MixWILD

Mixed Model Analysis With Intensive Longitudinal Data

User's Guide

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Chapter 1 Introduction

In this chapter, you will learn the basic concepts of the MixWILD software program. You will also learn how to install MixWILD (Section 1.3 Preparing for Use) and how to load data and start analysis using MixWILD (Section 1.4 Step by-step Instructions on Import Data in MixWILD).

1.1 What is MixWILD

Mixed model analysis **W**ith Intensive Longitudinal **D**ata (MixWILD) is a standalone statistical software program that 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, specifically in the context of studies using intensive sampling methods, such as ecological momentary assessment (EMA). It combines estimation of a Stage 1 mixed-effects model, including random subject effects, with a subsequent Stage 2 regression in which values sampled from each subject's random effect distributions can be used as regressors (Dzubur et al., 2020).

1.1.1 MixWILD Stage 1 vs. Stage 2 models

In MixWILD, we distinguish two parts of the total model: 1) 'Stage 1 mixed-effects model', in which random subject intercept and slopes (location effects) and random subject within-subjects variance (scale effect) are estimated, and 2) 'Stage 2 model', in which the Stage 1 random subject effect estimates are used as regressors and interaction terms to predict a Stage 2 outcome. In Stage 1, a mixed-effects location-scale (MELS) model is specified, which extends the conventional mixed-effects regression model by allowing modeling of both the between-subject (BS) and within-subjects (WS) variances in terms of covariates (Hedeker et al., 2008). Specifically, log-linear submodels for the BS and WS variances are used, allowing covariates to influence both types of variance. Additionally, besides the inclusion of a random subject effect in the Mean model, a random subject (scale) effect is added to the WS variance specification, allowing the WS variance to be subject-specific, as well as influenced by covariates. Thus, these MELS models

include both random subject location and scale effects, which are estimated using empirical Bayes methods (Bock, 1989). Also, MixWILD can allow for random subject intercept *and slopes* (of time-varying covariates) in the Mean model, which we refer to as mixed-effects multiple location scale (MEMLS) models. In all, these subject-specific parameters indicate a baseline mean level (random intercept), the effect of a (time-varying) covariate on the mean (random slope), and the degree of within-subject variability (random scale) (Dzubur et al., 2020). These random subject effects from the Stage 1 model can then be used in a regression model to predict a Stage 2 outcome. This Stage 2 outcome can be a subject-level outcome or an outcome nested within time or clusters (i.e., a 2-level multilevel model), and can be of four different outcome types: continuous (normal), dichotomous/ordinal, count, or nominal. The random effects (estimated in Stage 1) can be included in the Stage 2 regression model as main effects and as interactions with other regressors.

(Please check Dzubur et al., 2020 for more details)



* RL: Random Location; RS: Random Scale.

Figure 1-1. Illustration of a two-stage model.

For example, you may have a MELS model which estimates day-level minutes moderate-tovigorous physical activity (Y_1 = MVPA) in Stage 1 as a function of various time-varying and invariant predictors ($X_1 \sim X_n$, i.e., positive affect and sex). As shown in Figure 1-1, MixWILD will

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generate output to report regression coefficients, the effects of the various covariates on BS- and WS- variance in MVPA. Meanwhile, the software also creates estimates of the random subject effects of MVPA (i.e., random location and random scale effects) from the Stage 1 MELS model. Following the Stage 1 model, you can use the random location effect of MVPA (MVPA mean effect) and random scale effect of MVPA (MVPA variability effect) to predict one's BMI status (Y_2 = BMI) in the Stage 2 model in Figure 1-1. By doing this, you could understand if/how day-level MVPA mean and variability influence one's BMI.

1.1.2 General Terms

To set the stage for the discussion to follow, it is helpful to present a unified terminology for the various aspects of MixWILD.

- Random Location: Random Location (intercept) effect is defined as the degree to which
 a subject deviates from the population average. It typically represents a subject-level
 mean effect, over and above the effects of covariates on the mean, and accounts for the
 non-independence of observations within subjects (Dzubur et al., 2020). For example, a
 random location effect of positive affect can be interpreted as the subject-level mean of
 positive affect, beyond the effects of covariates on positive affect. It is a random effect
 because the subjects in the sample are thought to represent a population.
- Random Scale: Random Scale effect is defined as the degree of within-subject variability, over and above the effects of covariates on the within-subject variability (Dzubur et al., 2020). Random scale parameters allow subjects to have individual estimates of the within-subject variance, and this is the distinguishing feature of MELS and MEMLS models. It can be thought of as intraindividual variability or variance. For example, a random effect of MVPA can be interpreted as the degree of random subject variance in MVPA.
- Random Slope: Random Slope effect refers to associations between time-varying covariates and the time-varying outcome. In addition to the random location (intercept), random slope is also a type of location effect as it represents the relationship of the covariate and the mean response for each subject. For example, a random slope effect

of momentary positive affect and weekends/weekdays (weekends = 1; weekdays = 0) can be interpreted as the subject-level change in the mean of positive affect on weekends relative to weekdays, beyond the effects of covariates on positive affect.

- Level 1 variable: This is a basic concept in Mixed-effects model aka Multilevel Modeling (MLM) or Hierarchical Linear Modeling (HLM), and it denotes a variable at the lowest level. For example, an EMA study might include 10-20 observations (person-time or prompt) for each subject (person). The variables at the observation level (person-time or prompt) such as affective states or cognitive responses are all considered as level 1 variables.
- Level 2 variable: In contrast, Level 2 variable denotes a variable at the higher level in a Mixed-effects model. A level 2 variable typically represents a person-level variable such as sex, race, or baseline age. It is also possible to have level 3 variables if the structure of the data includes three more tiers (i.e., subject (Level 3) wave (Level 2) prompt (Level 1)), though currently the MixWild program only allows 2-level models.



Figure 1-2. Structure of Level 1 & Level 2 in mixed-effects data.

Between-subject (BS) Variance submodel: The BS Variance submodel allows for prediction of the BS variance (of the outcome) in terms of regressors in the Stage 1 model. For example, researchers may use social context ("alone" or "with other") in EMA data to predict how homogeneous or heterogeneous subjects are in terms of their positive affect when they are alone versus when they are with others.

- Within-subjects (WS) Variance submodel: The WS Variance submodel allows for prediction of the WS variance (of the outcome) in terms of regression in the Stage 1 model. For example, researchers may ask whether the degree of consistency/erraticism in mood within children is influenced by dietary intake behaviors (i.e., eating high-sugar snacks).
- MELS model: This refers to a mixed-effects location-scale (MELS) model which generally includes three components: a) Mean submodel, b) BS Variance submodel, and c) WS Variance submodel; along with a random subject intercept and a random subject scale effect.
- MEMLS model: This refers to a mixed-effects multiple location scale model (MEMLS), which augments the MELS model by including multiple subject-level random location effects in the Mean model (i.e., both random intercept and slope(s)). In this way, the BS variance is a function of the random intercept and slopes. The model still allows for the WS variance submodel, as well as random scale effect.
- Stage 1 model: The Stage 1 model is a MELS or MEMLS model that provides estimates of the random subject effects, which can then be used as predictors in a Stage 2 model. In addition to the random effects (location and scale), the Stage 1 model can include covariates for the Mean and Variance submodels. In this way, the random effects can either be unadjusted (submodels with no covariates) or adjusted for covariates (submodels including covariates).
- Stage 2 model: Stage 2 model is a regression that allows a subject-level outcome or outcome nested within time or clusters to be influenced by the Stage 1 random effects, as well as other covariates. This allows researchers to test whether the (Stage 1) random effects have predictive, mediating, and/or moderating effects on the Stage 2 outcome. As indicated, the Stage 2 model could be a subject-level or multilevel model, and the outcome types that are allowed include continuous (normal), binary, ordinal, nominal, or count outcomes.
- **Two-stage model:** This means the combination of Stage 1 (a MELS or MEMLS model) and Stage 2 models in MixWILD. The two-stage model allows for prediction of the outcome

in Stage 1 model and the MELS/MEMLS model parses the Stage 1 variance into the effects of locations (i.e., intercept and slope(s)) and variability, which are used as predictors in a regression model of associations with the Stage 2 outcome. For example, one may wonder if there is an association between weekends/weekdays and momentary negative affect (Stage 1 outcome) and may also want to explore if the difference of negative affect on weekends vs. weekdays predicts eating disorders (Stage 2 outcome). MixWILD can generate a MEMLS model to test the association between negative affect (Stage 1 outcome) and weekends/weekdays in Stage 1 model. Then using the random slope effect of weekends/weekdays predicting negative affect in Stage 2 model allows for examining if the change in negative affect on weekends relative to weekdays is associated with eating disorders.



Figure 1-3. Simple illustration of Stage 1 & Stage 2 models.

*Stage 1 model must be a multilevel model.

*Stage 2 model could be a subject-level or multilevel model.

1.2 Why MixWILD?

Thus, researchers have more capabilities to conduct sophisticated research designs and provide the answers with more details. MixWILD is useful for a variety of Intensive Longitudinal Data (ILD) collection strategies (i.e., EMA, sensors) as a robust and reproducible method to test predictors of variability in level 1 outcomes and the associations between subject-level parameters (variances and slopes) and level 2 outcomes (Dzubur et al., 2020). For example, MixWILD can address research questions such as the following.

- (1) <u>How do means, variances, and slopes of intensively time-varying variables predict overall</u> subject-level outcomes?
- (2) <u>Do means, variances, and slopes of intensively time-varying variables mediate or</u> moderate the effects of time-invariant factors on subject-level outcomes.
- (3) <u>How do changes in means, variances, and slopes for intensively time-varying variables</u> (over time or within clusters of people) predict subject-level outcomes?
- (4) <u>How do means, variances, and slopes for intensively time-varying variables predict</u> <u>changes in outcomes (over time or within clusters of people)?</u>
- (5) <u>What are the relative predictive strengths of two or more means, variances, and slopes</u> of intensively time-varying variables on subject-level outcomes?

1.2.1 Innovative approach to assess intraindividual means and variances

In EMA studies, it is common to have up to 30 or 40 observations per subject, and this allows us to model subject-level variances (i.e., how erratic is a subject's mood?) and slopes (i.e., how much does a subject's mood change across contexts?) for time-varying variables. Traditionally, intraindividual means and variances from Ecological Momentary Assessment (EMA) data have been computed for each person using standard formulas, such as subject-level standard deviations (i.e., SD and MSSD) (Jahng et al., 2008). These strategies ignore the fact that subjects can have unequal numbers of EMA observations and cannot account for the effects of covariates. Alternatively, the MixWILD approach recognizes that subjects can vary in terms of their numbers of observations, and can generate variability estimates adjusting for the effects of other variables. Furthermore, MixWILD uses the plausible values resampling approach to take into account for

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the variability that is inherent in these estimates, rather than simply treating these as known predictors (which is what is assumed if one uses SD estimates as regressors). As a result, MixWILD does not ignore this source of variation, which avoids leading to more false positive results.

1.2.2 Extension to behavioral processes and health outcomes

MixWILD can conduct MELS/MEMLS modeling parsing the variance of a Stage 1 outcome into mean and variability, which are used as predictors in Stage 2 regression models of a new outcome. This two-stage approach can be useful to address questions of interest in a variety of research areas in the social and behavioral sciences. These tools can be used to analyze data from and ultimately to design new mHealth interventions, Intensively Adaptive Interventions (IAIs), and Just-In-Time Adaptive Interventions (JITAIs) (Nahum-Shani et., 2018); where subjects provide a greater number of data points over time than in traditional RCT studies. For example, researchers are able to ask critical research questions such as whether erratic mood mediates the effects of depression on physical activity, or whether the effects of living in a highly walkable neighborhood on physical activity are attenuated for individuals with unstable self-efficacy beliefs by examining EMA data using the MixWILD two-stage models.

1.3 Preparing for Use

1.3.1 Download Software

- 1. Visit: https://reach-lab.github.io/MixWildGUI/
- 2. Submit your email prior to downloading the application in the web page to receive notifications on major software updates.
- 3. Click on macOS or Windows to download the program.
- 4. Select your directory to save the program.
- 5. When finished downloading, double-click on the MixWILD icon and follow the instructions

to complete installation.

MixWILD - Mixed models With Intensive Longitudinal Data	MIX{WILD} Mixed Model Analysis With Intensive Longitudinal Data
Mix-WILD is a statistical software designed to perform multilevel modeling on intensive longitudinal experience sampling data.	MixWild What is this project about?
View the Project on GitHub reach-lab/MtxWildGut	MixWILD (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. Please submit your email prior to downloading the application so we can notify you of major software updates
	Your email Send Send Download MixWild for Mac or PC
This project is maintained by reach-lab	macOS (current version: 1.3)
Hosted on GitHub Pages — Theme by orderedlist	Windows (current version: 1.3)

1.3.2 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 the MixWILD-2.0.exe, and click [More info] to continue the process.



2. Click [Run anyway].

	×				
Windows protected your PC					
Microsoft Defender SmartScreen prevented an unrecognized app from starting. Running this app might put your PC at risk.					
App: MixWILD-2.0_210907.exe Publisher: Unknown publisher					
Run anyway Don't run					

3. Click [Install] to complete the installation.

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🛃 Setup - MixWILD	_		×
Ready to Install Setup is now ready to begin installing MixWILD on your comp	outer.		(ii)
Click Install to continue with the installation.			
	Install	Ca	ancel

1.3.3 Set Up Data

- 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).
 - (i.e., Use **underscore** to replace **space**, the correct name should be "**My_Data**").
- 2. The dataset should be saved as a **.csv file** with variable names in the **first row**.
- 3. 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").

1.3.4 Example Data

You may also find our MixWILD example dataset in the link below.

https://reach-lab.github.io/MixWildGUI/Mixwild example data.csv

This is an example dataset which provides you the basic elements which MixWILD needs in the analysis. Some of our tutorials in the following chapters are using this dataset. We encourage you to download it and give it a try, especially if you don't have any EMA dataset on hand. Here, we present the steps involved in using the program with the example dataset, where EMA data were obtained from 94 subjects (1,635 observations). Variables in the example dataset include:

Variable	Level	Description			
ID		Participant ID number			
AGE	2	Number of years (centered around mean age=29.29)			
SEX	2	0 (female); 1 (male)			
WEEKEND 1		0 (weekday); 1 (weekend)			
DOW	1	Day of week; 0: Monday, 1: Tuesday,, 6: Sunday			
OBESE	2	0 (not obese); 1 (obese)			
BMI	2	Body Mass Index (mean = 24.22, min=13.9, max=48.68)			
NegMood		Levels of negative affect reported in each prompt			
PosMood	1	Levels of positive affect reported in each prompt			
MVPA_daily_mins	2	Daily averaged moderate-to-vigorous physical activity time in minutes			
SED_daily_hours	2	Daily averaged sedentary time in hours			
NEGMOOD10	1	A decile (10 category) recoding of the variable NEG_AFFECT			
POSMOOD10	1	A decile (10 category) recoding of the variable POS_AFFECT			
MVPA_daily4	2	a quartile (4 category) recoding of the variable MVPA_daily_mins			

The data are sorted by ID - this is important as the program will not produce correct results if the data are not sorted by the level-2 ID variable. Also, the variables in the dataset are numeric only (i.e., no letters or non-numeric text can be present in the dataset) and the variables are separated by tabs, commas, or one or more spaces in the dataset.

1.3.5 Resources for more data sets

There are more resources for EMA data sets which are publicly available. You may search on "intensive longitudinal" or "EMA" to access more datasets. Harvard Dataverse is a repository for research data. Deposit data and code here.

https://dataverse.harvard.edu/

Dataverse	Add Data 👻 Search	h 👻 About User Guide Support Sign Up Log In
Deposit and share your data. Get acader credit.	mic Organize datasets and gather metrics in yo own repository.	our Publishing your data is easy on Harvard Dataverse!
Harvard Dataverse is a repository for research data. Deposit data and code here.	. A dataverse is a container for all your datasets, files, ar metadata.	nd Learn about getting started creating your own dataverse repository here.
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Texas Data Repository Dataverse is a research data management system for Texas Digital Library (TDL) member institutions.

https://dataverse.tdl.org/

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	the user guide. act a local university librarian	for help.				

1.3.6 Compatibility Notes for Windows and macOS users

The user interface for MixWILD runs in a Java runtime environment that provides feature parity between Windows and Mac versions. Native 64-bit binaries for macOS and Windows written in Fortran are used to execute statistical analyses and generate model output.

- To allow for compatibility with older operating systems and architecture, the Windows version features an option to use 32-bit binaries.
- Users running MixWILD in a virtual machine, such as VMWare or Parallels, should ensure working directories are isolated from hypervisor processes that allow sharing between host and guest. These include common directories such as *Downloads*, *Desktop*, and *Documents*. Instead, create a new folder located at "C:/MixWILD" to improve compatibility.

Please check the project on Github for more details

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

1.3.7 Statistical Computations

The code for MixWILD is written in FORTRAN and uses maximum likelihood estimation, utilizing both the expectation-maximization (EM) algorithm and the Newton–Raphson method to obtain the parameter estimates. Additionally, the mean and variance of each subject's random effects are estimated using empirical Bayes methods (Dzubur et al., 2020). More information about the estimation procedure can be found in the MIXREGLS manual (Hedeker & Nordgren, 2013).

1.3.8 Suggested References

- Software
- 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*, 1-25.
- MixWILD: A tutorial of a simple multilevel model with intensive longitudinal data (Link: <u>https://youtu.be/ZqyCxrMG1R8</u> provided by Eldin Dzubur)

- Hedeker, D., & Nordgren, R. (2013). MIXREGLS: a program for mixed-effects location scale analysis. *Journal of statistical software*, *52*(12), 1.

• Methodology

- Nordgren, R., Hedeker, D., Dunton, G., & Yang, C. H. (2020). Extending the mixed-effects model to consider within-subject variance for Ecological Momentary Assessment data. *Statistics in Medicine*, *39*(5), 577-590.
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• Applied Papers

- Maher J.P., Dzubur, E., Nordgren, R. Huh, J., Chou, C.P., Hedeker, D., Dunton, G. F. Do fluctuations in positive affective and physical feeling states predict physical activity and sedentary time? *Psychology of Sport and Exercise.* 41, 153-161.
- Maher, J.P., Huh, J., Intille, S., Hedeker, D., & Dunton, G.F. (2018). Greater variability in daily physical activity is associated with poorer mental health profiles among obese adults. Mental Health and Physical Activity, 14, 74-81.
- 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.
- Yang, C. H., Maher, J. P., Ponnada, A., Dzubur, E., Nordgren, R., Intille, S., & Dunton, G. F. (2020). An empirical example of analysis using a two-stage modeling approach: within-subject association of outdoor context and physical activity predicts future daily physical activity levels. *Translational Behavioral Medicine*.

1.4 Step by-step Instructions to Import Data in MixWILD

- **1 Open MixWILD:** Double-click on the **MixWILD icon** to open the main window.
- 2 Start to load data:
 - Start with New CVS file: Load the file from your local address if you want to start a new model. Make sure your dataset is a CSV file with variable names in the first row. In addition, all data set should be numerical values (i.e., integers or floats), except for the first row. Finally, data should be in the long format and sorted ascending or descending by ID number.
 - Please make sure your dataset is saved in a folder and its name without any space.
 - Start with Previous Model: You may reload the configuration from your previous model settings and continue the analyses. The model settings are saved as a MW file (i.e., configuration.mw)

MixWILD-2.0-Beta6	
Model Configuration Help	:
	Mixed Model Analysis With Longitudinal Data Istri with New CBV File
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Mixwild ex	xample_data.csv
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Files of <u>T</u> ype:	Data files 🗸
	Open Cancel

- **3** Create a new title: It is optional and just for your own reference in the model.
- **4** Format missing value: Click on the options of missing values and indicate if there are any in your dataset; specify the numeric missing value code in the box (i.e., '-999').



- 5 Select the type of Stage 1 outcome: The Stage 1 outcome should be a time-varying (i.e., multilevel) outcome, and can be of three different outcome types:
 - Continuous: Continuous outcomes are numerical responses that arise from a measuring process. Weight is an example of a continuous numerical variable, because the response takes on any value within a continuum or interval.
 - Dichotomous: Dichotomous outcomes are binary categorical responses, such as "Yes" or "No" answers.
 - Ordinal: Ordinal outcomes refer to sequential categorical responses, such as from a Likert scale ("disagree," "not sure," "agree") or symptom severity ("low," "medium," "high")
 - Select the regression type of Stage 1 outcome: Users may choose between Probit or
 Logistic model if your Stage 1 outcome is dichotomous or ordinal.

6	Stage 1 outcome:	 Continuous 	Dichotomous Ordinal
	Stage 1 regression type:	O Probit	○ Logistic

- 6 Specify random location effects:
 - Select "Intercept only", and the model includes a random subject intercept only (in the Mean model).
 - **Select "Intercept and slope(s)"**, and the model includes a random subject intercept and random subject slope(s) for one or more time-varying variables (in the Mean model).

③ Specify random location effects:
● Intercept only ○ Intercept and slope(s)

7 Include estimates of random scale: Random scale parameters allow subjects to have individual estimates of the within-subject variance (i.e., random subject scale effects), and this is a distinguishing feature of a mixed-effects location scale model. Random scale is not currently allowed when the outcome is dichotomous or ordinal.

Include estimates of random scale:	🖲 Yes 🔾 No
------------------------------------	-------------

8 Select Stage 2 model: MixWILD allows a two-stage modeling approach in which the Stage 1 random effects (i.e., intercept, slope(s), scale) are used as regressors to predict an outcome in a Stage 2 model. Select "Yes" if you want this two-stage approach, or "no" when you just want a Stage 1 model.

(Include Stage 2 model:	🖲 Yes 🔾 No
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- 9 Select the type of Stage 2 model: The stage-2 outcome can be subject-level or multilevel.
 - **Single level** implies an ordinary regression of a subject-level outcome. For example, there is only one outcome per subject in your data (i.e., subject BMI in the example dataset).
 - Multilevel implies a random intercept (multilevel) model for the Stage 2 outcome. For this, the Stage 2 outcome can vary across time (i.e., be occasion varying, for example, NEGMOOD10 in the example dataset) or be clustered (i.e., students in classes).



- **10** Select the type of stage 2 outcome: The stage 2 outcome can be of four different outcome types: continuous (normal), dichotomous/ordinal, count, or multinomial.
- Stage 2 outcome:
 Continuous
 Dichotomous/Ordinal
 Count
 Multinomial
- **11 Set a random seed (optional):** Using the same seed for resampling of the random effects that are used in the Stage 2 model (as regressors) will allow you to get the same results (the seed is used in the random number generator that yields the resampled data).



- **12** Complete Model Configuration settings:
 - **Click "Continue":** Click Continue to enter Stage 1 Configuration window.
 - **Click reset (optional):** Click Reset to clear the specifications and start over.

- **Save model (optional):** Click Save Model to keep all the model configuration settings specified and save them as a .MW file.

Save Model	Reset	Continue

1.5 What is in this Users Guide?

This manual comprises four parts, in which various aspects of MixWILD models are discussed.

• Chapter 2. Stage 1 Model Only

Chapter 2 presents the Stage 1 basic multilevel model for analysis of repeated measurements. It describes the basic settings in MixWILD Stage 1 model and how to run MELS and MEMLS models which include random subject intercept, slope(s), and scale in the analysis of repeated measurements as well as some interpretation of the outputs.

• Chapter 3. Two-stage Model Approach

Chapter 3 introduces a two-stage model: MixWILD combines a Stage 1 MELS or MEMLS model of a Stage 1 outcome with a subsequent Stage 2 model in which the Stage 1 random effects (i.e., random subject intercept, slopes, and scale) are used as regressors in the Stage 2 model.

V2.0

Chapter 2 Stage 1 Model Only

Chapter 2 Stage 1 Model Only

Chapter 2 will focus on MixWILD Stage 1 model (e.g., MELS or MEMLS). You will learn how to include random subject intercept, slope(s), and scale in the analysis of repeated measurements. In addition, this chapter will give you details about the submodels of the Stage 1 model (e.g., BS and WS Variance submodels). We will provide simple examples and step-by-step instructions to run a Stage 1 model in MixWILD and interpret the output. Example 1 shows how to operate a MELS model with random scale (2.2 Instruction; 2.3 Results); in Example 2, we provide a tutorial to run a MEMLS model in MixWILD (2.4 Instruction; 2.5 Results).

2.1 What is MixWILD Stage 1 model

As mentioned in Chapter 1, the Stage 1 model is a mixed-effects model, in which random subject intercept and slope(s) (location effects) and random subject within-subjects variance (scale effect) are included. On the one hand, the Stage 1 model can be considered as an independent model which applies a mixed-effects modeling approach with random subject effects to examine the associations between a time-varying outcome and subject-level and/or time-varying covariates. On the other hand, the Stage 1 model can also be an antecedent model which generates necessary estimates (e.g., random subject intercept, slope(s), and scale effects) as regressors for use in a subsequent Stage 2 model. In this chapter, the discussion will focus on the application of the Stage 1 model only. We will describe use of Stage 1 estimates of random effects as regressors in a Stage 2 model in Chapter 3.

The Stage 1 model is a MELS or MEMLS model that includes and provides estimates of the random subject effects. The Stage 1 model can also include covariates for the mean and variance submodels. In this way, the random effects can either be unadjusted (submodels with no covariates) or adjusted for covariates (submodels including covariates). MELS and MEMLS in MixWILD offer an extra capability to handle random effects, compared to the standard Ordinary Least Squares regression (OLS), and goes beyond standard mixed model software by including random subject scale effects.

2.1.1 OLS model (Not Used in MixWILD)

As a preliminary, Figure 2.1 shows an example of an OLS model which uses WS positive affect (PA) to predict daily averaged moderate-to-vigorous physical activity (MVPA) time in minutes. In this model, we neglected the multilevel data structure (i.e., observations nested within person) and simply analyzed the observations using a standard OLS regression model.



Figure 2-1. OLS model (DV: MVPA; IV: WS PA)

For measurement y (i.e., Daily MVPA) of subject i (i = 1, 2, ..., N subjects) on occasion j (j = 1, 2, ..., t_i occasions):

$$y_{ij} = \beta_0 + \beta_1 x_{ij} + \epsilon_{ij} \tag{2.1}$$

In Equation 2.1, β_0 is the intercept and x_{ij} is the regressor (i.e., WS PA for a subject at a particular occasion) for the Mean model, and β_1 is the corresponding regression coefficient. ϵ_{ij} is subject *i*'s error at time *j*. With OLS, subjects share one regression line, and observations are dispersed around it comparably in all subjects. This model ignores the structure of the EMA data and potentially leads to impoverished analysis and inferential error due to the violation of Independent and identically distributed (i.i.d.) observations assumption.

2.1.2 MELS model

A MELS or MEMLS model is an extension of a multilevel model. Multilevel models typically include random subject intercepts and possibly random slopes to account for the correlation of the repeated observations within subjects. However, ordinarily, multilevel models do not include covariates to predict WS variance (models *without* Scale Parameters), but instead assume a common WS variance. Applying MELS or MEMLS models can allow covariates to influence the WS variance (models with Scale Parameters), and even further allow each subject to have their own degree of WS variance, above and beyond the effects of covariates (models with Random Scale). The random scale effect is often necessary to obtain correct inference for the covariate effects on the WS variance (Please see Nordgren et al., 2020).

Here, we applied the same DV (MVPA) and IV (WS) in a MELS model in MixWILD. As mentioned, this model decomposes the variance of the dependent variable (i.e., Daily MVPA) into BS and WS components. As shown in Figure 2.2, each subject is allowed to have their own intercept while the association (slope) between MVPA and WS PA remains the same.



Figure 2-2. MELS model (DV: MVPA; IV: WS PA)

MELS Mean Model

$$y_{ij} = (\beta_0 + v_{0_i}) + \beta_1 x_{ij} + x'_{ij} \beta + \epsilon_{ij}, \ v_{0_i} \sim N(0, \sigma_{v_0}^2), \ \epsilon_{ij} \sim N(0, \sigma_{\epsilon}^2)$$
(2.2)

In Equation 2.2, β_0 is the grand intercept and x_{ij} is the regressor (i.e., WS PA) for the Mean model, and β_1 is the corresponding regression coefficient. There is a new component, v_{0i} , to represent a subject's mean (deviation from grand mean, β_0), and it is referred to as a random location (intercept) effect in the MELS model. x'_{ij} are the other regressors for the Mean model and β are the corresponding regression coefficients. Please note that **bolded** x'_{ij} and β represent vectors. In other words, there could be more than one x variable, and therefore more than one *Beta* coefficient. ϵ_{ij} is subject *i*'s error at time *j* (deviation of a subject's observations from their mean and the fixed part of the model).

MELS BS Variance Submodel (MELS Only)

$$\sigma_{v_{0jj}}^2 = exp(\mathbf{u}_{ij}'\alpha) \tag{2.3}$$

In the BS Variance submodel (Equation 2.3), $\sigma_{v_{0ij}}^2$ refers to the BS variance and u_{ij}' are the regressors (typically including "1" and other covariates) for the BS Variance model, and α is the corresponding vector of regression coefficients. The BS variance is subscripted by *i* and *j* to indicate that the value changes depending on the covariates u_{ij}' and their coefficients α . Please note that **bolded** u_{ij}' and α represent vectors. As mentioned, there could be more than one u variable, and therefore more than one *Alpha* coefficient. The exponential function is used to ensure a positive multiplicative factor, and so the resulting BS variance is strictly positive.

MiX Friendly Note:

The BS variance $(\sigma_{v_{0ij}}^2)$ is defined as the variance across subject-level means. Thanks to the Intensive-longitudinal Study Design, the EMA data offer many modeling possibilities. The estimation of the BS variance in the MELS models is more complicated than the tradition variance equation. As a result, the BS variance could be time-varying and different across occasions within a person. In this way, it is possible that both BS (subject-varying) and WS (time-varying) variables may influence the BS variance.





Figure 2-3. MELS BS submodel (DV: BS Variance in MVPA; IV: WS PA)

In Figure 2-3, the BS variance is represented by the dispersion of the subject lines. In particular, the amount of spread (yellow area) across the lines indicates the magnitude of the BS variance. For example, if the lines are close together then subjects are more similar (smaller variance) and vice versa. The magnitude of $\sigma_{v_{0ij}}^2$ indicates how different subjects are from each other (heterogeneity).

MELS WS Variance Submodel without Random Scale Effect (with Scale Parameters Only)

$$\sigma_{\epsilon_{ij}}^2 = exp(\mathbf{w}_{ij}^\prime \tau) \tag{2.4}$$

MELS WS Variance Submodel with Random Scale Effect

$$\sigma_{\epsilon_{ij}}^2 = exp(w_{ij}'\tau + \omega_i), \ \omega_i \sim N(0, \sigma_{\omega}^2)$$
(2.5)

MELS WS Variance Submodel with Random Scale Effect and (Linear) Association between the Location and Scale Random Effect

$$\sigma_{\epsilon_{ij}}^2 = exp(w_{ij}'\tau + \tau_l v_{0_i} + \omega_i), \ \omega_i \sim N(0, \sigma_{\omega}^2)$$
(2.6)

In the WS Variance submodel without random scale effect (Equation 2.4), $\sigma_{\epsilon_{ij}}^2$ refers to the WS variance and w'_{ij} are the regressors (typically including "1" and other covariates) for the WS variance model, and τ is the corresponding vector of regression coefficients. The magnitude of $\sigma_{\epsilon_{ij}}^2$ indicates how data vary within subjects (erraticism). In the WS variance submodel with random scale effect (Equation 2.5), the random scale effect, ω_i , allows the WS variance to vary across subjects beyond the contribution of covariates (Dzubur et al., 2020). In Equation 2.6, the coefficient τ_l represents the linear association between a subject's location effect and the WS variance, and v_{0_i} is the subject-level random location/intercept. It is also possible to have a linear (v_{0_i}) and a quadratic $(v_{0_i}^2)$ term in the MELS WS Variance submodel, to allow for a non-linear mean/variance relationship, and the coefficients would then be τ_l and τ_q respectively.

The WS variance is subscripted by *i* and *j* to indicate that the value changes depending on the covariates w'_{ij} and their coefficients τ . Please note that **bolded** w'_{ij} and τ represent vectors. In other words, there could be more than one *w* variable, and therefore more than one *Tau* coefficient. The exponential function is used to ensure that the resulting WS variance is positive.



* Green area represents the magnitude of the WS variance.

Figure 2-4. MELS WS submodel with Random Scale effect

(DV: WS Variance in MVPA; IV: WS PA)

In Figure 2-4, the variation of the points within a subject relative to each subject's line indicates the WS variance (green area). Subject 1 with blue dots has a higher WS variance, compared to Subject 2 with orange dots. This difference in the WS variance across subjects is what the random scale effect (ω_i) represents in Equation 2.5 and 2.6.



Figure 2-5. An Example of Stage 1 Regressors in Mean, BSV and WSV Submodels

Table 2-1. An Example of Stage 1 Regressors in Mean, BSV and WSV Submodels

Model	Regressor	Regressor List	
Mean model	<i>x</i> ′	Weekend (LV1), Age (LV2), Sex (LV2)	
BS Variance Submodel	u ′	Weekend (LV1), Sex (LV2)	
WS Variance Submodel	<i>w</i> ′	Weekend (LV1), Sex (LV2)	

Please note although we have used different letters (x', u' and w') to represent the covariates in the different submodels (Mean, BS and WS Variance submodels), there is no restriction and the same covariates could be used (Dzubur et al., 2020). For instance, Figure 2-5 and Table 2-1 show

that the regressors are identical in BS and WS Variance submodels (Weekend and Sex), while it also allows a different variable set (Weekend, Age and Sex) in the Mean model.

Per Hedeker and Nordgren (2013), the parameters of these models (Mean, WS and BS Variance submodels) are estimated using maximum likelihood and the Newton–Raphson algorithm. Once the model has converged to a solution, empirical Bayes methods (Bock, 1989) are used to obtain subject-specific estimates for v_{0i} (random location intercept) and ω_i (random scale), along with the variance-covariance matrix associated with these estimates, which are saved for potential use in a Stage 2 model. These correspond to estimates of the mean and variance-covariance of the posterior distribution of the random effects (Dzubur et al., 2020).

2.1.3 MEMLS model

Extending the model presented in the previous section (2.1.2 MELS), one may be interested in understanding how the slopes of the lines vary by subject for time-varying covariates. Such random slopes can be used to generalize the above model, allowing for a vector of random location effects instead of only a random intercept.



Figure 2-6. MEMLS model (DV: MVPA; IV: WS PA)

MixWILD can allow for random subject intercept and slope(s) (of time-varying covariates) in the Mean model, which we refer to as MEMLS models to reflect the multiple location random effects. In all, these subject-specific parameters indicate a baseline mean level (random intercept when the covariate(s) equal 0), the effect of (time-varying) covariate(s) on the mean (random slope), and the degree of within-subject variability (random scale) (Dzubur et al., 2020).

Figure 2-6 shows how the slope of WS PA predicting daily MVPA can vary by subject. The average across all subjects is depicted with the solid black line, and the location averages (mean plus slope) of four subjects are presented as dashed lines.

MEMLS Mean Model

$$y_{ij} = (\beta_0 + v_{0_i}) + (\beta_1 + v_{1_i})x_{ij} + x'_{ij}\beta + \epsilon_{ij},$$

$$v_{0_i} \sim N(0, \sigma_{v_0}^2), \ v_{1_i} \sim N(0, \sigma_{v_1}^2), \ \epsilon_{ij} \sim N(0, \sigma_{\epsilon}^2)$$
(2.7)

In Equation 2.7, β_0 is the grand intercept and x_{ij} is the regressor (i.e., WS PA) for the Mean model, and β_1 is the corresponding regression coefficient. The random intercept, v_{0i} , represents subject's mean (deviation) when the regressor (i.e., WS PA) equals zero, as it is a deviation from the grand intercept, β_0 . The random slope, v_{1i} , indicates the extra random part (association) for a subject beyond the average slope β_1 of x_{ij} predicting y_{ij} . It is possible to have multiple random slope effects in a MEMLS model. x'_{ij} are the other regressors for the Mean model and β are the corresponding regression coefficients. Please note that **bolded** x'_{ij} and β represent vectors. ϵ_{ij} is subject *i*'s error at time *j* (deviation from subject's trend line).

Like MELS, MEMLS has Mean and WS Variance submodels, in which covariates can be included to examine their effects on the mean and WS variance. However, as mentioned, MEMLS augments the MELS model by including multiple random subject effects in the Mean model (i.e., both random intercept and slope(s)). In this way, the BS variance-covariance is a function of the random intercept as well as slopes. Please note the random slope effect is only possible for timevarying covariates.

MEMLS BS Variance-covariance Matrix

$$\begin{bmatrix} \boldsymbol{v}_{0_i} \\ \boldsymbol{v}_{1_i} \end{bmatrix} \sim N \left\{ \begin{bmatrix} \boldsymbol{0} \\ \boldsymbol{0} \end{bmatrix} \begin{bmatrix} \sigma_{\boldsymbol{v}_0}^2 & \sigma_{\boldsymbol{v}_0 \boldsymbol{v}_1} \\ \sigma_{\boldsymbol{v}_0 \boldsymbol{v}_1} & \sigma_{\boldsymbol{v}_1}^2 \end{bmatrix} \right\}$$
(2.8)

As the BS variance-covariance Matrix (2.8) shows, $\sigma_{v_0}^2$ and $\sigma_{v_1}^2$ refer to the variances of random intercept and slope effects respectively, and $\sigma_{v_0v_1}$ represents the covariance. By examining the variances and covariance(s), the MEMLS Stage 1 model can indicate the degree to which the random intercept and slope vary across subjects. The covariance can show the degree to which the random intercept and random slope are associated with each other.

MEMLS WS Variance Submodel with Random Scale Effect and Association(s) between the Location and Scale Random Effect

$$\sigma_{\epsilon_{ij}}^2 = exp(w_{ij}'\tau + v_i'\tau_v + \omega_i), \ \omega_i \sim N(0, \sigma_\omega^2)$$
(2.9)

In the WS Variance submodel (Equation 2.9), $\sigma_{\epsilon_{ij}}^2$ refers to the WS variance and w_{ij}' are the regressors (typically including "1" and other covariates) for the WS Variance model, and τ is the corresponding vector of regression coefficients. ω_i represents the random scale effect. As discussed in Hedeker and Nordgren (2013), an association between the location and scale random effects can be induced by including the location random effects (v_i') as predictors in the WS Variance model, using τ_v , which represent the association between the location and scale random effects. In this regard, MixWILD allows for two possibilities to describe the relationship between random location and random scale: (1) no association ($\tau_v = 0$) or (2) association ($\tau_v \neq 0$) (Dzubur et al., 2020). However, in the current version of MixWILD, there is no option for selecting "No Association". When using MEMLS models with the random scale effect, the association between random location and random scale will be on and this is the default setting. This option will be available in a future update.

MEMLS can have more than 2 random location effects (i.e., multiple random slopes), though often a random intercept and one slope is common. As shown in the variance-covariance matrix

(2.10), it represents a MEMLS model with parameters that consist of one random intercept, one random slope and one random scale. To estimate the variance-covariance in this model, it requires a 3×3 matrix. If there are *n* random location effects and one random scale effect in a MEMLS, the size of the variance-covariance matrix will be $(n + 1) \times (n + 1)$. In this case, the model will be more complicated and estimation time will be significantly increased with each additional random effect.

$$\begin{bmatrix} v_{0_i} \\ v_{1_i} \\ \omega_i \end{bmatrix} \sim N \left\{ \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \begin{bmatrix} \sigma_{v_0}^2 & \sigma_{v_0 v_1} & \sigma_{v_0 \omega} \\ \sigma_{v_0 v_1} & \sigma_{v_1}^2 & \sigma_{v_1 \omega} \\ \sigma_{v_0 \omega} & \sigma_{v_1 \omega} & \sigma_{\omega}^2 \end{bmatrix} \right\}$$
(2.10)

In MixWILD, the outcome of the Stage 1 model (both MELS and MEMLS) can be continuous, dichotomous or ordinal. However, a random scale parameter is not be available in Stage 1 models with dichotomous outcomes because dichotomous outcomes generally do not provide enough variance to allow for estimation of the random scale effect.

Submodel	Outcome	MELS	MEMLS
Mean Model with Random Intercept Only	Original outcome	V	N/A
Mean Model with Random Intercept and Random Slope(s)	Original outcome	N/A	V
BS Variance Submodel	Variance of the subject-level means in outcome	٧	N/A
WS Variance Submodel	Within-subject variance of the outcome	V	V

Table 2-2. Summary of Submodels in MELS and MEMLS

* Note: v – Available; N/A – Not Available

MiX Friendly Note:

As shown in Table 2-2, WS Variance submodel and Random Scale effects are distinctive features in MELS and MEMLS models. Models without random scale can still include modeling of the WS variance as a function of covariates. If, in addition to omitting random scale, they also do not include WS Variance modeling, then they are equivalent to standard mixed-effects (aka multilevel) models.

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2.2 Step by-step Instructions to MELS model {Example 1}

In this analysis, we will use our <u>example data</u> to run a MELS model to examine whether a person's positive mood is related to their negative mood. The flowchart shows that by selecting "Random Intercept Only" for "Random Location Effects", we can create a MELS model. Then we check the "Random Scale Effect" option to allow for the random scale effect in the model.



Figure 2-7. Example 1 MELS Flowchart

Q Research Question:

Does participants' day-level negative affect (continuous, time-varying variable) predict their day-level **positive affect** (continuous, time-varying variable) in the Mean, BS and WS Variance submodels, after controlling for weekend (dichotomous, time-varying variable) and baseline age (continuous, time-invariant variable)?

Data source: <u>https://reach-lab.github.io/MixWildGUI/Mixwild_example_data.csv</u>
Model Configuration Page

1 Import data into MixWILD and format missing value: Please check {Chapter 1 Section 1.4} for more details. Be sure your dataset is in CSV format and should be sorted ascending by ID.

	i	CSV file path:	heDrive\Documents\Mixwild_data_v2_mini.csv
Dataset		Title (optional):	Example 1 MELS
Dataset	1	Does your data contain missing values?	● Yes 🔾 No
		What is your missing data coded as?	-999

2 Select the type of Stage 1 outcome: The Stage 1 outcome should be a time-varying outcome. In this example, the Stage 1 outcome is **positive affect** which is continuous. Please select [Continuous].



- **3** Specify random location effects:
 - Select "Intercept only", and the model includes a random subject intercept only (in the Mean model). This is the key selection for creating a MELS model.
 - Specify random location effects:
 Intercept only O Intercept and slope(s)
- Include estimates of random scale: Random scale parameters allow subjects to have individual estimates of the within-subject variance (i.e., random subject scale effect).
 Please note: a random scale effect is not allowed if the outcome is dichotomous or ordinal.



5 Select Stage 2 model: MixWILD allows a two-stage modeling approach in which the Stage 1 random effects can be used as regressors to predict an outcome in a Stage 2 model. In this example, we will not have a Stage 2 model so please select "No".

1	Include Stage 2 model:	Yes	No	
---	------------------------	-----	----	--

- 6 Complete Model Configuration settings:
 - **Click "Continue":** Click Continue to enter {Stage 1 Configuration} page.



Stage 1 Configuration Page

After you submit the {Model Configuration} page, the MixWILD interface will switch to the {Stage 1 Configuration} page that enables you to set up your Stage 1 model.

lel Configuration Stage 1 Configuration	View Data	Help						
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	-							
Stage 1 Outcome:								
POS_AFFECT	-							
			Level-2	Mean	BS Variance	WS Variance		
Configure Stage 1 Regressors			Level-2					
Options								
Specify the relationship between mean and WS variance.	the							
 No Association 			L				1	
Linear Association				Save Model	Clear Stage 1	Run Stage 1]	
\cap Ouadratic Association							-	

7 Select ID: ID is the key variable to define the two levels of your data. It should be sorted by this variable before importing the dataset. In this analysis, please select [ID] variable in our example data. [CLiCK]

ID V	ariable:		
ID			-

8 Select Stage 1 Outcome: Please select [POS_AFFECT] variable, positive affect, as your outcome variable. [CLiCK]

Stage 1 Outcome:	
POS_AFFECT	-

9 Select Stage 1 Regressors (Configure Stage 1 Regressors): [CLiCK]

- Select Level 1 Variables: In an EMA study, Level 1 variables refer to the time-varying variables at observation level (person-time or prompt). In this analysis, please select the variables, [WEEKEND] and [NEG_AFFECT], in the data. Use Add button to move variables from the {Variables} to {Level-1 (Time Varying)}. Use Remove button to switch back.
- Select Level 2 Variables: In an EMA study, Level 2 variables generally represent personlevel or time-invariant variables. Please select [Age] here. Use Add button to move variables from the {Variables} to {Level-2 (Time Invariant)}. Use Remove button to switch back.
- Click Submit button to process the selection. Click Reset if you want to clear all the selections and do it over.

Variables		Lev	el-1 (Time Va	rying)	
SEX DOW OBE SE BMI MVPA_daily_mins SED_daily_hrs NEGMOOD10 PO SMOOD10 MVPA_daily4		WEEKEND NEG_AFFECT			
		Lev Age	el-2 (Time Inv	variant)	
	Add Remove	му с			

MiX Friendly Note:

Variables should be specified as Level-1 or Level-2 by users. MixWILD can't automatically identify the levels of the variables. Please classify them carefully.

10 Stage 1 Options (optional):

Please note these settings are all **OPTIONAL**. In most cases, you <u>DON'T</u> need to make any change in these settings. However, in some cases, the program does not converge to a solution. Trying to change these parameters (i.e., Quadrature Points or Ridge) could help. The other solution, which we also strongly recommend, is to estimate a simpler model. We discuss this further in the appendix {Appendix A: Steps to take when the program does not converge to a solution}.

🛓 Options	- 🗆 X							
Mean Intercept:	Maximum Iterations: 200							
BS Variance Intercept:	Ridge: 0.1 ÷							
WS Variance Intercept:	Standardize All Regressors?							
Convergence Criteria: 0.00001	Discard Subjects with no Variance?							
Quadrature Points: 11 -	Resample Stage 2:							
Adaptive Quadrature:	No. of Samples: 500 -							
Run in 32-bit mode (Experimental: for older Windows-based machines)								
	Cancel Reset Submit							

- Intercept Options: You may uncheck these boxes to remove the fixed intercept(s) in Mean,
 BS and WS Variance submodels. In most cases, these intercepts should remain checked.
- Convergence Criteria: It refers to convergence requirement for the maximum correction.
 This sets the accuracy level of the model. The range of the spinner is between 0 and 1 with 0.00001 as default.
- Quadrature Points (important): Estimation of the Stage 1 model involves a numerical integration (i.e., quadrature) over the random effect distribution. By default, MixWILD performs adaptive quadrature with 11 points to do this integration. The more points one uses, typically the more accurate is the solution, but also the more time it takes to estimate the model parameters. 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. The usage of "Adaptive"

Quadrature" is to personalize quadrature to each subject. Switching from adaptive to non-adaptive quadrature can sometimes work better, though typically adaptive quadrature is preferred.

- **Maximum Iterations:** The program uses an iterative Maximum Likelihood algorithm to estimate the model parameters, and this option indicates the maximum number of iterations before stopping, thus preventing the model from running indefinitely. In some cases, a large number of iterations may be required to achieve convergence, in which case this option can be set to a larger number. However, in most cases the program should be able to converge to a solution in the default number of 200 maximum iterations.
- Ridge (important): The value of the "Ridge" is usually set to a small fractional value, and it improves convergence for computationally challenging data. The range is between 0 and 1 with 0.1 as default. The ridge increases the values of the diagonal elements of the 2nd derivative matrix by a factor of 1 multiplied by the ridge value (i.e., if the ridge is set to 0.10, then the diagonal elements of the 2nd derivative matrix are all multiplied by 1.10). 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.
- Standardize All Regressor: Selecting this option will set variables on the same scale. In some cases, the scale of the regressors included in an analysis can be very large. For example, consider a scenario in which one has a variable for days in the study, which ranges from 1 to 365 for a year-long study. In this case, because of the large scale of the variable, any parameter associated with this variable will be quite small and can be difficult to estimate. In such cases, standardizing the regressors by selecting "Standardize All Regressors" might be considered. Checking the selection of this option will transform all regressors to be variables with 0 mean and variance of 1.

- **Discard Subjects with no Variance (important):** By checking this option, it will exclude the data from subjects with identical values for all observations of the outcome variable. Such subjects exhibit no variation on the Stage 1 outcome variable. In other words, their values on the outcome variable are exactly the same for all of their observations. This can be particularly true if there are subjects with few observations in the dataset and/or the Stage 1 outcome variable is not really continuous but an ordinal outcome with 5 or less categories. 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, selection of the "Discard Subjects with no Variance?" option (clicking on the box to the right of this question) on the {Options} window can facilitate model convergence. Selection of this option will remove these subjects from the Stage 1 analysis (and also the Stage 2 analysis if that is specified). However, leave "Discard Subjects with no Variance?" unchecked if you want to include all available data in the analysis.
- Resample Stage 2: This is a Stage 2 model option. Resampling of the subject-level random effects are conducted for all Stage 2 models to account for the fact that random effects are estimated quantities (Carsey & Harden, 2013). As estimated quantities, there is some degree of uncertainty in these estimates for each subject. Resampling is used to account for this uncertainty, and so this option is checked in most cases. This option does not matter if you run Stage 1 models only.
- No. of Samples: This is a Stage 2 model option. The random effects are resampled multiple times from a normal distribution using the mean and variance estimates of these random effects for each subject. In a similar manner as in multiple imputation, these resampled random effects are then used to rerun the Stage 2 model multiple times, and then averaged over to produce final Stage 2 model estimates. By default, the estimated random effects of the Stage 1 analysis (i.e., random location and scale effects) are resampled 500 times in the Stage 2 analysis. This option does not matter if you run Stage 1 models only.

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Program can't converge to a solution?

	Quadrature Point	Maximum Iterations	Ridge	Discard Subjects with no Variance
Default	11	200	0.10	Uncheck
Options	15 - 25	300 - 500	0.15 – 0.25	Check

Table 2-3. Summary of some potential Options.

11 Specify Stage 1 Regressors in Mean, BS and WS Variance submodels (important):

Please note it is critical to specify your Stage 1 regressors. If you just follow the <u>"Step 9"</u> instruction and assign variables into Level-1 and/or Level-2 columns *but you do not check any of these selected regressors* (i.e., all these boxes are unchecked), there will be no regressors in your submodels. To ensure that at less one submodel has one or more regressor(s), you have to specify variables and check the boxes in {Stage 1 Regressor}. Level-1 and Level 2 regressors are available in the Mean, BS and WS Variance submodels.



Model	Regressor	Regressor List
Mean model	<i>x</i> ′	Weekend (LV1), Neg_AFF_WS (LV1),
Mean model	X	Neg_AFF_BS (LV2), Age (LV2)
BS Variance Submodel	u ′	Weekend (LV1), NEG_AFFECT (LV1)
WS Variance Submodel	<i>w</i> ′	Weekend (LV1), NEG_AFFECT (LV1)

Table 2-3. Example 1 of Stage 1 Regressors in Mean, BSV and WSV Submodels

- <u>Mean model</u>: This represents a submodel that examines the relationship between one or more regressor(s) and the mean of the outcome. This is the primary specification of the regular mixed-effects/multilevel model with random intercept only. We use x' to represent the regressor(s) and β are the corresponding regression coefficients.
- In this example, please check the boxes of [WEEKEND], [NEG_AFFECT (Disaggregate)] and
 [Age] in the Mean model. [CLiCK]
- **Disaggregate:** Select the option for each of the time-varying variable(s) for which decomposition of the within- and between-subject effects in predicting the Stage 1 model outcome is desired. Given that time-varying regressors (x'_{ij}) produce pooled effects in multilevel models, for those variables that are continuous or binary, additional manipulation can be used to disaggregate the between- and within-subject effects. The within-subject component is created when a time-varying regressor is centered at its subject-level mean $(x_{ij} \bar{x}_i)$. The subject-level mean becomes an additional variable (\bar{x}_i) , and this is the between-subject component of the variable x_{ij} . The disaggregation procedure allows for interpretation of within- and between-subjects effects of regressors on the outcome (Dzubur et al., 2020).



 For example, there are three selected regressors in the Mean model. However, we select "Disaggregate" for [NEG_AFFECT] so the original effect of [NEG_AFFECT] becomes two components. As mentioned, the Level-1 variable [NEG_AFFECT] has been decomposed in terms of its the within-subject (WS) version (the subject's occasion specific deviation of the variable relative to the subject mean, with suffix **_WS**) and between-subject (BS) version (the subject mean of this variable across all occasions, with suffix **_BS**). The program creates these two versions from the Level-1 variable.

MiX Friendly Note:

The option "Disaggregate" is only available for time-varying variables, and it may not be necessary to apply this for all time-varying variables. In some cases, the distribution of certain variables is quite even or homogeneous between- and within-subjects. In these cases, you might just use the original variables in the models. For example, a time-varying variable such as "Weekday vs. Weekend" may not be appropriate for the decomposition because most participants could have quite the same distribution on this variable.

- The Mean model (Random Intercept only) with four regressors is as follows:

$$PosAFF_{ij} = (\beta_0 + v_{0i}) + \beta_W WEEKEND_{ij} + \beta_{BS}(\overline{NegAFF_i}) + \beta_{WS}(NegAFF_{ij} - \overline{NegAFF_i}) + \beta_A Age_i + \epsilon_{ij}, v_{0i} \sim N(0, \sigma_{v_0}^2), \ \epsilon_{ij} \sim N(0, \sigma_{\epsilon}^2)$$
(2.11)

- In Equation 2.11, **[WEEKEND]** and **[NegAFF_WS]** are Level-1 (time-varying) variables, while **[NegAFF_BS]** and **[Age]** are Level-2 variables. Random intercept, v_{0_i} , represents subject's mean. β_0 is the grand intercept. β are the equivalent of fixed effect coefficients in a traditional multilevel model. Please note the results of the decomposition will only be shown in the output.
- <u>BS Variance submodel</u> (MELS Only): This is defined as a submodel that examines the relationship between one or more regressor(s) and the variance of the subject-level outcome means. We use u' to represent the regressor(s) and α are the corresponding regression coefficients.
- In this example, please check the boxes of [WEEKEND] and [NEG_AFFECT] in the BS Variance submodel. Leave the variable [Age] uncheck and this can exclude [Age] in the BS Variance submodel. [CLiCK]

- The BS Variance submodel is as follows:

$$\sigma_{v_{0_{ij}}}^2 = exp(\alpha_0 + \alpha_W WEEKEND_{ij} + \alpha_{NA} NEG_AFFECT_{ij})$$
(2.12)

- In Equation 2.12, **[WEEKEND]** and **[NEG_AFFECT]** are Level-1 (time-varying) variables, while there is no Level-2 variable. α_0 represents the intercept in the BS variance submodel (the BS variance, on the log scale, when **[WEEKEND]** and **[NEG_AFFECT]** both equal zero). Note, one could also apply the BS/WS decomposition of the negative affect variable, as was done in the mean submodel. Here, for simplicity, this is not done.
- <u>WS Variance submodel</u>: This refers to a model that examines the relationship between one or more regressor(s) and the within-subject variance of the outcome. We use w' to represent the regressor(s) and τ are the corresponding regression coefficients.
- In this example, please check the boxes of [WEEKEND] and [NEG_AFFECT] in the WS
 Variance submodel. [CLiCK]
- The WS Variance submodel is as follows:

$$\sigma_{\epsilon_{ij}}^{2} = exp(\tau_{0} + \tau_{W}WEEKEND_{ij} + \tau_{NA}NEG_AFFECT_{ij} + \tau_{l}\upsilon_{0i} + \omega_{i}),$$
$$\omega_{i} \sim N(0, \sigma_{\omega}^{2})$$
(2.13)

- In Equation 2.13, **[WEEKEND]** and **[NEG_AFFECT]** are Level-1 (time-varying) variables, while there is no Level-2 variable. τ_0 represents the intercept in the WS Variance model (the WS variance, on the log scale, when **[WEEKEND]**, **[NEG_AFFECT]**, the random scale, and the linear association parameter all equal zero). The coefficient τ_l represents the linear association between a subject's location effect and the WS variance, with v_{0i} as the subject-level random intercept. ω_i represents the random scale effect which allows the WS variance to vary across subjects (over and above the effects of the regressors).

12 Specify the relationship between the mean and WS variance

This option is available if you checked "Yes" in the question about "Include estimates of random scale" in {Model Configuration} page. As mentioned in the section of <u>"WS Variance</u> <u>submodel"</u>, this allows the random intercept (v_{0_i}) to influence the WS variance.



- In this example, please select "Linear Association". [CLiCK]
- The general WS Variance submodel with full associations is as follows:

$$\sigma_{\epsilon_{ij}}^2 = exp(\mathbf{w}_{ij}^{\prime}\boldsymbol{\tau} + \tau_l v_{0i} + \tau_q v_{0i}^2 + \omega_i), \ \omega_i \sim N(0, \sigma_{\omega}^2)$$
(2.14)

- In Equation 2.14, the coefficient τ_l and τ_q represent the linear and quadratic associations between a subject's location effect and the WS variance. v_{0_i} and $v_{0_i}^2$ refer to the regressors of the subject-level random intercept.



Figure 2-8. Linear Association and Quadratic Association

- **No Association:** In this setting, it assumes that there is no association between random intercept and WS variance ($\tau_l = \tau_q = 0$), as in Equation 2.5.

- **Linear Association:** This means that the association between the random intercept and WS variance is linear ($\tau_l \neq 0$; $\tau_a = 0$). The model can be written as <u>Equation 2.6</u>.
- Quadratic association: This can capture nonlinear association(s) between the random intercept and WS variance ($\tau_l \neq 0$; $\tau_q \neq 0$). The model is listed as Equation 2.14. By default, "No Association" is assumed between the mean and within-subject variance (only relevant for models with random scale). For MELS models with random scale effects, a linear or quadratic association is also possible. Testing a linear relationship is a good try to explore if within-subject variability linearly relates to subject's mean levels. For example, one may find intraindividual variance in daily moderate-to-vigorous physical activity (MVPA) could be negatively associated with subject-level mean of MVPA. It reflects a possibility that subjects with higher daily physical activity level, on average, have a more consistent pattern in day-to-day physical activity. A quadratic relationship could be particularly useful for rating scale data with both ceiling and floor effects, where subjects that have mean levels (i.e., random intercept) at either the maximum or minimum value of the rating scale also have near-zero variance (i.e., scale) (Dzubur et al., 2020). For example, Figure 2-8 (quadratic association) shows the rating scale goes from 1 to 9, and then any subject with a mean level near either 1 or 9 would almost certainly have a small variance, giving rise to the potential for a quadratic relationship between the mean and variance. In this case, applying the quadratic association in the models would account for this possibility.
- 13 Run Stage 1 Model: Please verify your model specifications and click on "Run Stage 1" to generate the definition (DEF) file. You may also click "Save Model" to keep all parameters in MW format so you could reload the settings when needed. [CLiCK]



14 Preview DEF File and Proceed the Analysis: The DEF file is a copy of your model specifications which communicates with Fortran to execute statistical analyses. In the definition file, click on "Proceed" to run your model and generate model output files. [CLiCK]

45

V2.0

🛓 Definition File Preview	—		×
Created with MixWILD GUI Mixwild_data_v2_mini.dat Mixwild_data_v2_mini_Output 14 2 2 2 0 0 0 1 0 0 0.00001 11 1 200 -999 0 1 0.1 0 1 9 4 2 4 8 4 8 8	0 0 0 500	0 0 0 1	0 0
POS_AFFECT WEEKEND Age WEEKEND NEG_AFFECT WEEKEND NEG_AFFECT NEG_AFFECT			
Proceed Save Def File			

15 Model Estimation: A pop-up window will appear while model estimation is in progress. Please note the time of data processing could increase if the data size is large and/or the model includes multiple random effects.

MiX Friendly Note:

If you experience a model crash and the warning message below appears, it indicates that computational difficulties were likely encountered and prevented the model parameters from being estimated successfully. In this case, confirm the format of your dataset and check your model specifications (Table 2-3). **Troubleshooting** suggestions are listed in Appendix A: Steps to take when the program does not converge to a solution.

Message		×
i Failed		
	ОК	

Stage 1 Results Page

When the model estimation is completed, MixWILD will automatically switch to the {Stage 1 Results} page. If not, please click the "Stage 1 Results" tag to check the Stage 1 output.



By default, MixWILD stores your outputs in your Windows personal Documents folder. The default address in Win10 is in your account's **%UserProfile%** folder (i.e., "C:\Users\UserName\ OneDrive\Documents"). All files generated from the program can be found in a folder name with the prefix MixWILD and the 12-digit number labelling the date and time that this folder was created.

	This PC > Documents	~	ව	cuments
^	Name	Status	Date modified	Туре ^
	MIXWILD202104010742	S	4/3/2021 1:31 AM	File fold
	MIXWILD202104011137	C2	4/3/2021 1:27 AM	File fold 🗸

In the file with suffix **"_Output_stage1.out"**, you can find that the content is identical to the results found in the {Stage 1 Results} page. The estimated subject-specific random effects are saved to a data file with the suffix **"_ebvar.dat"**.

Name	Status	Date modified	Туре
📜 work	\odot	4/3/2021 2:07 AM	File folder
logger.log	C	4/3/2021 2:06 AM	Text Document
logger.log.lck	S	4/3/2021 2:05 AM	LCK File
Isboth_random_mixblank.def	\odot	4/3/2021 2:06 AM	DEF File
Mixwild_data.dat	\odot	4/3/2021 2:05 AM	DAT File
Mixwild_data_Output.def	\odot	4/3/2021 2:06 AM	DEF File
Mixwild_data_Output_ebvar.dat	\odot	4/3/2021 2:07 AM	DAT File
Mixwild_data_Output_stage1.out	\odot	4/3/2021 2:07 AM	OUT File
modelingProgress.txt	\odot	4/3/2021 2:07 AM	Text Document

Mixwild_data_Output_st	tage1.out - Notepad				-		<
File Edit Format View	Help						
Model WITH RANDOM S	Scale						
Total Iterations							
Final Ridge value	= 0.0						
Log Likelihood	=	-5385.679					
Akaike's Informati	ion Criterion =	-5400.679					
Schwarz's Bayesian	n Criterion =	-5419.754					
==> multiplied by	- 2						
Log Likelihood	- =	10771.359					
Akaike's Informati							
Schwarz's Bayesiar							
		1000000000					
Variable	Estimate	AsymStdError	z-value	p-value			
BETA (regression co	pefficients)						
intercept	47.55657	5.40992	8.79063	0.00000			
WEEKEND	1.20496	0.59715	2.01786	0.04361			
Age	-0.20820	0.05243	-3.97128	0.00007			
NEG AFFECT BS	-0.11113	0.18916	-0.58749	0.55687			
NEG AFFECT WS	-0.05355	0.02356	-2.27289	0.02303			
ALPHA (BS variance	parameters: log	-linear model)					
intercept	3.39942	0.26213		0.00000			
WEEKEND	0,08555	0.16148	0.52981	0,59625			÷
NEG AFFECT	0,01625	0.00550	2.95161	0,00316			
Age	0.01829	0.01096					
TAU (WS variance pa							
intercept	4,49482	0.11571	38,84520	0,00000			
WEEKEND	0,14750	0.08852					
NEG AFFECT	0.00363	0.00313					
Age	-0,00126	0.00360					
Random scale standa							
Std Dev	0.33630	0.06396	5,25832	0.00000			
Random location (me				0.00000			
Loc Eff	-0.13833	0.06357	-2.17606	0.02955			
<						>	ł
			Ln 1, Col 1	100% Windows (CRLF)	UTF-8		

2.3 Interpretation of MELS model Result {Example 1}

The output for the Stage 1 analysis is written to the file "Mixwild_data_Output_stage1.out" which includes some descriptive information. This analysis includes 94 subjects and a total of 1399 observations. An observation must have non-missing data on the Stage-1 dependent variable **[POS_AFFECT]**, and model covariates **[WEEKEND]**, **[NEG_AFFECT]** and **[Age]** for that particular observation to be included in the analysis. Here, **[Age]** refers to baseline age (Level-2 variable) and it has been centered around mean (mean = 29.29). The program lists out the number of Level-1 observations (days) for each Level-2 observation (subjects). For the dependent variable **[POS_AFFECT]** and model covariates, means, minimums, maximums, and standard deviations are listed in the descriptive tables.

Descriptives

Number	of	level-1	observations	=	1399
Number	of	level-2	clusters	=	94

Dependent variable

-	mean	min	max	std dev
POS_AFFECT	44.6011	10.0000	70.0000	13.4889
Mean model covaria	ates			
	mean	min	max	std dev
intercept	1.0000	1.0000	1.0000	0.0000
WEEKEND	0.4939	0.0000	1.0000	0.5001
Age	4.2298	-23.5300	47.4700	15.6966
NEG AFFECT BS	28.6011	19.9412	44.2000	4.1639
NEG AFFECT WS	-0.0000	-26.3182	47.8500	12.8632
BS variance model	covariates mean	min	max	std dev
intercept	1.0000	1.0000	1.0000	0.0000
WEEKEND		0.0000		
NEG AFFECT		10.0000		
WS variance model	covariates			
	mean	min	max	std dev
intercept	1.0000	1.0000	1.0000	0.0000
WEEKEND	0.4939	0.0000	1.0000	0.5001
NEG AFFECT				

Following the descriptive tables, the results of three different Stage 1 models are listed below, each with incrementally increased complexity.

The first one is the "Model without Scale Parameters". This model can be viewed as a regular mixed-effects model with a BS Variance submodel. As you can see, there is no random scale parameter in this model.

Model without Scale P	arameters			
Total Iterations = Final Ridge value =				
Log Likelihood Akaike's Information Schwarz's Bayesian C		-5413.810		
==> multiplied by -2 Log Likelihood Akaike's Information Schwarz's Bayesian C	= Criterion =			
Variable	Estimate	AsymStdError	z-value	p-value
BETA (regression coef	ficients)			
intercept	43.89846	5.43438	8.07791	0.00000
WEEKEND Age NEG_AFFECT_BS	0.92672	0.59280	1.56330	0.11798
Age	-0.18557	0.05206	-3.56470	0.00036
NEG_AFFECT_BS	0.02247	0.18997	0.11829	0.90584
NEG AFFECT WS	-0.06275	0.02361	-2.65728	0.00788
ALPHA (BS variance pa				
intercept	3.36195	0.27192	12.36377	0.00000
WEEKEND				
		0.17038		
NEG_AFFECT				
TAU (WS variance para	0.01844 meters: log-l	0.00586	3.14976	0.20443 0.00163

The second model refers to the **"Model with Scale Parameters"**. It includes scale parameters but not random scale parameters. The WS Variance model here is as presented in <u>Equation 2.4</u>. As the results in the "Model with Scale Parameters" shows there are two regressors **[WEEKEND]** and **[NEG_AFFECT]** predicting WS variance. However, the model does not include a random component to let the WS variance to vary across subjects beyond the covariate effects.



Log Likelihood	=	-5401.091
Akaike's Information Criterion	=	-5412.091
Schwarz's Bayesian Criterion	=	-5426.079
==> multiplied by -2 Log Likelihood Akaike's Information Criterion Schwarz's Bayesian Criterion	= = =	10802.181 10824.181 10852.158

Ch2

Variable	Estimate	AsymStdError	z-value	p-value
BETA (regression coe	fficients)			
intercept	43.79652	5.44345	8.04573	0.0000
WEEKEND	1.00948	0.59603	1.69367	0.09033
Age	-0.18441	0.05225	-3.52903	0.00042
NEG AFFECT BS	0.02385	0.19031	0.12534	0.90025
NEG AFFECT WS	-0.05389	0.02382	-2.26187	0.02371
ALPHA (BS variance p	arameters: log	-linear model)		
intercept	3.42199	0.26827	12.75593	0.0000
WEEKEND	0.13445	0.17506	0.76801	0.44248
NEG AFFECT	0.01783	0.00591	3.01947	0.00253
TAU (WS variance par	ameters: log-l	inear model)		
intercept	4.56750	0.10189	44.82621	0.00000
WEEKEND	0.22243	0.08532	2.60698	0.00913
NEG_AFFECT	0.00240	0.00295	0.81238	0.41657

The third sub-model, **"Model with Random Scale"**, includes both the scale and the random scale parameters. As mentioned, the Level-1 variable **[NEG_AFFECT]** has been decomposed in terms of its between-subject (BS) version (the subject mean of this variable across all occasions, **[NEG_AFFECT_BS]**) and the within-subject (WS) version (the subject's occasion specific deviation of the variable relative to the subject mean, **[NEG_AFFECT_WS]**). The program automatically created these two versions from the Level-1 variable when you checked the <u>"Disaggregate" in {Stage 1 Regressor} section</u> in {Stage 1 Configuration} page.

Model WITH RANDOM Scale Total Iterations = 17 Final Ridge value = 0.0 Log Likelihood = -5387.145 Akaike's Information Criterion = -5400.145 Schwarz's Bayesian Criterion = -5416.677 ==> multiplied by -2 Log Likelihood = 10774.290 Akaike's Information Criterion = 10800.290 Schwarz's Bayesian Criterion = 10833.353

Variable	Estimate	AsymStdError	z-value	p-value
BETA (regression coef	ficients)			
intercept	45.47985	5.45639	8.33516	0.0000
WEEKEND	1.18496	0.59370	1.99590	0.04594
Age	-0.17835	0.05127	-3.47904	0.00050
NEG AFFECT BS	-0.03896	0.19071	-0.20431	0.83811
NEG AFFECT WS	-0.05260	0.02344	-2.24413	0.02482
ALPHA (BS variance pa	arameters: log	-linear model)		
intercept	3.50678	0.25525	13.73867	0.0000
WEEKEND	0.08828	0.16250	0.54328	0.58694
NEG_AFFECT	0.01646	0.00547	3.00758	0.00263
TAU (WS variance para	ameters: log-l	inear model)		
intercept	4.49095	0.11522	38.97701	0.0000
WEEKEND	0.14735	0.08879	1.65962	0.09699
NEG_AFFECT	0.00349	0.00313	1.11346	0.26551
Random scale standard	d deviation			
Std Dev	0.34636	0.06252	5.53970	0.0000
Random location (mear	n) effect on W	S variance		
Loc Eff	-0.11818	0.06222	-1.89946	0.05750

In the Mean (BETA) model, this analysis shows that the intercept of positive affect is 45.480 (when all covariates are equal to 0), and a person's positive affect is significantly related to their baseline age (*beta* = -0.178; p < 0.001), with increasing baseline age (Level-2 variable) associated with lower positive mood. The time-varying (Level-1) variable weekend has a positive association with positive affect (*beta* = 1.185; p = 0.046), which suggests subjects' positive affect was higher on weekend days compared to weekdays. The within-subject effect of negative affect is the other Level-1 variable, and it is inversely associated with positive affect (*beta* = -0.053; p = 0.025). This indicates that if a subject had a lower negative affect compared to the subject's daily average, he or she would have a higher positive affect on the same day. The data does not support that there is any statistical association between [NEG_AFFECT_BS] and [POS_AFFECT] (*beta* = -0.039; p = 0.038). This implies that one with a lower/higher subject-level mean on negative affect does not have a higher/lower mean on positive affect. The finding suggests that the within-subject component of negative affect at Level 1 (day-level) is significantly associated with daily positive affect, but the between-subject component of negative affect.

<u>The BS Variance (ALPHA) submodel</u> shows that subject's mean of positive affect is different from person to person (*Variance* = Exp(3.50678) = 33.34074). In other words, the random intercept

varies significantly across subjects (*alpha* = 3.507; p < 0.001). While there is no significant effect of weekend (vs. weekday) on the between-subject variability (*alpha* = 0.088; p = 0.587), the variance of subjects' mean in positive affect is less similar (more heterogeneous) to each other with higher levels of negative affect (*alpha* = 0.016; p = 0.003).

The results in <u>the WS Variance (TAU) submodel</u> display the estimate of the within-subject variance (on the log scale) in positive affect when the covariates all equal zero (tau = 4.491; p < 0.001). The within-subject variance in positive affect does increase somewhat for subjects on the weekend days (weekend effect on the WS variance), though this is not significant at the .05 level (tau = 0.147; p = 0.097). The change in negative affect is not seen to be associated with the consistency in daily positive affect reports (tau = 0.003; p = 0.266).

<u>Table "Random scale standard deviation"</u> suggests there is considerable scale variability (ω_i) in positive affect across subjects, as indicated by the random scale standard deviation (Std Dev); a significant random scale standard deviation suggests that subjects differ from each other in their degree of WS variance (*scale sd* = 0.346; *p* < 0.001).

<u>The estimates of "Random location (mean) effect on WS variance"</u> show WS variance and location intercept are marginally and negatively related (*estimate* = -0.118; p = 0.058) indicating that subjects with higher positive affect intercepts exhibit more consistency in their mood reports (less within-subject variability in their daily responses related to positive affect). It may imply that there was a ceiling effect in the positive affect response scale.

MiX Friendly Note:

As mentioned, the exponential function is used to ensure a positive multiplicative factor, and so the resulting BS and WS variance is strictly positive. Thus, it is totally fine to have "negative" estimates/coefficients in a BS/WS Variance submodel. By using the exponential function to transform the estimate (i.e., *Variance* = Exp(-1) = 0.367879), the value of the variance is still positive. The negative estimate just refers to a different direction in the relationship. For example, a result shows a negative value in the coefficient of "weekend" on the WS Variance in "anxiety levels", this can be interpreted as that the WS variance in "anxiety levels" was smaller on weekend days, compared to subjects' WS variability in "anxiety levels" on weekdays.

BS variance ratios and 95% CIs

Variable	Ratio	Lower	Upper
ALPHA (BS variance	- 2		
intercept	33.34078	20.21657	54.98499
WEEKEND	1.09230	0.79436	1.50198
NEG_AFFECT	1.01660	1.00575	1.02757

WS variance ratios and 95% CIs

Variable	Ratio	Lower	Upper
TAU (WS variance param	eters: log-li	near model)	
intercept	89.20587	71.17339	111.80706
WEEKEND	1.15876	0.97369	1.37902
NEG AFFECT	1.00349	0.99735	1.00967
Random location (mean)	effect on WS	variance	
Location Effect	0.88853	0.78653	1.00377
Random scale standard	deviation		
Std Dev	1.41391	1.25084	1.59824

Finally, the program also exponentiates all of the BS and WS variance parameter estimates, and lists out 95% confidence intervals for these parameters. For the covariates, these represent variance ratios. Thus, for example, the WS variance ratio for weekend is approximately 1.16 (*ratio* = 1.159), indicating that the WS variance increases by about 16% when subjects report on the weekend days.

2.4 Step by-step Instructions to MEMLS model {Example 2}

In this analysis, we will also use our <u>example data</u> to run a MEMLS model to examine whether positive affect (PA) differs on weekend days (vs. weekdays). In this example, we will have two random location effects. One is random intercept, subject-level mean of PA, and the other is random slope, subject-level slope of weekend predicting PA. The flowchart shows that by selecting "Random Intercept and Slope(s)" in the option of "Random Location Effects", a MEMLS model can be generated. Then we check the "Random Scale Effect" option to allow for the random scale effect in the model.



Figure 2-8. Example 2 MEMLS Flowchart

Q Research Question:

Does **positive affect** (continuous, time-varying variable) differ across weekend days vs. weekdays (dichotomous, time-varying variable) in the Mean and WS Variance submodels? Data source: https://reach-lab.github.io/MixWildGUI/Mixwild example data.csv

Model Configuration Page

1 Import data into MixWILD and format missing value: Please check {Chapter 1 Section 1.4} for more details. Be sure your data is CSV format and should be sorted ascending by ID.

	1	CSV file path:	heDrive\Documents\Mixwild_data_v2_mini.csv Change Dataset
Detect		Title (optional):	Example 2 MEMLS
Dataset	()	Does your data contain missing values?	● Yes O No
		What is your missing data coded as?	-999

2 Select the type of Stage 1 outcome: The Stage 1 outcome should be a time-varying outcome. In this example, the Stage 1 outcome is positive affect which is continuous. Please select [Continuous].

() Stage 1 outcome:

 Ordinal

- **3** Specify random location effects:
 - Select "Intercept and slope(s)", and the model includes a random subject intercept and slope(s) (in the Mean model). This is the key selection for creating a MEMLS model.



Include estimates of random scale: Random scale parameters allow subjects to have individual estimates of the within-subject variance (i.e., random subject scale effect).
 Please note a random scale effect is not allowed when the outcome is dichotomous.



5 Select Stage 2 model: MixWILD allows a two-stage modeling approach in which the Stage 1 random effects are used as regressors to predict an outcome in a Stage 2 model. In this example, we will not have a Stage 2 model so please select "No".



- 6 Complete Model Configuration settings:
 - Click "Continue": Click Continue to enter {Stage 1 Configuration} page.

Save Model	Continue
------------	----------

After you submit the {Model Configuration} page, MixWILD interface will switch to the {Stage 1 Configuration} page that enables you to set up your Stage 1 model.

ixWILD-2.0-Beta11			
I Configuration Stage 1 Configuration View Data Help			
Selected Model Configuration		Stage 1 Regresso	rs
Stage 1 model: Intercept + Slope(s) State 1 outcome: Continuous	Me	an Random Slop	e WS Variance
ID Variable:	Level-1		
ID			
Stage 1 Outcome:			
POS_AFFECT			
	Level-2	an	WS Variance
Configure Stage 1 Regressors	Level-2		
Options			
Association of random location & scale?			
Yes			
O No	Save Mod	el Clear Stage 1	Dun Stene 4
			Run Stage 1

7 Select ID: ID is the key variable to designate the 2-level data structure (i.e., observations at level-1 nested within level-2 subjects, who are distinguished by the ID variable). It should be sorted by this variable before importing the data. In this analysis, please select [ID] variable in our example data. [CLICK]

ID Variable:	
ID	-

8 Select Stage 1 Outcome: Please select [POS_AFFECT] variable, positive affect, as your outcome variable. [CLiCK]

Stage 1 Outcome:	
POS_AFFECT	-

Ch2

9 Select Stage 1 Regressors (Configure Stage 1 Regressors): [CLiCK]

- Variables should be specified as Level-1 or Level-2 by users.
- Select Level 1 Variables: In an EMA study, Level 1 variables refer to the time-varying variables at the observation level (person-time or prompt). In this analysis, please select the variable [WEEKEND] in the data. Use Add button to move variables from the {Variables} to {Level-1 (Time Varying)}. Use Remove button to switch back.
- Select Level 2 Variables: In an EMA study, Level 2 variables generally represent personlevel or time-invariant variables. Please select [Age] here. Use Add button to move variables from the {Variables} to {Level-2 (Time Invariant)}. Use Remove button to switch back.
- Click **Submit** button to process the selection. Click **Reset** if you want to clear all the selections and do it over.

\$	Add Stage 1 Regressors					-		×
	Variables			Lev	el-1 (Ti	me Var	ying)	
	SEX		WEEKEND					
	DOW]						
	OBESE BMI	Add						
	NEG_AFFECT	Remove						
	MVPA_daily_mins							
	SED_daily_hrs NEGMOOD10							
	POSMOOD10							
	MVPA_daily4							
				Lev	el-2 (Ti	me Inv	ariant)	
			Age					
		Add						
		Auu						
		Remove						
			Cancel		Res	set	Subm	lit

10 Stage 1 Options (optional):

Please note these settings are all **OPTIONAL**. Please check the details in the prior example.

MiX Friendly Note:

For more details about options in MixWILD, please check <u>"Point 10" in {Chapter 2 Section 2.2}</u> and Appendix B: Table 1 in Dzubur and his colleagues' article (2020).

11 Specify Stage 1 Regressors in Mean and WS Variance submodels (important):

Please note it is critical to specify your Stage 1 regressors. If you just follow the <u>"Step 9"</u> instruction and assign variables into Level-1 and/or Level-2 columns **but you do not check any of these selected regressors** (i.e., all these boxes are unchecked), there will be no regressor in your submodels. To ensure that at least one submodel has one or more regressor(s), you have to specify variables and check the boxes in the {Stage 1 Regressor} section.



- <u>Mean model</u>: This consists of a submodel that examines the relationship between one or more regressor(s) and the mean of the outcome. This can be considered as the regular mixed-effects/multilevel model with random intercept only. We use x' to represent the regressor(s) and β are the corresponding regression coefficients.
- In this example, please check the boxes of [WEEKEND] and [Age] in the Mean model.
 [CLICK]
- Disaggregate: Select the option for each of the time-varying variable(s) for which decomposition of the within- and between-subject effects in predicting Stage 1 model outcome(s) is desired. The selected Level-1 variable will be decomposed in terms of its the within-subject (WS) version and between-subject (BS) version. In this example, please keep the [Disaggregate] option unchecked.

MiX Friendly Note:

The option "Disaggregate" is only available for time-varying variables. Please check <u>"Point 11"</u> in {Chapter 2 Section 2.2} for more details.

- Random Slope (important): In a MEMLS model, the specification of "Random Slope" means the option/procedure which allows for extra random location(s) aka random slope(s) in the Mean model. The term, "Random Slope" in the {Stage 1 Regressor} section, does not suggest that it is a submodel which uses random slope(s) as the outcome variable such as the format and design we see in the MELS BS Variance submodel in {Chapter 2 Section 2.2}. The interface layout between <u>"MELS BS Variance"</u> and "MEMLS Random Slope" specification may be similar. However, instead, the function/usage of "Random Slope" represents a selection of variables that will be treated as subject-level random (location) effects. As mentioned in <u>the Variance-covariance Matrix</u>, MEMLS models will be complicated and estimation time will be significantly increased with each additional random effect. Please add the random slope effect judiciously.
- Please check the box of **[WEEKEND]** in "Random Slope" specification so Equation 2.15 is able to include the random slope coefficient (v_{W_i}) of **[WEEKEND]** [CLICK].

MiX Friendly Note:

Please note the option of **"Random Slope"** is **only available** for **time-varying variables** because time-invariant observations have no within-subject variance. As a result, random slope specification is excluded from "Level-2 regressors" and "between-subject (BS) version of Level-1 variables" (when using "Disaggregate").

- The Mean model with Random Intercept and Random Slope is as follows:

$$y_{ij} = (\beta_0 + v_{0_i}) + (\beta_W + v_{W_i}) WEEKEND_{ij} + \beta_A Age_i + \epsilon_{ij},$$
$$v_{0_i} \sim N(0, \sigma_{v_0}^2), \ v_{1_i} \sim N(0, \sigma_{v_1}^2), \ \epsilon_{ij} \sim N(0, \sigma_{\epsilon}^2)$$
(2.15)

- In Equation 2.15, **[WEEKEND]** is a Level-1 (time-varying) variable, while **[Age]** is Level-2 variable. Random intercept, v_{0_i} , represents subject's mean (when weekend=0). Random slope, v_{W_i} , indicates the extra random part (association) for a subject beyond the average slope β_W (slope of **[WEEKEND]** predicting **[POS_AFFECT]**). β_0 is the grand intercept. β are the equivalent of fixed effect coefficients in a traditional multilevel model.
- <u>WS Variance submodel</u>: This refers to a submodel that examines the relationship between one or more regressor(s) and within-subject variance of the outcome. We use w' to represent the regressor(s) and τ are the corresponding regression coefficients.
- Please check the boxes of [WEEKEND] in the WS Variance submodel. [CLICK]
- The WS Variance submodel is as follows:

$$\sigma_{\epsilon_{ij}}^{2} = exp(\tau_{0} + \tau_{W}WEEKEND_{ij} + \tau_{v}v_{i}' + \omega_{i}),$$

$$\omega_{i} \sim N(0, \sigma_{\omega}^{2})$$
(2.16)

In Equation 2.16, **[WEEKEND]** is Level-1 (time-varying) regressor, while there is no Level-2 variable. τ_0 represents the intercept in the WS Variance model when the WSV intercept option has been checked in <u>{Intercept Options}</u>. τ_W is the coefficient of regressor **[WEEKEND]**. τ_v (coefficient) and v'_i (multiple random location effects: random intercept and slope(s)) show that an association between the location and scale random effects can be induced by including the location random effects as predictors in the WS Variance. ω_i represents the random scale effect which allows the within-subject variance to vary across subjects.

- Please note Level-1 and Level-2 regressors are all available in the WS Variance submodels although this example did not include any Level-2 variable in the submodel.

12 Specify the relationship between the random location & scale

The option is available when you check "Yes" in the question about "Include estimates of random scale" in {Model Configuration} page. As mentioned in the section of <u>"WS Variance submodel"</u>, this allows the random intercept and random slope(s) (v'_i) to influence the WS variance. MixWILD theoretically allows for two possibilities to describe the relationship between random location and random scale: (1) no association ($\tau_v = 0$) or (2) association ($\tau_v \neq 0$) (Dzubur et al., 2020). However, in current version of MixWILD, there is no option for selecting "No". When using MEMLS models with the random scale effect, the association between random location and random scale will be ("Yes") as default. The specification has been locked for now. This option will be available in the future update.

Association of random location & scale?
Yes
⊖ No

13 Run Stage 1 Model: Please verify your model specifications and click on "Run Stage 1" to generate the definition (DEF) file. You may also click "Save Model" to keep all parameters in MW format so you could reload the settings when needed. [CLiCK]

	Save Model	Clear Stage 1	Run Stage 1
--	------------	---------------	-------------

- **14 Preview DEF File and Proceed the Analysis:** The DEF file is a copy of your model specifications which communicates with Fortran to execute statistical analyses. In the definition file, click on "Proceed" to run your model and generate model output files. [CLiCK]
- **15 Model Estimation:** A pop-up window will appear while model estimation is in progress. Please note the time of data processing and parameter estimation will increase if the data size is large or the model includes multiple random effects.

MiX Friendly Note:

If you experience a model crash and the warning message below appears, it indicates that computational difficulties were likely encountered and prevented the model parameters from being estimated successfully. In this case, confirm the format of your dataset and check your model specifications (<u>Table 2-3</u>). **Troubleshooting** suggestions are listed in Appendix A: Steps to take when the program does not converge to a solution.

Message		×
i Faile	d	
	ОК	

Stage 1 Results Page

When the model estimation is completed, MixWILD will automatically switch to the {Stage 1 Results} page. If not, please click the "Stage 1 Results" tag to check the Stage 1 output.

Model Configuration	Stage 1 Configuration	Stage 1 Results	View Model	View Data	Help		
Results fro	om stage 1 analysis						
MIXREGLS	_both: Mixed-effects Lo	cation Scale Mode	:1]
mixREGLS	_both.DEF specification	5				=	
Created	with MixWILD GUI						
Mixwild	d output files: _data_v2_mini.dat _data_v2_mini_Output_st	agel.out					
SCALE E CONVERGI RIDGEIN NQ QUADRAT	E LOCATION EFFECTS = T FFECT = T ENCE CRITERION = 0.0000 = 0.1500 = 11 JRE = 1 (0=non-adapt: = 200	01000					
Descript:	ives						
Number (of level-1 observations	= 1523					
	of level-2 clusters		_				
	of level-1 observations 16 15 23 22			17 22	20	•	
						Save Results As	

By default, MixWILD stores your outputs in your Windows personal Documents folder. The default address in Win10 is in your account's **%UserProfile%** folder (i.e., "C:\Users\UserName\ OneDrive\Documents"). All files generated from the program can be found in a folder name with the prefix MixWILD and the 12-digit number labelling the date and time that this folder was created.

	>	This PC > Documents	~	ひ 。 Search Docu	uments
^		Name	Status	Date modified	Туре ^
		MIXWILD202104060942	S	4/6/2021 9:46 AM	File fold
		MIXWILD202104060944	C	4/6/2021 9:48 AM	File fold
~	<	• • • •		1/2/2021 1 22 111	>

In the file with suffix **"_Output_stage1.out"**, you can find that the content is identical to the results found in the {Stage 1 Results} page. The estimated subject-specific random effects are saved to a data file with the suffix **"_ebvar.dat"**.

Name	Status	Date modified	Туре
📕 work	\odot	4/6/2021 9:48 AM	File folder
📄 logger.log	C	4/6/2021 9:44 AM	Text Document
logger.log.lck	g	4/6/2021 9:44 AM	LCK File
Isboth_random_mixblank.def	\odot	4/6/2021 9:44 AM	DEF File
Isboth_random_mixblank64.exe	\odot	4/6/2021 9:45 AM	Application
Mixwild_data.dat	\odot	4/6/2021 9:44 AM	DAT File
Mixwild_data_Output.def	\odot	4/6/2021 9:45 AM	DEF File
Mixwild_data_Output_ebvar.dat	\odot	4/6/2021 9:48 AM	DAT File
Mixwild_data_Output_stage1.out	\odot	4/6/2021 9:48 AM	OUT File
modelingProgress.txt	\odot	4/6/2021 9:48 AM	Text Document
📧 stage2only64.exe	\odot	4/6/2021 9:45 AM	Application

2.5 Interpretation of MELS model Result {Example 2}

The output for the Stage 1 analysis is written to the file "Mixwild_data_Output_stage1.out" which includes some descriptive information. This analysis includes 94 subjects and a total of 1523 observations. An observation must have non-missing data on the Stage-1 dependent variable **[POS_AFFECT]**, and model covariates **[WEEKEND]** and **[Age]** for that particular observation to be included in the analysis. Here, **[Age]** refers to baseline age (Level-2 variable) and it has been centered around mean (mean = 29.29). The program lists out the number of Level-1 observations (days) for each Level-2 observation (subjects). For the dependent variable **[POS_AFFECT]** and model covariates, means, minimums, maximums, and standard deviations are listed in the descriptive tables.

Descriptives				
Number of level-1	observations	= 1523		
Number of level-2	clusters	= 94		
Dependent variabl	e			
-	mean	min	max	std dev
POS_AFFECT	44.1884	10.0000	70.0000	13.3476
Mean model covari		min	max	std dev
intercept WEEKEND Age	0.4938	1.0000 0.0000 -23.5300	1.0000	0.5001
BS variance model		min	max	std dev
intercept WEEKEND	1.0000 0.4938	1.0000 0.0000		
WS variance model		min	max	std dev
intercept WEEKEND		1.0000 0.0000		

Following the descriptive tables, the results of three different Stage 1 models of increasing complexity are listed. The program does this sequential building of the model complexity to improve the convergence of the final model stage.

The first one is the **"Model without Scale Parameters"**. This model can be viewed as a regular mixed-effects model. As you can see, there is no random scale parameter in this model. The second model refers to the **"Model with Scale Parameters"**. It includes scale parameters but not random scale parameters. While the "Model with Scale Parameters" includes one regressor **[WEEKEND]** to predict WS variance, this model does not include a random component to let the WS variance vary across subjects beyond the covariate effects. We skip these two submodels here. Please check the interpretation in <u>{Chapter 2 Section 2.3}</u> for more details.

The third and final sub-model, **"Model with Random Scale"**, includes both the scale and the random scale parameters. In <u>the Mean (BETA) model</u>, this analysis shows that the intercept of positive affect is 44.033 (when all covariates are equal to 0), and the time-varying (Level-1) variable weekend has a positive association with positive affect (*beta* = 1.398; *p* = 0.035), which suggests subjects' positive affect was higher on weekend days compared to weekdays. In addition, a person's positive affect is significantly related to their baseline age (*beta* = -0.166; *p* = 0.001), with increasing baseline age (Level-2 variable) associated with lower positive mood.

Model WITH RANDOM S	cale			
Total Iterations Final Ridge value				
Log Likelihood	=	-5837.005		
Akaike's Informati	on Criterion =	-5848.005		
Schwarz's Bayesian	Criterion =	-5861.993		
==> multiplied by Log Likelihood Akaike's Informati Schwarz's Bayesian	= on Criterion =	110/11000		
Variable	Estimate	AsymStdError	z-value	p-value
BETA (regression co	efficients)			
intercept	44.03320	0.91409	48.17156	0.00000
WEEKEND	1.39758	0.66252	2.10950	0.03490
Age	-0.16584	0.05203	-3.18745	0.00144

The estimates of "Random (location) Effect Variances and Covariances" show that subjects differed significantly between each other based on mean levels (random intercept) of positive affect (*estimate* = 59.240; p < 0.001) and differed in their association (random slope as indicated by the weekend regressor) between weekend and positive affect (*estimate* = 13.707; p < 0.019). However, 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 positive affect and the coupling association of weekend and positive affect (*estimate* = -5.639; p = 0.323). Please note the estimates are based on results of the Variance-covariance Matrix. It is *NOT* a report of the BS Variance submodel in MELS model in {Chapter 2 Section 2.3}.

Variable	Estimate	AsymStdError	z-value	p-value
Random (location)	Effect Variances	and Covariances		
intercept	59.24007	10.29749	5.75287	0.0000
Covariance	-5.63862	5.70737	-0.98795	0.32318
WEEKEND	13.70715	5.85948	2.33931	0.01932

The results in <u>the WS Variance (TAU) submodel</u> provides an estimate of the within-subject variance (on the log scale) of positive affect when all covariates equal zero (tau = 4.539; p < 0.001). The within-subject variance in positive affect is not associated with the weekend days (weekend effect on the WS variance) (tau = 0.125; p = 0.124).

Variable	Estimate	AsymStdError	z-value	p-value
<mark>TAU (WS variance</mark> intercept WEEKEND	parameters: log-1: 4.53923 0.12493	<mark>inear model)</mark> 0.06936 0.08122	65.44131 1.53820	0.00000 0.12400

<u>The estimates of "Random Scale Variance and Covariance"</u> shows neither the WS variance and location intercept are related (*estimate* = -0.462; p = 0.345), nor the WS variance and the slope of weekend predicting positive affect are associated (*estimate* = -0.409; p = 0.237). In addition, there is considerable scale variability (ω_i) in positive affect across subjects (Scale int var); a significant random scale estimate suggests that subjects differ from each other in their degree of WS variance (*estimate* = 0.151; p < 0.001).

Variable	Estimate	AsymStdError	z-value	p-value
Random Scale Varianc	e and Covarian	ce		
Cov intercept	-0.46224	0.48968	-0.94396	0.34519
Cov WEEKEND	-0.40871	0.34581	-1.18192	0.23724
Scale int var	0.15138	0.04571	3.31174	0.00093

Finally, the program also exponentiates all of the WS variance parameter estimates, and lists out 95% confidence intervals for these parameters. For the covariates, these represent variance ratios. Thus, for example, the WS variance ratio for weekend is approximately 1.13 (*ratio* = 1.133), indicating that the WS variance increases by about 13% when subjects report on the weekend days.

WS variance ratios and 95% CIs

Variable	Ratio	Lower	Upper
TAU (WS variance intercept WEEKEND	parameters: log-linear 93.61848 1.13306	model) 81.71831 0.96633	107.25160 1.32857
Chapter 3

Two-stage Model Approach

Chapter 3 Two-stage Model Approach

Chapter 3 will go beyond the Stage 1 model by introducing a two-stage model. MixWILD combines a Stage 1 mixed-effects location-scale (**MELS**) or mixed-effects multiple location scale (**MEMLS**) model of a Stage 1 outcome with a subsequent Stage 2 regression model in which the Stage 1 random effects are used as regressors. This Stage 2 outcome can be a subject-level (single level) or 2-level (multilevel) outcome, and it can be of four different outcome types: continuous (normal), dichotomous/ordinal, count, or nominal. In this chapter, we will provide two examples to show how to interpret the associations of Stage 1 random effects with a Stage 2 outcome.

3.1 Build on Stage 1 model

As discussed in Chapters 1 and 2, MixWILD can incorporate two stages of the total model: 1) *'Stage 1 mixed-effects model'*, in which random subject intercept and slopes (location effects) and random subject within-subjects variance (scale effect) are estimated, and 2) *'Stage 2 model'*, in which the Stage 1 random subject effect estimates are used as regressors and interaction terms to predict a Stage 2 outcome.

3.1.1 Stage 1 model

In Stage 1, a mixed-effects location-scale (MELS) model is specified, which extends the conventional mixed-effects regression model by allowing modeling of both the between-subject (BS) and within-subjects (WS) variances in terms of covariates (Hedeker et al., 2008). Specifically, log-linear submodels for the BS and WS variances are used, allowing covariates to influence both types of variance. Additionally, besides the inclusion of a random subject location effect in the Mean model, a random subject scale effect is added to the WS variance specification, allowing the WS variance to be subject-specific, as well as influenced by covariates. Thus, these MELS models include both random subject location and scale effects, which are estimated using empirical Bayes methods (Bock, 1989). MixWILD can also allow for random subject intercept and slopes (of time-varying covariates) in the Mean model, which we refer to as mixed-effects

multiple location scale (MEMLS) models. In all, these subject-specific parameters indicate a baseline mean level (random intercept), the effect of a (time-varying) covariate on the mean (random slope), and the degree of within-subject variability (random scale) (Dzubur et al., 2020).

3.1.2 Stage 2 model

These random subject effects from the Stage 1 analysis can then be used in a regression model to predict a Stage 2 outcome. Stage 2 is a regression model that allows a subject-level outcome or multilevel outcome (nested within time or clusters) to be influenced by the Stage 1 random effects, as well as other covariates. The Stage 2 outcome can be of four different outcome types: continuous (normal), dichotomous/ordinal, count, or nominal.



Figure 3-1. Simple illustration of Stage 1 & Stage 2 models.

*Stage 1 model must be a multilevel model.

*Stage 2 model could be a subject-level or multilevel model.

3.1.3 Two-stage modelling approach

Two-stage here refers to the combination of Stage 1 and Stage 2 models in MixWILD. The Stage 1 MELS/MEMLS model parses the variance into the effects of locations and variability, which are used as predictors in a regression model of associations with the Stage 2 outcome. <u>This two-stage</u> <u>model approach provides the capacity for allowing researchers to test whether the Stage 1</u>

random effects (means, variances, slopes) have predictive, mediating, and/or moderating effects on the Stage 2 outcome.

For example, one may wonder whether there is an association between alone/with others (Stage 1 covariate) and momentary positive affect (Stage 1 outcome) and would like to further explore if the association of being alone predicting positive affect (i.e., subject-level slope) may influence momentary physical activity (Stage 2 multilevel outcome). MixWILD can generate a MEMLS model to examine the association between positive affect (Stage 1 outcome) and alone/with others (Stage 1 covariate) in the Stage 1 model. Then using the random slope of alone/with others (along with the random intercept and scale) predicting positive affect in the Stage 2 model allows for examining whether the change in positive affect when being alone relative to being with others is associated with momentary physical activity (Stage 2 multilevel activity (Stage 2 multilevel outcome).



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3.2 Stage 1 and Stage 2 model in two-stage mixed effects approach

To better understand how the Stage 1 and Stage 2 models work together, we provide two examples to illustrate the basic formation of the MELS model and the MEMLS model in Stage 1, and then the summaries are presented in Table 3-1 and 3-2. The examples in Table 3-1 and 3-2 use a continuous Stage 1 outcome with a continuous Stage 2 outcome (though, as noted, the Stage 2 outcome could instead be binary/ordinal, count, or nominal).

3.2.1 Stage 1 MELS model and Stage 2 Mixed-effects regression model

	Equation (Level 1 & Level 2)
	Mean Model:
	$y_{ij} = (\beta_0 + v_{0_i}) + \beta_1 x_{ij} + \epsilon_{ij}$
Stage 1: Mixed-effects location-scale (MELS) model [continuous	BS Variance Submodel: $\sigma_{v_{0_{ij}}}^2 = exp(\alpha_0 + \alpha_1 u_{ij})$ WS Variance Submodel: $\sigma_{\epsilon_{ij}}^2 = exp(\tau_0 + \tau_1 w_{ij} + \tau_l v_{0_i} + \omega_i)$
outcome]	Pogrossors
	Regressors: x_{ij} , u_{ij} , and w_{ij} : Regressors for the three models (can be the same variable)
	v_{ij} , u_{ij} , and w_{ij} . Regressors for the three models (can be the same variable) v_{0i} : Location "random" effect of Stage 1 outcome (y_{ij})
	ω_i : Scale "random" effect of Stage 1 outcome (y_{ij})
	Mixed Model:
Stage 2: Mixed-effects	$y_{ij}^{*} = \beta_{0}^{*} + u_{0i} + \beta_{1}^{*} \hat{v}_{0i} + \beta_{2}^{*} \hat{\omega}_{i} + \epsilon_{ij}^{*}$
regression	
model (MRM)	Regressors: \hat{c} = 5 stimulated regions in a f Stand 4 systems (w.)
[continuous	\hat{v}_{0i} : Estimated random location of Stage 1 outcome (y_{ij})
outcome]	$\widehat{\omega}_i$: Estimated random scale of Stage 1 outcome (y_{ij})
	u_{0_i} : Random intercept of Stage 2 outcome (y_{ij}^*)

Table 3-1. Stage 1 M	ELS model and Stage 2 MRM
TUDIC D I. DLUGC I IV	LES model and Stage 2 minut

Stage 1 MELS model

Consider a simple MELS model (Stage 1) for the measurement y of individual i (i = 1, 2, ..., N subjects) on occasion j (j = 1, 2, ..., n_i occasions) in Table 1, this model represents the regression of outcome variable y_{ij} (i.e., positive affect) on the one independent variable x_{ij} (i.e., social context: alone vs. with others). Additionally, v_{0i} represents a subject's mean (deviation from grand mean, β_0), and it is referred to as a random location/intercept effect in the MELS model. β_0 is the grand intercept, and ϵ_{ij} is subject *i*'s error at time *j* (deviation of a subject's observations from their mean and the fixed part of the model). In the BS Variance submodel, $\sigma_{v_0ij}^2$ refers to the BS variance and u_{ij} is the regressor for the BS Variance model, and α_0 and α_1 are the corresponding regression coefficients.

In the WS variance submodel with random scale effect and linear association between the location and scale random effect, $\sigma_{\epsilon_{ij}}^2$ refers to the WS variance and w_{ij} is the regressor for the WS variance model, and τ_0 and τ_1 are the corresponding regression coefficients. Additionally, the random scale effect, ω_i , allows the WS variance to vary across subjects beyond the contribution of covariates, and the coefficient τ_l represents the linear association between a subject's location effect and the WS variance (here, the random subject location effect v_{0i} is akin to a regressor in the WS variance submodel).

Stage 1 MELS model to Stage 2 MRM

As mentioned in {Chapter 3 Section 1.2}, the Stage 2 model can be a subject-level or mixed-effects (multilevel) regression model (MRM). For the Stage 2 mixed-effects modeling, this program can only estimate a MRM with a random intercept at this point (random slopes are not yet possible). In Table 1, the example shows a mixed-effects linear regression model for the measurement y^* of individual i (i = 1, 2, ..., N subjects) on occasion j ($j = 1, 2, ..., n_i$ occasions). The example in Table 1 shows there are two subject-level (Level-2) regressors in the Stage 2 model: \hat{v}_{0_i} represents the random intercept, and $\hat{\omega}_i$ represents the random scale from the Stage 1 model. Please note a "hat" symbol (^) placed over the variable is the statistical designation of an estimated parameter (i.e., $\hat{\omega}_i$). β_0^* is the grand intercept; β_1^* is the coefficient of the random intercept effect; β_2^* is the

coefficient of the random scale effect; ϵ_{ij}^* is subject *i*'s error at time *j*. Please note the β^* (i.e., β_0^*) is used to designate the fixed effects in the Stage 2 model as different from those β (i.e., β_0) in the Stage 1 model. Similarly, y_{ij}^* and ϵ_{ij}^* are used to distinguish the outcome and the error terms in the Stage 2 model, respectively.

MiX Friendly Note:

The unit of Level 1 in the Stage 2 model could be different from the unit of Level 1 in the Stage 1 model. However, the unit of Level 2 in the Stage 1 and Stage 2 models should be the same in order to link the two datasets properly.

3.2.2 Stage 1 MEMLS model to Stage 2 MRM

	Equation (Level 1 & Level 2)		
	Mean Model:		
Stage 1:	$y_{ij} = (\beta_0 + v_{0i}) + (\beta_1 + v_{1i})x_{ij} + \epsilon_{ij}$		
Mixed-			
effects	WS Variance Submodel:		
multiple	$\sigma_{\epsilon_{ij}}^2 = exp(\tau_0 + \tau_1 w_{ij} + \boldsymbol{v}'_i \boldsymbol{\tau}_{\boldsymbol{v}} + \omega_i)$		
location			
scale	Regressors:		
(MEMLS) x_{ij} and w_{ij} : Regressors for the two models (can be the same regressor)			
[continuous	v_{0_i} : Location "random" effect of Stage 1 outcome (y_{ij})		
outcome]	v_{1i} : Slope "random" effect of Stage 1 regressor (x_{ij}) predicting outcome (y_{ij})		
	ω_i : Scale "random" effect of Stage 1 outcome (y_{ij})		
Stage 2:	Mixed Model:		
Mixed-	$y_{ij}^{*} = \beta_{0}^{*} + u_{0_{i}} + \beta_{1}^{*} \hat{v}_{0_{i}} + \beta_{2}^{*} \hat{v}_{1_{i}} + \beta_{3}^{*} \hat{\omega}_{i} + \epsilon_{ij}^{*}$		
effects			
regression	Regressors:		
model	${\hat{v}_0}_i$: Random intercept of Stage 1 outcome (y_{ij})		
(MRM)	\hat{v}_{1i} : Random slope of Stage 1 regressor (x_{ij}) predicting outcome (y_{ij})		
[continuous	$\widehat{\omega}_i$: Random scale of Stage 1 outcome (y_{ij})		
outcome]	u_{0_i} : Random intercept of Stage 2 outcome (y_{ij}^*)		

Stage 1 MEMLS model

Table 2 shows a MEMLS model (Stage 1) for the measurement y of individual i (i = 1, 2, ..., N subjects) on occasion j (j = 1, 2, ..., n_i occasions). The model represents the regression of outcome variable y_{ij} (i.e., positive affect) on the one independent variable x_{ij} (i.e., social context: alone vs. with others), and ϵ_{ij} is subject i's error at time j. The MEMLS extends the prior example (the MELS model), and it allow subjects to have their own mean (random intercept) as well as their own unique association (random slope) between the outcome and regressor x_{ij} in Stage 1. As shown in Table 2, β_0 is the grand intercept and β_1 is the corresponding regression coefficient of the regressor (x_{ij}). The random intercept, v_{0i} , represents subject's mean (deviation) when the regressor (i.e., social context: alone vs. with others) equals zero, as it is a deviation from the grand intercept. The random slope, v_{1i} , indicates the extra random part (association) for a subject beyond the average slope β_1 of x_{ij} predicting y_{ij} .

In the WS Variance submodel, $\sigma_{\epsilon_{ij}}^2$ refers to the WS variance and w_{ij} is the regressor for the WS variance model, and τ_0 and τ_1 are the corresponding regression coefficients. ω_i represents the random scale effect. As discussed in Hedeker and Nordgren (2013), an association between the location and scale random effects can be induced by including the location random effects (v'_i) as predictors in the WS Variance model, with coefficients τ_v . In this regard, MixWILD allows for two possibilities to describe the relationship between random location and random scale: (1) no association ($\tau_v = 0$) or (2) association ($\tau_v \neq 0$) (Dzubur et al., 2020). Please note that **bolded** v'_i and τ_v represent vectors. In other words, there could be more than one v'_i variable (random intercept and slope(s)), and therefore more than one *Tau* coefficient.

Stage 1 MEMLS model to Stage 2 MRM

A Stage 1 MEMLS model estimates more than one location effect, such as location and slope. In Table 2, this example shows a model for the measurement y^* of individual i (i = 1, 2, ..., N subjects) on occasion j ($j = 1, 2, ..., n_i$ occasions). Further extending the prior example in Table 1, the Stage 1 MEMLS model is not only able to test whether subject's intercept of Stage 1 outcome (i.e., positive affect) varies across, but also is capable of exploring whether a subject's responses to a time-varying covariate (i.e., momentary association of being alone predicting positive affect) could be different across people (i.e., random slope). Also, the MEMLS model allows for examining the random scale effect of Stage 1 outcome (i.e., positive affect) on Stage 2 outcome (i.e., momentary physical activity). In the equation, \hat{v}_{0_i} represents the subject-level random intercept estimate; \hat{v}_{1_i} represents the subject-level random slope estimate; and $\hat{\omega}_i$ is the subject-level random scale estimate. β_0^* is the grand intercept; β_1^* is the coefficient of the Stage 1 random intercept effect; β_2^* is the coefficient of the Stage 1 random slope effect; β_3^* is the coefficient of the Stage 1 random slope effect; β_3^* is the coefficient of the Stage 1 random scale effect; ϵ_{ij}^* is subject *i*'s error at time *j*. Please note the β^* (i.e., β_0^*) is used to designate the fixed effects in the Stage 2 model as different from those β (i.e., β_0) in the Stage 1 model. y_{ij}^* and ϵ_{ij}^* is used to distinguish the outcome and the error terms in the Stage 2 model respectively.

		Default Subject-level Stage 2 Regressor			Additional Stage 2 Regressor	
Stage 1	Stage 2	Random Intercept	Random Slope	Random Scale	Time-varying Variable (Level 1)	Time- invariant Variable (Level 2)
MELS	Subject-level Model	v	N/A	v	N/A	V
Model	Multilevel Model	v	N/A	v	V	V
MEMLS Model	Subject-level Model	v	V	V	N/A	V
	Multilevel Model	V	٧	٧	v	V

Table 3-3. Summary of two-stage model approach

* V: available; N/A: not available.

In sum, two-stage model approach can be considered as four sub-types based on the model types in Stage 1 and Stage 2. If you apply a MELS model in Stage 1, MixWILD will automatically generate two default subject-level regressors (random location and random scale effects) in the Stage 2 model, so you are able to use these variables as predictors, mediators or moderators of a Stage 2 outcome. By selecting a MEMLS model (random intercept, random slope(s) and random scale effects model) in Stage 1, there will be at least an extra subject-level regressor (random slope(s)) in the Stage 2 model compared to when a Stage 1 MELS model feeds into the Stage 2 model.

3.2.3 Uncertainty in the Random Effect Estimates

Resampling of the Stage 1 random effect estimates is conducted as an additional step when using the estimates of these random effects as predictors in the Stage 2 models. Resampling accounts for the fact that the Stage 1 analysis generates subject-level random effects as *estimated* parameters, which are then used as predictors in the Stage 2 analysis. As estimated quantities, these estimates can have varying degrees of uncertainty (Carsey & Harden, 2013). Since the random subject effects are estimates with estimated uncertainty, the "plausible value" replications of the random effects are performed, and this procedure is akin to multiple imputation for missing values (Mislevy, 1991). Therefore, for each subject, the random effects will be resampled multiple times to generate replications of the random effect estimates, and then these resampled data will be used to re-run the Stage 2 modeling procedure multiple times. Finally, results will be averaged for the coefficients and standard errors across the resamples. The recommendation for the number of resamples is 500 because this allows an estimation error of 1% at 95% coverage.

Dptions		-	×		
Mean Intercept: BS Variance Intercept: WS Variance Intercept:	× ×	Maximum Iterations: Ridge: Standardize All Regressors?	200 × 0.1 ×		
Convergence Criteria:	0.00001	Discard Subjects with no Variance?			
Quadrature Points:	11 -	Resample Stage 2:	2		
Adaptive Quadrature:	×	No. of Samples:	500 -		
Run in 32-bit mode (Experimental: for older Windows-based machines)					
		Cancel Reset	Submit		

Figure 3-2. Resample options

You can locate the "Resample" options in **[Stage 1 Options]** in {Stage 1 Configuration} page (Figure 3-2). The default value is 500, and please check "Point 10" in {Chapter 2 Section 2.2} or later session in {Chapter 3} for more details.

3.2.4 Interactions between random effects and covariates

As mentioned in <u>{Chapter 3 Section 1.3}</u>, the MixWILD two-stage approach extracts random effects from the Stage 1 analysis and these can be used in the Stage 2 model as predictors, mediators and/or moderators. On the {Stage 2 Configuration} page, the program provides a very handy graphical user interface (GUI) to include these possibilities in the Stage 2 model.

🕌 MixWILD-2.0							_		×
Model Configuration Sta	age 1 Configuration	Stage 2 Configuration	n View C)ata Help					
Selected Model Configuration Stage 2 Interactions						1			
Stage 1 model: Stage 1 outcom Stage 2 model ty Stage 2 outcom	ype: Multi-level	Le	evel-1	Main Effects	Random Loc	ation Random Scal	e Location X Scale		
	mples (stage 2): 500	s	Q						
Stage 2 Outc	:ome:			Main Effects	Random Loc	ation Random Scal	e Location X Scale		
Configure	Stage 2 Regressors		evel-2	main Enects	Random LOC	ation Ranuom Scal			
		н	ISG						
			Suppress	2-way Location	X Scale Interacti	on			
					Save Model	Clear Stage 2	Run Stage 1 and 2		

Figure 3-3 Stage 2 Interactions

No Interaction in Stage 2 Analysis

In Figure 3-3, it shows how you may modify your interaction effects in {Stage 2 Configuration} page. In the up-right corner (green dash line), the information displays that it is a Stage 1 MEMLS model (random intercept + random slope(s)) with a Stage 2 multilevel model. The outcome of

V2.0

Stage 2 model is **[LGA]** (learning goal achievement). Assume the Stage 1 model only has one timevarying regressor (i.e., survey day sequence) with a random slope effect to predict the Stage 1 outcome (i.e., positive affect). The mean model of the Stage 1 MEMLS model is presented as Equation 3.1.

Stage 1 MEMLS Mean Model:

$$PosAFF_{ij} = (\beta_0 + v_{0i}) + (\beta_1 + v_{1i})Day_{ij} + \epsilon_{ij}$$

$$v_{0i} \sim N(0, \sigma_{v_0}^2), v_{1i} \sim N(0, \sigma_{v_1}^2), \epsilon_{ij} \sim N(0, \sigma_{\epsilon}^2)$$
(3.1)

 $PosAFF_{ij}$ is the Stage 1 outcome, and Day_{ij} is the Stage 1 regressor. β_0 is the grand intercept and β_1 is the corresponding regression coefficient of regressor **[Day]**. The random intercept, v_{0i} , represents subject's mean, and the random slope, v_{1i} , indicates the extra random part (association) for a subject beyond the average slope β_1 of Day_{ij} predicting $PosAFF_{ij}$. ϵ_{ij} is subject *i*'s error at time *j*.

This configuration means that there are three default regressors (a random intercept effect (\hat{v}_{0i}) , a random slope effect (\hat{v}_{1i}) , and a random scale effect $(\hat{\omega}_i)$) in the Stage 2 model. By selecting **[Configure Stage 2 Regressors]**, the Stage 2 model now includes two additional regressors as follows:

Table 3-4. Additional Regressors

Name	Description	Level	Туре	Range
SQ	Sleep quality	1	Continuous	1-4
HSG	High school grades	2	Continuous	1-6

As shown in Figure 3-3, the Stage 2 model includes no interaction effect, there are only main effects of the regressors. The Stage 2 MRM is presented as Equation 3.2.

Stage 2 Mixed-effects Model:

$$LGA_{ij} = \beta_0^* + u_{0_i} + \beta_1^* SQ + \beta_2^* HSG + \beta_3^* \hat{v}_{0_i} + \beta_4^* \hat{v}_{1_i} + \beta_5^* \hat{\omega}_i + \epsilon_{ij}^*, u_{0_i} \sim N(0, \sigma_{u_0}^2), \epsilon_{ij}^* \sim N(0, \sigma_{\epsilon^*}^2)$$
(3.2)

In Equation 3.2, **[SQ]** is a time-varying regressor (Level 1), and **[HSG]** is a time-invariant regressor (Level 2). \hat{v}_{0i} represents random intercept effect of positive affect; \hat{v}_{1i} represents random slope of survey day predicting positive affect; $\hat{\omega}_i$ represents random scale effect of positive affect. These random effects are all subject-level (Level 2) regressors. β^* refers the corresponding regression coefficient of the each regressor in the Stage 2 model. u_{0i} is the Stage 2 random



Interaction in Stage 2 Analysis

intercept for subject *i*, and ϵ_{ij}^* is subject *i*'s error at time *j*.

Figure 3-4 Stage 2 Interactions (with 2-way and 3-way Interactions)

In Figure 3-4, the Stage 2 Interaction configuration shows that in addition to the main effect of [SQ] on the Stage 2 outcome **[LGA]**, the model estimates the interactions of **[SQ]** with the random

intercept, random slope, and random scale in predicting the **[LGA]**. Additionally, the model estimates a three-way interaction of **[SQ]** x **[random location]** x **[random scale]**.

There is also a level-2 regressor, **[HSG]**, in the Stage 2 model. Per the configuration (Figure 3-4), the model estimates a main effect of **[HSG]** on **[LGA]** and an interaction between [HSG] and random scale.

Stage 2 Mixed Model:

$$LGA_{ij} = \beta_{0}^{*} + u_{0_{i}} + \beta_{1}^{*}SQ + \beta_{2}^{*}HSG + \beta_{3}^{*}\hat{v}_{0_{i}} + \beta_{4}^{*}(\hat{v}_{0_{i}} \times SQ) + \beta_{4}^{*}\hat{v}_{1_{i}} + \beta_{5}^{*}(\hat{v}_{1_{i}} \times SQ) + \beta_{6}^{*}\hat{\omega}_{i} + \beta_{7}^{*}(\hat{\omega}_{i} \times SQ) + \beta_{7}^{*}(\hat{\omega}_{i} \times HSG) + \beta_{8}^{*}(\hat{v}_{0_{i}} \times \hat{\omega}_{i}) + \beta_{9}^{*}(\hat{v}_{0_{i}} \times \hat{\omega}_{i} \times SQ) + \beta_{10}^{*}(\hat{v}_{1_{i}} \times \hat{\omega}_{i}) + \beta_{11}^{*}(\hat{v}_{1_{i}} \times \hat{\omega}_{i} \times SQ) + \epsilon_{ij}^{*} u_{0_{i}} \sim N(0, \sigma_{u_{0}}^{2}), \epsilon_{ij}^{*} \sim N(0, \sigma_{\epsilon^{*}}^{2})$$
(3.3)

The order of the variables displayed in the Stage 2 output will be as follows:

- 1) Level-1 regressor(s)
- 2) Level-2 regressor(s)
- 3) Location effect 1: Random intercept
- 4) Interaction of random intercept and Level-1 regressor(s)
- 5) Interaction of random intercept and Level-2 regressor(s)
- 6) Location effect 2: Random slope(s)
- 7) Interaction of random slope(s) and Level-1 regressor(s)
- 8) Interaction of random slope(s) and Level-2 regressor(s)
- 9) Scale effect: Random scale
- 10) Interaction of random scale and Level-1 regressor(s)
- 11) Interaction of random scale and Level-2 regressor(s)
- 12) Interaction of random intercept and random scale
- 13) Interaction of random intercept, random scale, and Level-1 regressor(s)
- 14) Interaction of random intercept, random scale, and Level-2 regressor(s)
- 15) Interaction of random slope(s) and random scale
- 16) Interaction of random slope(s), random scale, and Level-1 regressor(s)
- 17) Interaction of random slope(s), random scale, and Level-2 regressor(s)

MiX Friendly Note:

Please note you need to check the box of **[Main Effects]** first to unlock the further options of interaction effects (Random Location or Random Scale). You also have to check both boxes of **[Random Location]** and **[Random Scale]** to allow selection of **[Location x Scale]** to enter the three-way interaction. Removal of either the Random Intercept or Random Scale interactions will lead to the automatic cancellation of the **[Location x Scale]** interaction with your selected variable(s).



Interaction in Stage 2 Analysis (Suppress 2-way Interactions)

Figure 3-5 Stage 2 Interactions (Suppress 2-way Interactions)

Adding multiple interaction effects can make the model more complicated. Sometimes you might want to have a simpler Stage 2 model specification and just desire to focus on basic interaction (i.e., interaction between random intercept and a regressor). By checking the box of **[Suppress 2-way Location X Scale Interaction]** (red solid line), you can remove all interactions between random location(s) and scale (Figure 3-5). As a result, the two-way interaction(s) such as

[Random Location(s) X Scale] will be completely excluded in the analysis. This provides a handy option to generate an analysis with basic interactions between each random effect and regressors.

In Figure 3-5, it also indicates that the three-way interaction (red dot line) between [SQ] and [Location X Scale] will be automatically removed when checking the box of [Suppress 2-way Location X Scale Interaction]. The rationale of the design is to make sure that the three-way interaction should be only available when the model includes all of the two-way interaction effects. If the model specification cannot meet the requirement, there will be no three-way interaction. The model specification in Figure 3-5 can be represented as Equation 3.4. Compared to Equation 3.3, Equation 3.4 removes "the two-way interaction between random intercept and random scale" and "the two-way interaction between random slope and random scale." In addition, Equation 3.5 does not have any three-way interaction such as the interaction among random intercept x random scale x sleep quality [SQ] because three-way interaction has been eliminated automatically when selecting [Suppress 2-way Location X Scale Interaction].

Stage 2 Mixed Model:

$$LGA_{ij} = \beta_0^* + u_{0_i} + \beta_1^* SQ + \beta_2^* HSG + \beta_3^* \hat{v}_{0_i} + \beta_4^* (\hat{v}_{0_i} \times SQ) + \beta_4^* \hat{v}_{1_i} + \beta_5^* (\hat{v}_{1_i} \times SQ) + \beta_6^* \hat{\omega}_i + \beta_7^* (\hat{\omega}_i \times SQ) + \beta_7^* (\hat{\omega}_i \times HSG) + \epsilon_{ij}^* u_{0_i} \sim N(0, \sigma_{u_0}^2), \epsilon_{ij}^* \sim N(0, \sigma_{\epsilon^*}^2)$$
(3.4)

MiX Friendly Note:

Please create interaction terms with caution. Adding too many two-way interaction terms or even three-way interaction terms may be at risk of generating computational issues in analysis. Starting your model with a simplified variable/interaction set is a good practice.

3.2.5 Terminology in two-stage approach method

In Chapters 1 - 3, this users' guide introduced many new terms (e.g., random intercept, random scale). While some terms are interchangeable (i.e., intraindividual variance = within-subject variability), some terms may have similar meanings, but they are used in different phase/stages of the model (i.e., random location \approx subject-level mean). In this section, let's review some terminology and see how they are used in the MELS/MEMLS model in MixWILD.

• **Random Location:** The random location effect is a general term which represents the degree to which a subject deviates from the population average. In the MEMLS model, random location effect can be decomposed into random intercept and random slope.



Figure 3-6 Terminology

- Random Intercept: The random Intercept effect is defined as the degree to which a subject deviates from the population average. It typically represents a subject-level mean effect, over and above the effects of covariates on the mean, and accounts for the non-independence of observations within subjects (Dzubur et al., 2020). For example, a random intercept effect of positive affect can be interpreted as the subject-level mean of positive affect, beyond the effects of covariates on positive affect. It is a random effect because the subjects in the sample are thought to represent a population, and each subject has their own intercept.
- Random Slope: The random slope effect refers to the association between a time-varying covariate and the time-varying outcome. In addition to the random intercept, random slope is also a type of location effect as it represents the relationship of the covariate and the mean response for each subject. Random slope effect indicates the degree to which

a subject varies from the population average association. The term can be interpreted as the coupling of the Stage 1 time-varying outcome variable (y) and the time-varying regressor (x). For example, a random slope effect of momentary positive affect and weekends/weekdays (weekends = 1; weekdays = 0) can be interpreted as the subject-

level change in the mean of positive affect on weekends relative to weekdays, beyond the effects of covariates on positive affect.

Random Scale (Within-subjects (WS) Variance): The random scale effect is defined as
the degree of within-subject variability, over and above the effects of covariates on the
within-subject variability (Dzubur et al., 2020). Random scale parameters allow subjects
to have individual estimates of the within-subject variance, and this is the distinguishing
feature of MELS and MEMLS models. It can be thought of as intraindividual variability or
variance when interpreting the data in analysis. The random scale effect has many aliases.
It is known as "Within-subject Variance", "Subject-level Variance", and as "Intraindividual
Variability". While these terms are used in different contexts, they all point to the same
concept which represents within-subject variability. For example, a random scale effect
of MVPA can be interpreted as the degree of subject-level variance in MVPA.

Model	Stage 1 Outcome	Stage 1 Regressor	Random Intercept	Random Slope	Random Scale
MELS	MVPA	N/A	Subject-level Mean of MVPA	N/A	Subject-level Variance of MVPA
MELS	Sleep	Negative Affect	Subject-level Mean of Sleep	N/A	Subject-level Variance of Sleep
MEMLS	Sleep	Negative Affect	Subject-level Mean of Sleep	Subject-level Slope of Negative Affect Predicting Sleep	Subject-level Variance of Sleep
MEMLS	Fast Food Intake	Weekend	Subject-level Mean of Fast Food Intake	Subject-level Slope of Weekend Predicting Fast Food Intake	Subject-level Variance of Fast Food Intake

Here, we give you simple examples to illustrate how these terms work in data.

* Random Slope Effect(s) are only available in MEMLS models; N/A: not available.

Ch3

3.3 Step by-step Instructions to Two-stage Modelling (Stage 1 MEMLS Model with



Stage 2 Multilevel Model without Interaction) {Example 1}

In this analysis, we will use <u>the data collected from Flueckiger and colleagues</u> to run a Stage 1 MEMLS model with Stage 2 MRM and examine if a person's daily learning goal achievement is associated with positive affect. Furthermore, we would like to explore if a subject's mean level and variability of positive affect, and the coupling of learning goal achievement and positive affect may influence sleep quality. The flowchart shows by selecting "Random Intercept and slope(s)" in the option of "Random Location Effects", we can create a MEMLS model in Stage 1. Then we check the "Random Scale Effect" option to allow for the random scale effect in the model. Finally, we include a Stage 2 model and specify the model configuration (i.e., model type) to allow for using random effects as regressors in the two-stage modeling approach.

Q Research Question:

Does **learning goal achievement** (continuous, time-varying variable) predict daily **positive affect** (continuous, time-varying variable) in the Mean and WS Variance submodels of the MEMLS?. Do the random intercept, slope, and scale of positive affect predict **sleep quality** (continuous, time-varying variable) in the Stage 2 MRM?

Data source: <u>https://dataverse.harvard.edu/dataverse/healthbehav</u>

You may need to convert the data into CSV format.

(i.e., Use EXCEL to read the SPSS/Tab-Delimited file and save as new CSV file).

Import data into MixWILD and format missing value: Please check {Chapter 1 Section 1.4} for more details. Be sure your dataset is in the CSV format and sorted by ID. Additionally, all data should consist of numerical values (i.e., integers or floats), except for the first row which includes the variable names.

	1	CSV file path:	hents\Dataset_HealthBehavAcadPerfAffect.csv	Change Dataset
Dataset		Title (optional):	Example 1 MEMLS and MRM	
Dataset	1	Does your data contain missing values?	● Yes 🔾 No	
		What is your missing data coded as?	-99	

2 Select the type of Stage 1 outcome: The Stage 1 outcome should be a time-varying outcome. In this example, the Stage 1 outcome is **positive affect** which is continuous. Please select

[Continuous].



- **3** Specify random location effects:
 - Select "Intercept and slope(s)", and the model includes a random subject intercept and slope(s) (in the Mean model). This is the key selection for creating a MEMLS model.

Specify random location effects:
 O Intercept only
 Intercept and slope(s)

Include estimates of random scale: Random scale parameters allow subjects to have individual estimates of the within-subject variance (i.e., random subject scale effect).
 Please note a random scale effect is not allowed when the outcome is dichotomous.



- 5 Select Stage 2 model: MixWILD allows a two-stage modeling approach in which the Stage 1 random effects are used as regressors to predict an outcome in a Stage 2 model. In this example, we will have a Stage 2 model so please select "Yes".
 - Include separate Stage 2 data file: Select "Yes" in this option when your Stage 1 and Stage
 2 data are located/saved in different data sets. In this case, you will need to specify the
 Stage 2 ID later in the [Stage 2 Configuration] page.

Select "No" when all Stage 1 and Stage 2 data come from the same dataset.

Stage 2 CSV file path: If the option, "Include separate Stage 2 data file" is applied, please specify the address of the Stage 2 dataset. Like the Stage 1 dataset, the first row should be variable names and all other data need to be numerical. Last but not least, the Stage 2 dataset must include a key variable (i.e., ID variable) that should be sorted in the same order as the Stage 1 dataset so both datasets can be linked properly.

i	Include Stage 2 model:	● Yes 🔾 No	
	Include separate Stage 2 data file:	○ Yes	
	Stage 2 CSV file path:		Import Dataset

- 6 Stage 2 model type: Stage 2 analysis can have two types. Please select "Multilevel".
 - **Single level:** The outcome of the Stage 2 model is at the subject-level.
 - **Multilevel:** The outcome of the Stage 2 model is a repeated measures variable that is nested within subjects, or subjects are nested within clusters.



- 7 Stage 2 outcome: The Stage 2 model allows for four types of outcomes.
 - Continuous: This type refers to a ratio variable (i.e., weight) or an interval variable (i.e., positive affect measured on a Likert scale), and assumed to be (conditionally) normally distributed.
 - Dichotomous/Ordinal: Variables have two or more categories, and these categories must also be ordered or ranked.

- **Count:** It consists of non-negative integers and discretely distributed (i.e., number of times snacks were consumed in a day).
- **Multinomial:** Variables have two or more categories, but the categories do not have an intrinsic order (i.e., types of physical activity).
- This example uses **sleep quality** as the Stage 2 outcome, please select [Continuous].

8 Set a seed for Stage 2 resampling (optional):

Since the random subject effects are estimates with estimated uncertainty, the program performs resampling of the random effects in the Stage 2 analysis. As a result, each analysis may yield slightly different results (i.e., different coefficients and significance levels) even under the same settings. MixWILD allows users to set a seed that varies between 1 and 65,000, which indicates the sample number for their posterior distribution. Users can edit the default seed randomly chosen by MixWILD. Select a custom seed value for the Stage 2 resampling can ensure the same result for the Stage 2 analysis when you re-run the model at another time.

() Set a seed for Stage 2 resampling (optional): 12345

9 Complete Model Configuration settings:

- **Click "Continue":** Click Continue to enter {Stage 1 Configuration} page.



After you submit the {Model Configuration} page, the MixWILD interface will switch to the {Stage 1 Configuration} page that enables you to set up your Stage 1 model.

MixWILD-2.0						_
del Configuration Stage 1 Config	uration Stage 2 Configuration	View Data Hel	р			
Selected Model Configuration			Stag	e 1 Regressors		
Stage 1 model: Intercept + S State 1 outcome: Continuous			Mean	Random Slope	WS Variance	-
ID Variable:		Level-1				
ID	•	LGA	r	*	¥	
Stage 1 Outcome:		Disaggregate?				
PA	•					
Configure Stage 1 Re	gressors	Level-2	Mean		WS Variance	
Options						
Association of random I	ocation & scale?					
Yes						
O No						-

10 Select ID: ID is the key variable to designate the 2-level data structure (i.e., observations at level-1 nested within level-2 subjects, who are distinguished by the ID variable). It should be sorted by this variable before importing the data. In this analysis, please select [ID] variable in our example data. This is also the variable that links with your Stage 2 data if the Stage 2 data are saved as a separate dataset. [CLiCK]

ID Variable:	
ID	-

11 Select Stage 1 Outcome: Please select **[PA]** variable, positive affect, as your Stage 1 outcome variable. **[CLiCK]**

Stage 1 Outcome:	
PA	•

- 12 Select Stage 1 Regressors (Configure Stage 1 Regressors): [CLiCK]
 - Variables should be specified as Level-1 or Level-2 by users.

- Select Level 1 Variables: In an EMA study, Level 1 variables refer to the time-varying variables at the observation level (person-time or prompt). In this analysis, please select the variable [LGA] in the dataset. Use Add button to move variables from the {Variables} to {Level-1 (Time Varying)}. Use Remove button to switch back.
- Select Level 2 Variables: In an EMA study, Level 2 variables generally represent person-level or time-invariant variables. Use Add button to move variables from the {Variables} to {Level-2 (Time Invariant)} if necessary. Use Remove button to switch back. In this example, we don't use any Level 2 variable so please just leave it blank.
- Click Submit button to process the selection. Click Reset if you want to clear all the selections and do it over.

13 Stage 1 Options (optional):

Please note these settings are all **OPTIONAL**. In most cases, you <u>DON'T</u> need to make any changes to these settings. However, in some cases, the program does not converge to a solution. Trying to change some of these parameters (i.e., Quadrature Points or Ridge) could help. The other solution in this situation, which we also strongly recommend, is to estimate a simpler model. We describe this more fully in Appendix A: Steps to take when the program does not converge to a solution. Please check "Point 10" in {Chapter 2 Section 2.2} for more details. Here, we just mention the settings that are related to Stage 2 analysis.

差 Options			_		×		
Mean Intercept:	1	Maximum Iteration	¢.		200		
BS Variance Intercept:	×	Ridge:			0.1		
WS Variance Intercept:	V	Standardize All Re	gressors?				
Convergence Criteria:	0.00001	Discard Subjects with no Variance?					
Quadrature Points:	11 +	Resample Stage 2	:		V		
Adaptive Quadrature:	~	No. of Samples:			500 ÷		
Run in 32-bit mode (Experimental: for older Windows-based machines)							
		Cancel	Reset		Submit		

- Resample Stage 2: This is a Stage 2 model option. Resampling of the subject-level random effects are conducted for all Stage 2 models to account for the fact that random effects are estimated quantities (Carsey & Harden, 2013). This option does not matter if you run Stage 1 models only.
- No. of Samples: This is a Stage 2 model option. Random effects are resampled multiple times from a normal distribution using the mean and variance estimates of these random effects for each subject. By default, the estimated random effects of the Stage 1 analysis (i.e., random location and scale effects) are resampled 500 times in the Stage 2 analysis. This option does not matter if you run Stage 1 models only.

14 Specify Stage 1 Regressors in Mean and WS Variance submodels (important):

Please note it is critical to specify your Stage 1 regressors. If you just follow the **"Point 12"** instruction and assign variables into Level-1 and/or Level-2 columns **but you do not check any of these selected regressors** (i.e., all these boxes are unchecked), there will be no options to include regressor(s) in your submodels. If you want your submodels to have options to include regressor(s), you have to specify variables and check the boxes in the {Stage 1 Regressor} section.

Stage 1 Regressors								
Level-1	Mean	Random Slope	WS Variance					
LGA Disaggregate?	¥	V	Ľ					
Level-2	Mean		WS Variance					

- **Mean model:** This consists of a submodel that examines the relationship between one or more regressor(s) and the mean of the outcome. This can be considered as the regular mixed-effects/multilevel model with random intercept only. We use x' to represent the regressor(s) and β are the corresponding regression coefficients.
- In this example, please check the boxes of [LGA] in the Mean model. [CLiCK]
- Disaggregate: Select the option for each of the time-varying variable(s) for which decomposition of the within- and between-subject effects in predicting the Stage 1 model outcome is desired. The selected Level-1 variable will be decomposed in terms of its the within-subject (WS) version and between-subject (BS) version. In this example, please keep the [Disaggregate] option unchecked.

MiX Friendly Note:

The option "Disaggregate" is only available for time-varying variables. Please check <u>"Point 11"</u> in {Chapter 2 Section 2.2} for more details.

- Random Slope (important): In a MEMLS model, the specification of "Random Slope" is the option/procedure which allows for extra random location(s) aka random slope(s) in the Mean model. The term, "Random Slope" represents a selection of variables that will be treated as subject-level random (location) effects.
- As mentioned in describing <u>the Variance-covariance Matrix</u>, MEMLS models are more complicated and estimation time will be significantly increased with each additional random effect. Please add the random slope effect(s) judiciously.
- Please check the box of [LGA] in "Random Slope" specification so the Mean model is able to include the random slope coefficient of [LGA] [CLiCK].

MiX Friendly Note:

Please note the option of **"Random Slope"** is **only available** for **time-varying variables** because time-invariant variables have no within-subject variance. As a result, random slope specification is excluded from "Level-2 regressors" and "between-subject (BS) version of Level-1 variables" (when using "Disaggregate").

- The Mean model with Random Intercept and Random Slope is as follows:

$$y_{ij} = (\beta_0 + v_{0_i}) + (\beta_L + v_{L_i})LGA_{ij} + \epsilon_{ij},$$

$$v_{0_i} \sim N(0, \sigma_{v_0}^2), \ v_{1_i} \sim N(0, \sigma_{v_1}^2), \ \epsilon_{ij} \sim N(0, \sigma_{\epsilon}^2)$$
(3.5)

- In Equation 3.5, **[LGA]** is a Level-1 (time-varying) variable, while there is no Level-2 variable. Random intercept, v_{0_i} , represents subject's mean (when **[LGA]** = 0). Random slope, v_{L_i} , indicates the extra random part (association) for a subject beyond the average slope β_L (slope of **[LGA]** predicting **[PA]**). β_0 is the grand intercept, and β_L is the coefficient of regressor, LGA. β are the equivalent of fixed effect coefficients in a traditional multilevel model.
- **WS Variance submodel:** This submodel examines the relationship between one or more regressor(s) and within-subject variance of the outcome. We use w' to represent the regressor(s) and τ are the corresponding regression coefficients.
- Please check the boxes of [LGA] in the WS Variance submodel. [CLiCK]
- The WS Variance submodel is as follows:

$$\sigma_{\epsilon_{ij}}^2 = exp(\tau_0 + \tau_L LGA_{ij} + \boldsymbol{v}'_i \boldsymbol{\tau}_{\boldsymbol{v}} + \omega_i),$$

$$\omega_i \sim N(0, \sigma_{\omega}^2)$$
(3.6)

- In Equation 3.6, **[LGA]** is Level-1 (time-varying) regressor, while there is no Level-2 variable. τ_0 represents the intercept in the WS Variance model (i.e., WS variance when **[LGA]** and the random effects equal 0). τ_L is the coefficient of regressor **[LGA]**. τ_v (coefficient) and v'_i (multiple random location effects) allow for association between the mean, as characterized by the location random effects, and the WS Variance. ω_i represents the random scale effect which allows the within-subject variance to vary across subjects.
- Please note Level-1 and Level-2 regressors are all available in the WS Variance submodels although this example did not include any Level-2 variable in the submodel.

15 Specify the relationship between the random location & scale:

The option is available when you check "Yes" in the question about "Include estimates of random scale" in {Model Configuration} page. As mentioned in the section of <u>"WS Variance submodel"</u>, this allows the random intercept and random slope(s) (v'_i) to influence the WS variance. MixWILD theoretically allows for two possibilities to describe the relationship between random location and random scale: (1) no association ($\tau_v = 0$) or (2) association ($\tau_v \neq 0$) (Dzubur et al., 2020). However, in the current version of MixWILD, there is no option for selecting "No Association". When using MEMLS models with the random scale effect, the association between random location and random scale will be ("Yes") as default. The specification has been locked for now. This option will be available in a future update.

Association of random location & scale?
Yes
O No

16 Configure Stage 2: Click "Configure Stage 2" to enter {Stage 2 Configuration} page. [CLiCK]



After you submit the {Stage 1 Configuration} page, the MixWILD interface will switch to the {Stage 2 Configuration} page that enables you to set up your Stage 2 model.

🕌 MixWILD-2.0						-	×
Model Configuration	Stage 1 Configuration	Stage 2 Configuration	View Data Help				
	Nodel Configuration			Stage 2 I	nteractions		
Stage 1 ou	odel: Intercept + Slope(s) Itcome: Continuous odel type: Multi-level	⊢ Leve	Main Effe	ects Random Lo	cation Random Sca	ale Location X Scale	
Stage 2 ou	tcome: Continuous resamples (stage 2): 500						
Stage 2	Outcome:						
	gure Stage 2 Regresso		Main Effe	ects Random Lo	cation Random Sca	ale Location X Scale	
Com	Jure Stage 2 Negresson	3					
		⊮ Su	ppress 2-way Loca	tion X Scale Interact	tion		
				Save Model	Clear Stage 2	Run Stage 1 and 2	

17 Select Stage 2 Outcome: Please select [SQ] variable, sleep quality, as your Stage 2 outcome variable. [CLiCK]

Stage 2 Outcome:	
SQ	-

18 Configure Stage 2 Regressors: Similar to Point 12, this step allows adding variables to Level 1 and Level 2 of Stage 2. Level 1 and Level 2 regressors are added from Stage 2 regressor window. We don't use any regressor in this example, except for random effects. Please leave it blank.

🔬 Add Stage 2 regressors		-		×
③ Variables		Level 1 (Tim	ne Variant	:)
Day				_
Sex				
Age				
Sem	Add			
PhysAct	Remove			
PA	Remove			
NA				
LGA				
Exam				
HSG		Level 2 (Tim	ie Invaria	nt)
BDI				
Day_c				
PA_ord				
HSG_rank	Add			
	Remove			
	Cancel	Reset	Subm	it

19 Stage 2 Interactions: This is the matrix that allows for specifying the interactions between Level 1/Level 2 regressor(s) and random effects (i.e., random intercept/slope(s)/scale). Note adding three-way interaction term(s) (Location X Scale X Regressor) may create model complexity. Please use it with caution.



As mentioned in Point 18, we don't add any regressors so there is no interaction option between the regressor and random effects. The equation of Stage 2 model is as below:

Stage 2 Mixed Model:

$$SQ_{ij} = \beta_0^* + u_{0_i} + \beta_1^* \hat{v}_{0_i} + \beta_2^* \hat{v}_{1_i} + \beta_3^* \hat{\omega}_i + \epsilon_{ij}^* u_{0_i} \sim N(0, \sigma_{u_0}^2), \ \epsilon_{ij}^* \sim N(0, \sigma_{\epsilon^*}^2)$$
(3.7)

- \hat{v}_{0_i} : Random intercept of Stage 1 outcome (y_{ij})
- \hat{v}_{1i} : Random slope of Stage 1 regressor (x_{ij}) predicting outcome (y_{ij})
- $\widehat{\omega}_i$: Random scale of Stage 1 outcome (y_{ij})
- u_{0_i} : Random intercept of Stage 2 outcome (SQ_{ij})
- 20 Suppress 2-way Location x Scale Interaction: The interaction(s) of location by scale are automatically specified in the default Stage 2 model, but this option can be disabled by checking the box "Suppress 2-way Location X Scale Interaction", which limits the model to include the main effects of random effects only. Note, once the "2-way Location X Scale Interaction" is disabled, any kind of three-way interaction would be removed automatically. Please check {Chapter 3 Section 3.2.4} for more details. In this example, we would like to test the main effects of random effects on the Stage 2 outcome. Please check the box to suppress the interaction between random location and random scale effects. [CLICK]

Suppress 2-way Location X Scale Interaction

21 Run Stage 1 and Stage 2: Please verify your model specifications and click on "Run Stage 1 and 2" to generate the definition (DEF) file. You may also click "Save Model" to keep all parameters in MW format so you could reload the settings when needed. [CLiCK]



22 Preview DEF File and Proceed with the Analysis: The DEF file is a copy of your model specifications which communicates with the Fortran program to execute the statistical analyses. In the definition file, click on "Proceed" to run your model and generate model output files. [CLiCK]



23 Model Estimation: A pop-up window will appear while model estimation is in progress. Please note the time of data processing and parameter estimation will increase if the data size is large or the model includes multiple random effects.

🛓 Please wait	- 🗆 X	
MINHILD. 1.49214000371332092-002 00.170430330300250		
MIXWILD: -2 Log-Likelihood = 6566.04601		
MIXWILD: Newton-Raphson Iteration 10 with ridge 0.1500	I	
MIXWILD: maximum correction and derivative		
MIXWILD: 1.5137382493852969E-002 62.261325762799579		
MIXWILD: -2 Log-Likelihood = 6565.94862		
MIXWILD: Newton-Raphson Iteration 11 with ridge 0.1500	l i i i i i i i i i i i i i i i i i i i	
MIXWILD: maximum correction and derivative		
MIXWILD: 4.4206819264721274E-003 18.628519442404098		
MIXWILD: -2 Log-Likelihood = 6565.84094		
MIXWILD: Newton-Raphson Iteration 12 with ridge 0.1500	I	
MIXWILD: maximum correction and derivative		
MIXWILD: 2.0618700250962262E-003 10.537166376240492		
MIXWILD: -2 Log-Likelihood = 6565.82763		
MIXWILD: Newton-Raphson Iteration 13 with ridge 0.1500	I	
MIXWILD: maximum correction and derivative		
MIXWILD: 1.1777860693789003E-003 5.9967745632048093		
MIXWILD: -2 Log-Likelihood = 6565.82391		
MIXWILD: Newton-Raphson Iteration 14 with ridge 0.1500	I	
MIXWILD: maximum correction and derivative		
MIXWILD: 6.7143652132312624E-004 3.4151164019348528		
MIXWILD: -2 Log-Likelihood = 6565.82273		
MIXWILD: Newton-Raphson Iteration 15 with ridge 0.1500	I	
MIXWILD: maximum correction and derivative		
MIXWILD: 3.8251931733157405E-004 1.9447153311182319		
MIXWILD: -2 Log-Likelihood = 6565.82234		
MIXWILD: Newton-Raphson Iteration 16 with ridge 0.1500	I	
MIXWILD: maximum correction and derivative		
MIXWILD: 2.1786985886398184E-004 1.1073684491643121		
MIXWILD: -2 Log-Likelihood = 6565.82222		
		-
	•	
	Cancel Analysis	
	Cancer Analysis	

MiX Friendly Note:

If you experience a model crash and the warning message below appears, it indicates that computational difficulties were likely encountered and prevented the model parameters from being estimated successfully. In this case, confirm the format of your dataset and check your model specifications (<u>Table 2-3</u>). **Troubleshooting** suggestions are listed in Appendix A: Steps to take when the program does not converge to a solution.

Failed	Message	×

When the model estimation is completed, MixWILD will automatically switch to the {Stage 1 Results} page. If not, please click the "Stage 1 Results" tag to check the Stage 1 output. You may check your Stage 2 output in the {Stage 2 Results} page.

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MixWILD-2.0								_	\times
Model Configuration	Stage 1 Configuration	Stage 2 Configuration	Stage 1 Results	Stage 2 Results	View Model	View Data	Help		
Results fr	om stage 1 analysis								
MIXREGLS	_both: Mixed-effects Lo	cation Scale Model							
	both.DEF specification	15				=			
	1 MEMLS and MRM with MixWILD GUI								
Dataset	d output files: _HealthBehavAcadPerfAff _HealthBehavAcadPerfAff								
SCALE E	E LOCATION EFFECTS = F FFECT = T ENCE CRITERION = 0.000 = 0.1500								
NQ	= 0.1500 = 11 URE = 1 (0=non-adapt = 200	ive, l=adaptive)							
 Descript	ives								
		= 2101							
	of level-2 clusters								
		for each level-2 clust 31 31 32 3	er 2 30 20	32 32		-			
				Save	e Results As				

By default, MixWILD stores your outputs in your Windows personal Documents folder. The default address in Win10 is in your account's **%UserProfile%** folder (i.e., "C:\Users\UserName\ OneDrive\Documents"). All files generated from the program can be found in a folder name with the prefix MixWILD and the 12-digit number labelling the date and time that this folder was created.

This PC > Documents ・ ひ ・ ・ ・ ・ ・ ・ ・ ・ ・ ・ ・ ・ ・ ・ ・ ・ ・ ・ ・ ・ ・ ・		ර 🔎 Search Docu	Search Documents		
^	Na	ame ^	Status	Date modified	Туре ^
		MIXWILD202104060942	2	4/6/2021 9:46 AM	File fold
	1	MIXWILD202104060944	S	4/6/2021 9:48 AM	File fold
~	<			1/2/2024 122 111	>

In the file with suffix **"_Output_stage1.out"**, you can find that the content is identical to the results found in the {Stage 1 Results} page. The file with suffix **"_Output_stage2.out"** is the Stage 2 result. The estimated subject-specific random effects are saved to a data file with the suffix **"_ebvar.dat"**.

3.4 Interpretation of Two-stage Model (Stage 1 MEMLS Model with Stage 2 Multilevel Model without Interaction) Results {Example 1}

[Stage 1 Results]

The output for the Stage 1 analysis is written to the file with suffix "_Output_stage1.out", which includes descriptive information. This analysis includes 72 subjects and a total of 2039 observations. An observation must have non-missing data on the Stage-1 dependent variable positive affect [PA], and model covariates learning goal achievement [LGA] for that particular observation to be included in the analysis. The output lists out the number of Level-1 observations (days) for each Level-2 observation (subjects). For the dependent variable [PA] and model covariates, means, minimums, maximums, and standard deviations are listed in the descriptive tables.

Descriptives -----Number of level-1 observations = 2039 Number of level-2 clusters = 72 Dependent variable mean min max std dev _____ 4.1502 1.0000 7.0000 1.6066 PA Mean model covariates mean min std dev max _____ 1.00001.00001.00000.00002.16140.00004.00001.0784 intercept LGA BS variance model covariates min mean max std dev _____ 1.00001.00001.00000.00002.16140.00004.00001.0784 intercept LGA WS variance model covariates mean min max std dev 1.00001.00001.00000.00002.16140.00004.00001.0784 intercept LGA

Following the descriptive tables, the results of three different Stage 1 models of increasing complexity are listed. The program does this sequential building of the model complexity to improve the convergence of the final model stage.

The first one is the **"Model without Scale Parameters"**. This model can be viewed as a regular mixed-effects model. As you can see, there is no random scale parameter in this model. The second model refers to the **"Model with Scale Parameters"**. It includes scale parameters but not random scale parameters. While the "Model with Scale Parameters" includes one regressor **[LGA]** to predict WS variance, this model does not include a random component to let the WS variance vary across subjects beyond the covariate effects. We skip these two submodels here because they have been discussed in previous chapters. Please check the interpretation in {Chapter 2 Section 2.3} for more details.

Variable	Estimate	AsymStdError	z-value	p-value
BETA (regression				
intercept	3.57565	0.10914	32.76248	0.00000
LGA	0.27121	0.03313	8.18530	0.00000

The third and final sub-model, **"Model with Random Scale"**, includes both the scale and the random scale parameters. In the Mean (BETA) model, this analysis shows that the intercept of positive affect (PA) is 3.576 (when all covariates are equal to 0), and the time-varying (Level-1) variable, learning goal achievement (LGA), has a positive association with positive affect (*beta* = 0.271; *p* < 0.001), which suggests subjects' positive affect increased for each additional unit of learning goal achievement.

Variable	Estimate	AsymStdError	z-value	p-value
Random (location)	Effect Variances	and Covariances		
intercept	1.70153	0.23082	7.37182	0.00000
Covariance	-0.11069	0.04307	-2.57015	0.01017
LGA	0.02860	0.00612	4.66986	0.0000

The estimates of "Random (location) Effect Variances and Covariances" show that subjects differed significantly from each other based on mean levels (random intercept) of PA (*estimate* = 1.702; p < 0.001) and differed from each other in their association (random slope) between LGA

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and PA (*estimate* = 0.029; p < 0.001). Additionally, the random intercept and random slope were statistically associated with each other (Covariance), indicating that there was a negative association between the mean levels of PA and the coupling of LGA and positive affect (*estimate* = -0.111; p = 0.010). In other words, if a subject had a higher mean PA, then their slope is lower (and vice versa).

Variable	Estimate	AsymStdError	z-value	p-value		
TAU (WS variance parameters: log-linear model)						
intercept	-0.04141	0.13205	-0.31363	0.75381		
LGA	-0.07342	0.03829	-1.91716	0.05522		

The results in the WS Variance (TAU) submodel provide an estimate of the within-subject variance (on the log scale) when LGA=0. Since this test is a log-linear model for the WS variance, it is a test of whether the log of the WS variance (when LGA = 0) equals 0, or namely that the WS variance (when LGA=0) equals 1. Thus, this test isn't terribly meaningful; it indicates that the WS variance (when LGA = 0) is approximately equal to 1. Results also show that the within-subject variance in PA was marginally associated with LGA (*tau* = -0.073; p = 0.055), suggesting that the WS variance decreased as LGA increased.

Variable	Estimate	AsymStdError	z-value	p-value		
Random Scale Variance and Covariance						
Cov intercept	-0.52814	0.15607	-3.38390	0.00071		
Cov LGA	0.06114	0.02650	2.30712	0.02105		
Scale int var	0.75206	0.14033	5.35921	0.00000		

The estimates of "Random Scale Variance and Covariance" show the WS variance and location intercept are negatively associated (*estimate* = -0.528; p < 0.001), and the WS variance and the slope of LGA predicting PA are negatively associated (*estimate* = -0.0611; p = 0.021). In addition, there is considerable scale variability (ω_i) in PA across subjects (Scale int var); a significant random scale estimate suggests that subjects differ from each other in their degree of WS variance (*estimate* = 0.752; p < 0.001).
[Stage 2 Results]

We will now examine whether the random effects (a subject's intercept, slope, and scale estimates) from the mixed-effects location scale analysis in Stage 1 are associated with a Stage-2 outcome, sleep quality. The multilevel (MRM) Stage-2 analysis is performed treating sleep quality [SQ] as the occasion-varying outcome. For this, the program only considers the 72 subjects that were included in the Stage-1 analysis and uses all non-missing SQ observations for these 72 subjects from the original dataset. This results in 2101 SQ observations clustered within the 72 subjects. Treating these SQ observations as the outcomes, clustered within subjects, it uses the Stage-1 random effect estimates (intercept = Locat1, slope = Locat2, and scale = Scale) as regressors. Please note, that this analysis was replicated 500 times using random draws based on the random location and scale effects of each subject (which were estimated in the Stage 1 analysis above). The results listed below are averages from these 500 replications. Additionally, the standard deviation associated with the log likelihood values is listed in parentheses. For the 72 subjects, the program lists out the mean, minimum, maximum, and standard deviation of the sleep quality [SQ], model covariates, as well as descriptives for the random subject effects (intercept = Locat 1, slope = Locat 2, and Scale). The output for the Stage 2 analysis is written to the file with suffix "_Output_stage2.out", which includes some descriptive information.

Level 2 units = 7 Level 1 observations =	2 2101			
Descriptives				
Dependent variable	mean	min	max	std dev
SQ	2.9929	1.0000	4.0000	0.7961
Random Location and Scale	EB mean esti mean	.mates min	max	std dev
Locat_1 Locat_2 Scale	-0.0119	-1.8211 -1.6826 -2.7968		

The results of the Stage 2 regression analysis indicates that the subject-level random intercept of PA (Locat_1) was positively associated with their reported sleep quality (*estimate* = 0.182; p < 0.001), and a random scale was negatively associated with SQ (*estimate* = -0.103; p < 0.031). In other words, subject-level mean PA was greater and subject-level PA variance was lower for individuals who had better sleep quality. The random slope of LGA predicting PA is not significantly related to SQ (*estimate* = 0.044; p = 0.473).

In this multilevel analysis, the subject intercept variance was estimated to be 0.104, and the residual variance was estimated to be 0.480. These values result in an ICC = 0.104 / (0.104 + 0.480) = .178. Thus, SQ is correlated within subjects, as 17.8% of the unexplained variance of SQ is at the subject level.

Variable	Estimate	AsymStdError	z-value	p-value
Intercept	2.99691	0.04285	69.94344	0.00000
Locat 1	0.18243	0.04204	4.33943	0.00001
Locat 2	0.04417	0.06160	0.71706	0.47334
Scale_1	-0.10320	0.04779	-2.15943	0.03082
Random.Int.Var	0.10399	0.02153	4.83096	0.00000
Residual.Varianc	0.48043	0.01510	31.82026	0.00000



3.5 Step by-step Instructions for Two-stage Modelling (Stage 1 MELS Model with



In this analysis, we will use <u>the data collected from Flueckiger and colleagues</u> to run a Stage 1 MELS model with a Stage 2 subject-level outcome, and examine whether a person's learning goal achievement (repeatedly measured) is related to the sequence of day. Furthermore, we would like to explore whether subject's mean level and variability of learning goal achievement predicts their subject-level examination success. The flowchart shows that by selecting "Random Intercept only" in the option of "Random Location Effects", we can create a MELS model in Stage 1. Then we check the "Random Scale Effect" option to allow for the random scale effect in the model. Finally, we include a Stage 2 model and specify the model configuration (i.e., model type) to allow for using random effects as regressors in a two-stage model approach.

Q Research Question:

Does day elapsed in the sequence (continuous, time-varying variable) predict **learning goal achievement** (continuous, time-varying variable) in the Mean, BS and WS Variance submodels? Do subject-level means and variances predict the subject-level **examination success** (dichotomous, time- invariant variable) in the Stage 2 subject-level model.

Data source: <u>https://dataverse.harvard.edu/dataverse/healthbehav</u>

You may need to convert the data into CSV format.

(i.e., Use EXCEL to read the SPSS/Tab-Delimited file and save as new CSV file).

1 Import data into MixWILD and format missing value: Please check {Chapter 1 Section 1.4} for more details. Be sure your dataset is in CSV format and should be sorted by ID. Additionally, all data should consist of numerical values (i.e., integers or floats), except for the first row, which includes the names of the variables.

6	CSV file path:	ients\Dataset_HealthBehavAcadPerfAffect.csv	Change Dataset	
	Title (optional):	Example 2 MELS and Single model		

2 Select the type of Stage 1 outcome: The Stage 1 outcome should be a time-varying outcome. In this example, the Stage 1 outcome is learning goal achievement which is continuous. Please select [Continuous].



- **3** Specify random location effects:
 - Select "Intercept only", and the model includes a random subject intercept only (in the Mean model). This is the key selection for creating a MELS model.

1	Specify random location effects:	Intercept only	 Intercept and slope(s)
---	----------------------------------	----------------	--

4 Include estimates of random scale: Random scale parameters allow subjects to have individual estimates of the within-subject variance (i.e., random subject scale effect). Please note a random scale effect is not allowed when the outcome is dichotomous.



- 5 Select Stage 2 model: MixWILD allows a two-stage modeling approach in which the Stage 1 random effects are used as regressors to predict an outcome in a Stage 2 model. In this example, we will have a Stage 2 model so please select "Yes".
 - Include separate Stage 2 data file: Select "Yes" in this option when your Stage 1 and Stage
 2 data are located/saved in different data sets. In this case, you will need to specify the
 Stage 2 ID later in the [Stage 2 Configuration] page.

Select "No" when all Stage 1 and Stage 2 data come from the same dataset.

Stage 2 CSV file path: If the option, "Include separate Stage 2 data file" is applied, please specify the address of the Stage 2 data set. Like Stage 1 data, the first row should be variable names and all other data need to be numerical. Stage 2 data must include a key variable (i.e., ID variable) that should be sorted in the same order with Stage 1 data so both data sets can be linked properly.

6	Include Stage 2 model:	● Yes 🔾 No	
	Include separate Stage 2 data file:	○ Yes	
	Stage 2 CSV file path:		Import Dataset

- 6 Stage 2 model type: Stage 2 analysis can have two types. Please select "Single level".
 - **Single level:** The outcome of the Stage 2 model is at the subject-level.
 - **Multilevel:** The outcome of Stage 2 model is nested within subjects or clusters.



- 7 Stage 2 outcome: The Stage 2 model allows for four types of outcomes.
 - Continuous: This type refers to a ratio variable (i.e., weight) or an interval variable (i.e., positive affect measured on a Likert scale), and assumed to be (conditionally) normally distributed.
 - Dichotomous/Ordinal: Variables have two or more categories, and these categories must also be ordered or ranked.

- **Count:** It consists of non-negative integers and discretely distributed (i.e., number of times snacks were consumed in a day).
- **Multinomial:** Variables have two or more categories, but the categories do not have an intrinsic order (i.e., types of physical activity).
- This example uses **sleep quality** as the Stage 2 outcome, please select [Continuous].

8 Set a seed for Stage 2 resampling (optional):

Since the random subject effects are estimates with estimated uncertainty, the program performs resampling of the random effects in the Stage 2 analysis. As a result, each analysis may yield slightly different results (i.e., different coefficients and significance levels) even under the same settings. MixWILD allows users to set a seed that varies between 1 and 65,000, which indicates the sample number for their posterior distribution. Users can edit the default seed randomly chosen by MixWILD. Select a custom seed value for the Stage 2 resampling can ensure the same result for the Stage 2 analysis when you re-run the model at another time.



9 Complete Model Configuration settings:

- **Click "Continue":** Click Continue to enter {Stage 1 Configuration} page.

Save Model	Reset	Continue
------------	-------	----------

After you submit the {Model Configuration} page, MixWILD interface will switch to the {Stage 1 Configuration} page that enables you to set up your Stage 1 model.

MixWILD-2.0						—	E
odel Configuration Stage 1 Configuration	Stage 2 Configuration	View Data	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	V	×	r		
Stage 1 Outcome:		Disaggregate?					
LGA	-						
Configure Stage 1 Regressor	s	Level-2	Mean	BS Variance	WS Variance	1	
Options							
Options							
Specify the relationship betwee mean and WS variance.	n the						
Specify the relationship betwee	n the						
Specify the relationship betwee mean and WS variance.	n the						

10 Select ID: ID is the key variable to designate the 2-level data structure (i.e., observations at level-1 nested within level-2 subjects, who are distinguished by the ID variable). It should be sorted by this variable before importing the data. In this analysis, please select [ID] variable in our example data. This is also the variable that links with your Stage 2 data if Stage 2 data are saved as a separate data set. [CLICK]

ID Variable:	
ID	

11 Select Stage 1 Outcome: Please select **[LGA]** variable, learning goal achievement, as your Stage 1 outcome variable. **[CLiCK]**

Stage 1 Outcome:	
LGA	-

12 Select Stage 1 Regressors (Configure Stage 1 Regressors): [CLiCK]

- Variables should be specified as Level-1 or Level-2 by users.
- Select Level 1 Variables: In an EMA study, Level 1 variables refer to the time-varying variables at the observation level (person-time or prompt). In this analysis, please select the variable [Day] in the data. Use Add button to move variables from the {Variables} to {Level-1 (Time Varying)}. Use Remove button to switch back.
- Select Level 2 Variables: In an EMA study, Level 2 variables generally represent person-level or time-invariant variables. Use Add button to move variables from the {Variables} to {Level-2 (Time Invariant)} if necessary. Use Remove button to switch back. In this example, we don't use any Level 2 variable so please just leave it blank.
- Click **Submit** button to process the selection. Click **Reset** if you want to clear all the selections and do it over.

🛓 Add Stage 1 Regressors					—		×
Variables			Level	-1 (Tim	e Vary	/ing)	
Sex Age Sem SQ PhysAct PA NA Exam HSG	Add Remove	Day					
BDI Day_C PA_ord HSG_rank	Add Remove		Level	-2 (Tim	e Inva	ariant)	
	[Cancel		Rese	t	Subm	it

13 Stage 1 Options (optional):

Please note these settings are all **OPTIONAL**. In most cases, you <u>DON'T</u> need to make any change in these settings. However, in some cases, the program does not converge to a solution. Trying to change some of these parameters (i.e., Quadrature Points or Ridge) could help. The other solution, which we also strongly recommend, is to estimate a simpler model. We describe this more fully in Appendix A: Steps to take when the program does not converge to a solution. Please check "Point 10" in {Chapter 2 Section 2.2} for more details. Here, we just mention the settings that are related to Stage 2 analysis.

- Resample Stage 2: This is a Stage 2 model option. Resampling of the subject-level random effects are conducted for all Stage 2 models to account for the fact that random effects are estimated quantities (Carsey & Harden, 2013). This option does not matter if you run Stage 1 models only.
- No. of Samples: This is a Stage 2 model option. Random effects are resampled multiple times from a normal distribution using the mean and variance estimates of these random effects for each subject. By default, the estimated random effects of the Stage 1 analysis (i.e., random location and scale effects) are resampled 500 times in the Stage 2 analysis. This option does not matter if you run Stage 1 models only.

14 Specify Stage 1 Regressors in Mean and WS Variance submodels (important):

Please note it is critical to specify your Stage 1 regressors. If you just follow the **"Point 12"** instruction and assign variables into Level-1 and/or Level-2 columns **but you do not check any of these selected regressors** (i.e., all these boxes are unchecked), there will be no regressor in your submodels. To ensure that at least one submodel has one or more regressor(s), you have to specify variables and check the boxes in the {Stage 1 Regressor} section.

Stage 1 Regressors							
Level-1	Mean	BS Variance	WS Variance				
Day Disaggregate?							
Level-2	Mean	BS Variance	WS Variance				

- **Mean model:** This consists of a submodel that examines the relationship between one or more regressor(s) and the mean of the outcome. This can be considered as the regular mixed-effects/multilevel model with random intercept only. We use x' to represent the regressor(s) and β are the corresponding regression coefficients.
- In this example, please check the boxes of [Day] in the Mean model. [CLICK]
- Disaggregate: Select the option for each of the time-varying variable(s) for which decomposition of the within- and between-subject effects in predicting Stage 1 model outcome(s) is desired. The selected Level-1 variable will be decomposed in terms of its the within-subject (WS) version and between-subject (BS) version. In this example, please keep the [Disaggregate] option unchecked.

MiX Friendly Note:

The option "Disaggregate" is only available for time-varying variables. Please check "Point 11" in {Chapter 2 Section 2.2} for more details.

- The Mean model with Random Intercept and Random Slope is as follows:

$$y_{ij} = (\beta_0 + v_{0_i}) + \beta_D Day_{ij} + \epsilon_{ij},$$

$$v_{0_i} \sim N(0, \sigma_{v_0}^2), \ \epsilon_{ij} \sim N(0, \sigma_{\epsilon}^2)$$
(3.8)

- In Equation 3.8, **[Day]** is a Level-1 (time-varying) variable, while there is no Level-2 variable. Random intercept, v_{0_i} , represents subject's mean LGA (relative to the fixed part of the model). β_0 is the grand intercept, and β_D is the coefficient of regressor, Day. β are the equivalent of fixed effect coefficients in a traditional multilevel model.
- **BS Variance submodel (MELS Only):** This is defined as a submodel that examines the relationship between one or more regressor(s) and the variance of the subject-level outcome means. We use u' to represent the regressor(s) and α are the corresponding regression coefficients.
- In this example, please check the boxes of [Day] in the BS Variance submodel. [CLICK]
- The BS Variance submodel is as follows:

$$\sigma_{v_{0_{ij}}}^2 = exp(\alpha_0 + \alpha_D Day_{ij})$$
(3.9)

- In Equation 3.9, **[Day]** is a Level-1 (time-varying) variable, while there is no Level-2 variable. α_0 represents the intercept in the BS variance submodel (the BS variance, on the log scale, when **[Day]** equals zero). α_D is the coefficient of regressor, Day, in BS Variance submodel.
- WS Variance submodel: This refers to a submodel that examines the relationship between one or more regressor(s) and within-subject variance of the outcome. We use w' to represent the regressor(s) and r are the corresponding regression coefficients.
- Please check the boxes of [Day] in the WS Variance submodel. [CLiCK]
- The WS Variance submodel is as follows:

$$\sigma_{\epsilon_{ij}}^{2} = exp(\tau_{0} + \tau_{D}Day_{ij} + \tau_{l}v_{0i} + \omega_{i}),$$

$$\omega_{i} \sim N(0, \sigma_{\omega}^{2})$$
(3.10)

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- In Equation 3.10, **[Day]** is a Level-1 (time-varying) variables, while there is no Level-2 variable. τ_0 represents the intercept in the WS Variance model (the WS variance, on the log scale, when **[Day]**, the random scale, and the random location all equal zero). The coefficient τ_l represents the linear association between a subject's location effect and the WS variance, with v_{0i} as the subject-level random intercept. ω_i represents the random scale effect which allows the WS variance to vary across subjects (over and above the effects of the regressors).
- Please note Level-1 and Level-2 regressors are all available in the Mean, BS, and WS
 Variance submodels although this example did not include any Level-2 variable in the submodel.

15 Specify the relationship between the random location & scale:

This option is available if you checked "Yes" in the question about "Include estimates of random scale" in {Model Configuration} page. As mentioned in the section of <u>"WS Variance</u> <u>submodel"</u>, this allows the random intercept (v_{0_i}) to influence the WS variance.

Specify the relationship between the mean and WS variance.
O No Association
Linear Association
○ Ouadratic Association

- In this example, please select "Linear Association". [CLiCK]
- **Linear Association:** This means that the association between the random intercept and WS variance is linear ($\tau_l \neq 0$; $\tau_a = 0$).
- Please check "Point 12" in {Chapter 2 Section 2.2} for more details.
- 16 Configure Stage 2: Click "Configure Stage 2" to enter {Stage 2 Configuration} page. [CLiCK]



After you submit the {Stage 1 Configuration} page, MixWILD interface will switch to the {Stage 2 Configuration} page that enables you to set up your Stage 2 model.

					-	
Stage 2 Configuratio	on View Data	Help				
_			Stage 2 Inter	ractions		
L.		in Effects	Random Locatio	n Random Scale	e Location X Scale	
ors		In Effects	Random Locatio	n Random Scale	e Location X Scale	
es	HSG	V	V	V		
	Suppress 2-wa	y Location X	Scale Interaction			
		5	ave Model	Clear Stage 2	Run Stage 1 and 2	
	ors	■ Level-1 ■ Ma ors Ma ■ HSG	■ Main Effects Ors es HSG Suppress 2-way Location X	Main Effects Random Location		Main Effects Random Location Random Scale Location X Scale

17 Select Stage 2 Outcome: Please select [Exam] variable, examination success, as your Stage
2 outcome variable. [CLiCK]

Stage 2 Outcome: Exam	•
Configure Stage 2 Regressors	
Check outcome categories	
2 Categories: 1) 0.0 2) 1.0	

This program provides a handy function to check how many categories in the Stage 2 outcome variable when your Stage 2 outcome is dichotomous/ordinal, or multinominal. In this example, **[Exam]** is a subject-level dichotomous variable (0 = Fail, 1 = Pass).

24 Configure Stage 2 Regressors: Similar to Point 12, this step allows adding variables to Level 1 and Level 2 of Stage 2. Level 1 and Level 2 regressors are added from Stage 2 regressor window. We don't use any regressor in this example, except for random effects. Please leave it blank. We use one regressor, [HSG], in this example. Please Add button to move variable [HSG] from the {Variables} to {Level-2 (Time Invariant)}. [CLICK]

Please note the option of {Level-1 (Time Variant)} is locked because it is a subject-level model. Level-1 variable selection option will be disabled when selecting "Single level" model in the option of "Stage 2 model type" {Stage 1 Configuration}.



18 Stage 2 Interactions: This is the matrix that allows for specifying the interactions between Level 1/Level 2 regressor(s) and random effects (i.e., random intercept/slope(s)/scale). Note adding three-way interaction term(s) (Location X Scale X Regressor) may create model complexity. Please use it with caution. In this example, we have one regressor **[HSG]** and would like to model the interaction between **[HSG]** and random effects (random location and scale effects). We don't want to make the model too complicated so the three-way interaction (HSG x random location x random scale) is unchecked.

In the next step, we don't check "Suppress 2-way Location x Scale Interaction" as well. The full formula will be shown in Equation 3.11.



19 Suppress 2-way Location x Scale Interaction: The interaction(s) of location by scale are automatically specified in the default Stage 2 model, but this option can be disabled by checking the box "Suppress 2-way Location X Scale Interaction", which limits the model to show the main effects of random effects only. Please check {Chapter 3 Section 3.2.4} for more details.

In this example, we just would like to examine the relationship between the main effects of random effects and the Stage 2 outcome **[Exam]**. In addition, we want to explore the effect of the two-way location and scale interaction on the outcome. Please uncheck the box of "Suppress 2-way Location X Scale Interaction". **[CLICK]**

Suppress 2-way Location X Scale Interaction

Stage 2 Logistic Regression Model (Subject-level Model):

$$\log \left[\frac{P(Exam_i = 1)}{1 - P(Exam_i = 1)} \right]$$

= $\beta_0^* + \beta_1^* HSG_i + \beta_2^* \hat{v}_{0_i} + \beta_3^* (\hat{v}_{0_i} \times HSG_i) + \beta_4^* \hat{\omega}_i + \beta_5^* (\hat{\omega}_i \times HSG_i) + \beta_6^* (\hat{v}_{0_i} \times \hat{\omega}_i)$

(3.11)

- \hat{v}_{0_i} : Estimated random location of Stage 1 outcome (y_{ij}) $\hat{\omega}_i$: Estimated random scale of Stage 1 outcome (y_{ij})
- 20 Run Stage 1 and Stage 2: Please verify your model specifications and click on "Run Stage 1 and 2" to generate the definition (DEF) file. You may also click "Save Model" to keep all parameters in MW format so you could reload the settings when needed. [CLiCK]



21 Preview DEF File and Proceed the Analysis: The DEF file is a copy of your model specifications which communicates with the Fortran program to execute the statistical analyses. In the definition file, click on "Proceed" to run your model and generate model output files. [CLICK]



22 Model Estimation: A pop-up window will appear while model estimation is in progress. Please note the time of data processing and parameter estimation will increase if the data size is large or the model includes multiple random effects.

🔊 Please wait 🦳 🗕		×
MINHILD. 1.49214000371302092-002 00.17043030300250		
MIXWILD: -2 Log-Likelihood = 6566.04601		
MIXWILD: Newton-Raphson Iteration 10 with ridge 0.1500		
MIXWILD: maximum correction and derivative		
MIXWILD: 1.5137382493852969E-002 62.261325762799579		
MIXWILD: -2 Log-Likelihood = 6565.94862		
MIXWILD: Newton-Raphson Iteration 11 with ridge 0.1500		
MIXWILD: maximum correction and derivative		
MIXWILD: 4.4206819264721274E-003 18.628519442404098		
MIXWILD: -2 Log-Likelihood = 6565.84094		
MIXWILD: Newton-Raphson Iteration 12 with ridge 0.1500		
MIXWILD: maximum correction and derivative		
MIXWILD: 2.0618700250962262E-003 10.537166376240492		
MIXWILD: -2 Log-Likelihood = 6565.82763		
MIXWILD: Newton-Raphson Iteration 13 with ridge 0.1500		
MIXWILD: maximum correction and derivative		
MIXWILD: 1.1777860693789003E-003 5.9967745632048093		
MIXWILD: -2 Log-Likelihood = 6565.82391		
MIXWILD: Newton-Raphson Iteration 14 with ridge 0.1500		
MIXWILD: maximum correction and derivative		
MIXWILD: 6.7143652132312624E-004 3.4151164019348528		
MIXWILD: -2 Log-Likelihood = 6565.82273		
MIXWILD: Newton-Raphson Iteration 15 with ridge 0.1500		
MIXWILD: maximum correction and derivative		
MIXWILD: 3.8251931733157405E-004 1.9447153311182319		
MIXWILD: -2 Log-Likelihood = 6565.82234		
MIXWILD: Newton-Raphson Iteration 16 with ridge 0.1500		
MIXWILD: maximum correction and derivative		
MIXWILD: 2.1786985886398184E-004 1.1073684491643121		
MIXWILD: -2 Log-Likelihood = 6565.82222		
		-
		•
	Cancel	Analysis

MiX Friendly Note:

If you experience a model crash and the warning message below appears, it indicates that computational difficulties were encountered and prevented the model parameters from being estimated successfully. In this case, confirm the format of your dataset and check your model specifications (<u>Table 2-3</u>). **Troubleshooting** suggestions are listed in Appendix A: Steps to take when the program does not converge to a solution.

Message	×
i Failed	
OK	

When the model estimation is completed, MixWILD will automatically switch to the {Stage 1 Results} page. If not, please click the "Stage 1 Results" tag to check the Stage 1 output. You may check your Stage 2 output in the {Stage 2 Results} page.

🛓 MixWILD-2.0								_	\times
Model Configuration	Stage 1 Configuration	Stage 2 Configuration	Stage 1 Results	Stage 2 Results	View Model	View Data	Help		
Results fr	om stage 1 analysis								
MIXREGLS	_both: Mixed-effects Lo	ocation Scale Model							
mixREGLS	both.DEF specification	15				=			
Example	1 MEMLS and MRM with MixWILD GUI								
Dataset	d output files: _HealthBehavAcadPerfAff _HealthBehavAcadPerfAff								
SCALE E	E LOCATION EFFECTS = F FFECT = T ENCE CRITERION = 0.000								
NQ	= 0.1500 = 11 URE = 1 (0=non-adapt = 200	ive, l=adaptive)							
Descript									
	of level-1 observations								
	of level-2 clusters of level-1 observations		er						
	31 32 32 32			32 32		•			
				Sav	e Results As				

By default, MixWILD stores your outputs in your Windows personal Documents folder. The default address in Win10 is in your account's **%UserProfile%** folder (i.e., "C:\Users\UserName\ OneDrive\Documents"). All files generated from the program can be found in a folder name with the prefix MixWILD and the 12-digit number labelling the date and time that this folder was created.

<u></u>	> This PC > Documents	~	· ි Search Do	ocuments
^	Name	Status	Date modified	Туре ^
	MIXWILD202104060942	S	4/6/2021 9:46 AM	File fold
	MIXWILD202104060944	C	4/6/2021 9:48 AM	File fold
~	<	<u>^</u>		>

In the file with suffix **"_Output_stage1.out"**, you can find that the content is identical to the results found in the {Stage 1 Results} page. The file with suffix **"_Output_stage2.out"** is the Stage 2 result. The estimated subject-specific random effects are saved to a data file with the suffix **"_ebvar.dat"**.

3.6 Interpretation of Two-stage Model (Stage 1 MELS Model with Stage 2 subjectlevel Model with Interaction) Result {Example 2}

[Stage 1 Results]

The output for the Stage 1 analysis is written to the file with suffix "_Output_stage1.out," which includes some descriptive information. This analysis includes 72 subjects and a total of 2049 observations. An observation must have non-missing data on the Stage-1 dependent variable, learning goal achievement [LGA], and model covariate, day elapsed [Day], for that particular observation to be included in the analysis. The program lists out the number of Level-1 observations (days) for each Level-2 observation (subjects). For the dependent variable [LGA] and model covariates, means, minimums, maximums, and standard deviations are listed in the descriptive tables.

Descriptives -----Number of level-1 observations = 2049 Number of level-2 clusters = 72 Dependent variable mean min max std dev _____ 2.1611 0.0000 4.0000 1.0791 LGA Mean model covariates mean min std dev max _____ 1.0000 1.0000 1.0000 16.1440 1.0000 31.0000 intercept 0.0000 8.8761 Day BS variance model covariates mean min max std dev _____ 1.0000 1.0000 1.0000 16.1440 1.0000 31.0000 intercept 1.0000 0.0000 Day 8.8761 WS variance model covariates mean min max std dev 1.00001.00001.00000.000016.14401.000031.00008.8761 intercept Day

Following the descriptive tables, the results of three different Stage 1 models of increasing complexity are listed. The program does this sequential building of the model complexity to improve the convergence of the final model stage.

The first one is the **"Model without Scale Parameters"**. This model can be viewed as a regular mixed-effects model with a BS Variance submodel. As you can see, there is no random scale parameter in this model. The second model refers to the **"Model with Scale Parameters"**. It includes scale parameters but not random scale parameters. While the "Model with Scale Parameters" includes one regressor **[Day]** to predict WS variance, this model does not include a random component to let the WS variance vary across subjects beyond the covariate effects. We skip these two submodels here. Please check the interpretation in {Chapter 2 Section 2.3} for more details.

Variable	Estimate	AsymStdError	z-value	p-value
BETA (regression	coefficients)			
intercept	2.18052	0.07629	28.58113	0.0000
Day	-0.00214	0.00222	-0.96410	0.33499

The third and final sub-model, **"Model with Random Scale"**, includes both the scale and the random scale parameters. In the Mean (BETA) model, this analysis shows that the intercept of learning goal achievement (LGA) was 2.180 (when all covariates are equal to 0). There was no statistical association between the time-varying (Level-1) covariate, Day, and LGA (*beta* = -0.002; p = 0.335).

Variable	Estimate	AsymStdError	z-value	p-value
ALPHA (BS variance) intercept Day	parameters: log- -1.22023 0.01374	linear model) 0.21864 0.00701	-5.58108 1.96023	0.00000 0.04997

The BS Variance (ALPHA) submodel shows that subject's mean of LGA (when Day = 0) was different from person to person (*Variance* = Exp(-1.220) = 0.295). In other words, the random intercept varied significantly across subjects. In addition, there was a significant effect of day elapsed on the between-subject variability (*alpha* = 0.014; *p* = 0.05), suggesting that the variance

between subjects' mean in LGA was less similar (more heterogeneous) to each other as days passed.

Variable	Estimate	AsymStdError	z-value	p-value
TAU (WS variance p	arameters: log-li	near model)		
intercept	-0.11704	0.08540	-1.37047	0.17054
Day	-0.01147	0.00385	-2.98136	0.00287

The results in the WS Variance (TAU) submodel display that within-subject variance in LGA (when Day = 0) is not statistically significant (tau = -0.117; p = 0.171). Since this is a log-linear submodel, this is a test of whether the intercept WS variance equals 1 (which is 0 on the log scale); not a terribly interesting or important test. The within-subject variance in LGA is negatively associated with day elapsed (tau = -0.011; p = 0.003), which suggests that the variance within a subject became more stable with each additional day.

Variable	Estimate	AsymStdError	z-value	p-value
Random scale standa Std Dev	rd deviation 0.40978	0.04889	8.38095	0.00000

Table "Random scale standard deviation" suggests there was considerable scale variability (ω_i) in LGA across subjects, as indicated by the random scale standard deviation (Std Dev); a significant random scale standard deviation suggests that subjects differed from each other in their degree of WS variance (*scale sd* = 0.410; *p* < 0.001).

Variable	Estimate	AsymStdError	z-value	p-value
Random location Loc Eff	(mean) effect on WS -0.07005	variance 0.06292	-1.11342	0.26553

The estimates of "Random location (mean) effect on WS variance" show WS variance and location intercept were not related (*estimate* = -0.070; *p* = 0.266).

[Stage 2 Results]

We will now examine whether the random effects (a subject's intercept and scale estimates) for LGA from the mixed-effects location scale analysis are associated with a Stage 2 outcome, examination success. Since the outcome, examination success, is subject-level and dichotomous (1 = Pass, 0 = Not Pass), a subject-level logistic regression model treating the stage-1 subject-level random effects for LGA as regressors will be run. The output for the Stage 2 analysis is written to the file with suffix "_Output_stage2.out", which includes some descriptive information.

Level 2 units =	72			
Descriptives				
Categories of the	Dependent Variable			
Category 0.00 1.00	Frequency 38.00 34.00			
Independent variabl		min	max	std dev
HSG	4.6750	3.4000	5.6000	0.4440
Random Location an	nd Scale EB mean est: mean	imates min	max	std dev
Locat_1 Scale Locat_1*Scale	-0.0000	-2.0445 -1.6312 -3.4948	2.2749	0.8314

Note, that this analysis was replicated 500 times using random draws based on the random location and scale effects of each subject (which were estimated in the Stage 1 analysis above). The results listed below are averages from these 500 replications. Additionally, the standard deviation associated with the log likelihood values is listed in parentheses. Note that this analysis is performed on 72 Level-2 units (subjects). For the 72 subjects, the program lists out the frequency of examination success, as well as descriptives for the covariate(s) and the random subject effects (intercept = Locat_1 and scale = Scale).

Variable	Estimate	AsymStdError	z-value	p-value
Intercept	-7.97983	3.48256	-2.29137	0.02194
HSG	1.67381	0.74153	2.25726	0.02399
Locat_1	-0.70210	3.64750	-0.19249	0.84736
Locat_1*HSG	0.29699	0.77987	0.38082	0.70333
Scale_1	-0.91784	3.97122	-0.23112	0.81722
Scale_1*HSG	0.20865	0.84291	0.24754	0.80449
Locat_1*Scale	0.01837	0.41547	0.04423	0.96472

This regression analysis indicates that as subject's high school grades increased, their likelihood of a passing exam in college increased. For one unit increase in grade, we expect a 433% increase in log odds of passing the exam (Exp(1.67381) = 5.33). There was no statistical association between random location and scale effects for LGA and examination success. The data also didn't support the hypothesis that independent variable high school grades was moderated by these random effects.

MiX Friendly Note:

It's important to try centering your regressor(s) to its mean, especially for the regressor is a continuous variable but the range does not cover 0 (i.e., day is ranged from 1 to 31). This may help you to avoid estimating errors in both Stage 1 and Stage 2 analyses as well as improving the quality of interpretation.

Appendix A: Steps to take when the program does not converge to a solution

MixWILD can be used to estimate some rather advanced and complicated statistical models. In some cases, the program does not converge to a solution. This can be because the data does not contain enough information to estimate all of the parameters of the specified model. In this case, trying to estimate a simpler model is warranted. In general, it is good practice to start simply and build model complexity incrementally. In this way, users can get a feel for which variables and/or options may be causing trouble in estimation.

In addition to simplifying the model that one is attempting to estimate, the MixWILD program does include some options that can sometimes be modified to help in estimation of the model parameters. These are included on the Options page and will be described below.

1. This first comment pertains to models that include random scale parameters. Random scale parameters allow subjects to have individual estimates of the within-subject variance, and this is the distinguishing feature of a **mixed-effects location scale model**. The possibility of random scale parameters is specified on the first page that is encountered in the MixWILD program under the **"Random Scale?"** selection. In the graphic below, this is not specified, but clicking on the box to the right of **"Random Scale?"** adds random scale parameters to the Stage 1 model.

<u>\$</u>	– 🗆 X				
Is your dataset Mix{WILD} friendly? Check here					
Data File: Title:	dard MLMMixwild_example_data.csv Browse Mixwild_Mixreg_output				
Random Location Effects:	Intercept Intercept + Slope(s)				
Random Scale?					
Stage 2 Outcome:	○ Continuous ○ Dichotomous/Ordinal				
Contains missing values?	● Yes 🔾 No				
Missing value code:	-999				
MIX*	Cancel Reset Submit				

In some cases, there may be subjects in the dataset that exhibit no variation on the Stage 1 outcome variable. In other words, their values on the outcome variable are exactly the same for all of their observations. This can be particularly true if there are subjects with few observations (say 2 or 3) in the dataset and/or the Stage 1 outcome variable is not really continuous but an

ordinal outcome with say 5 categories. 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, selection of the **"Discard Subjects with no Variance?"** option (clicking on the box to the right of this question) on the Options page can facilitate model convergence. Selection of this option will remove these subjects from the Stage 1 analysis (and also the Stage 2 analysis if that is specified).

실 Options		– 🗆 X
		[]
Mean Intercept:	*	Maximum Iterations: 200 -
BS Variance Intercept:	×	Ridge: 0.1 ÷
WS Variance Intercept:	V	Standardize All Regressors?
Convergence Criteria:	0.00001	Discard Subjects with no Variance?
Quadrature Points:	11 ×	Resample Stage 2:
Adaptive Quadrature:	2	No. of Samples: 500 -
		Cancel Reset Submit

2. In some cases, the scale of the regressors included in an analysis can be very large. For example, consider a scenario in which one has a variable for days in the study, which ranges from 1 to 365 for a year-long study. In this case, because of the large scale of the variable, any parameter associated with this variable will be quite small and can be difficult to estimate. In such cases, standardizing the regressors by selecting "Standardize All Regressors" might be considered. Selection of this option will transform all regressors to be variables with 0 mean and variance of 1.

3. Estimation of the Stage 1 model involves a numerical integration (i.e., quadrature) over the random effect distribution. By default, MixWILD performs adaptive quadrature with 11 points to do this integration. The more points one uses, typically the more accurate is the solution, but also the more time it takes to estimate the model parameters. 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. Switching from adaptive to non-adaptive quadrature can sometimes work, though typically adaptive quadrature is preferred.

4. The value of the "Ridge" is usually set to a small fractional value. The ridge increases the values of the diagonal elements of the 2nd derivative matrix by a factor of 1 multiplied by the ridge value (i.e., if the ridge is set to .1, then the diagonal elements of the 2nd derivative matrix are all multiplied by 1.1). 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, 0.2, or even 0.25. This will slow down the estimation, but in some cases can aid in model convergence.

Ultimately, if one tries these options and still experiences convergence problems, it is probably the case that the data does not contain enough information to estimate the specified model. Again, it is a good idea to start simply and to build model complexity in an incremental manner. For example, one might start with a model that does not include any regressors (i.e., a null model) and then to add in regressors one by one or in sets of variables. This will help to isolate where problems develop and to indicate what is and what is not possible with a given dataset.