (LGA)? Is the association between LGA and SQ different across subjects?



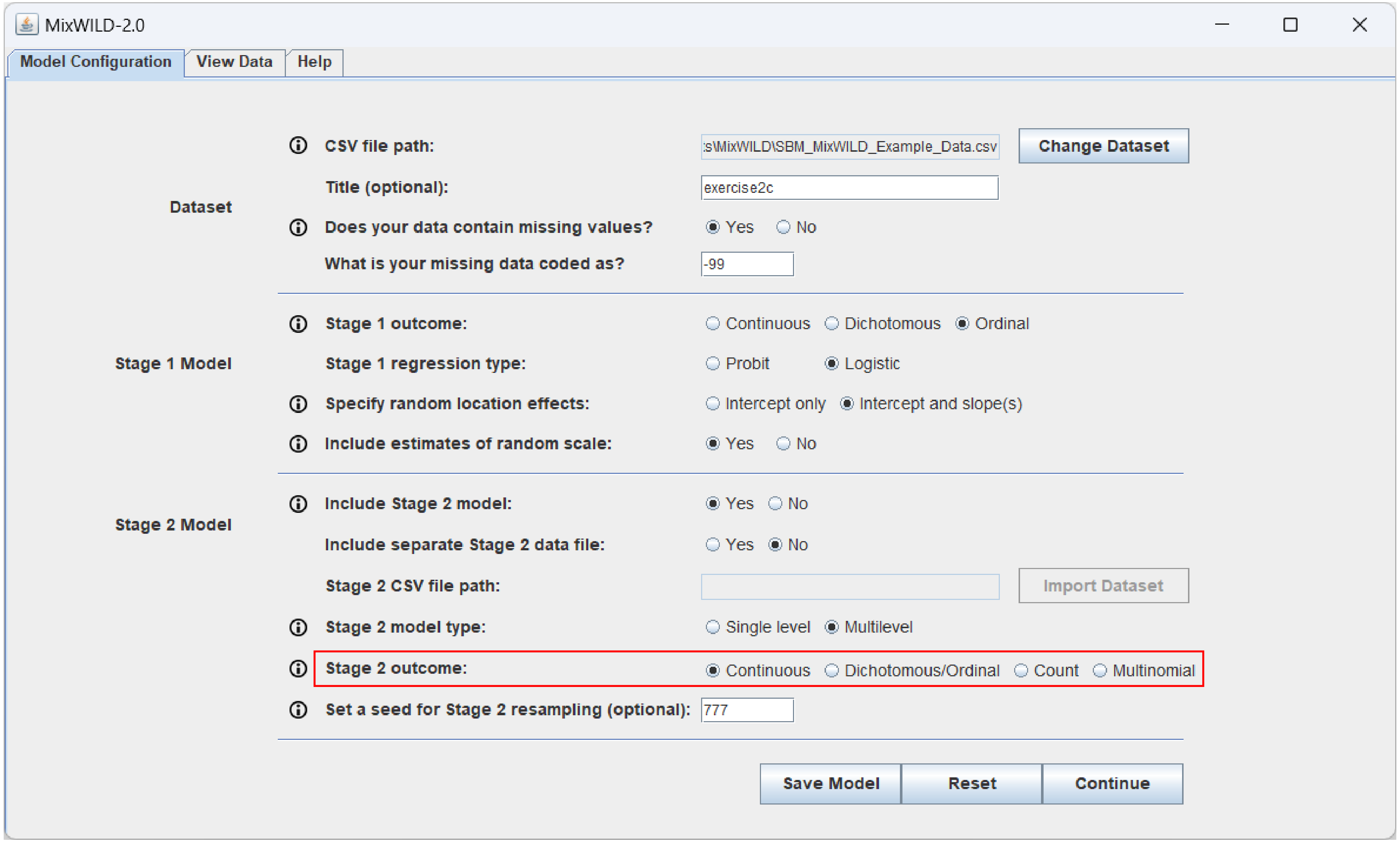
Specify random effects (Select "Intercept only and slope(s)")

Q2c: (Stage 2) Does subject's mean level of-, or intraindividual variance in LGA, or random-subject slope of SQ predicting LGA influence one's daily positive affect?



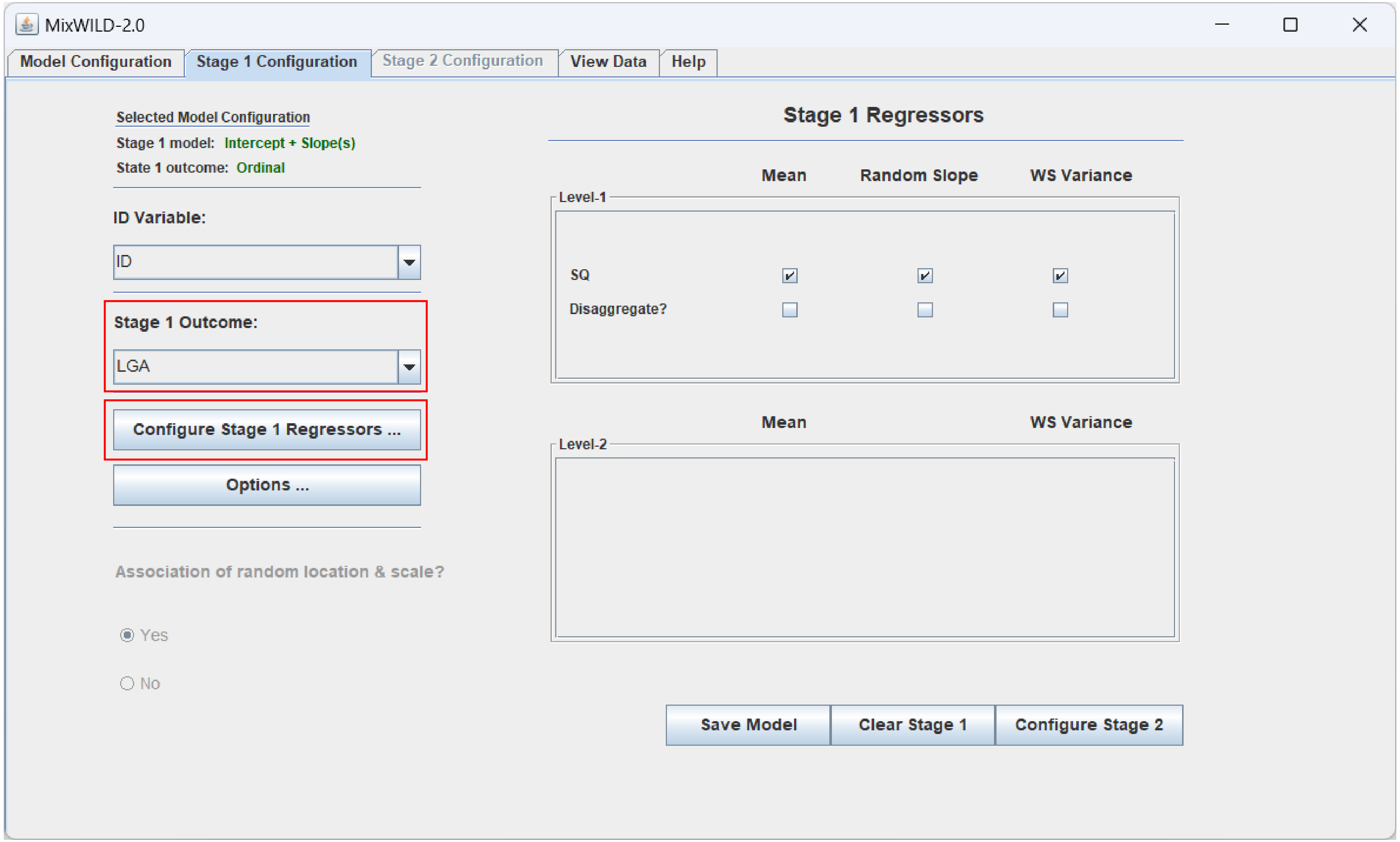
Select "Multilevel" since the new outcome, "positive affect", is at level 1

Q2c: (Stage 2) Does subject's mean level of-, or intraindividual variance in LGA, or random-subject slope of SQ predicting LGA influence one's daily positive affect?



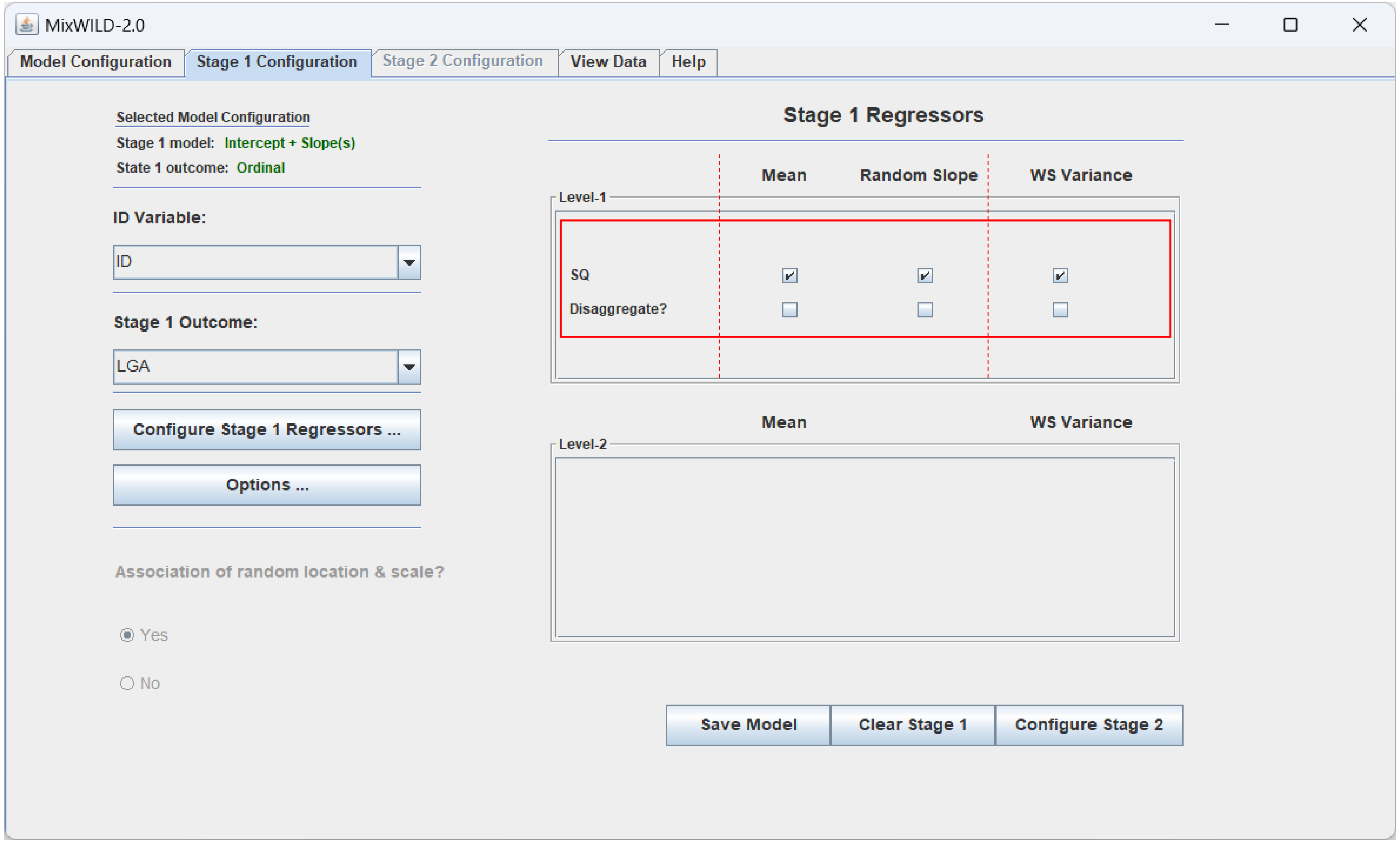
Select "Continuous" for the new Stage 2 outcome, "positive affect (PA)"

Q2c: (Stage 1) Does sleep quality (SQ) influence one's learning goal achievement (LGA)? Is the association between LGA and SQ different across subjects?



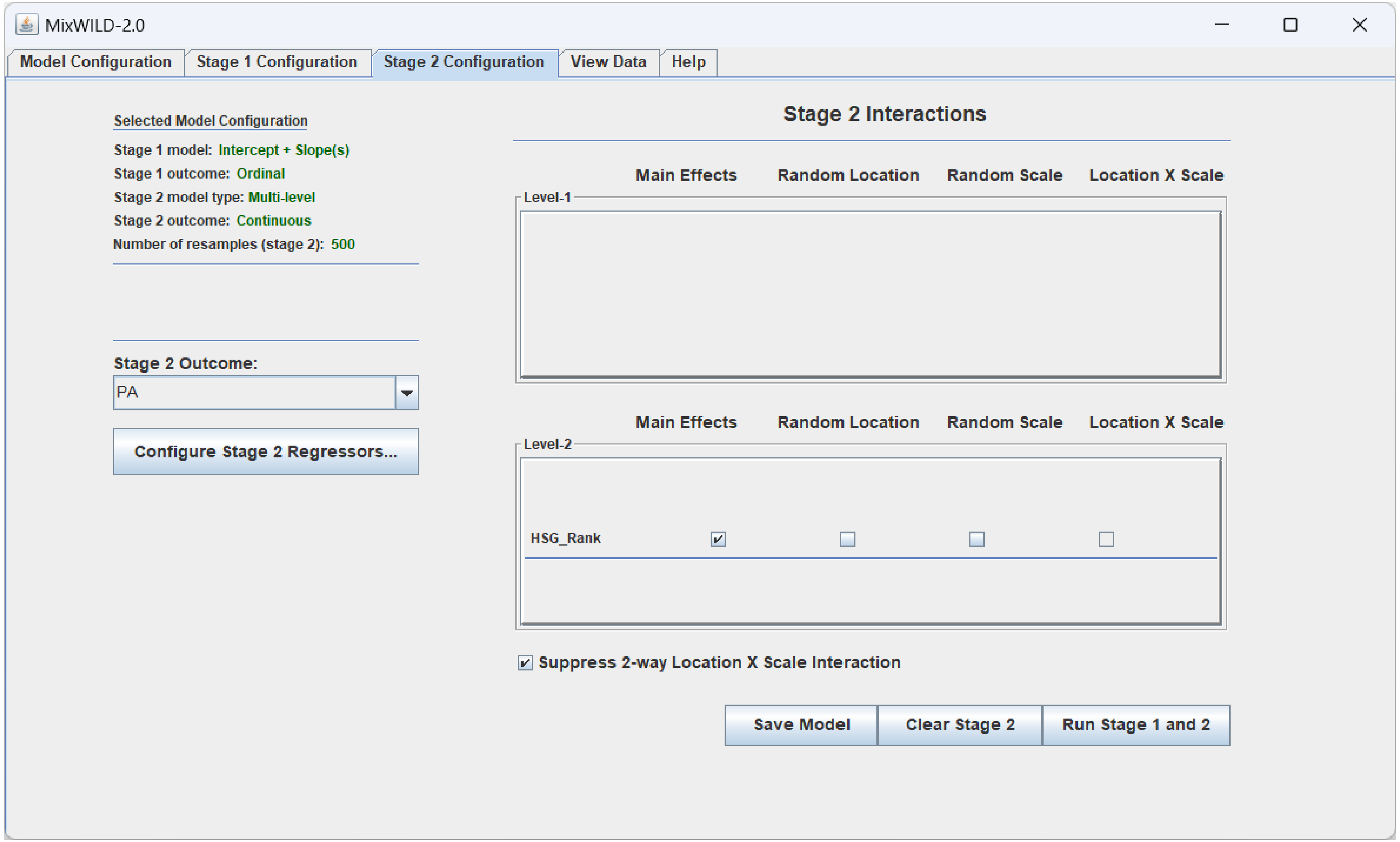
Select "LGA" as the Stage 1 outcome and "SQ" as a time-varying predictor

Q2c: (Stage 1) Does sleep quality (SQ) influence one's learning goal achievement (LGA)? Is the association between LGA and SQ different across subjects?



Add a random slope of "SQ" in the Mean model

Q2c: (Stage 2) Does subject's mean level of-, or intraindividual variance in LGA, or random-subject slope of SQ predicting LGA influence one's daily positive affect?



Select "PA" as Stage 2 Outcome and add "HSG_Rank" as Level-2 covariate

Q2c: (Stage 1) Does sleep quality (SQ) influence one's learning goal achievement (LGA)? Is the association between LGA and SQ different across subject?

Variable	Estimate	AsymStdError	z-value	p-value
BETA (regression coefficients)				
SQ	0.19774	0.07007	2.82197	0.00477
Random (location) Effect Variances and Covariances				
Intercept	1.58607	0.27494	5.76887	0.00000
Covariance12	-0.06054	0.07820	-0.77419	0.43882
SQ	0.03154	0.05814	0.54247	0.58749
TAU (WS variance parameters: log-linear model)				
SQ	-0.03770	0.03321	-1.13524	0.25628
Thresholds (for identification)				
1	-2.19205	0.78148	-2.80500	0.00503
2	-0.68741	0.28521	-2.41015	0.01595
3	1.02594	0.10671	9.61429	0.00000
4	3.33576	0.47548	7.01558	0.00000
Random location effects on WS variance (log-linear model)				
Intercept	0.16154	0.07123	2.26769	0.02335
SQ	-0.10438	0.03679	-2.83755	0.00455
Random scale standard deviation				
Std Dev	0.26672	0.02501	10.66580	0.00000

Mean model (BETA): the slope of SQ is positive (beta = 0.19774; p = -.00477). For every one unit increase in student's SQ, the odds of being more likely to make higher learning goal achievement (versus "not at all") is multiplied 1.22 times (i.e., increases 22%), holding constant all other variables.

Q2c: (Stage 1) Does sleep quality (SQ) influence one's learning goal achievement (LGA)? Is the association between LGA and SQ different across subject?

Variable	Estimate	AsymStdError	z-value	p-value
BETA (regression coefficients)				
SQ	0.19774	0.07007	2.82197	0.00477
Random (location) Effect Variances and Covariances				
Intercept	1.58607	0.27494	5.76887	0.00000
Covariance12	-0.06054	0.07820	-0.77419	0.43882
SQ	0.03154	0.05814	0.54247	0.58749
TAU (WS variance parameters: log-linear model)				
SQ	-0.03770	0.03321	-1.13524	0.25628
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1	-2.19205	0.78148	-2.80500	0.00503
2	-0.68741	0.28521	-2.41015	0.01595
3	1.02594	0.10671	9.61429	0.00000
4	3.33576	0.47548	7.01558	0.00000
Random location effects on WS variance (log-linear model)				
Intercept	0.16154	0.07123	2.26769	0.02335
SQ	-0.10438	0.03679	-2.83755	0.00455
Random scale standard deviation				
Std Dev	0.26672	0.02501	10.66580	0.00000

Random (Location) Effect: the subjects differ significantly between each other based on mean levels (random intercept) of LGA (estimate = 1.58607; $p < 0.001$).

Q2c: (Stage 1) Does sleep quality (SQ) influence one's learning goal achievement (LGA)? Is the association between LGA and SQ different across subject?

Variable	Estimate	AsymStdError	z-value	p-value
BETA (regression coefficients)				
SQ	0.19774	0.07007	2.82197	0.00477
Random (location) Effect Variances and Covariances				
Intercept	1.58607	0.27494	5.76887	0.00000
Covariance12	-0.06054	0.07820	-0.77419	0.43882
SQ	0.03154	0.05814	0.54247	0.58749
TAU (WS variance parameters: log-linear model)				
SQ	-0.03770	0.03321	-1.13524	0.25628
Thresholds (for identification)				
1	-2.19205	0.78148	-2.80500	0.00503
2	-0.68741	0.28521	-2.41015	0.01595
3	1.02594	0.10671	9.61429	0.00000
4	3.33576	0.47548	7.01558	0.00000
Random location effects on WS variance (log-linear model)				
Intercept	0.16154	0.07123	2.26769	0.02335
SQ	-0.10438	0.03679	-2.83755	0.00455
Random scale standard deviation				
Std Dev	0.26672	0.02501	10.66580	0.00000

Random (Location) Effect: the random intercept and random slope were not statistically associated with each other (Covariance), indicating that there is no relationship between the mean levels of LGA and the coupling association of SQ and LGA (estimate = -0.06054; p = 0.43882).

Q2c: (Stage 1) Does sleep quality (SQ) influence one's learning goal achievement (LGA)? Is the association between LGA and SQ different across subject?

Variable	Estimate	AsymStdError	z-value	p-value
BETA (regression coefficients)				
SQ	0.19774	0.07007	2.82197	0.00477
Random (location) Effect Variances and Covariances				
Intercept	1.58607	0.27494	5.76887	0.00000
Covariance12	-0.06054	0.07820	-0.77419	0.43882
SQ	0.03154	0.05814	0.54247	0.58749
TAU (WS variance parameters: log-linear model)				
SQ	-0.03770	0.03321	-1.13524	0.25628
Thresholds (for identification)				
1	-2.19205	0.78148	-2.80500	0.00503
2	-0.68741	0.28521	-2.41015	0.01595
3	1.02594	0.10671	9.61429	0.00000
4	3.33576	0.47548	7.01558	0.00000
Random location effects on WS variance (log-linear model)				
Intercept	0.16154	0.07123	2.26769	0.02335
SQ	-0.10438	0.03679	-2.83755	0.00455
Random scale standard deviation				
Std Dev	0.26672	0.02501	10.66580	0.00000

Random (Location) Effect: there is no statistical difference in their association (random slope) between SQ and LGA (estimate = 0.03154; p = 0.58749) across subjects.

Q2c: (Stage 1) Does sleep quality (SQ) influence one's learning goal achievement (LGA)? Is the association between LGA and SQ different across subject?

Variable	Estimate	AsymStdError	z-value	p-value
BETA (regression coefficients)				
SQ	0.19774	0.07007	2.82197	0.00477
Random (location) Effect Variances and Covariances				
Intercept	1.58607	0.27494	5.76887	0.00000
Covariance12	-0.06054	0.07820	-0.77419	0.43882
SQ	0.03154	0.05814	0.54247	0.58749
TAU (WS variance parameters: log-linear model)				
SQ	-0.03770	0.03321	-1.13524	0.25628
Thresholds (for identification)				
1	-2.19205	0.78148	-2.80500	0.00503
2	-0.68741	0.28521	-2.41015	0.01595
3	1.02594	0.10671	9.61429	0.00000
4	3.33576	0.47548	7.01558	0.00000
Random location effects on WS variance (log-linear model)				
Intercept	0.16154	0.07123	2.26769	0.02335
SQ	-0.10438	0.03679	-2.83755	0.00455
Random scale standard deviation				
Std Dev	0.26672	0.02501	10.66580	0.00000

The relationship between **the random intercept** and **scale effects of LGA** is positive and significant, indicating that subjects with higher average are also more erratic.

The relationship between **the random slope of SQ predicting LGA** and **scale effect of LGA** is negative and significant, indicating that subjects with higher slope are less erratic.

Q2c: (Stage 1) Does sleep quality (SQ) influence one's learning goal achievement (LGA)? Is the association between LGA and SQ different across subject?

Variable	Estimate	AsymStdError	z-value	p-value
BETA (regression coefficients)				
SQ	0.19774	0.07007	2.82197	0.00477
Random (location) Effect Variances and Covariances				
Intercept	1.58607	0.27494	5.76887	0.00000
Covariance12	-0.06054	0.07820	-0.77419	0.43882
SQ	0.03154	0.05814	0.54247	0.58749
TAU (WS variance parameters: log-linear model)				
SQ	-0.03770	0.03321	-1.13524	0.25628
Thresholds (for identification)				
1	-2.19205	0.78148	-2.80500	0.00503
2	-0.68741	0.28521	-2.41015	0.01595
3	1.02594	0.10671	9.61429	0.00000
4	3.33576	0.47548	7.01558	0.00000
Random location effects on WS variance (log-linear model)				
Intercept	0.16154	0.07123	2.26769	0.02335
SQ	-0.10438	0.03679	-2.83755	0.00455
Random scale standard deviation				
Std Dev	0.26672	0.02501	10.66580	0.00000

The standard deviation of the random scale effect is estimated to be 0.26672, and this is a highly significant effect. Thus, subjects vary considerably in terms of how consistent/erratic they are in their LGA.

Q2c: (Stage 2) Does subject's mean level of-, or intraindividual variance in LGA, or random-subject slope of SQ predicting LGA influence one's daily positive affect?

```
-------------
Final Results
-------------
 Average Log Likelihood         =    -3311.270 (sd=       2.057)
 Akaike's Information Criterion =    -3317.270
 Schwarz's Bayesian Criterion   =    -3324.100

 ==> multiplied by -2
 Log Likelihood                 =     6622.540
 Akaike's Information Criterion =     6634.540
 Schwarz's Bayesian Criterion   =     6648.200
```

Variable	Estimate	AsymStdError	z-value	p-value
Intercept	4.33165	0.37209	11.64135	0.00000
HSG_Rank	-0.01435	0.02756	-0.52080	0.60250
Locat_1	0.47664	0.11872	4.01484	0.00006
Locat_2	0.57032	0.17890	3.18791	0.00143
Scale_1	0.13953	0.15861	0.87974	0.37900
Random.Int.Var	0.89552	0.16570	5.40441	0.00000
Residual.Varianc	1.21729	0.03818	31.88212	0.00000

Subject-level random intercept effect: the subject-level random intercept of learning goal achievement (Locat_1) is positively associated with their reported positive affect (beta = 0.47664; $p < 0.001$). It suggests that students with a higher subject-level mean of LGA, on average, have higher PA.

Q2c: (Stage 2) Does subject's mean level of-, or intraindividual variance in LGA, or random-subject slope of SQ predicting LGA influence one's daily positive affect?

```
-------------
Final Results
-------------
 Average Log Likelihood         =     -3311.270 (sd=       2.057)
 Akaike's Information Criterion =     -3317.270
 Schwarz's Bayesian Criterion   =     -3324.100

 ==> multiplied by -2
 Log Likelihood                 =      6622.540
 Akaike's Information Criterion =      6634.540
 Schwarz's Bayesian Criterion   =      6648.200
```

Variable	Estimate	AsymStdError	z-value	p-value
Intercept	4.33165	0.37209	11.64135	0.00000
HSG_Rank	-0.01435	0.02756	-0.52080	0.60250
Locat_1	0.47664	0.11872	4.01484	0.00006
Locat_2	0.57032	0.17890	3.18791	0.00143
Scale_1	0.13953	0.15861	0.87974	0.37900
Random.Int.Var	0.89552	0.16570	5.40441	0.00000
Residual.Varianc	1.21729	0.03818	31.88212	0.00000

Subject-level random slope effect: the subject-level random slope of sleep quality predicting learning goal achievement (Locat_2) is positively associated with their reported positive affect (beta = 0.57032; p = 0.00143). It indicates that students with a higher subject-level slope of SQ predicting LGA (association between SQ and LGA) have higher PA.

Troubleshooting

Troubleshooting

Limited variable number (Maximum ≈ 256)

Although there seems to be no limited of the sample size, the capacity of the maximum variable number could potentially be caped. Please keep the dataset as lite as possible and only include the variables that you will use in analysis.

1	ID	Day	Sex	Age	Sem	SQ	PhysAct	PA	NA	LGA	Exam	HSG	BDI
2	1	1	1	22	2	3	30	2.666667	3.666667	2	1	4.6	2
3	1	2	1	22	2	3	60	3.333333	3	1	1	4.6	2
4	1	3	1	22	2	3	360	2.666667	4	0	1	4.6	2
5	1	4	1	22	2	3	780	1.333333	5	1	1	4.6	2
6	1	6	1	22	2	3	210	3	4.666667	2	1	4.6	2
7	1	8	1	22	2	3	310	4	3.666667	2	1	4.6	2
8	1	9	1	22	2	3	90	3.333333	3.333333	0	1	4.6	2
9	1	10	1	22	2	3	405	3.333333	2.666667	2	1	4.6	2
10	1	11	1	22	2	3	405	2.333333	2.666667	2	1	4.6	2
11	1	12	1	22	2	3	360	3	4	2	1	4.6	2
12	1	13	1	22	2	3	270	1.666667	5.666667	1	1	4.6	2
13	1	14	1	22	2	3	30	3.333333	2.333333	2	1	4.6	2
14	1	15	1	22	2	3	540	2.666667	2	1	1	4.6	2
15	1	17	1	22	2	2	405	4.333333	3.333333	1	1	4.6	2
16	1	18	1	22	2	3	405	2.666667	3	1	1	4.6	2
17	1	19	1	22	2	3	540	2.666667	3.333333	1	1	4.6	2
18	1	21	1	22	2	3	60	3.666667	2.666667	2	1	4.6	2
19	1	22	1	22	2	3	405	3.333333	3	1	1	4.6	2
20	1	23	1	22	2	3	405	3.333333	3.333333	2	1	4.6	2
21	1	24	1	22	2	2	60	1.666667	4.666667	2	1	4.6	2
22	1	25	1	22	2	3	405	5	2.666667	2	1	4.6	2
23	1	26	1	22	2	3	330	3.666667	2.666667	1	1	4.6	2
24	1	27	1	22	2	3	435	2	3.666667	2	1	4.6	2
25	1	29	1	22	2	3	525	3.666667	2.666667	2	1	4.6	2

Dataset_HealthBehavAcadPerfAffe

Starting your model with a simplified variables/specification

Adding the random slope/scale effect may make your model overly complicated and generate some estimate difficulties. If you experience the model crash issue with no issue above, please try to start your model with simple settings. Also using Probit/Logistic model for dichotomous/ordinal outcome may increase estimate difficulties. Please check your outcomes before doing nonlinear models.

$$\begin{bmatrix} \upsilon_{0_i} \\ \upsilon_{1_i} \\ \omega_i \end{bmatrix} \sim N \left\{ \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \begin{bmatrix} \sigma_{\upsilon_0}^2 & \sigma_{\upsilon_0 \upsilon_1} & \sigma_{\upsilon_0 \omega} \\ \sigma_{\upsilon_0 \upsilon_1} & \sigma_{\upsilon_1}^2 & \sigma_{\upsilon_1 \omega} \\ \sigma_{\upsilon_0 \omega} & \sigma_{\upsilon_1 \omega} & \sigma_{\omega}^2 \end{bmatrix} \right\}$$

Troubleshooting

Correct / Error

1 No blank SPACE in dataset name / folder name

The dataset should be saved in a folder, and the folder name **CANNOT** have any **blank SPACES** ( ).

Error: The data be loaded correctly, but the analysis will be shut down immediately when running the data.

Correct: C:\MyData\data_1.csv

Error: C:\My Data\data 1.csv

2 Variable names in the first row

The dataset should be saved as a **.CSV file** with variable names in the **first row**.

Error: The software could not access to correct variable names/labels, and the first row data will be cut.

Correct:

	A	B	C	D	E	F
1	ID	Sex_F	Age_C	Exam	HSG	PA_Mean
2	1	1	-1	1	4.6	3.11
3	2	1	-2	0	4.9	5.76
4	3	1	13	1	4.7	3.94
5	4	1	-2	0	4.3	2.9
6	5	1	-1	1	4.7	4.61

Dataset_HealthBehavAcadPerfAf

Error:

	A	B	C	D	E	F
1	1	1	-1	1	4.6	3.11
2	2	1	-2	0	4.9	5.76
3	3	1	13	1	4.7	3.94
4	4	1	-2	0	4.3	2.9
5	5	1	-1	1	4.7	4.61
6	6	1	-3	0	4.5	3.22

Dataset_HealthBehavAcadPerfAf

3 No blank ( ) / Periods (.) / String ('miss') in data

Missing values should **NOT** be **blank ( )** or **periods (.)** or **string** in the dataset. All data should be coded as **numeric values** only, except for the fist row (variable names).

Error: The data cannot be read correctly, and it will end up to wrong estimates or model crash.

Correct:

	A	B	C	D	E	F
1	ID	Sex_F	Age_C	Exam	HSG	PA_Mean
6	5	1	-1	1	4.7	4.61
7	6	1	-3	0	4.5	3.22
8	7	0	8	1	4.4	6.04
9	8	-99	-99	0	4.5	6.62
10	9	1	-3	1	5.3	5.03

Dataset_HealthBehavAcadPerfAf

Error:

	A	B	C	D	E	F
1	ID	Sex_F	Age_C	Exam	HSG	PA_Mean
6	5	1	-1	1	4.7	4.61
7	6	1	-3	0	4.5	3.22
8	7	0	8	1	4.4	6.04
9	8	.		0	4.5	6.62
10	9	1	-3	1	5.3	5.03

Dataset_HealthBehavAcadPerfAf

4 Sorted by ID

Data should be sorted ascending or descending by ID number.

Error: The data cannot be read correctly, and it will end up to get wrong estimates or model crash.

Correct:

	A	B	C	D	E	F
1	ID	Sex_F	Age_C	Exam	HSG	PA_Mean
2	1	1	-1	1	4.6	3.11
3	2	1	-2	0	4.9	5.76
4	3	1	13	1	4.7	3.94
5	4	1	-2	0	4.3	2.9
6	5	1	-1	1	4.7	4.61

Dataset_HealthBehavAcadPerfAf

Error:

	A	B	C	D	E	F
1	ID	Sex_F	Age_C	Exam	HSG	PA_Mean
2	1	1	-1	1	4.6	3.11
3	2	1	-2	0	4.9	5.76
4	5	1	13	1	4.7	3.94
5	4	1	-2	0	4.3	2.9
6	3	1	-1	1	4.7	4.61

Dataset_HealthBehavAcadPerfAf

Website: https://reach-lab.github.io/MixWildGUI/

User Guide: https://reach-lab.github.io/MixWildGUI/MixWild_User_Guide.pdf

THE UNIVERSITY OF CHICAGO
Northeastern University
USC University of Southern California

Troubleshooting

Quick Summary of the Optimal Options

(Please try to change these key parameters one by one in the model)

	Default	Optimization
Quadrature Point	11	15 - 25
Maximum Iterations	200	300 - 500
Ridge	0.1	0.15 – 0.25
Discard Subjects with no Variance	Uncheck	Check

Quadrature Point
Usually, 11 points is sufficient, but if model convergence is not achieved, then increasing the points can sometimes help. So, for example, one might try 15, 21, or 25 points rather than the default of 11.

Maximum Iterations
For example, beyond some number of iterations there are no practical gains. You can increase the number of iterations allowed to see if they will converge if the estimation doesn't converge within the default number. By default, the number of maximum iterations is 200.

Ridge
The ridge increases the values of the diagonal elements of the 2nd derivative matrix by a factor of 1 multiplied by the ridge value. The reason that this is helpful is that this matrix must be inverted at each iteration of the solution, and inversion of this matrix becomes computationally difficult to the extent that the off-diagonal elements of this matrix get large, relative to the diagonal elements. Thus, in cases of non-convergence, one might try increasing the ridge value to 0.15, 0.20, or even 0.25. This will slow down the estimation, but in some cases can aid in model convergence.

Discard Subjects with no Variance
For such subjects with no variation on the outcome, the estimate of their random scale goes to negative infinity and can cause the program to fail to converge. In this case, the selection of the option can facilitate model convergence. Please note selecting this option will remove these subjects from the stage 1 analysis.

MixWILD website: https://reach-lab.github.io/MixWildGUI/

MixWILD GitHub: https://github.com/reach lab/MixWildGUI/discussions







Thank You!!!

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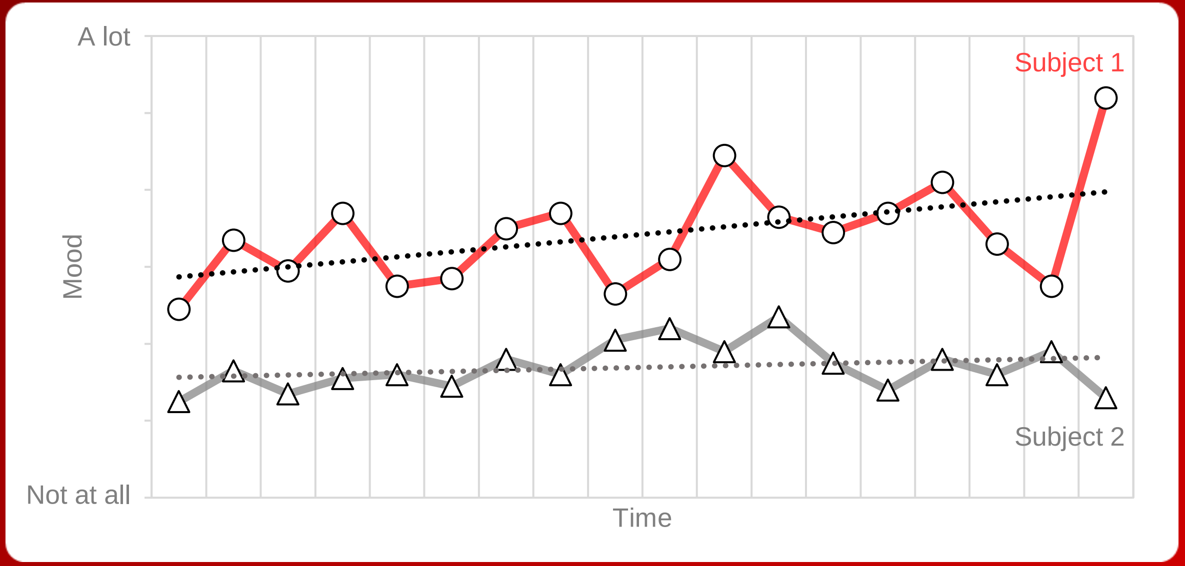
REACH

Harnessing the power of fluctuation:

New horizons in modeling intraindividual variability with intensive longitudinal data



Date:

Wednesday April 26, 2023
11:00 AM – 1:00 PM

Presenters:

Genevieve F. Dunton
Donald Hedeker
Wei-Lin Wang

Mini MixWILD Installation Handbook

MIX{WILD}

Mixed Model Analysis With Longitudinal Data

Download Software

1. Visit our website: https://reach-lab.github.io/MixWildGUI/

2. Click on **MacOS** or **Windows** to download the program.

- **MacOS:** https://github.com/reach-lab/MixWildGUI/releases/download/v2.0-stable/MixWILD-2.0.dmg
- **Windows:** https://github.com/reach-lab/MixWildGUI/releases/download/v2.0-stable/MixWILD-2.0.exe

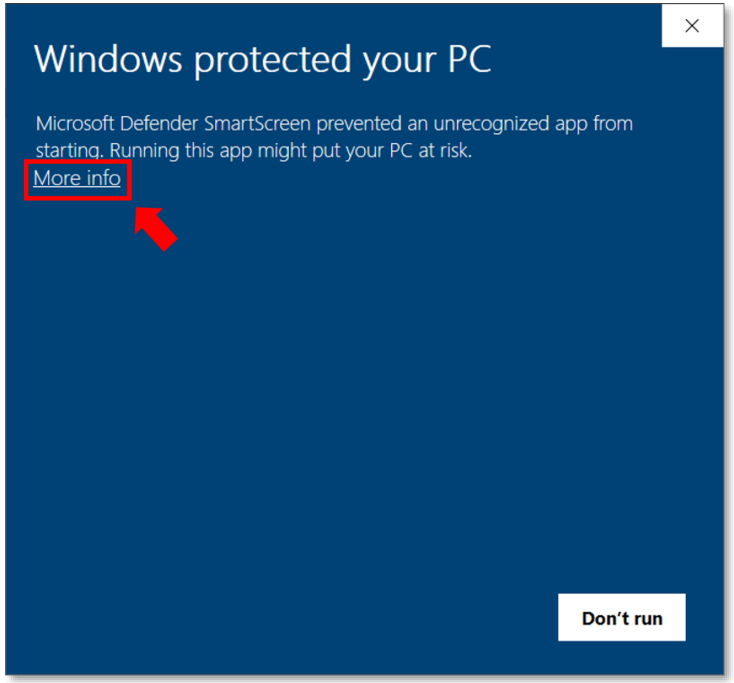
3. Select your directory to save the program.

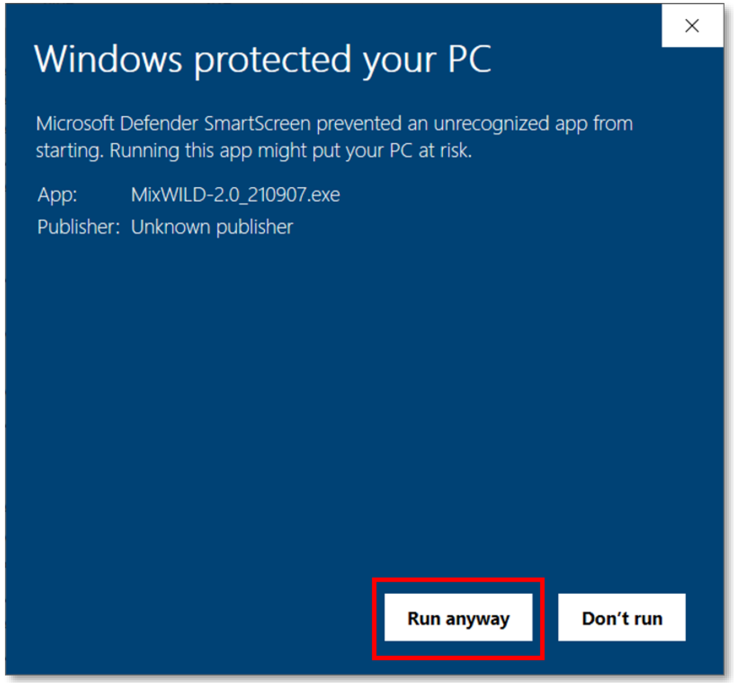
4. When finished downloading, double-click on the MixWILD icon and follow the instructions to complete installation.

Install Software

If this is your first time to install MixWILD, the Windows system may ask you to do some extra steps to successfully install the software.

1. Click on the MixWILD-2.0.exe, and click on **[More info]** to continue the process.

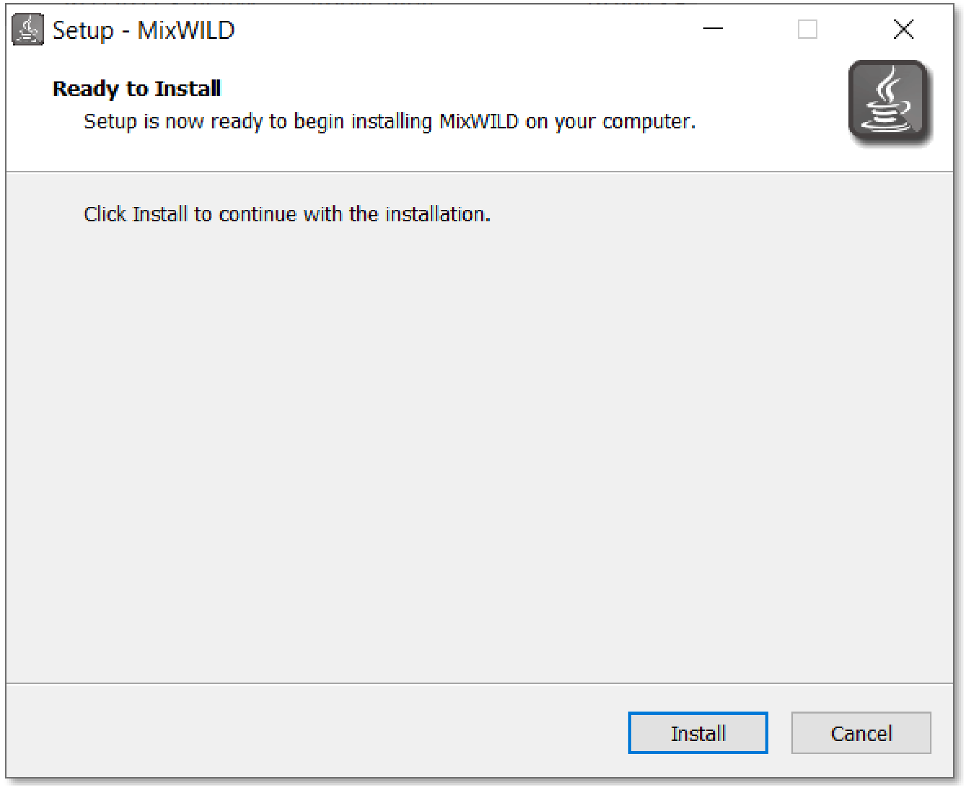




2. Click on **[Run anyway]**.

Install Software

3. Click on [Install] to complete the installation.



4. Well done! You are all set! Please try MixWILD!

Data for MixWILD

- The dataset should be saved in a folder, and the folder name CANNOT have any blank SPACES. (i.e., Please don't name your folder as "My Data" which will lead to an error. Please use underscore to replace space, the correct name should be "My_Data").

- The dataset should be saved as a .csv file with variable names (no blank SPACES in variable names as well) in the first row.

- Data should be in the long format and sorted ascending or descending by ID number.

- Missing values should not be blank or periods (.) in the dataset and should be coded as numeric values only (i.e., "-999").

Resources

MixWILD User's Guide:

https://reach-lab.github.io/MixWildGUI/

MixWILD Cheat Sheets:

https://reach-lab.github.io/MixWildGUI/resources/cheat_sheets/MixWILD_UG_CS_220124.html

MixWILD GitHub Discussion:

https://github.com/reach-lab/MixWildGUI/discussions

Introduction of Mixed-effects Location Scale Model Video:

https://www.youtube.com/watch?v=wCEHuv9t1xw

MIX{WILD}
Mixed Model Analysis With Longitudinal Data

Thank You Very Much! Look Forward to Meeting You on Wednesday April 26, 2023, in the SBM MixWILD Workshop!

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