From the lab to the real world

Multilevel Analysis of Intensive Longitudinal Data in Ambulatory Psychophysiology

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SPR - Society for Psychophysiological Research

Pre-conference workshop
Multiverse, Multilevel, and Bayesian data analysis in psychophysiology

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Outline

- **Ambulatory PsyPhy**
  From the lab to to the real world
- **LMER intro**
  From linear models to multilevel modeling
- **HandZone**
  From data centering to cross-level interactions

From the lab to the real world

Ambulatory Assessment (AA)

Ecological methods to asses ongoing behaviors and physiology in natural environments

Society for Ambulatory Assessment

Experience Sampling Methods (ESM)

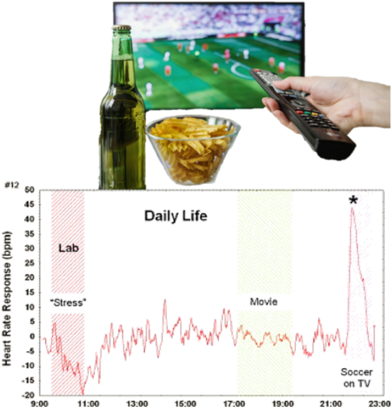
Repeated sampling of ongoing psychology, experiences, and activities to study their intensity, frequency, and temporal patterns

Csikszentmihalyi & Larson (2014)

Ecological Momentary Assessment (EMA)

Repeated sampling of subjects' behaviors and experiences in real time, in particpants' natural environments

Shiffman et al (2008)



Wilhelm & Grossman (2010)

Laboratory vs. Ambulatory assessment

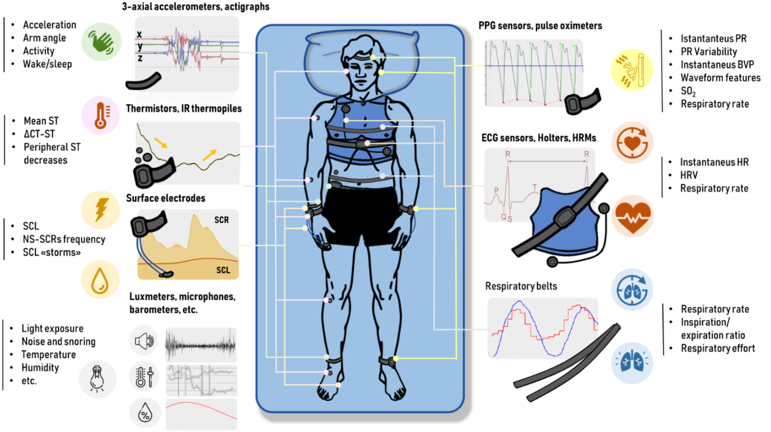
- Real-time recording ✓
- High internal validity ✓
- Low ecological validity ✗
- Gold-standard recording ✓

- Real-time recording ✓
- Low internal validity ✗
- High external validity ✓
- Ambulatory recording ✗

Lab-to-real world generalizability

Lab stressors are *not* representative of 'natural' stressors in terms of duration, number, nature, and intensity
+ **measurement reactivity** (e.g., white coat effect)

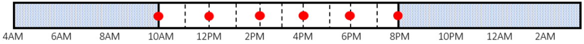
Wearable tech

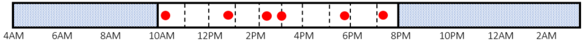


de Zambotti, M., Cellini, N., Menghini, L., Sarlo, M., & Baker, F. C. (2020). Sensors capabilities, performance, and use of consumer sleep technology. *Sleep medicine clinics, 15*(1), 1-30.

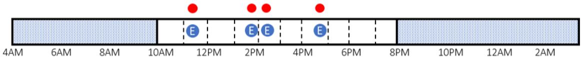
Intensive Longitudinal Designs (ILD)

Signal-contingent sampling: Recording at fixed (e.g., hourly), random, or semi-random intervals (e.g., each 90 ± 30 min)

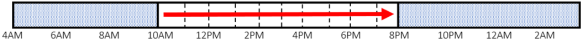




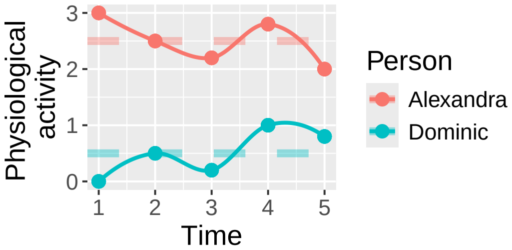
Event-contingent sampling: Recording conditional to events (e.g., bedtime, activity, physiological trigger)



Continuous sampling: Passive monitoring (e.g., pedometer)



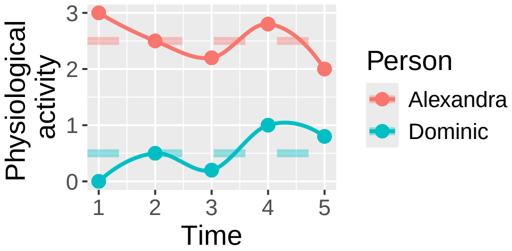
From ILD data to Multilevel modeling



When a random variable **y** is measured repeatedly over time, multilevel models **partition the variance** into the within-subject (level 1) and the between-subject (level 2) components

Note: The same applies when individuals (e.g., students) are nested within groups (e.g., schools) → within-group vs. between-group

Between & Within

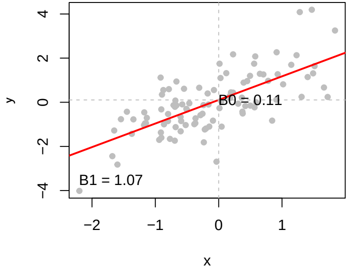


- **Between (lv2)**: Stable individual traits (time-invariant component)
  e.g. *Do **individuals** with higher trait calmness show a lower HR than individuals with lower trait calmness?*
- **Within (lv1)**: Variable transient states (time-varying component)
  e.g. *Is HR higher than usual in those **occasions** when individuals experience higher calmness than usual?*

Linear models

Linear models (LM) allow to determinate the link between two variables as expressed by a linear function: $y_i = \beta_0 + \beta_1 x_i + \epsilon_i$
Such a function can be graphically represented as a **straight line**, where:

- β_0 is the **intercept** (value assumed by y when x = 0)
- β_1 is the **slope** (predicted change in y when x increases by 1 unit)
- ϵ_i are the **errors** (distance between observation i and the regression line)



x_i and y_i are the values of observation i for the **casual variables** x and y

β_0, β_1, and ϵ_i are called "**parameters**", or "**coefficients**". They are *estimated* from the sampled data and *generalized* to the whole population.

LM core assumptions

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   x_i and y_i are linearly associated $\rightarrow$ the expected (mean) value of ϵ_i is zero

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   ϵ_i variance is constant over the levels of x_i (homogeneity of variance)

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5. **Independence of observations**
   for any two observations i and j with $i \neq j$, the residual terms ϵ_i and ϵ_j are independent (no common disturbance factors)

Nested data & Local dependencies

	Person	Time	Y
1	Alexandra	1	3.0
2	Alexandra	2	2.5
3	Alexandra	3	2.2
4	Alexandra	4	2.8
5	Alexandra	5	2.0
6	Dominic	1	0.0
7	Dominic	2	0.5
8	Dominic	3	0.2
9	Dominic	4	1.0
10	Dominic	5	0.8

- Repeated-measure designs always result in **nested data structures** where level-1 individual observations (statistical units) are nested within level-2 **cluster variables** (e.g., participants)

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- Nested data structures are incompatible with the LM assumption of independence of observations
- **Local dependencies** = correlations that exist among observations within a specific cluster (but the software doesn't know!)
  → Biased standard errors (++ false positives)
  → Neglected cluster-level variables potentially affecting level-1 relationships (e.g., cross-level interactions)

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Linear mixed-effects regression models

Multilevel models are part of the largest **linear mixed-effects regression (LMER)** family that include **additional variance terms** for handling local dependencies.

Why 'mixed-effects'?
Because such additional terms come from the distinction between:

- **Fixed effects**: effects that remain ***constant across clusters*** whose levels are *exhaustively considered* by the researcher (e.g., gender, steps of Likert scales, experimental conditions)
- **Random effects**: effects that ***vary from cluster to cluster*** whose levels are *randomly sampled* from a population (e.g., schools, people)

Let the visuals talk!
http://mfviz.com/hierarchical-models/
Michael Freeman (2017)

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From LM to LMER

LM formula: $y_i = \beta_0 + \beta_1 x_i + \epsilon_i$
Intercept and slope are **constant across all individual observations** i within the population; x, y, and the error term ϵ only variate across individual observations i

LMER formula: $y_{ij} = \beta_{0j} + \beta_{1j} x_{ij} + \epsilon_{ij}$
Intercept and slope have both a **fixed** $(_{0/1})$ and a **random** component $(_j)$; y, x, and ϵ variate across **individual observations** i as well as across **clusters** j

$$y_{ij} = \beta_{0j} + \beta_{1j} x_{ij} + \epsilon_{ij} = (\beta_{00} + \lambda_{0j}) + (\beta_{10} + \lambda_{1j})x + \epsilon_{ij}$$

LMER are an extension of LM where the intercept and the slope are decomposed into the **fixed components** β_{00} and β_{10} referred to the whole sample, and the **random components** λ_{0j} and λ_{1j} randomly varying across clusters.

Random intercept

Let's start with an **null model** (intercept-only) where physiologial activity (y_{ij}) is only predicted by the intercept β_{00} and the residuals ϵ_{ij}

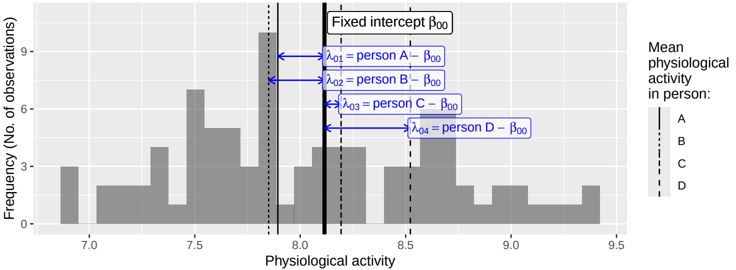
- *LM*: $y_i = \beta_0 + \epsilon_i$

  The intercept value β_0 is common to all observations

- *LMER*: $y_{ij} = \beta_{0j} + \epsilon_{ij} = (\beta_{00} + \lambda_{0j}) + \epsilon_{ij}$

  - β_{00} is the **fixed intercept** that applies to all observations

  - λ_{0j} is the **random intercept** = *cluster-specific deviation from the fixed intercept* (= person's average activity - fixed intercept)



Random slope

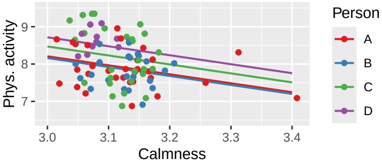
Let's now add a predictor: state `calmness` levels x_{ij}.

Random intercept model

$y_{ij} = \beta_{0j} + \beta_1 x_{ij} + \epsilon_{ij}$

$= (\beta_{00} + \lambda_{0j}) + \beta_1 x_{ij} + \epsilon_{ij}$

y_{ij} is predicted by the overall mean activity β_{00}, its ***average relationship*** with calmness β_{10}, the random variation among clusters λ_{0j} (***random intercept***), and the random variation within clusters ϵ_{ij} (*residuals*).

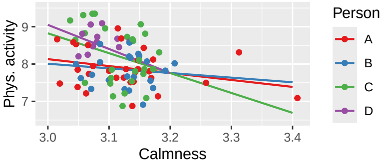


Random intercept & **random slope** model

$y_{ij} = \beta_{0j} + \beta_{1j} x_{ij} + \epsilon_{ij}$

$= (\beta_{00} + \lambda_{0j}) + (\beta_{10} + \lambda_{1j})\, x_{ij} + \epsilon_{ij}$

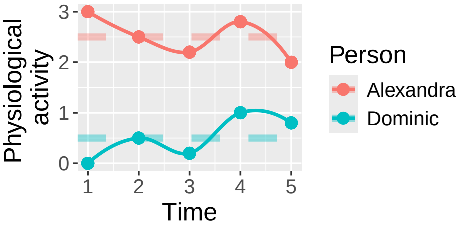
Since the effect of calmness might not be the same across all persons, we partition β_1 into the overall ***average relationship*** between calmness and physiological activity β_{10} (*fixed slope*) and the cluster-specific variation in the relationship λ_{1j} (***random slope***) - basically an interaction.



From LMER to multilevel modeling

LMER is often called *'multilevel modeling'* due to the underlying **variance decomposition** of the y_{ij} variable into the *within-cluster* and the *between-cluster* levels. Indeed, the LMER formula can be splitted in two separate levels:

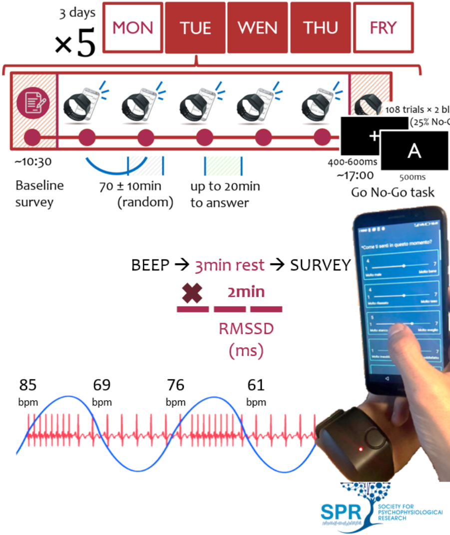
$$\begin{aligned} \textit{Level 1 (within)}: y_{ij} &= \beta_{0j} + \beta_{1j}x_{ij} + \epsilon_{ij} \\ \textit{Level 2 (between)}: \beta_{0j} &= \beta_{00} + \lambda_{0j} \\ \beta_{1j} &= \beta_{10} + \lambda_{1j} \end{aligned}$$



The case study

Unpublished dataset from a 3-day ambulatory assessment involving 91 participants aged 22.5 ± 2.2 (52.7% F)
Here, we focus on 3 variables:

- RMSSD (ms) = vagally-mediated HRV index computed over 2-min recording intervals at rest
- Calmness (1-7) = 3-item Multidimensional Mood Qs subscale (Wilhelm & Schoebi, 2007)
  How do you feel right now?
  1. Very relaxed - Very tense
  2. Very agitated - Very calm
  3. Very nervous - Very placid
- Gender (M/F) = binary variable measured with a preliminary questionnaire



The dataset

Download the `dataset_ema.RData` file from https://osf.io/c3a9q/ and load it in R

```
library(osfr) # Direct download from OSF
proj <- "https://osf.io/c3a9q/" # link to the OSF project
osf_download(osf_ls_files(osf_retrieve_node(proj))[3,]) # download
load("Section 2 - Luca Menghini/dataset_ema.RData") # reading data
head(ema) # showing first lines
```

```
subject day time    vmHRV Calmness gender
     s1   1    1 25.77279 3.000000      M
     s1   1    2 23.27229 2.666667      M
     s1   1    3 28.76841 2.333333      M
     s1   1    4 22.74052 4.666667      M
     s1   1    5 45.60953 4.333333      M
     s1   2    1 28.27870 3.333333      M
     s1   2    2 31.60962 4.000000      M
     s1   2    3 29.21525 4.000000      M
```

- `subject`: participants ID code
- `day`: protocol day (1-3)
- `time`: occasion within day (1-6)
- `vmHRV`: RMSSD (ms)
- `Calmness`: calmness mean score (1-7)
- `gender`: participant's gender (F/M)

From data cleaning to cross-level interactions

1. Data pre-processing: cleaning & centering
2. Level-specific correlations
   Are Calmness and HRV more strongly correlated at lv1 or lv2?
3. Null model & ICC
   Does HRV variate more at lv1 or at lv2?
4. Main effects
   Is HRV higher than usual when Calmness is higher than usual?
   Is it lower in females than in males?
5. Random slope & cross-level interactions
   Is the within-subject relationship between Calmness
   and HRV moderated by participants' gender?

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1. Data pre-processing (1/2)

First, we need to prepare the dataset for the analysis:

1. **Data cleaning** (Let's turn multiverse!)

- Group 1 (left): No filtering

- Group 2 (middle): Exclude participants with a response rate $< 70\%$

```
ema <- ema[ema$RRate70 == 0,]
```

1. Data pre-processing (2/2)

First, we need to prepare the dataset for the analysis:

2. **Data centering** = subtracting the mean of a variable from each value

```
# a) computing mean score for each participant
wide <- aggregate(x=long[,c("x","y")],
                  by = list(long$subject),
                  FUN = mean, na.rm = T)
colnames(wide) <- c("subject","x.m","y.m") # renaming variables

# c) joining cluster means to long-form dataset
long <- plyr::join(long, wide, by="subject")

# d) person mean centering
long$x.mc<- long$x - long$x.m
long$y.mc <- long$y - long$y.m
```

```
##   subject    vmHRV  vmHRV.m   vmHRV.mc
## 1      s1 25.77279 28.59955 -2.8267633
## 2      s1 23.27229 28.59955 -5.3272621
```

2. Level-specific correlations

Second, let's see if the two variables correlate similarly across levels:

Level 1: Within-cluster correlation = correlation between cluster-mean-centered scores

```
cor(long[,c("x.mc","y.mc")])
```

```
            Calmness.mc   vmHRV.mc
Calmness.mc  1.00000000 0.03558461
vmHRV.mc     0.03558461 1.00000000
```

Level 2: Between-cluster correlation = correlation between cluster means

```
cor(wide[,c("x.m","y.m")])
```

```
           Calmness.m   vmHRV.m
Calmness.m  1.0000000 0.1307318
vmHRV.m     0.1307318 1.0000000
```

3. Null model & ICC

Third, let's specify the null model and compute the intraclass correlation coefficient (ICC) = Estimate of the proportion of between-cluster variance over the total variance.

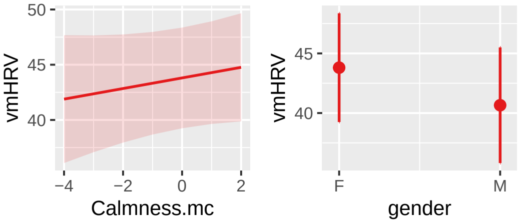
```
# fitting a null LMER model
library(lme4)
m0 <- lmer(y ~ (1|subject), data = long)

# extracting random intercept variance (lv2)
rinV <- summary(m0)$varcor$subject[[1]]

# extracting residual variance (lv1)
resV <- summary(m0)$sigma^2

# computing total variance (lv1 + lv2)
totV <- rinV + resV

# computing ICC = lv-2 variance / tot variance
ICC <- rinV / totV
```

4. Main effects (random intercept model)

Fourth, let's include the 2 main effects of interest:

- Level 1: vmHRV is predicted by cluster-mean-centered Calmness
- Level 2: vmHRV is predicted by participants' gender

```
# fitting main-effect model
m1 <- lmer(y ~ x1.mc + x2 + (1|subject), data = long)
summary(m1) # to inspect the main results
```



5. Random slope model

Fifth, let's include the random slope for `Calmness` by `gender`:

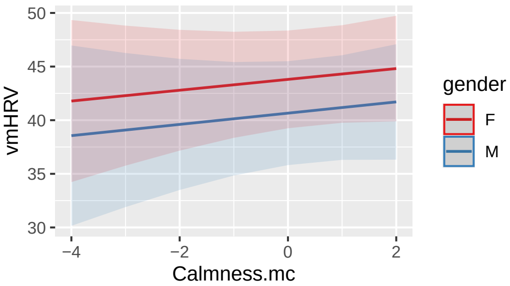
```
# fitting main-effect model
m2 <- lmer(y ~ x1.mc + x2 + (x1.mc|subject),
           data = long)
summary(m2) # to inspect the main results
```

```
##              Estimate Std. Error    t value
## (Intercept) 43.802238  2.3101537 18.9607463
## Calmness.mc  0.510546  0.5146609  0.9920047
## genderM     -3.145137  3.3523960 -0.9381758
```

6. Cross-level interaction

Finally, let's include the interaction between participant's gender and Calmness in predicting anxiety.

```
# fitting main-effect model
m3 <- lmer(y ~ x1.mc + x2 + x1.mc:x2 + (x1.mc|subject),
           data = long)
summary(m3) # to inspect the main results
```



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References

- Csikszentmihalyi, M., & Larson, R. (2014). Validity and reliability of the experience-sampling method. In Csikszentmihalyi, M., & Larson, R. (Eds.) *Flow and the foundations of positive psychology* (pp. 35-54). Springer, Dordrecht
- Freeman, M. (2017). An Introduction to Hierarchical Modeling. Available from http://mfviz.com/hierarchical-models/
- Shiffman, S., Stone, A. A., & Hufford, M. R. (2008). Ecological momentary assessment. *Annual Reviews in Clinical Psychology, 4*, 1-32.
- Wilhelm, F. H., & Grossman, P. (2010). Emotions beyond the laboratory: Theoretical fundaments, study design, and analytic strategies for advanced ambulatory assessment. *Biological psychology, 84*(3), 552-569.

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Additional resources

- Bates, D. (2022). lme4: Mixed-effects modeling with R. https://stat.ethz.ch/~maechler/MEMo-pages/lMMwR.pdf
- Bliese, P. (2022). Multilevel modeling in R (2.7). https://cran.r-project.org/doc/contrib/Bliese_Multilevel.pdf
- Menghini, L. (2023). Introduction to multilevel modeling (full slides presented at the "Advanced data analysis for psychological science" master course). Available from: https://github.com/Luca-Menghini/advancedDataAnalysis-course