

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







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- 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)









How to Download MixWILD



MixWILD for Mac

MixWILD for Windows

•Please visit: <u>https://reach-lab.github.io/MixWildGUI/</u>

•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

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MixWILD - Mixed models With Intensive Longitudinal Data

Mixed-WILD is a statistical software designed to perform multilevel modeling (with mixed effects) on longitudinal experience sampling data. Analysing intensive longitudinal data from EMA is a challenging task and the currently available desktop applications are often insufficient for this purpose. Using Mix-WILD, behavioral researchers with no background in programming (e.g., R) can perform complex modeling on PRISPRALCEST hat the arter of the second

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MixWild

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Please submit your email prior to downloading the application so we can notify you of major software updates

Your email Send Download MixWild for Mac or PC

macOS (64-bit)

Windows (32-bit)

What is this project about?

MixWILD (Also Mixed model analysis with Intensive Longitudinal Data) is a desktop GUI based application to easily perform multilevel mixed model analysis of intensive longitudinal data.

Join the Reach Lab Slack for development discussion:

You may post an issue in Github to request access if you do not have a compatible email address.

Reach Lab mixregmls Channel

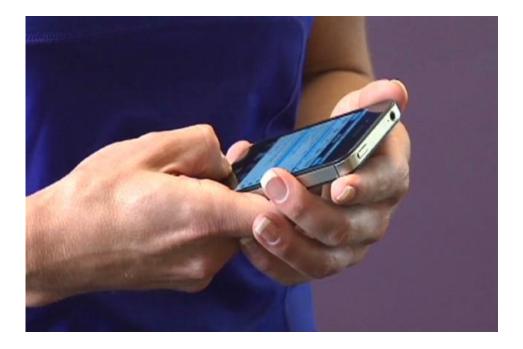


- User guide
- Cheat sheets
- Example datasets
- Video tutorial
- Published papers
- User discussion board





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-</u> <u>timescales</u> (e.g., min, hours)



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

<u>Types of ILD from mobile and sensor devices</u>: 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

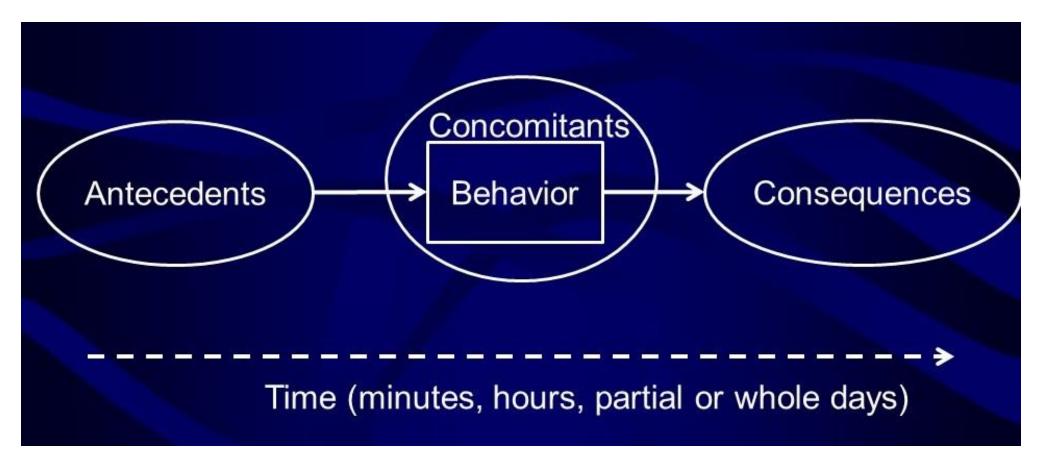








Common Use of ILD: Examining Momentary Within-Subject Effects of Time-Varying Variables on Health Behaviors

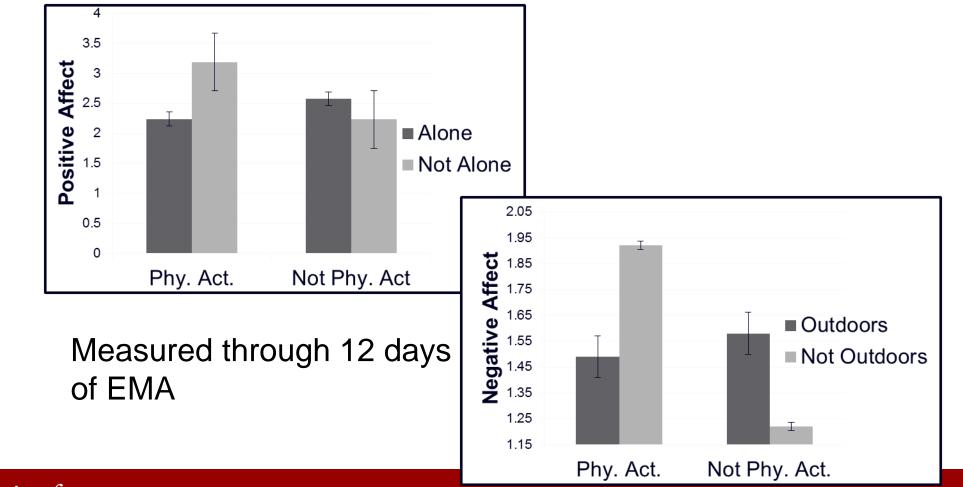


USCUniversity of Dunton, G. F. (2017). Ecological Momentary Assessment in physical activity research. Exercise and Southern California Sports Sciences Reviews, 45(1), 48-54.



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

Contextual Influences on Affective Response During Physical Activity



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



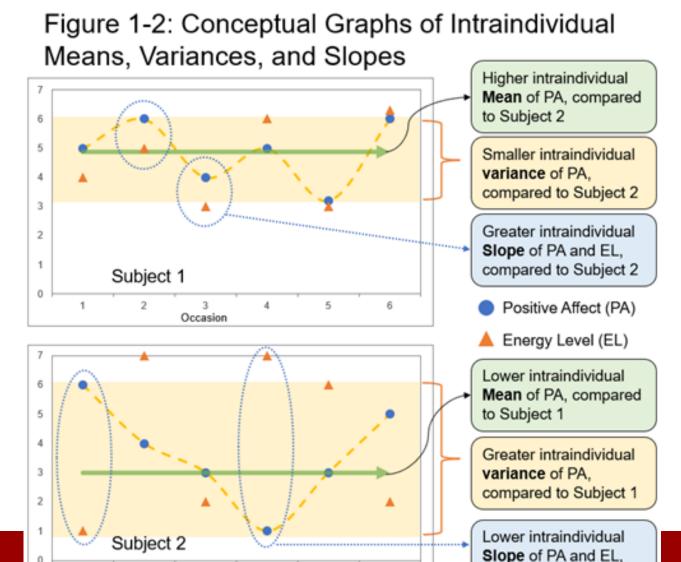
Less Common Use of ILD: Examining Aggregated Intraindividual Effects of Within-Subject Effects of Time-Varying Variables on Health Behaviors

- 1. <u>Intraindividual means (i.e., random location effect</u>) *How happy is a subject, on average, across occasions?*
- 2. <u>Intraindividual variances (i.e., random scale effect)</u> *How erratic is a subject's mood across occasions?*
- 3. <u>Intraindividual slopes (i.e., random slope effect</u>) *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 a program for examining the effects of variance and slope of time-varying variables in intensive longitudinal data. *Behavior Research Methods*, *52*, 1403-1427.





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Occasion

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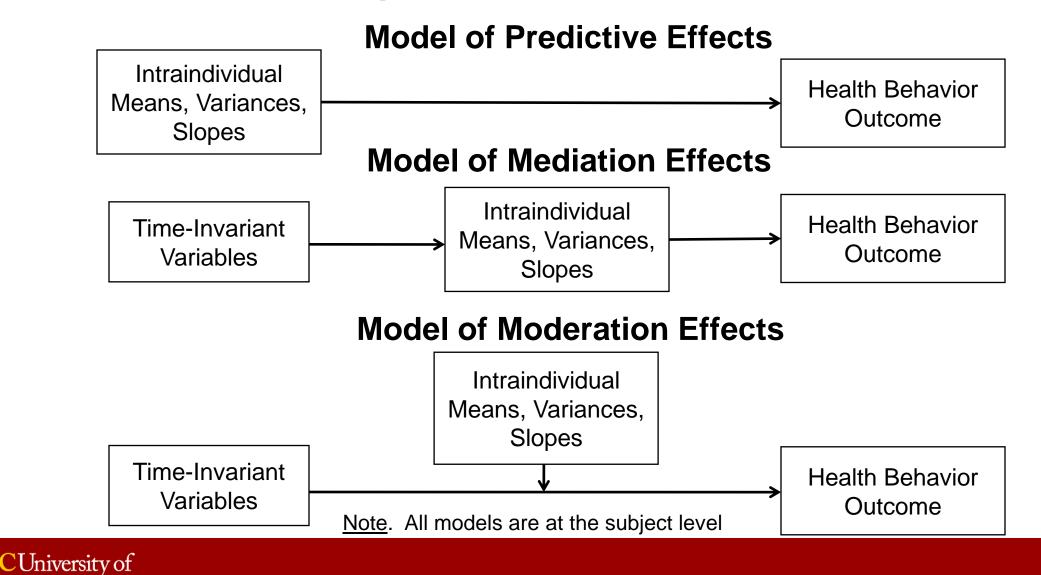
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compared to Subject 1



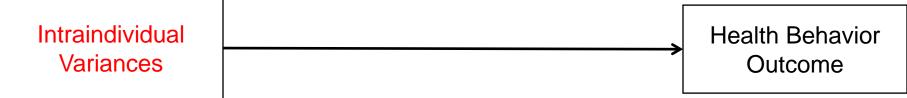




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Model of Predictive Effects



Note. All models are at the subject level





Intraindividual Variance Predicting a Subject-Level Health Behavior Outcome

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

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

Predicting Odds of Meeting Physical Activity Guidelines Estimate (Standard Error)	Predicting Minutes of Sedentary Time per Valid Hour of Wear Estimate (Standard Error)
0.58 (0.32)	33.74** (0.68)
0.09 (0.10)	0.33 (0.31)
0.07 (0.09)	0.16 (0.23)
-0.92^{**} (0.21)	1.04* (0.41)
0.01 (0.01)	0.11** (0.01)
0.51 (0.55)	34.93** (1.03)
-0.09 (0.18)	-0.26 (0.30)
(-0.43* (0.21)	0.15 (0.37)
-1.13** (0.36)	1.40* (0.58)
-0.01 (0.01)	0.07** (0.02)
	Guidelines Estimate (Standard Error) 0.58 (0.32) 0.09 (0.10) 0.07 (0.09) $-0.92^{**} (0.21)$ 0.01 (0.01) 0.51 (0.55) -0.09 (0.18) $-0.43^{*} (0.21)$ $-1.13^{**} (0.36)$

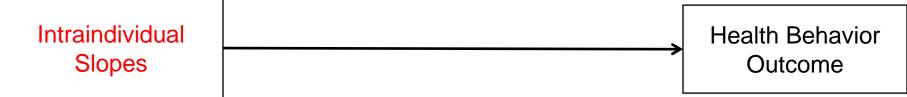
Note. Model using positive affect data are based on 617 participants. Model using feelings of energy data are based on 245 participants. For logistic regression models predicting odds of meeting physical activity guidelines, logit (i.e., log odds) estimates are displayed. *p < 0.05. **p < 0.01.



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..



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

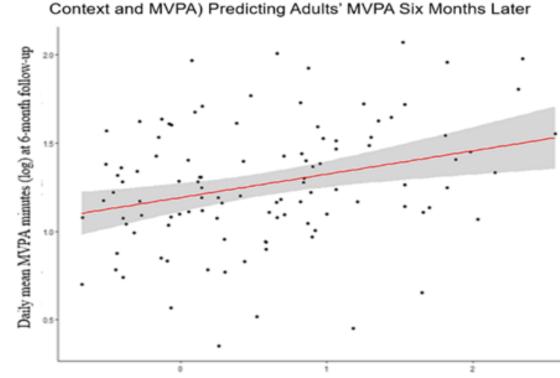


Figure 6: Intraindividual Slope (i.e., Momentary Association of Outdoor

Random slope for outdoor context and MVPA minutes during baseline

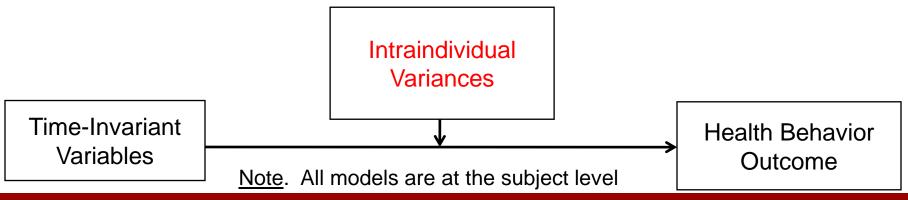
Participants, who had more momentary MVPA when outdoors (vs. indoors) during baseline (i.e., higher intraindividual lope), had higher daily MVPA six months later



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.



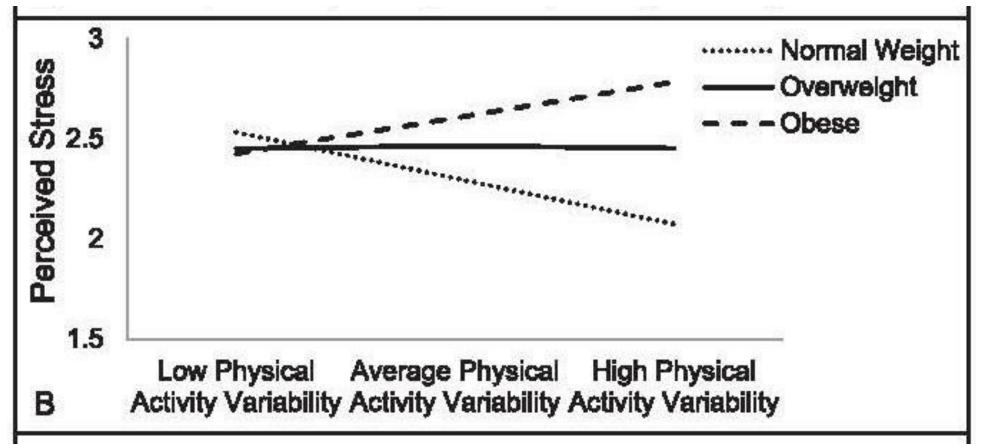
Model of Moderation Effects







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



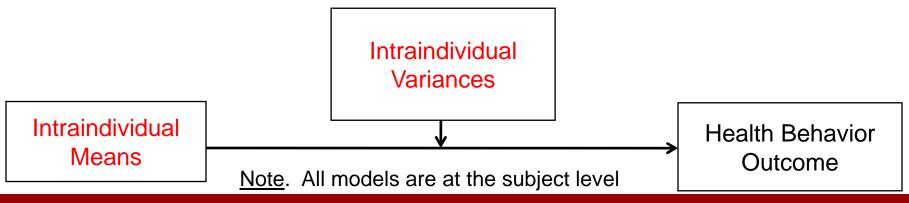
Individuals with obesity have higher levels of perceived stress, but only for those with high day-to-day variability in physical activity



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.



Model of Moderation Effects

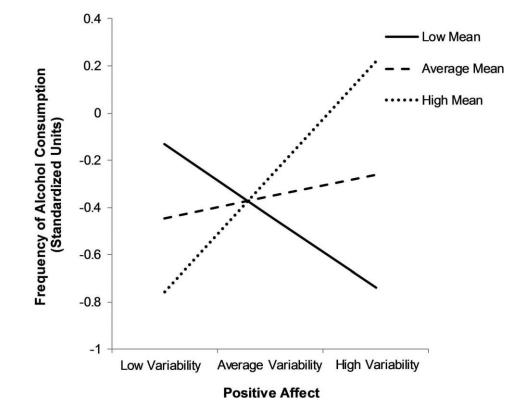


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Intraindividual Variance Moderating the Effect of a Intraindividual Mean on a Subject-Level Outcome



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.



Model of Predictive Effects

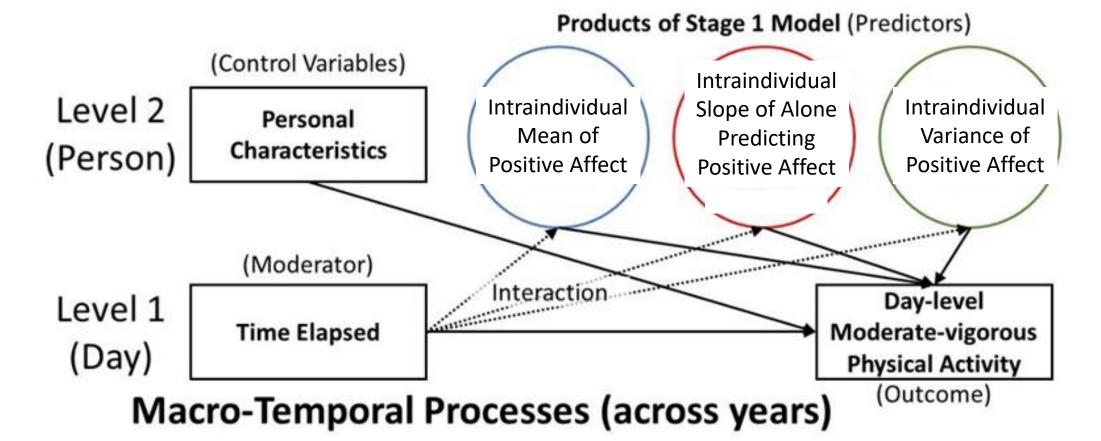


Note. Outcome is no longer at the subject level





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

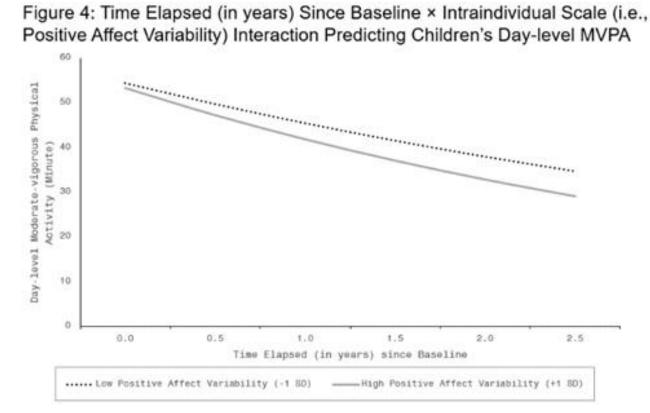




Dunton, G. F., Wang, W. L., Intille, S. S., Dzubur, E., Ponnada, A., & Hedeker, D. (2022). How acute affect dynamics impact longitudinal changes in physical activity among children. *Journal of Behavioral Medicine*, *45*(3), 451-460.



Intraindividual Variance Predicting Change in an Outcome over Time



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.



Model of Predictive Effects



Note. Outcome is no longer at the subject level

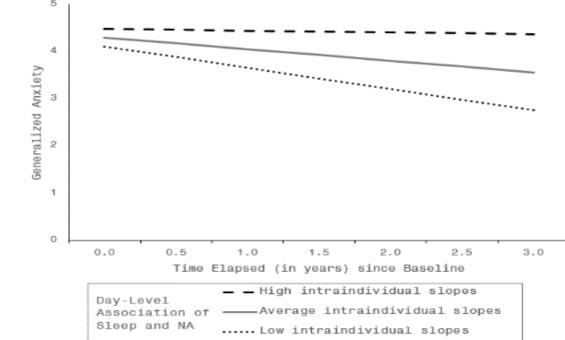




Intraindividual Slope Predicting Change in an Outcome over Time

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

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



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

USC University of Southern California 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





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 withinperson 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





Collaborators

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Acknowledgments

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- NCI R01CA240713 (Hedeker & Dunton, PIs)

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

Twitter: @GenevieveDunton









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, ..., N) on occasion j($j = 1, 2, ..., n_i$)

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

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

 $\beta = p \times 1$ vector of regression coefficients

 $v_i \sim N(0, \sigma_v^2)$ BS variance; how homogeneous/heterogeneous are subjects?

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

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

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

 \Rightarrow magnitude of σ_v^2 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_{ϵ}^2 will approach 0 - if subjects are not well-fit, $\epsilon_{ij} \neq 0$ and σ_{ϵ}^2 will increase from 0

 \Rightarrow magnitude of σ_{ϵ}^2 indicates how data vary within subjects (consistency/erraticism)

Log-linear models for variances

BS variance
$$\sigma_{v_{ij}}^2 = \exp(u_{ij}' \alpha)$$
 or $\log(\sigma_{v_{ij}}^2) = u_{ij}' \alpha$

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

- \boldsymbol{u}_{ij} and \boldsymbol{w}_{ij} include covariates (and $\boldsymbol{1}$)
- subscripts *i* and *j* on variances indicate that these change depending on covariates u_{ij} and 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?

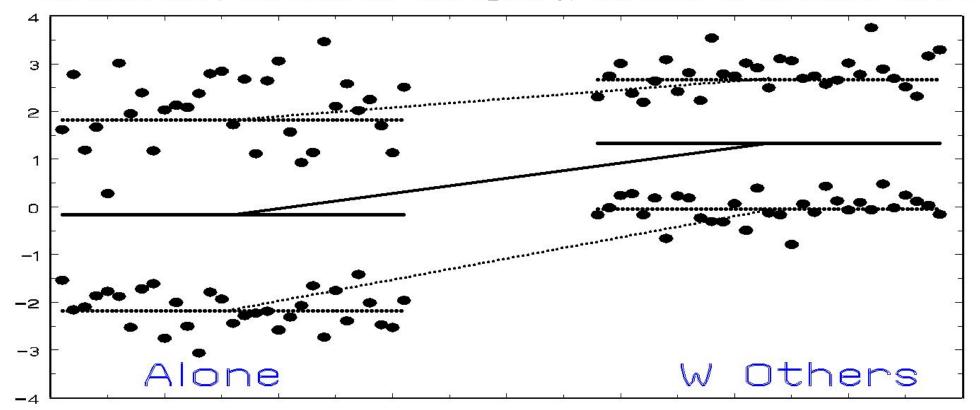
$$\sigma_{v_{ij}}^2 = \exp(u_{ij}' \alpha)$$

- 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)

Location Scale Model Increased Mean, Decreased BS heterogeneity, Decreased WS variance w 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

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

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

- 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
- v_i are "location" random effects how does a subject differ in terms of the mean of their data

Multilevel model of WS variance

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

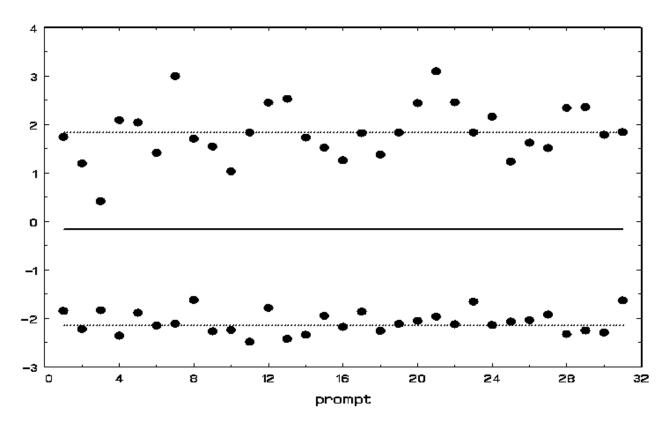
Why not use some summary statistic per subject (say, calculated subject standard deviation S_{y_i}) in a second-stage model?

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

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

$Dataset_HealthBehavAcadPerfAffect.csv$

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6	1			1 22		3		2.666667	3	1	1			0.214286	
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9	1		-	1 22		3		3.333333	2.000007		1			0.642857	
9 0	1			1 22		3		3.333333		2	1			0.928571	
1	1		-	1 22		2		1.666667		2	1			1.071429	
2	1			1 22					2.666667	2	1			1.214286	
-	•		-	vAcadPerf								: •			

MELS model of PA

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

$$PA_{ij} = \beta_0 + \beta_1 Day_{-}c_{ij} + v_i + \epsilon_{ij}$$

$$\sigma_{v_{ij}}^2 = \exp(\alpha_0 + \alpha_1 Day_- c_{ij})$$

$$\sigma_{\epsilon_{ij}}^2 = \exp(\tau_0 + \tau_1 Day_- c_{ij} + \tau_v v_i + \omega_i)$$

Here, v_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

<u></u>			_	\times
Model Configuration	Stage 1 Configuration	Stage 2 Configuration Stage 1 Results Stage 2 Results View Model View Data Postestimation Help		
		Is your dataset Mix{WILD} friendly? Check here		
		Data File: 2020IntensiveLong\Dataset_HealthBehavAcadPerfAffect.csv Browse		
		Title: Positive Affect across Centered Day		
		Does your data contain missing values? (In Yes Contain Note: Not		
		What is your missing data coded as? -99		
		Stage 1 outcome: Continuous Dichotomous Ordinal		
	Stage 1 Model	Specify random location effects:		
		Include estimates of random scale: Yes No 		
		Include Stage 2 model: O Yes IN ?		
		Save Model Reset Submit		

Select PA as the Stage 1 Outcome, select linear association

<u>≰</u> ,										- 🗆	\times
Model Configuration	Stage 1 Configuration	Stage 2 Configuration	Stage 1 Results	Stage 2 Results	View Model	View Data	Postestimation	Help			
Selected model co					Sta	age 1 Regr	ressors				
Random location e Stage 2 outcome: I		Level-1	Mean	BS Variance	WS Varia		evel-2	Mean	BS Variance	WS Varian	ice
ID Variable: ID	-]									
Stage 1 Outco	ome:	1									
	tage 1 Regressors						L.				
	Options						-0				
Specify the rela mean and WS v	ationship between the variance.										
O No Associat											
Linear Asso Quadratic A	ssociation										
MIX{w	ILD}						Save Model	Clea	ar Stage 1	Run Stage *	1

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

<u></u>										$ \Box$ \times
Model Configuration	Stage 1 Configuration	Stage 2 Configuration	Stage 1 Results	Stage 2 Results	View Model	View Data	Postestimation	Help		
Selected model co	onfiguration:	Add Stage 1 Regressor	s			_	· 🗆 X			
Random location e Stage 2 outcome: I		Variables				Level-1	(Time Varying)	Mean	BS Variance	WS Variance
ID Variable: ID		Day Sex Age Sem		Add	ay_c					
Stage 1 Outco	ome:	SQ PhysAct NA		Remove						
		LGA Exam HSG								
	itage 1 Regressors Options	BDI		-		Level-2	(Time Invariant)			
Specify the rela mean and WS v	ntionship between the /ariance.			Add Remove						
 No Associat Linear Association 										
○ Quadratic A		MIX (WIL	.D}		Cancel	Reset	Submit			
MIX{w	in LDS						Save Model	Clear	Stage 1	Run Stage 1

el Configuration	Stage 1 Configuration	Stage 2 Configuration	Stage 1 Results	Stage 2 Results	View Model	View Da	ata Postestimation	Help		
elected model co	onfiguration:				St	age 1 Re	egressors			
andom location e	effects: Intercept									
tage 2 outcome:	None		Mean	BS Variance	WS Varia	nce		Mean	BS Variance	WS Variance
		Level-1					Level-2			
ID Variable:		_								
ID										
Stage 1 Outco	ome:									
PA										
Configure S	Stage 1 Regressors						₽			
Configure 3	stage i riegi essoi s		Day_c 🖌	×	*		~			
	Options	Disaggr	egate?							
Specify the rela	ationship between the									
mean and WS v										
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O Quadratic A		1								
MIX{w	ILD}						Come Made		an Ghann d	Dum Otaria d
Muad Modal Analoris With Intanzi	ia Londo dinal Pata						Save Model	Cle	ar Stage 1	Run Stage 1

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

DEF file is created, click on Proceed

<u>چ</u>	📓 Definition File Preview — 🗆 🗙	1	- 🗆 X
Model Configuration Stage 1 Configuration Stage 2 Con		timation Help	
Results from stage 1 and	ositive Affect across Centered Day reated with MixWILD GUI Dataset_HealthBehavAcadPerfAffect.dat" ataset_HealthBehavAcadPerfAffect_Output		
	4 1 1 1 0 0 0 0 0 0 0.00001 11 1 200 -99 0 1 0.15 5 0 0.00000 0 1 0 0 8 4 4 4 4		
	À ay_c ay_c ay_c	I	
	0 0 0 Proceed Save Def File		

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 o	f leve	l-1 ob	servat	ions f	or each	n leve	1-2 cl	uster				
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 			st 	d dev	
Intercept					.0000	1	.0000	1	.0000	0	.0000	
Day_c				С	0.0160	-2	.2143	2	.2143	1	.3061	
BS varia	nce mo	del co	variate	25								
					mean				max		d dev	
Intercep									.0000		.0000	
Day_c				С	0.0160	-2	.2143	2	.2143	1	.3061	
WS varia	nco mo	del co	variata	29								
WD Valla		der co	variati	55	mean		min		max	st	d dev	
Intercep							.0000	 1	.0000	0	.0000	
Day_c	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	1 =	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 m	odel)		
Intercept	0.33310	0.17051	1.95351	0.05076
Day_c	0.11952	0.01981	6.03332	0.00000
TAU (WS variance parameters: 1	Log-linear mod	lel)		
Intercept	-0.09005	0.10237	-0.87967	0.37904
Day_c	0.13537	0.02615	5.17739	0.00000
Random scale standard deviation	on			

 Std Dev
 0.73614
 0.07047
 10.44576
 0.00000

 Random location (mean) effect on WS variance
 -0.36749
 0.09955
 -3.69164
 0.00022

BS variance ratios and $95\%~{\rm CIs}$

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 $95\%~{\rm CIs}$

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	t on WS variance		
Location Effect	0.69247	0.56972	0.84166
Random scale standard deviat:	ion		
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 (â = 0.11952, p = 0.00001). The exponentiated slope is 1.12695 with a 95% confidence interval of 1.08404 to 1.17157. The exponentiated 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 (\$\tilde{\tau}\$ = 0.13537, \$p\$ = 0.00001\$). The exponentiated slope is 1.14496 with a 95% confidence interval of 1.08776 to 1.20516. The exponentiated 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{v}_{0i} , slope \hat{v}_{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

$$y_i = \beta_0 + \beta_1 \hat{v}_{0i} + \beta_2 \hat{v}_{1i} + \beta_3 \hat{\omega}_i + \boldsymbol{x}'_i \boldsymbol{\beta} + \varepsilon_i$$

- 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

MixWILD-2.0										_	×
Model Configuration	View Data	He	эlр								
· · · ·		-									
		6	CSV file path:	(Sets\Data	aset_HealthBe	ehavAcad	PerfAffect.cs	v	Change Dataset		
			Title (optional):	MELS to S	stage 2 model						
Da	ataset	6	Does your data contain missing values?	• Yes	○ No						
			What is your missing data coded as?	-99							
		(j)	Stage 1 outcome:	Conti	nuous 🔾 Di	ichotom	ious 🔾 O	rdinal			
Stage 1 I	Model										
		1	Specify random location effects:	Interc	ept only	Interce	pt and slop	oe(s)			
		1	Include estimates of random scale:	Yes	○ No						
Stago 2 I	Model	(j	Include Stage 2 model:	MELS to Stage 2 model Yes 99 Continuous Dichotomous Ordinal Ordinal Intercept only Intercept and slope(s) Yes Yes No Yes No Yes No Import Dataset Single level Multilevel Continuous Dichotomous/Ordinal Count Multinomial							
Image: Constraint of the second se	WOUEI		Include separate Stage 2 data file:	O Yes	No						
				Import Dataset							
		1	Stage 2 model type:	Single	e level 🔍 M	Iultileve	I				
		1	Stage 2 outcome:	 Conti 	nuous 🖲 Di	ichotom	nous/Ordin	al O	Count O Multinomia	I	
		1	Set a seed for Stage 2 resampling (optional):	23041							
					Save Moo	del	Rese	t	Continue		

All as before; click on Configure Stage 2

MixWILD-2.0 odel Configuration Stage 1 Configuration Stage 2 Configuration	figuration View Data H	lelp		
Selected Model Configuration		Stag	e 1 Regressors	
Stage 1 model: Intercept Only State 1 outcome: Continuous		Mean	BS Variance	WS Variance
ID Variable:	Level-1			
ID 🗸	Day_c	V	V	×
Stage 1 Outcome:	Disaggregate?			
PA 🗸				
Configure Stage 1 Regressors	Level-2	Mean	BS Variance	WS Variance
Options	Level-z			
Specify the relationship between the mean and WS variance.			Ľ	3
○ No Association				
Linear Association				
○ Quadratic Association		Save Model	Clear Stage 1	Configure Stage 2

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

🔬 MixWILD-2.0							
Model Configuration	Stage 1 Configuration	Stage 2 Configuration	View Data	Help			
Selected	Model Configuration				Stage 2 Int	eractions	
Stage 1 o	odel: Intercept Only utcome: Continuous odel type: Single-level	⊢ Leve		ain Effects	Random Locat	tion Random Sca	le Location X Scale
Stage 2 o	utcome: Dichot/Ord f resamples (stage 2): 500						
Stage 2 Exam	Outcome:	•	Ma	ain Effects	Random Locat	tion Random Sca	le Location X Scale
Confi	gure Stage 2 Regresso	rs	1-2				
Ch	eck outcome categorie	S					
		🗆 SI	ippress 2-wa	y Location	X Scale Interactio	n	

Click on Proceed

MixWILD-2.0									— [
del Configuration	Stage 1 Configuration	Stage 2 Configuration	Stage 1 Results	Stage 2 Results	View Model	View Da	ta Help)		
Results fr	om stage 1 analysis	🛓 Definition File Preview	N			- 0	×			
		MELS to Stage 2 mode								
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		0 0 23041 2 0 0)							
		1 8								
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		Day_c								
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		0 0 0 0								
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		0.0 1.0								
		11								
		Exam								
			Proceed	Save Def	File					

After completing Stage 1, it performs 500 logistic regressions

odel Configuration	Stage 1 Configuration	Stage 2 Configuration	Stage 1 Results	Stage 2 Results	View Model	View Data	Help	
		실 Please wait			_	- 🗆	X	
Results fr	om stage 1 analysis	MIXWILD: Newton-kapn						
		-	prrection and der	-	.1300			
				0.2390096754538	7086			
			kelihood = 61		,			
		MIXWILD: Newton-Raph			.0000			
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				6.085865834079	2182E-002			
				98.95344				
		MIXWILD: Newton-Raph		14 with ridge 0	.0000			
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		MIXWILD: 1.7922	627882764002E-007	8.482198064818	6468E-006			
		MIXWILD: -2 Log-Li	kelihood = 61	98.95344				
		MIXWILD: maximum c	orrection and der	ivative				
		MIXWILD: 8.7061	951016809379E-008	4.460480359069	7628E-006			
		MIXWILD: -2 Log-Li	kelihood = 61	98.95344				
		MIXWILD:mixREGLS_bot						
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			le(s) copied.					
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		MIXWILD: 110						
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						Cancel Analysi	IS	

Stage 2 Results: descriptive statistics

Configuration	Stage 1 Configuration	Stage 2	Configuration	Stage 1 Re	esults	Stage 2 Results	View Model	View Data	Help		
Results fro	om stage 2 analysis										
Level 2	units = 72							^			
Descript											
	ies of the Dependent Va				_						
Categor	y Frequency	7	Proportion								
0.0			0.52778 0.47222								
1.0	0 34.00		0.47222								
Random	Location and Scale EB m	mean estim mean	min	max	std der	7					
			-1.7555		0.992						
Locat_1 Scale			-3.3078		0.938						
Locat_1	*Scale -	0.0131	-5.3343	2.3261	1.073	L					
There a	re 0 subjects	with une	stimable rando	om effect va	alues						
Number	of replications =	500									
Final Re											
	Log Likelihood		47.107 (sd=	1.038)							
	s Information Criterior		51.107								
Schwarz	's Bayesian Criterion	= -	55.660					–			
L											
						Save	Results As				

Stage 2 Results: no significant effects on exam success

C	Stars & Cas Barry 1	Change 2 Campions it	Channeld D	Change 2 Day 11	Maria Maria 1	Manu Dat	U.J.	
figuration	Stage 1 Configuration	Stage 2 Configuration	Stage 1 Result	s Stage 2 Results	View Model	View Data	Help	
Results fro	om stage 2 analysis							
Locat_1		0.0146 -1.7555		.9921				
Scale Locat 1		-0.0000 -3.3078 -0.0131 -5.3343		.9385 .0731				
There as	re 0 subject	s with unestimable rand	dom effect value:	5				
Number (of replications =	500						
Final Res								
	Log Likelihood	= -47.107 (sd=	1.038)					
Akaike'	s Information Criteric	n = -51.107						
Schwarz	's Bayesian Criterion	= -55.660						
==> mult	tiplied by -2							
Log Like		= 94.214						
	s Information Criteric 's Bayesian Criterion					=		
	-							
Variable	Estima	te AsymStdError	z-value	p-value				
Intercept Locat 1	t -0.121 0.008		-0.48739 0.02798	0.62599 0.97768				
Scale_1	0.325	21 0.32502	1.00059	0.31702				
Locat_1*	ScaleD -0.544	75 0.34826	-1.56420	0.11777				
P .						-		
				Save	Results As			

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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).

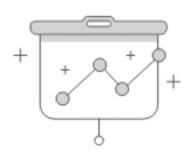
What can MixWILD do

- 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

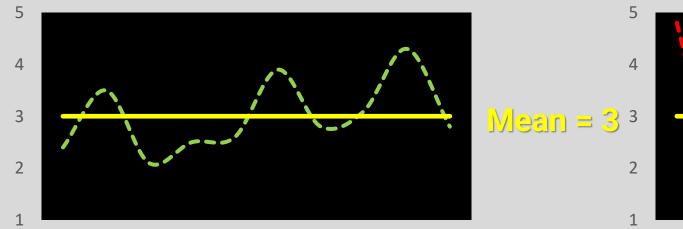
Novel Statistical Models for EMA Studies of Physical Activity 1R01HL121330 & R01CA240713 (Dunton and Hedeker, PIs)

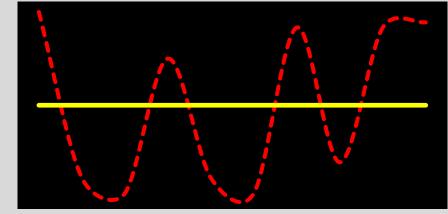
MixWILD is a handy and free standalone application to run Mixed-effects location and scale models.

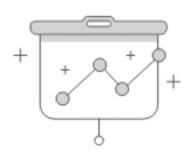




Subject B





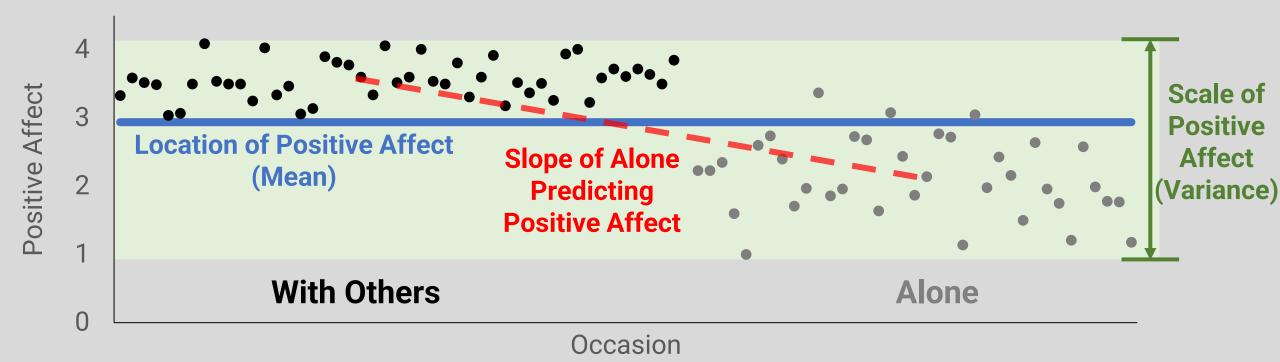


Novel Stat Project

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

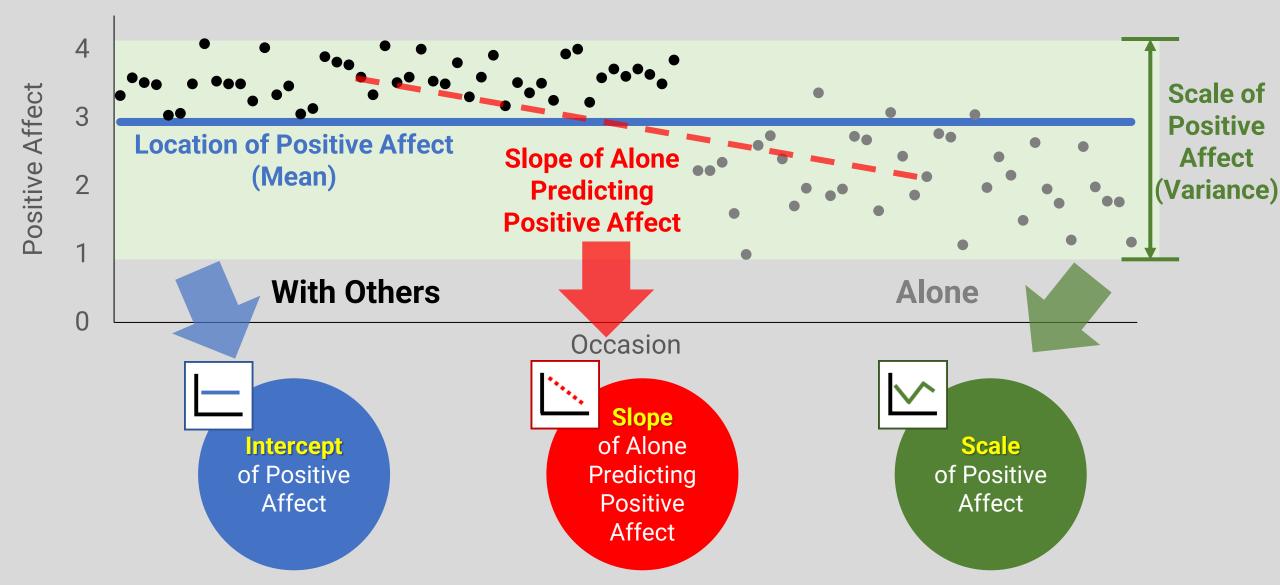
MixWILD (Stage 1 Model)

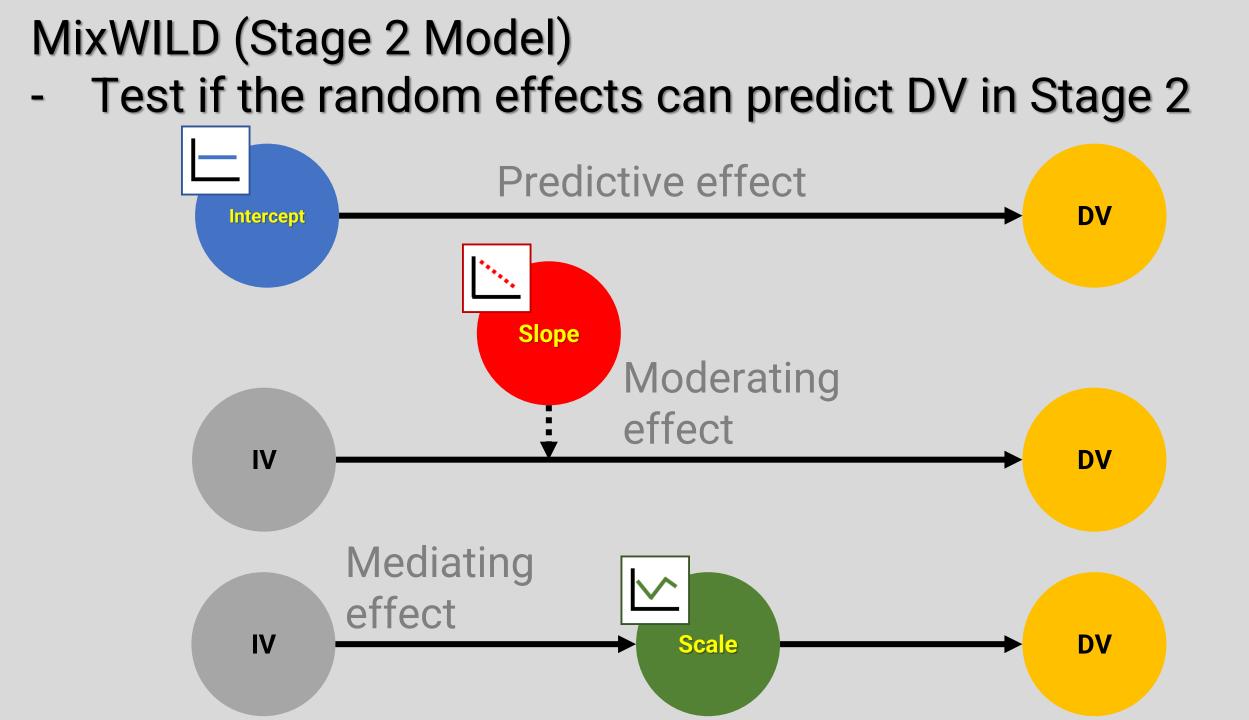
- Go above and beyond the effects of mean!



MixWILD (Stage 2 Model)

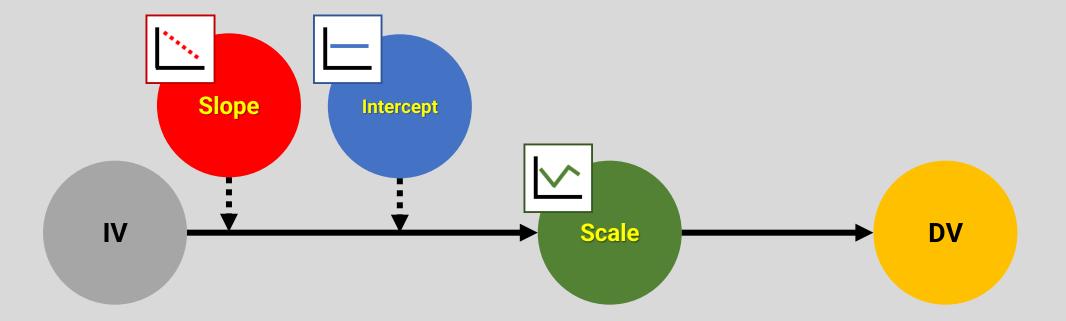
- Extract the estimated random effects as regressors.





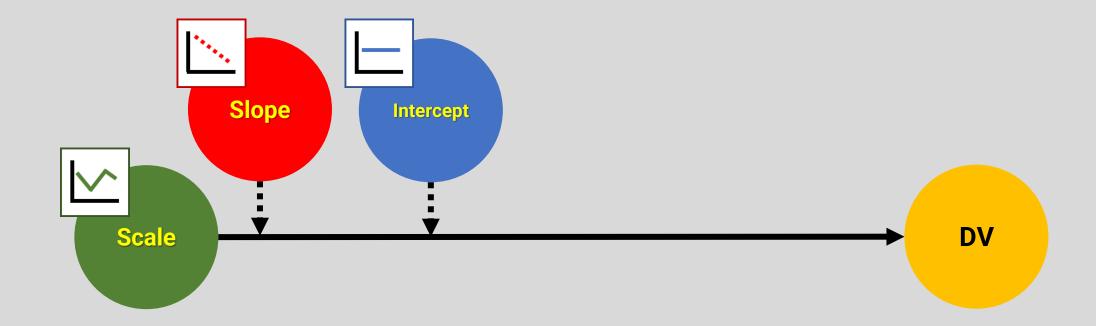
MixWILD (Stage 2 Model)

 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

🛓 MixWILD-2.0					_	×
Model Configuration	View Data	Hel	p			
Da	ataset	1	CSV file path: Title (optional): Does your data contain missing values? What is your missing data coded as?	s\MixWILD\SBM_MixWILD_Example_Data.csv example Yes ONo -99		
Stage 1 I	Model	1	Stage 1 outcome: Stage 1 regression type: Specify random location effects: Include estimates of random scale:	 Continuous Dichotomous Ordinal Probit Logistic Intercept only Intercept and slope(s) Yes No 		
Stage 2 I	Model	١	Include Stage 2 model:	○ Yes ○ No		
	-			Save Model Reset		

Open a new .CSV file Load the file from your local address. Folder name CANNOT have any blank SPACES

🛓 MixWILD-2.0					_	×
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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

🛃 MixWILD-2.0			_	×
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Stage 2 Model	Include Stage 2 model:	⊖ Yes ⊖ No		
		Save Model Reset		

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**.

🛓 MixWILD-2.0			-	
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	Specify random location effects:	● Intercept only ○ Intercept and slope(s)		
	Include estimates of random scale:	● Yes O No		
Stage 2 Model	① Include Stage 2 model:	⊖ Yes ⊖ No		
		Save Model Reset		

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).

🛓 MixWILD-2.0					_		×	
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		i	Include estimates of random scale:	● Yes 🔾 No				
Stage 2	Model	1	Include Stage 2 model:	⊖ Yes ⊖ No				
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Select random scale Select "Yes" if the model includes random subject scale (allowing subjects to have individual withinsubject variance effects); otherwise "No".

MixWILD-2.0			-	×
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Stage 2 Model	① Include Stage 2 model:	⊖ Yes ⊃ No		
		Save Model Reset		

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.

🛓 MixWILD-2.0					_	Х
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D.	alasel	(Does your data contain missing values?	● Yes O No		
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		1	Stage 1 outcome:	○ Continuous ○ Dichotomous ⑧ Ordinal		
Stage 1 I	Model		Stage 1 regression type:	O Probit		
	1	Specify random location effects:	● Intercept only ○ Intercept and slope(s)			
		(Include estimates of random scale:	● Yes 🔘 No		
Stage 2 I	Model -	(i)	Include Stage 2 model:	◉Yes ⊖No		
Stage 21	Nodel		Include separate Stage 2 data file:	⊖ Yes		
			Stage 2 CSV file path:	Import Dataset		
		(Stage 2 model type:	○ Single level		
		()	Stage 2 outcome:	${\small \textcircled{\sc opt}}$ ${\small \textcircled{\sc opt}}$ Continuous \bigcirc Dichotomous/Ordinal \bigcirc Count \bigcirc Multinomial		
		1	Set a seed for Stage 2 resampling (optional):	777		
				Save Model Reset Continue		

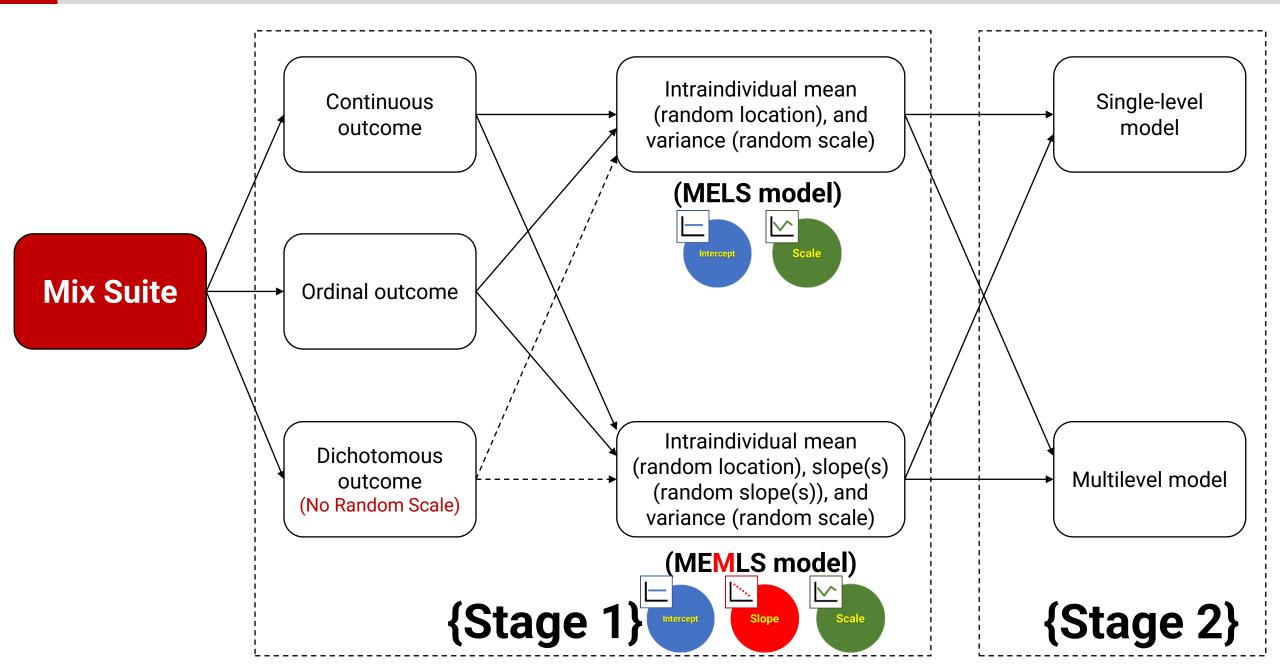
Select stage 2 model The stage-2 outcome can be single- or multilevel.

Select stage 2 outcome

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

🕌 MixWILD-2.0					_		×			
Model Configuration	View Data	Help	p							
Di	ataset	() ()	CSV file path: Title (optional): Does your data contain missing values? What is your missing data coded as?	s:WixWILD\SBM_MixWILD_Example_Data.csv Change Dataset example Yes O No -99						
Stage 1 I	Model	(j) (Stage 1 outcome: Stage 1 regression type: Specify random location effects: Include estimates of random scale:	ession type: Probit Logistic om location effects: Intercept only Intercept and slope(s) 						
Stage 2	Model	1	Include Stage 2 model: Include separate Stage 2 data file: Stage 2 CSV file path:	Yes No Yes No Import Dataset						
		()	Stage 2 model type: Stage 2 outcome: Set a seed for Stage 2 resampling (optional):	 Single level Multilevel Continuous Dichotomous/Ordinal Count Multinomial 						
				Save Model Reset Continue						

Basic Settings



Exercise







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
\mathbf{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: <u>https://dataverse.harvard.edu/dataverse/harvard</u> "How health behaviors relate to academic performance via aect: An intensive longitudinal study" by Flueckiger L, Lieb R, Meyer AH, Mata J

{Stage 1 Model}

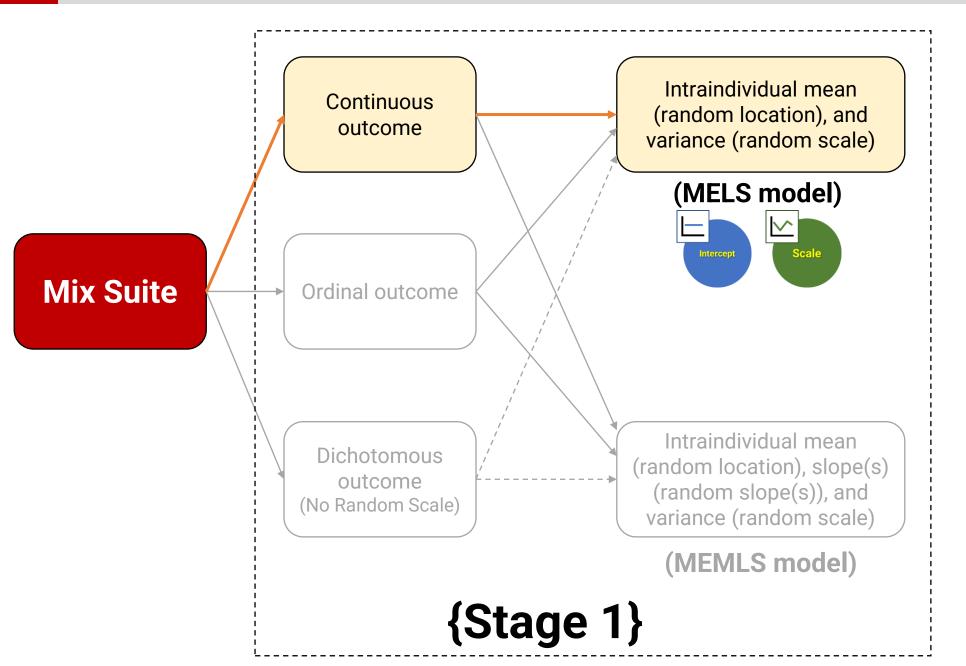
Does the number of days in the study influence one's positive affect (PA)?



{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?



MixWILD-2.0	_		×
Model Configuration Help			
	WILD}		
Mixed Model Analysis	With Longitudinal Data		
	() Or un		
Start with New COV File	Se Open	×	
Start with New CSV File		D	
	SBM_MixWILD_Example_Data.csv		
	File Name: SBM_MixWILD_Example_Data.csv		
	Files of <u>Type</u> : Data files	-	
	Open Cance	ei	
		-	

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

🛓 MixWILD-2.0					_	×
Model Configuration	View Data	Help	ס			
		i	CSV file path:	:s\MixWILD\SBM_MixWILD_Example_Data.csv Change Dataset		
D	ataset		Title (optional):	exercise1		
-		6	Does your data contain missing values?	● Yes O No		
			What is your missing data coded as?	-99		
	-	()	Stage 1 outcome:	Continuous Dichotomous Ordinal		
Stage 1	Model					
		1	Specify random location effects:	Intercept only ○ Intercept and slope(s)		
		i	Include estimates of random scale:	● Yes ○ No		
	-	()	Include Stage 2 model:	⊖ Yes		
	-					
				Save Model Reset Continue		

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

🛓 MixWILD-2.0							_	×
Model Configuration View Da	a He	lp						
Dataset	(i) (i)	CSV file path: Title (optional): Does your data contain missing values?	sWixWII exercise		ample_Data.csv	Change Dataset		
Stage 1 Model		What is your missing data coded as? Stage 1 outcome:	-99	tinuous 🔾 Dichoto	omous 🔾 Ordin	lal		
	6	Specify random location effects:	Inter	rcept only 🔘 Interd	cept and slope(s	;)		
	6	Include estimates of random scale:	Yes	⊖ No				
	③ Include Stage 2 model: ○ Yes ● No							
				Save Model	Reset	Continue		

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

🛓 MixWILD-2.0				_	×
Model Configuration	View Data	Hel	p		
D	ataset		CSV file path: Title (optional): Does your data contain missing values?	:s\MixWILD\SBM_MixWILD_Example_Data.csv Change Dataset exercise1 • Yes • No	
			What is your missing data coded as?	-99	
Stage 1	Model	1	Stage 1 outcome:	Continuous O Dichotomous O Ordinal	
		1	Specify random location effects:	Intercept only	
		1	Include estimates of random scale:	● Yes ○ No	
		()	Include Stage 2 model:	⊖ Yes	
	-			Save Model Reset Continue	

Select "Continue" to enter the next page

el Configuration	Stage 1 Co	nfiguration	View Data	Help									
Imported	data file:	SBM_MixV	VILD_Exampl	e_Data.cs	v								
ID	Day_C	Sex_F	Age_C	Sem	Exam	HSG	HSG_Rank	BDI	SQ	PhysAct	PhysAct_L		
1	-2.21	1		2	1	4.6	12	2	3	30	3.4		
1	-2.07	1	-1	2	1	4.6		2	3	60	4.09	=	
1	-1.93	1	-1	2	1	4.6	12	2	3	360	5.89		
1	-1.79	1		2	1	4.6	12	2	3	780	6.66		
1	-1.5	1		2	1	4.6	12	2	3	210	5.35		
1	-1.21	1		2	1	4.6	12	2	3	310	5.74		
1	-1.07	1		2	1	4.6	12	2	3	90	4.5		
1	-0.93	1		2	1	4.6	12	2	3	405	6		
1	-0.79	1		2	1	4.6	12	2	3	405	6		
1	-0.64	1		2	1	4.6	12	2	3	360	5.89		
1	-0.5	1		2	1	4.6	12	2	3	270	5.6		
1	-0.36	1		2	1	4.6	12	2	3	30	3.4		
1	-0.21	1		2	1	4.6	12	2	3	540	6.29		
1	0.07	1		2	1	4.6		2	2	405	6		
1	0.21	1		2	1	4.6	12	2	3	405	6		
1	0.36	1		2	1	4.6	12	2	3	540	6.29		
1	0.64	1		2	1	4.6		2	3	60	4.09		
1	0.79	1		2	1	4.6	12	2	3	405	6		
1	0.93	1		2	1	4.6	12	2	3	405	6		
1	1.07	1		2	1	4.6		2	2	60	4.09		
1	1.21	1		2	1	4.6	12	2	3	405	6		
1	1.36	1		2	1	4.6	12	2	3	330	5.8		
1	1.5	1		2	1	4.6		2	3	435	6.08		
1	1.79 1.93	1		2	1	4.6 4.6	12 12	2	3	525 270	6.26 5.6		
1	2.07	1		2	1	4.0	12	2	3	405	5.0 6		
1	2.07	1		2	1	4.0	12	2		390	5.97		
2	-2.21	1	-	2	0	4.0	12	2	2	190	5.25		
	-2.21	1		2	0	4.9	10	4	3	190	E 07	-	
4											•		

Review your data in "View Data" page

MixWILD-2.0		- 🗆 X
Model Configuration Stage 1 Configuration View Data H	elp	
Selected Model Configuration Stage 1 model: Intercept Only State 1 outcome: Continuous	Stag Add Stage 1 Regressors	ge 1 Regressors — 🗆 🗙
ID Variable:	Variables	Level-1 (Time Varying)
	Sex_F Age_C	Day_C
Stage 1 Outcome:	Sem Exam HSG	Add Remove
Configure Stage 1 Regressors	HSG_Rank BDI SQ	
Options	PhysAct PhysAct_LN PA_D PA_Ord	Level-2 (Time Invariant)
Specify the relationship between the mean and WS variance.	NA_D NA_Mean	Add
O No Association		Remove
Inear Association		
 Quadratic Association 		Cancel Reset Submit

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

WILD-2.0							
Configuration Stage 1 Co	nfiguration	View Data	Help				
Selected Model Configur Stage 1 model: Intercep					Stage	e 1 Regressors	
State 1 outcome: Contin				Level-1	Mean	BS Variance	WS Variance
ID Variable:							
ID		-		Day_C	V	V	V
Stage 1 Outcome:				Disaggregate?			
PA		-					
Configure Stage 1	l Regressor	rs		Level-2	Mean	BS Variance	WS Variance
Option	ıs						
Specify the relation mean and WS variar		en the					
 No Association 							
Linear Association							

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

🕌 MixWILD-2.0							
Model Configuration	Stage 1 Configuration	View Data	Help				
	Model Configuration nodel: Intercept Only				Stag	e 1 Regressors	
	itcome: Continuous			Level-1	Mean	BS Variance	WS Variance
ID Varia	ble:						
ID		-		Day_C	×	M	R
Stage 1	Outcome:			Disaggregate?	?		
PA		-		L			
Confi	gure Stage 1 Regressor	rs		Level-2	Mean	BS Variance	WS Variance
	Options						
	the relationship between the relationship between the second second second second second second second second s	en the					
◯ No A	ssociation						
Linea	ar Association						
O Quad	Iratic Association				Save Model	Clear Stage 1	Run Stage 1

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

MixWILD-2.0	Stage 1 Configuration	View Data	Help					_	×
Selected	Model Configuration	The Pula	noip		Stag	e 1 Regressors			
	odel: Intercept Only tcome: Continuous			1	Mean	BS Variance	WS Variance		
ID Variat	ble:			Level-1					
ID		-		Day_C	V	V	V		
Stage 1 (Outcome:			Disaggregate?	?				
PA		•							
Config	gure Stage 1 Regressor	′s		Level-2	Mean	BS Variance	WS Variance	٦	
	Options								
	the relationship betwee d WS variance.	en the							
🔾 No As	sociation								
Linea	r Association							_	
🔾 Quad	ratic Association				Save Model	Clear Stage 1	Run Stage 1		

Click on "Run Stage 1"

🛓 MixWILD-2.0							_	×
Model Configuration	Stage 1 Configuration	Stage 1 Results	View Model	View Data	Help			
Results fr	om stage 1 analysis							
Def	inition File Preview			— C	× נ			
SBM_MixW SBM_MixW	with MixWILD GUI ILD_Example_Data.dat ILD_Example_Data_Output 1 0 0 0 0 0 0 1.0F	-5 11 1 200 -99	0 1 0.15 0	0 0 500 0	0 0 0 0			
PA Day_C Day_C Day_C		Proceed S	ave Def File					
		roceed				▼ Save Results As		

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

🛓 MixWILD-2.0									_	\times
Model Configuration	Stage 1 Configuration	Stage 1 Results	View Model	View Data	Help					
Results fro	om stage 1 analysis							1		
	_both: Mixed-effects Lo	cation Scale Mode	1							
mixREGLS	_both.DEF specification	s					=			
Created	with MixWILD GUI									
SBM_Mix1	d output files: WILD_Example_Data.dat WILD_Example_Data_Outpu	t_stagel.out								
SCALE E CONVERG	E LOCATION EFFECTS = F FFECT = T ENCE CRITERION = 0.000									
NQ QUADRAT	= 0.1500 = 11 URE = 1 (0=non-adapt = 200	ive, l=adaptive)								
Descript:	ives									
Number (of level-l observations	= 2109								
Number	of level-2 clusters	= 72								
	of level-1 observations 32 32 32 32 32	for each level-2 31 31 3		20 32	32		•			
						Save Results As				

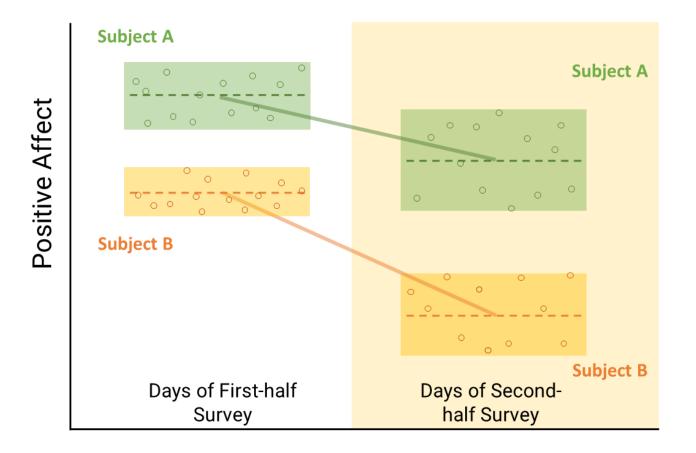
Check the Stage 1 Results

Variable	Estimate	AsymStdError	z-value	p-value
BETA (regression coe	fficients)			
intercept	4.13072	0.14192	29.10578	0.00000
Day_C	-0.10383	0.01829	-5.67717	0.00000
ALPHA (BS variance p	arameters: 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 par	ameters: log-l	inear model)		
intercept	-0.09010	0.10237	-0.88010	0.37881
Day_C	0.13547	0.02616	5.17843	0.00000
Random scale standar	d deviation			
Std Dev	0.73612	0.07047	10.44548	0.00000
Random location (mea	n) effect on W	S 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.

(Mean model) Does positive affect change across days?

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

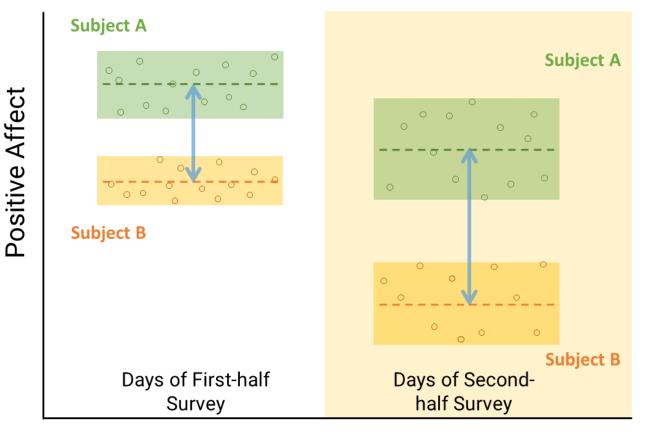


Variable	Estimate	AsymStdError	z-value	p-value
BETA (regression co	efficients)			
intercept	4.13072	0.14192	29.10578	0.00000
Day_C	-0.10383	0.01829	-5.67717	0.00000
ALPHA (BS variance	parameters: log	-linear model)		
intercept	0.33320	0.17051	1.95409	0.05069
Day_C	0.11952	0.01981	6.03246	0.00000
TAU (WS variance pa	rameters: log-l	inear model)		
intercept	-0.09010	0.10237	-0.88010	0.37881
Day_C	0.13547	0.02616	5.17843	0.00000
Random scale standa	rd deviation			
Std Dev	0.73612	0.07047	10.44548	0.00000
Random location (me	an) effect on W	S 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.

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

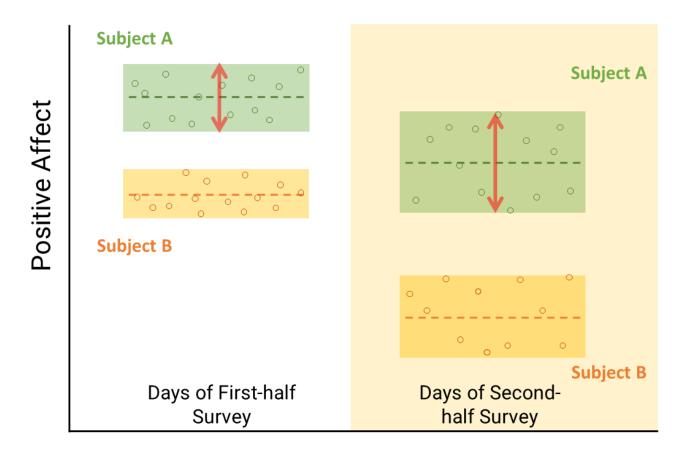
– The effect of Day_C is positive and significant, and it indicates that subjects become more heterogeneous over time.



Variable	Estimate	AsymStdError	z-value	p-value
BETA (regression coe	efficients)			
intercept	4.13072	0.14192	29.10578	0.00000
Day_C	-0.10383	0.01829	-5.67717	0.00000
ALPHA (BS variance p	arameters: 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 par	rameters: log-l	inear model)		
intercept	-0.09010	0.10237	-0.88010	0.37881
Day_C	0.13547	0.02616	5.17843	0.00000
Random scale standar	rd deviation			
Std Dev	0.73612	0.07047	10.44548	0.00000
Random location (mea	an) effect on W	S variance		
Loc Eff	-0.36756	0.09955	-3.69233	0.00022

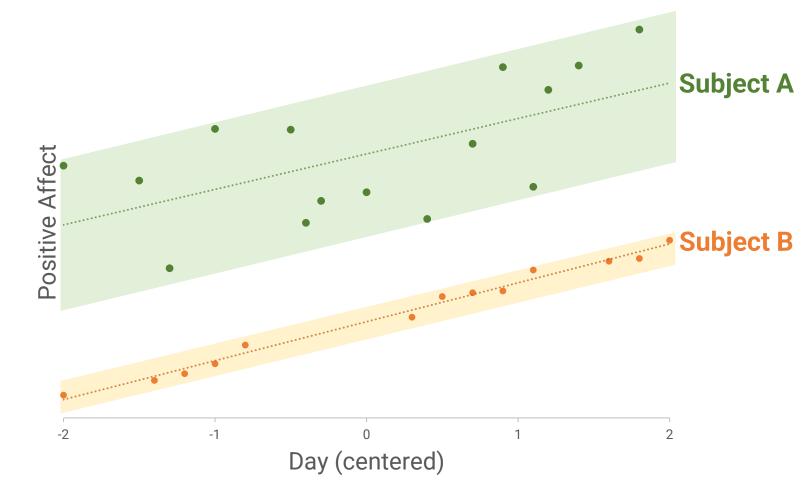
WS variance model (TAU): the effect of Day_C is positive and significant (tau = 0.13547; p < 0.001). The exponentiated slope is 1.14507. From the estimate of 1.15, we can conclude that the WS variance increases by a factor of 15% per week; thus, subjects exhibit more erraticism (less consistency) over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

(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.



Variable	Estimate	AsymStdError	z-value	p-value
BETA (regression co	pefficients)			
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 pa	arameters: log-l	inear model)		
intercept	-0.09010	0.10237	-0.88010	0.37881
Day_C	0.13547	0.02616	5.17843	0.00000
Random scale standa	ard deviation			
Std Dev	0.73612	0.07047	10.44548	0.00000
Random location (me	ean) effect on W	S variance		
Loc Eff	-0.36756	0.09955	-3.69233	0.00022

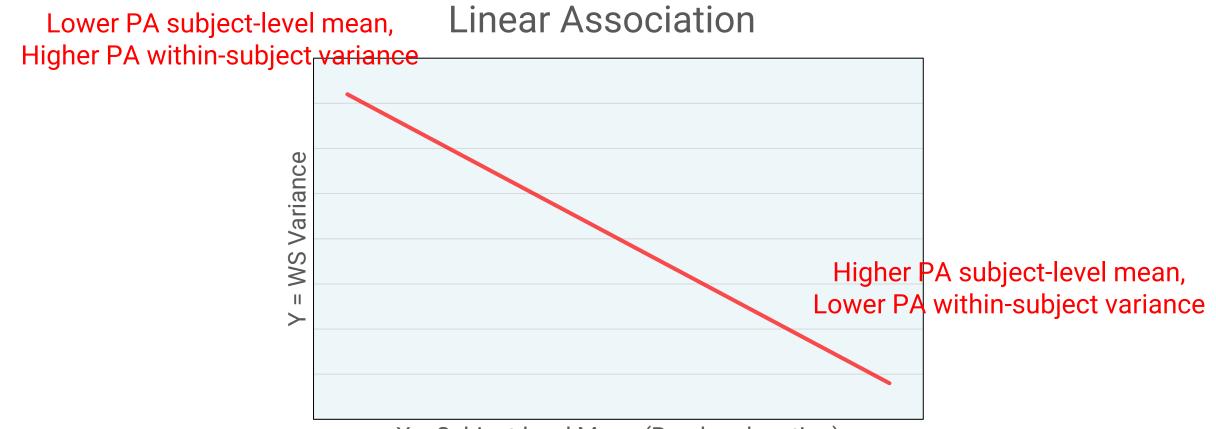
The standard deviation of the random scale effect is estimated to be 0.73614, and this is a highly significant effect. Thus, subjects vary considerably in terms of how consistent/erratic they are in their PA reports.



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.

Variable	Estimate	AsymStdError	z-value	p-value
DETA (nognoscion c				
BETA (regression c				
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 p	arameters: log-l	inear model)		
intercept	-0.09010	0.10237	-0.88010	0.37881
Day_C	0.13547	0.02616	5.17843	0.00000
Random scale stand	ard deviation			
Std Dev	0.73612	0.07047	10.44548	0.00000
Random location (m	ean) effect on W	S 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).



X = Subject-level Mean (Random location)

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)

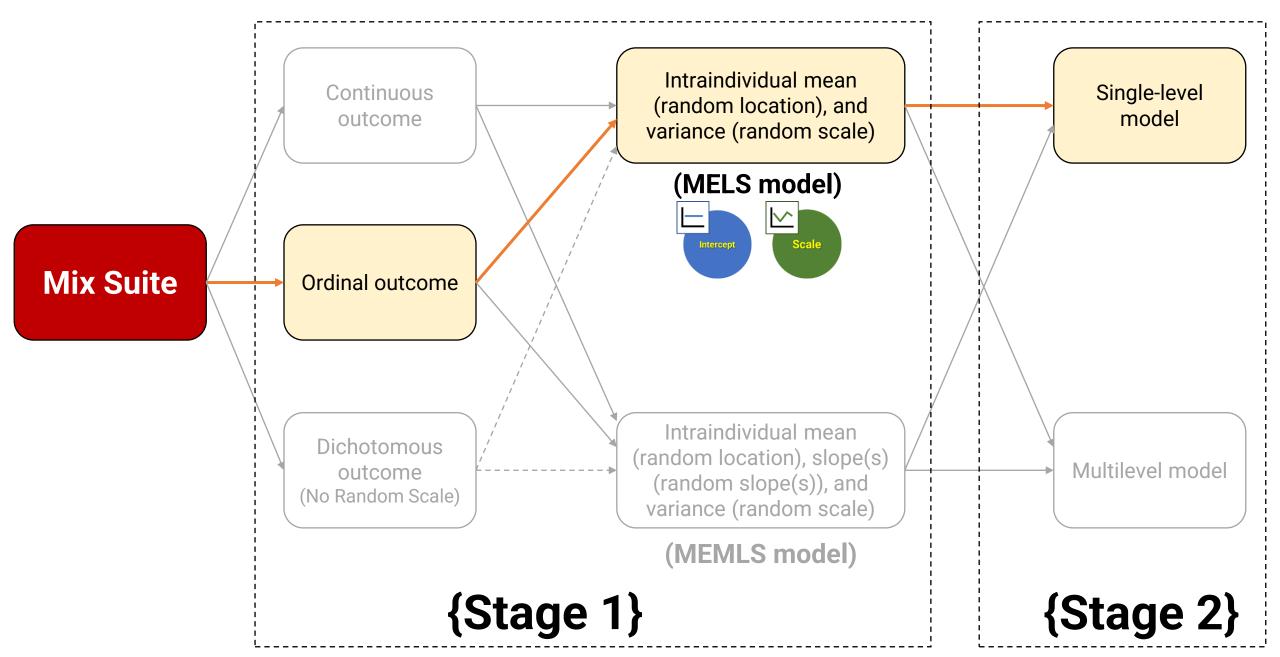
{Stage 1 Model}

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?

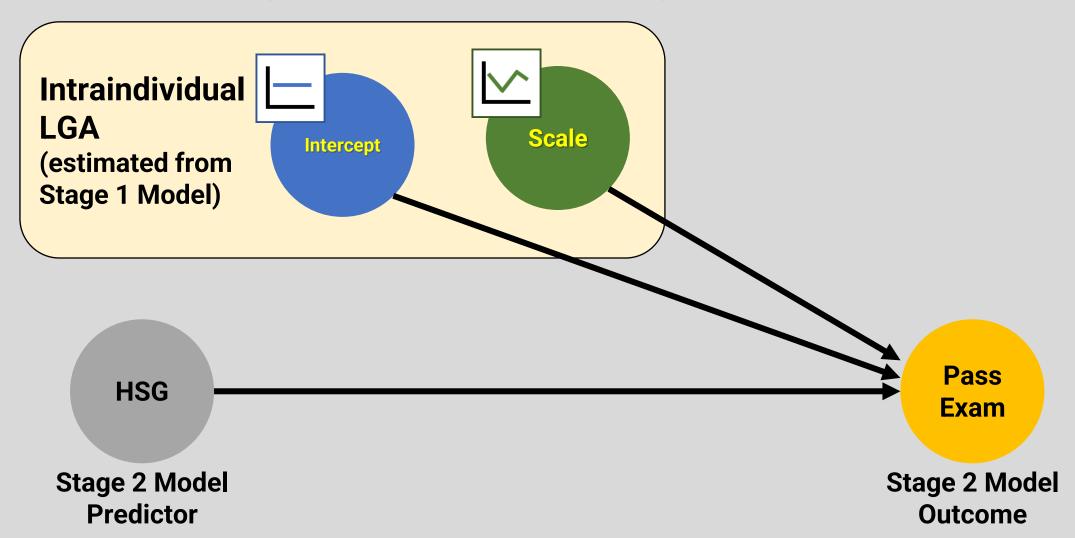
{Stage 2 Model}

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



MixWILD (Stage 2 Model)

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



Research Question 2 (Q2)

MixWILD-2.0	- D X
Model Configuration Help	
MIX{	
IVIIA	
Mixed Model Analysis	With Longitudinal Data
	Sopen X
Start with New CSV File	Look In: Data
	File Name: SBM_MixWILD_Example_Data.csv
	Files of Type: Data files
	Open Cancel

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)?

🕌 MixWILD-2.0				_	×
Model Configuration	View Data	Help	p		
		(i)	CSV file path:	:s\MixWILD\SBM_MixWILD_Example_Data.csv Change Dataset	
			Title (optional):	exercise2	
Data	aset	1	Does your data contain missing values?	● Yes ◯ No	
			What is your missing data coded as?	-99	
	_	()	Stage 1 outcome:	⊖ Continuous ⊖ Dichotomous	
Stage 1 Mo	odel		Stage 1 regression type:	 Probit Logistic 	
		1	Specify random location effects:	● Intercept only ○ Intercept and slope(s)	
		()	Include estimates of random scale:	● Yes ○ No	
Stage 2 M		1	Include Stage 2 model:	● Yes O No	
otage 2 mil	Juci	I	Include separate Stage 2 data file:	⊖ Yes	
			Stage 2 CSV file path:	Import Dataset	
		1	Stage 2 model type:	Single level Multilevel	
		1	Stage 2 outcome:	○ Continuous	
		1	Set a seed for Stage 2 resampling (optional):	777	
	_			Save Model Reset Continue	

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

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

🕌 MixWILD-2.0				_	×
Model Configuration View Data	He	lp			
	()	CSV file path:	s\MixWILD\SBM_MixWILD_Example_Data.csv Change Dataset		
		Title (optional):	exercise2		
Dataset	1	Does your data contain missing values?	● Yes 🔾 No		
		What is your missing data coded as?	-99		
	()	Stage 1 outcome:	○ Continuous ○ Dichotomous ● Ordinal		
Stage 1 Model	_	Stage 1 regression type:	O Probit		
	1	Specify random location effects:	Intercept only		
	1	Include estimates of random scale:	● Yes ○ No		
Stage 2 Model	()	Include Stage 2 model:	● Yes O No		
		Include separate Stage 2 data file:	⊖ Yes ⑧ No		
		Stage 2 CSV file path:	Import Dataset		
	1	Stage 2 model type:	Single level Multilevel		
	1	Stage 2 outcome:	\bigcirc Continuous \circledast Dichotomous/Ordinal \bigcirc Count \bigcirc Multinomial		
	1	Set a seed for Stage 2 resampling (optional):	777		
			Save Model Reset Continue		

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

🛓 MixWILD-2.0				- 🗆 ×
Model Configuration	View Data	He	lp	
		()	CSV file path:	:s\MixWILD\SBM_MixWILD_Example_Data.csv Change Dataset
Dat	taset		Title (optional):	exercise2
Dat	user	1	Does your data contain missing values?	● Yes ○ No
			What is your missing data coded as?	-99
		1	Stage 1 outcome:	⊖ Continuous ⊖ Dichotomous ● Ordinal
Stage 1 M	lodel		Stage 1 regression type:	Probit Idit Logistic
		1	Specify random location effects:	Intercept only ○ Intercept and slope(s)
	_	1	Include estimates of random scale:	● Yes ○ No
Stage 2 M	lodel	1	Include Stage 2 model:	● Yes 🔾 No
otage 2 m	louer		Include separate Stage 2 data file:	○ Yes
			Stage 2 CSV file path:	Import Dataset
		1	Stage 2 model type:	Single level Multilevel
		1	Stage 2 outcome:	◯ Continuous
		()	Set a seed for Stage 2 resampling (optional):	777
	-			Save Model Reset Continue

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

🛓 MixWILD-2.0					_	×
Model Configuration	View Data	Hel	p			
		1	CSV file path:	:s\MixWILD\SBM_MixWILD_Example_Data.csv Change Dataset		
D	ataset		Title (optional):	exercise2		
	ataset	()	Does your data contain missing values?	● Yes ○ No		
			What is your missing data coded as?	-99		
	-	()	Stage 1 outcome:	⊖ Continuous ⊖ Dichotomous ● Ordinal		
Stage 1 I	Model		Stage 1 regression type:	Probit Icogistic		
		()	Specify random location effects:	Intercept only		
	1	Include estimates of random scale:	● Yes ○ No			
Stage 2 I	Model	1	Include Stage 2 model:	● Yes O No		
otage 21	liouer		Include separate Stage 2 data file:	○ Yes		
			Stage 2 CSV file path:	Import Dataset		
		1	Stage 2 model type:	Single level Multilevel		
		1	Stage 2 outcome:	○ Continuous		
		1	Set a seed for Stage 2 resampling (optional):	777		
	-			Save Model Reset Continue		

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)?

MixWILD-2.0							_	
del Configuration	Stage 1 Configuration	Stage 2 Configuration	View Data	Help				
	Nodel Configuration			Stag	e 1 Regressors			
	Stage 1 model: Intercept Only State 1 outcome: Ordinal ID Variable:			Mean	BS Variance	WS Variance	-	
ID Variab	le:		Level-1					
ID		-	SQ	V	V	r		
Stage 1 (Dutcome:		Disaggregate	2				
LGA		•						
Config	ure Stage 1 Regressor	·s	Level-2	Mean	BS Variance	WS Variance		
	Options							
	he relationship betwee d WS variance.	en the						
🔾 No As	sociation							
Linear	Association						1	
Quad	ratic Association			Save Model	Clear Stage 1	Configure Stage 2		

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)?

Stage 1 Configuration lodel Configuration odel: Intercept Only	Stage 2 Configuration	View Data	Help			
del: Infercept Only				Stage	e 1 Regressors	
come: Ordinal		Level-1		Mean	BS Variance	WS Variance
le:						
	-	sQ		V	×	×
utcome:		Disaggregate	?			
	-					
ure Stage 1 Regressor	s	Level-2		Mean	BS Variance	WS Variance
Options						
he relationship betwee d WS variance.	en the					
sociation						
Association						
atic Association			Sav	ve Model	Clear Stage 1	Configure Stage 2
	outcome: ure Stage 1 Regressor Options he relationship betwee d WS variance. sociation Association	vutcome: vutco	e: SQ Disaggregate Disaggregate ure Stage 1 Regressors Options he relationship between the d WS variance. sociation Association	e: SQ Disaggregate? Disaggregate? Ure Stage 1 Regressors Options he relationship between the d WS variance. sociation Association	le: SQ P Disaggregate? Disaggregate? Disaggregate? Disaggregate? Disaggregate? Mean Level-2 Mean Level-2 Sociation Association	le: SQ P P P P P P P P P P P P P P P P P P P

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

😹 MixWILD-2.0						-	×
Model Configuration Stage 1 Configuration	Stage 2 Configuration	View Data	Help				
Selected Model Configuration				Stage 2 Inte	eractions		
Stage 1 model: Intercept Only Stage 1 outcome: Ordinal Stage 2 model type: Single-level Stage 2 outcome: Dichot/Ord	Leve		ain Effects	Random Locat	ion Random Scale	Location X Scale	
Number of resamples (stage 2): 500							
Stage 2 Outcome:							
Exam		Ma	ain Effects	Random Locat	ion Random Scale	Location X Scale	
Configure Stage 2 Regressor	s	1-2					
Check outcome categories		6_Rank	V				
2 Categories: 1) 0.0 2) 1.0							
	r su	ippress 2-wa	ay Location X	Scale Interaction	n]	
				Save Model	Clear Stage 2	Run Stage 1 and 2	

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

🛓 MixWILD-2.0						—	×
Model Configuration	Stage 1 Configuration	Stage 2 Configuration Vie	ew Data Help				
Stage 1 mo	lodel Configuration odel: Intercept Only	Add S	tage 2 regressors	Stage 2 Inte		<	
Stage 2 mo Stage 2 ou	tcome: Ordinal odel type: Single-level tcome: Dichot/Ord resamples (stage 2): 500	③ Var Day_C			Level 1 (Time Variant)	cale	
Exam	Dutcome: gure Stage 2 Regressor			Add Remove	Level 2 (Time Invariant)	cale	
Che 2 Categ 1) 0.0 2) 1.0	ories:	PA PA_D PA_Ord NA NA_D NA_D NA_Mea LGA		Add Remove	HSG_Rank		
				Cancel	Reset Submit	12	

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

							_	· 🛛	
Stage 1 Configuration	Stage 2 Configur	ation	View Data	Help					
Nodel Configuration					Stage 2 Int	eractions			
odel: Intercept Only itcome: Ordinal odel type: Single-level		- Level-		ain Effects	Random Locat	tion Random Sca	le Location X Scale	-	
itcome: Dichot/Ord f resamples (stage 2): 500									
Outcome:	-								
gure Stage 2 Regressor	·S	Level-		ain Effects	Random Locat	tion Random Sca	le Location X Scale		
eck outcome categories		HSG	Rank	V					
gories:									
			opress 2-w	ay Location	C Scale Interactio	n			
					Save Model	Clear Stage 2		1	
	Iodel Configuration odel: Intercept Only tcome: Ordinal odel type: Single-level tcome: Dichot/Ord resamples (stage 2): 500 Dutcome: gure Stage 2 Regressor	Model Configuration odel: Intercept Only tcome: Ordinal odel type: Single-level tcome: Dichot/Ord resamples (stage 2): 500	Model Configuration odel: Intercept Only tcome: Ordinal odel type: Single-level tcome: Dichot/Ord resamples (stage 2): 500 Outcome: gure Stage 2 Regressors eck outcome categories pories:	Model Configuration odel: Intercept Only tcome: Ordinal odel type: Single-level tcome: Dichot/Ord iresamples (stage 2): 500 Outcome: Qure Stage 2 Regressors Method eck outcome categories pories:	Model Configuration odel: Intercept Only tcome: Ordinal odel type: Single-level tcome: Dichot/Ord resamples (stage 2): 500 Outcome: Image: Stage 2 Regressors ack outcome categories HSG_Rank	Indel Configuration Stage 2 Int odel: Intercept Only Main Effects tcome: Ordinal Main Effects Controme: Image: Control of the second	Model Configuration Stage 2 Interactions odel: Intercept Only Main Effects tcome: Ordinal Main Effects Coutcome: Level-1 Outcome: Main Effects gure Stage 2 Regressors Main Effects eck outcome categories HSG_Rank	Indel Configuration Stage 2 Interactions odel Configuration Main Effects Main Effects Random Location Random Scale Location X Scale Level-1 Level-1 Level-2 Main Effects Main Effects Random Location Random Scale Location X Scale Level-2 Level-2 HSG_Rank Image: Control of the state of	Indel Configuration odel Lintercept Only tcome: Ordinal odel type: Single-Jevel tcome: Dichot/Ord resamples (stage 2): 500 Dutcome: Image: Dichot/Ord gure Stage 2 Regressors eck outcome categories pories: Image: Dichot/Ord Image: Dichot/Ord

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

🛓 MixWILD-2.0							_	×
Model Configuration	Stage 1 Configuration	Stage 2 Configura	tion View Da	ata Help				
	Nodel Configuration				Stage 2 Interac	ctions		
Stage 1 ou	tcome: Ordinal odel type: Single-level		- Level-1	Main Effects	Random Location	Random Scale	Location X Scale	
Stage 2 ou	tcome: Dichot/Ord resamples (stage 2): 500							
Stage 2 C	Dutcome:	•						
Config	gure Stage 2 Regressor	s	Level-2	Main Effects	Random Location	Random Scale	Location X Scale	
Che	eck outcome categories		HSG_Rank	V				
2 Categ 1) 0.0 2) 1.0	jories:							
			☑ Suppress 2	-way Location	X Scale Interaction			
					Save Model Cle	ar Stage 2 R	Run Stage 1 and 2	

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

🛓 MixWILD-2.0									_	×
Model Configuration	Stage 1 Configuration	Stage 2 Configurat	ion View	Data Help						
	lodel Configuration odel: Intercept Only	_				Stage 2 Inte	eractions		_	
Stage 1 ou Stage 2 mo Stage 2 ou	tcome: Ordinal odel type: Single-level tcome: Dichot/Ord resamples (stage 2): 500		Level-1	Main Eff	ects	Random Locati	on Random Sc	ale Location X Scale	e]	
Stage 2 (Exam	Dutcome:	-		Main Eff	ects	Random Locati	on Random Sc	ale Location X Scale	e	
Config	jure Stage 2 Regressor	's	Level-2						Г	
Che	ck outcome categories	;	HSG_Rank		V					
2 Categ 1) 0.0 2) 1.0	ories:		_						-	
		Į.	Suppress	s 2-way Loca	ation X S	Scale Interaction			-	
					Si	ave Model	Clear Stage 2	Run Stage 1 and 2		

Run Stage 1 and 2

😹 MixWILD-2.0			- 🗆 X
Model Configuration	Stage 1 Configuration	▲ Please wait	
Model Configuration	Stage 1 Configuration om stage 1 analysis	Please wait With the set of the set	
		Cancel Analysis	

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 coefficien	ts)			
SQ	0.22590	0.05959	3.79082	0.00015
ALPHA (BS variance paramete	rs: 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 mo	del)		
sQ	-0.03627	0.03271	-1.10881	0.26751
Thresholds (for identificat	ion)			
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 (lo	g-linear model)		
Linear		0.05563	1.82469	0.06805
Random scale standard devia	tion			
Std Dev		0.03770	8.29837	0.00000
nodel (BETA): the slope	e of sleep qua	ality (SQ) is pos	sitive and signif	ficant (beta

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.

Number of replication	s =	500		
Final Results				
			>	
Average Log Likelihoo		-42.094 (sd:	= 0.762)	
Akaike's Information	Criterion =	-46.094		
Schwarz's Bayesian Cr	iterion =	-50.647		
==> multiplied by -2 Log Likelihood Akaike's Information Schwarz's Bayesian Cr		92.188		
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 $1.19 \text{ times } (\exp(0.17185) = 1.19).$

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

Number of replicatio	ns = 5	500		
Final Results				
Average Log Likeliho Akaike's Information Schwarz's Bayesian C	Criterion =	-46.094	0.762)	
==> multiplied by -2 Log Likelihood Akaike's Information Schwarz's Bayesian C	= Criterion =			
Variable	Estimate	AsymStdError	z-value	p-value
Intercept HSG Rank	-2.33488 0.17185	0.91741 0.06764	-2.54509 2.54081	0.01092 0.01106
Locat_1 Scale_1	0.65342 0.01781	0.31175 0.31544	2.09596 0.05646	0.03609 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		,	
Schwarz's Bayesian Criterion	= -50.647		
==> multiplied by -2			
	= 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)?

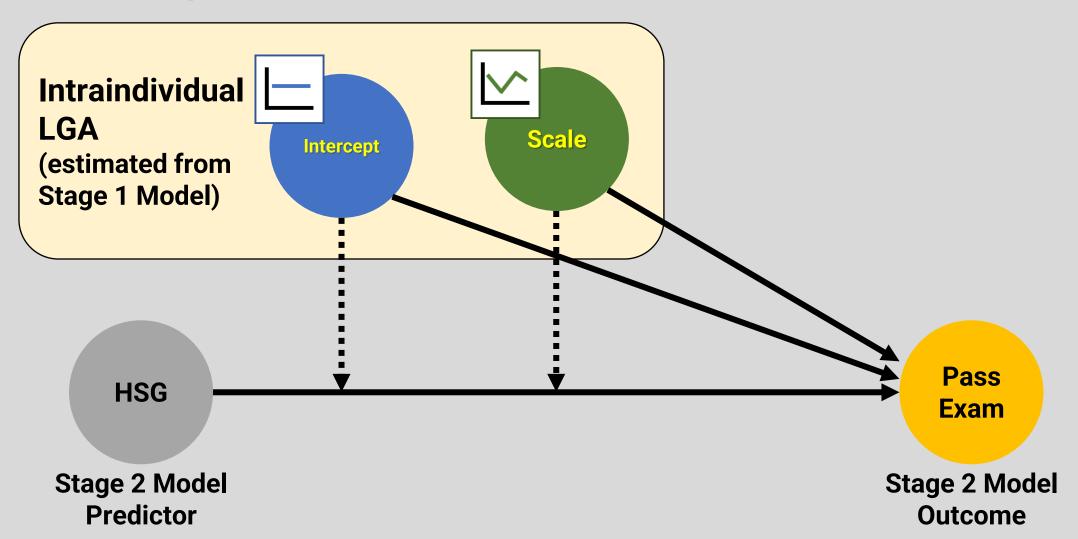
- (Mean model) Does a subject have a higher LGA on days with higher SQ?
- (BSV model) Does the sample become more homogeneous in LGA on days with higher SQ?
- (WSV model) Does a subject's LGA become more consistent on days with higher SQ?

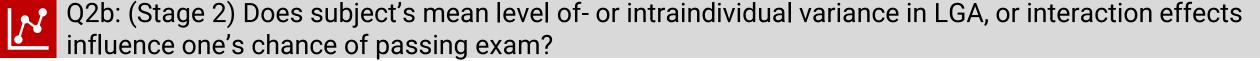
{Stage 2 Model}

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





🛓 MixWILD-2.0							_		\times
Model Configuration	Stage 1 Configuration	Stage 2 Configuration	on View Data	Help					
	lodel Configuration				Stage 2 In	teractions		-	
Stage 1 ou Stage 2 mo	odel: Intercept Only tcome: Ordinal odel type: Single-level	ſĹ	evel-1	ain Effects	Random Loca	ation Random Scal	e Location X Scale		
	tcome: Dichot/Ord resamples (stage 2): 500								
Stage 2 (Exam	Dutcome:								
Exam		•	M	ain Effects	Random Loca	ation Random Scal	e Location X Scale		
Config	jure Stage 2 Regressor	's	.evel-2						
Che	ck outcome categories		HSG_Rank	×	×.	V			
2 Categ 1) 0.0 2) 1.0	ories:								
] Suppress 2-wa	ay Location X	Scale Interactio	on			
				S	ave Model	Clear Stage 2	Run Stage 1 and 2		
								1	

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 replicat:	ions =	500		
Final Results				
Average Log Likeli	hood =	-41.213 (sd=	1.042)	
Akaike's Informatio	on Criterion =	-48.213		
Schwarz's Bayesian	Criterion =	-56.181		
==> multiplied by	-2			
Log Likelihood	=			
Akaike's Informatio				
Schwarz's Bayesian	Criterion =	112.362		
Variable	Estimate	AsymStdError	7-value	n-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

{Stage 1 Model}

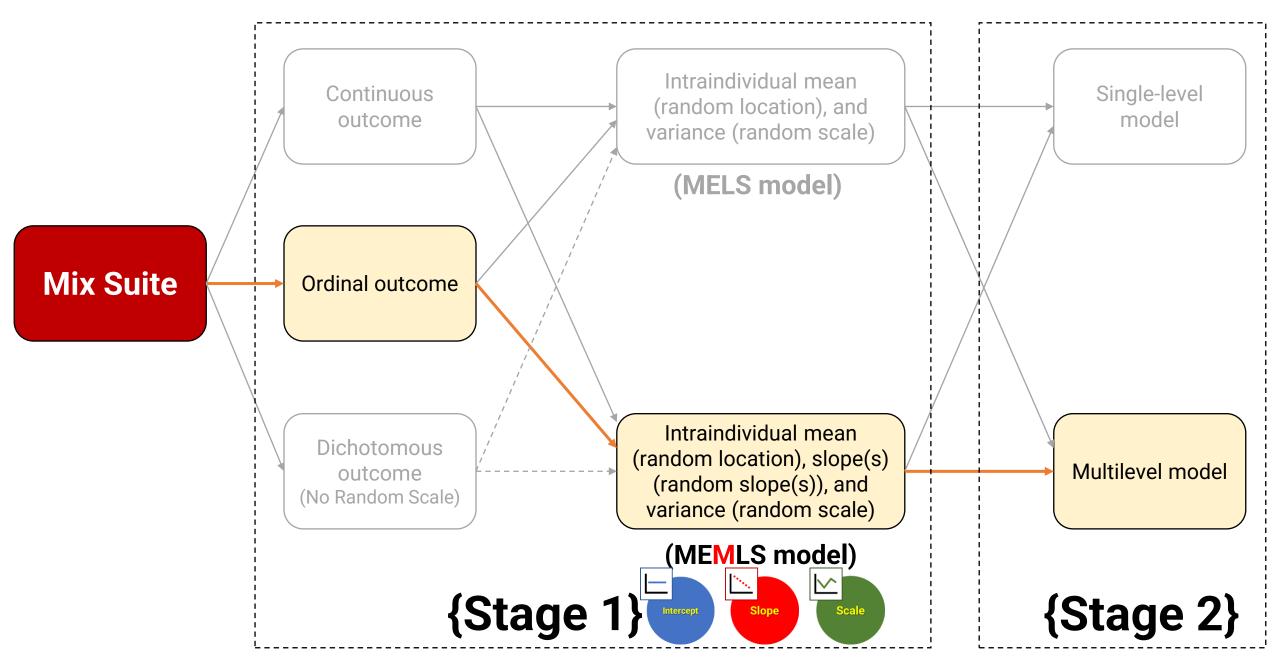
Does sleep quality (SQ) influence one's learning goal achievement (LGA)?

- (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}

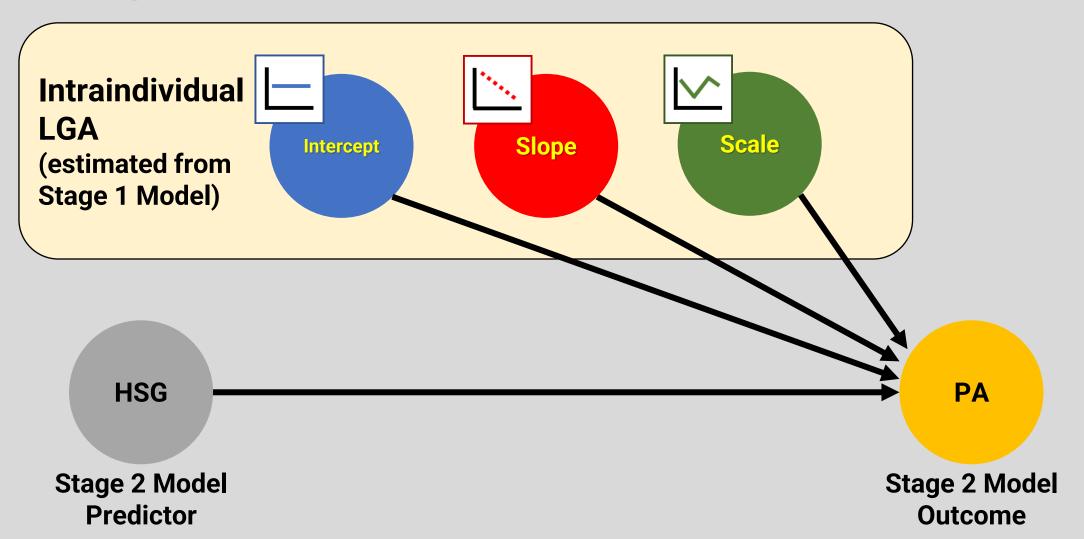
Does subject's mean level of-, or intraindividual variance in LGA, or **random-subject slope of SQ predicting LGA** influence one's daily positive affect? (Multilevel model, Level 1: Day; Level 2: Subject)

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?

🛓 MixWILD-2.0								-	×
Model Configuration	View Data	Не	lp						
		1	CSV file path:	:s\MixWILD	\SBM_MixWILD_Ex	ample_Data.csv	Change Dataset		
			Title (optional):	exercise20	;				
Da	ataset	6	Does your data contain missing values?	Yes	○ No				
			What is your missing data coded as?	-99					
	-	1	Stage 1 outcome:	 Contin 	iuous 🔾 Dichot	omous 💿 Ordin	al		
Stage 1 M	Nodel		Stage 1 regression type:	O Probit	Logisti	с	_		
		1	Specify random location effects:	○ Interce	ept only 💿 Inter	cept and slope(s)		
		6	Include estimates of random scale:	Yes	○ No				
Stage 2 I	Model	1	Include Stage 2 model:	• Yes	⊃ No				
Stage 2 i	locel		Include separate Stage 2 data file:	⊖ Yes (No				
			Stage 2 CSV file path:				Import Dataset		
		1	Stage 2 model type:	 Single 	level Multile				
		1	Stage 2 outcome:	Contin	iuous 🔾 Dichot	omous/Ordinal	🔾 Count ု Multinomia	al	
		1	Set a seed for Stage 2 resampling (optional):	777					
	-				.	D ensit	0		
					Save Model	Reset	Continue		

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?

🕌 MixWILD-2.0				_	×
Model Configuration View Data	He	þ			
Dataset		CSV file path: Title (optional): Does your data contain missing values? What is your missing data coded as?	:s\MixWILD\SBM_MixWILD_Example_Data.csv Change Dataset exercise2c • Yes • No -99 • • • • • • • • • • • • • • • • • • •		
Stage 1 Model	() ()	Stage 1 outcome: Stage 1 regression type: Specify random location effects:	 Continuous O Dichotomous O Ordinal Probit O Logistic Intercept only Intercept and slope(s) 		
	()	Include estimates of random scale:	● Yes 🔾 No		
Stage 2 Model	١	Include Stage 2 model: Include separate Stage 2 data file: Stage 2 CSV file path:	 ● Yes ○ No ○ Yes ● No Import Dataset 		
	()	Stage 2 model type:	○ Single level		
	(i) (i)	Stage 2 outcome: Set a seed for Stage 2 resampling (optional):	Continuous Dichotomous/Ordinal Count Multinomial		
			Save Model Reset Continue		

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?

🕌 MixWILD-2.0				_	×
Model Configuration View Data	Не	lp			
	•				
	1	CSV file path:	:sWixWILD\SBM_MixWILD_Example_Data.csv Change Dataset		
Dataset		Title (optional):	exercise2c		
	1	Does your data contain missing values?	● Yes 🗠 No		
		What is your missing data coded as?	-99		
-	1	Stage 1 outcome:	○ Continuous ○ Dichotomous Ordinal		
Stage 1 Model		Stage 1 regression type:	O Probit		
	1	Specify random location effects:	 Intercept only Intercept and slope(s) 		
	1	Include estimates of random scale:	● Yes 🔾 No		
Stage 2 Model	1	Include Stage 2 model:	● Yes O No		
otage 2 model		Include separate Stage 2 data file:	○ Yes ● No		
		Stage 2 CSV file path:	Import Dataset		
	1	Stage 2 model type:	○ Single level		
	1	Stage 2 outcome:	$\ensuremath{}$ Continuous $\ensuremath{\bigcirc}$ Dichotomous/Ordinal $\ensuremath{\bigcirc}$ Count $\ensuremath{\bigcirc}$ Multinomial		
	1	Set a seed for Stage 2 resampling (optional):	777		
			Save Model Reset Continue		

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?

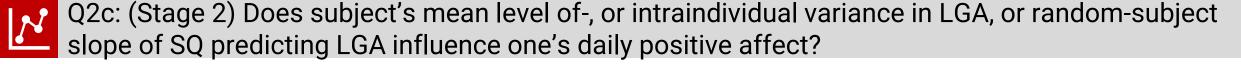
del Configuration	Stage 1 Configuration	Stage 2 Configuration	View Data	Help		
	lodel Configuration odel: Intercept + Slope(s)			Stag	e 1 Regressors	
	come: Ordinal		Level-1	Mean	Random Slope	WS Variance
ID Variab	le:		Level-1			
ID		•	SQ	*	V	Z
Stage 1 C)utcome:		Disaggregate	?		
LGA		-				
Config	ure Stage 1 Regresso	rs		Mean		WS Variance
			Level-2			
	Options					
Associati	ion of random location	& scale?				
Yes]
⊖ No						Configure Stage 2

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?

🛓 MixWILD-2.0								_	\times
Model Configuration	Stage 1 Configuration	Stage 2 Configuration	View Data	Help					
	Model Configuration odel: Intercept + Slope(s)	-			Stag	e 1 Regressors		_	
	tcome: Ordinal				Mean	Random Slope	WS Variance		
ID Variat	ble:		Level-1						
ID		-	SQ		V	r	V		
Stage 1	Outcome:		Disaggregate	?					
LGA		-							
Config	gure Stage 1 Regresso	rs	Level-2		Mean		WS Variance	1	
	Options								
Associat	tion of random location	& scale?							
Yes									
⊖ No									
				Sav	e Model	Clear Stage 1	Configure Stage 2		

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



🕌 MixWILD-2.0							_	×
Model Configuration	Stage 1 Configuration	Stage 2 Configuration	on View Data	Help				
	odel Configuration				Stage 2 Intera	actions		
Stage 1 out	del: Intercept + Slope(s) come: Ordinal del type: Multi-level	ר ^ו	Ma Level-1	ain Effects	Random Location	Random Scale	Location X Scale	
	come: Continuous resamples (stage 2): 500							
Stage 2 C	Outcome:							
PA	ure Stage 2 Regressor	I	Ma	ain Effects	Random Location	Random Scale	Location X Scale	
comg				_				
		-	HSG_Rank	K				
			Suppress 2-wa	ay Location X	Scale Interaction		J	
					Save Model C	lear Stage 2 F	Run Stage 1 and 2	

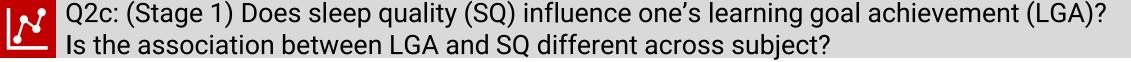
Select "PA" as Stage 2 Outcome and add "HSG_Rank" as Level-2 covariate



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

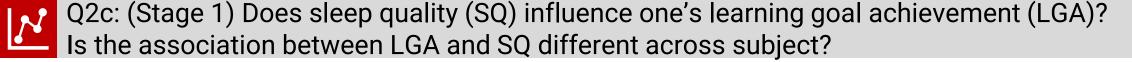
Variable	Estimate	AsymStdError z-value		p-value						
BETA (regression coeffi	cients)									
sq	0.19774	0.07007	2.82197	0.00477						
Random (location) Effor	t Vaniances and Cou	aniancos								
Random (location) Effec Intercept	1.58607	0.27494	5,76887	0.00000						
Covariance12	-0.06054	0.07820	-0.77419	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 identif	ication)									
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 offects	on WS vaniance (le	g lincon model)								
Random location effects		-	2 26760	0 00005						
Intercept	0.16154	0.07123	2.26769	0.02335						
SQ	-0.10438	0.03679	-2.83755	0.00455						
Random scale standard d	eviation									
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.



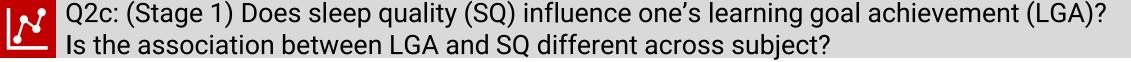
Variable	Estimate	AsymStdError	z-value	p-value						
BETA (regression coefficients) SQ	0.19774	0.07007	2.82197	0.00477						
Random (location) Effect Varia	nces and Cov	ariances								
Intercept	1.58607	0.27494	5.76887	0.00000						
Covariance12	-0.06054	0.07820	-0.77419	0.43882						
SQ	0.03154	0.05814	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 Intercept	variance (lo 0.16154	g-linear model) 0.07123	2.26769	0.02335						
sq	-0.10438		-2.83755	0.00455						
Random scale standard deviatio	n									
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).



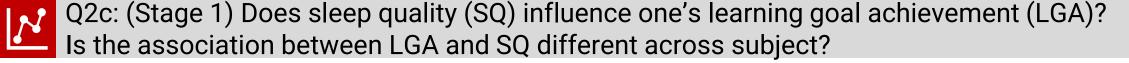
Variable	Estimate	AsymStdError	z-value	p-value
BETA (regression coefficients) SQ	0.19774	0.07007		0.00477
Random (location) Effect Varian	ces and Cov	ariances		
Intercept	1.58607	0.27494	5.76887	0.00000
Covariance12	-0.06054	0.07820	-0.77419	0.43882
SQ	0.03154	0.05814	0.54247	0.58749
TAU (WS variance parameters: lo SQ	g-linear mo -0.03770	del) 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 v	ariance (lo	g-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).



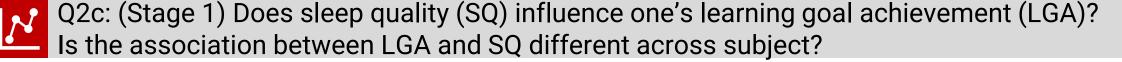
Variable	Estimate	AsymStdError	z-value	p-value
BETA (regression coefficients) SQ		0.07007	2.82197	0.00477
Random (location) Effect Varia	nces and Cov	/ariances		
Intercept	1.58607	0.27494	5.76887	0.00000
Covariance12	-0.06054	0.07820	-0.77419	0.43882
SQ	0.03154	0.05814	0.54247	0.58749
TAU (WS variance parameters: 1 SQ	og-linear mo -0.03770	odel) 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 (lo	g-linear model)		
Intercept	0.16154	0.07123	2.26769	0.02335
SQ	-0.10438	0.03679	-2.83755	0.00455
Random scale standard deviatio	n			
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.



Variable	Estimate	AsymStdError	z-value	p-value
BETA (regression coefficients SQ	5)	0.07007		0.00477
Random (location) Effect Vari	iances and Cov	ariances		
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 mo	del)		
sq	-0.03770	0.03321	-1.13524	0.25628
Thresholds (for identification	on)			
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 W	5 variance (lo	g-linear model)		
Intercept	0.16154	0.07123	2.26769	0.02335
SQ	-0.10438	0.03679	-2.83755	0.00455
Random scale standard deviati	ion			
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.



Variable		•	z-value	
BETA (regression coefficient SQ		0.07007	2.82197	0.00477
Random (location) Effect Var	iances and Cov	ariances		
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 mo	del)		
SQ	-0.03770	0.03321	-1.13524	0.25628
Thresholds (for identification	on)			
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 W	5 variance (lo	g-linear model)		
Intercept		0.07123	2.26769	0.02335
SQ	-0.10438		-2.83755	0.00455
Random scale standard deviat	ion			
Std Dev	0.26672	0.02501	10.66580	0.0000

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 Likeli	hood =	-3311.270 (sd=	2.057)	
Akaike's Informati	on Criterion =	-3317.270		
Schwarz's Bayesian	Criterion =	-3324.100		
==> multiplied by	-2			
Log Likelihood	=	6622.540		
Akaike's Informati	on Criterion =	6634.540		
Schwarz's Bayesian				
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
	0.09552	0.10570	2.40441	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 Likelih		-3311.270 (sd=	2.057)	
Akaike's Informatio	n Criterion =	-3317.270		
Schwarz's Bayesian	Criterion =	-3324.100		
==> multiplied by -	2			
Log Likelihood	=	6622.540		
Akaike's Informatio	n 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





X 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.

4	A	В	С	D	E	F	G	Н		J	K	L	М	N
1	ID	Day	Sex	Age	Sem	SQ	PhysAct	PA	NA	LGA	Exam	HSG	BDI	L
2	1	1						2.666667	3.666667	2				
3	1	2				3			3	1	1			
4	1	3	-			3			4	0	1			
5	1	4				3			5	1	1		_	
6	1	6				3		3	4.666667	2	1			
7	1	8				3	310	4	3.666667	2	1			
8	1	9	1	. 22	2	3	90	3.333333	3.333333	0	1	4.6	2	
9	1	10	1	. 22		3	405	3.333333	2.666667	2	1	4.6	2	
10	1	11				3		2.333333	2.666667	2	1			
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	
	<	Datase	t_HealthB	ehavAcadP	erfAffe	+								Þ

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.

 $\begin{bmatrix} v_{0_i} \\ v_{1_i} \\ \omega_i \end{bmatrix} \sim N \left\{ \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \begin{bmatrix} \sigma_{v_0}^2 & \sigma_{v_0 v_1} & \sigma_{v_0 \omega} \\ \sigma_{v_0 v_1} & \sigma_{v_1}^2 & \sigma_{v_1 \omega} \\ \sigma_{v_0 v_1} & \sigma_{v_1 \omega} & \sigma_{\omega}^2 \end{bmatrix} \right\}$

Website: <u>https://reach-lab.github.io/MixWildGUI/</u>

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



X Troubleshooting





C:\My Data\data 1.csv 4.6 3.11 -1 -2 4.9 5.76 1 4.7 13 3.94 2.9 4.3 4.7 4.61 4.5 3.22 🔽 -3 Dataset_HealthBehavAcadPerfAf (+)1 ID Sex F Age_C Exam HSG PA Mean 6 1 -1 4.7 4.61 7 4.5 3.22 8 4.4 6.04 9 4.5 6.62 10 5.3 5.03 🔻 Dataset HealthBehavAcadPerfAf (+)Sex F PA Mean Age_C Exam HSG 4.6 -1 3.11 -2 4.9 5.76 13 4.7 3.94 -2 4.3 2.9 4.7 -1 4.61 Dataset_HealthBehavAcadPerfAf (+)

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.

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.

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.

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.

C:\MyData\data_1.csv

	А	В	С	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	i 1	-1	1	4.7	4.61
-	Dat	aset_HealthBel	navAcadPerfAf	(+) : (•

	А		В	С	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 (+) = (+)									

	A		В	С	D	E	F
1	ID	Ī	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
-	() D	ata	set_HealthBeh	avAcadPerfAf	(+) : 1		•







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

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

in dataset name /

X 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	ſ
Maximum Iterations	200	300 - 500	
Ridge	0.1	0.15 – 0.25 🥆	
Discard Subjects with no Variance	Uncheck	Check	

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.

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.

Website: <u>https://reach-lab.github.io/MixWildGUI/</u> User Guide: <u>https://reach-lab.github.io/MixWildGUI/MixWild_User_Guide.pdf</u>







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



Thank You!!!

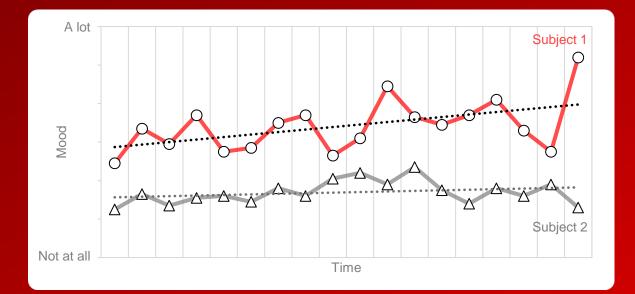
Wei-Lin Wang weilinwa@usc.edu Department of Department of Population and Public Health Sciences University of Southern California







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





Content Download Software

- 1. Visit our website: https://reach-lab.github.io/MixWildGUI/
- 2. Click on MacOS or Windows to download the program.
- MacOS: <u>https://github.com/reach-lab/MixWildGUI/releases/download/v2.0-stable/MixWILD-</u> 2.0.dmg
- Windows: <u>https://github.com/reach-lab/MixWildGUI/releases/download/v2.0-stable/MixWILD-</u>
 <u>2.0.exe</u>
- 3. Select your directory to save the program.
- 4. When finished downloading, double-click on the MixWILD icon s and follow the instructions to complete installation.

MixWILD - Mixed models With Intensive Longitudinal Data

Mix-WILD is a statistical software designed to perform multilevel modeling

View the Project on GitHub

sampling data.

on intensive longitudinal experience

MIX{WILD}

Mixed Model Analysis With Intensive Longitudinal Data

MixWild

What is this project about?

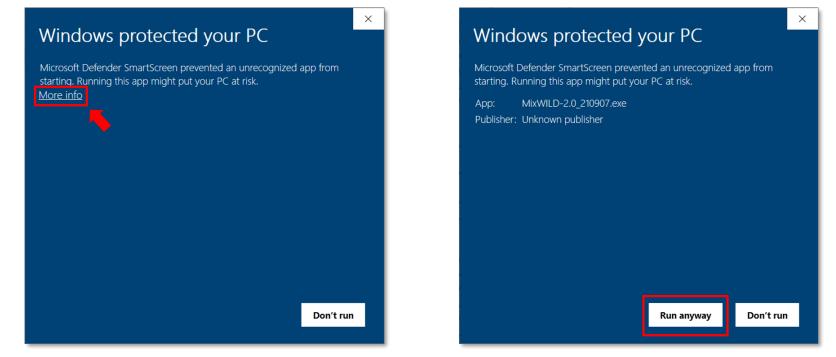
MixWLD (Also Mixed model analysis with Intensive Longitudinal Data) is a desktop GUI-based application for examining the effects of variance and slope of time-varying variables in intensive longitudinal data, especially the ones collected using ecological momentary assessments.



✿ 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.

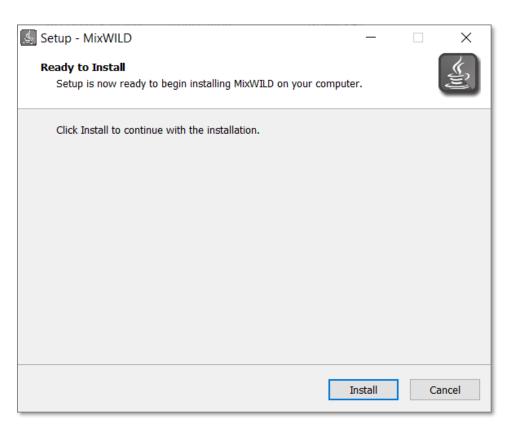


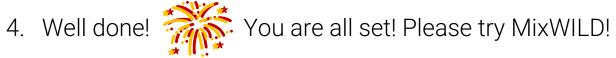
2. Click on [Run anyway].





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







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").





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







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



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