Running head: Understanding and analyzing multilevel data from real-time monitoring studies

**Understanding and analyzing multilevel data from real-time monitoring studies: An easily-
accessible tutorial using R**

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Abstract

Although real-time monitoring methodology (also called ecological momentary assessment or experience sampling methodology) has become far more accessible in recent years, the methodologies to analyze data from real-time monitoring studies has not. The goal of this tutorial is to provide an easily-accessible overview of the basic theoretical concepts of multilevel modeling and the basics of conducting multilevel analyses in R. Topics in this tutorial include the theory behind multilevel modeling, structuring multilevel data, testing unconditional, two- and three-level models, logistic models, fixed and random effects, and centering data.

In recent years, there has been a flood of interest in real-time monitoring methodologies (also called Ecological Momentary Assessment [EMA] or Experience Sampling Methodology [ESM]; Shiffman, Stone, & Hufford, 2008) that allow psychological scientists unprecedented access to understanding how their phenomena of interest operate in everyday life by repeatedly assessing these phenomena as they occur. One reason for this interest in real-time monitoring is that smartphones are nearly ubiquitous in many countries (e.g., nearly 90% of 18-49 year olds own a smartphone; Pew Research Center, 2017) and there are now many real-time monitoring apps available at relatively low cost. This has made real-time monitoring methodology far more accessible than it has ever been before (where the norm was to use expensive external devices that had to be manually uploaded). Although real-time monitoring methodology has become more accessible in recent years, the strategies to analyze real-time monitoring data have not. These analyses are necessarily more complex than traditional models because real-time monitoring data involve multiple measurements per participant, presenting multiple “levels” of data that must be taken into account when conducting analyses.

The goal of this paper is to present an easy-to-follow basic tutorial of how to conduct multilevel analyses of real-time monitoring data. Several excellent tutorials for multilevel analyses exist but tend to be written towards different, albeit related, paradigms of multilevel modeling, making it difficult to apply the examples and terminology to real-time monitoring datasets. For example, some tutorials are written from the perspective of data from people within groups (e.g., patients within different doctors’ offices; Hayes, 2006; and students within classrooms; Woltman, Feldstain, MacKay, & Rocchi, 2012), instead of observations within people, or do not use any specific paradigm (e.g., Nezlek, 2001, 2008). Beyond presenting examples in a paradigm that matches real-time monitoring data, this tutorial teaches readers how

to conduct these analyses in R, which has not been done in prior papers. In recent years, R has become increasingly popular and is incredibly versatile for conducting analyses of real-time monitoring data. Indeed, more than one third of all data scientists (including people in academia, but also industry) now report that R is their primary analysis tool, up from under 10% just 10 years prior (Rexer, Gearan, & Allen, 2015). However, since R is far closer to a computer programming language than a traditional statistics program (even text-based programs like Mplus), using R can also be inaccessible to users unfamiliar with computer programming.

This paper is intended to teach the basic theoretical concepts of multilevel modeling and the basics of conducting multilevel analyses in R. These two topics are integrated throughout the tutorial such that readers will learn the concepts behind multilevel modeling while seeing how the analyses are conducted. By the end of this paper, readers will be able to analyze a variety of multilevel models, including those most relevant to real-time monitoring data. This tutorial assumes only the most basic experience with R (i.e., installing and launching R, installing packages, and loading datasets). If readers are not familiar with these basics, easy-to-follow tutorials for using R programming environments like RStudio are available on several sites (e.g., <http://web.cs.ucla.edu/~gulzar/rstudio/>). Example data from this tutorial come from a random sample of cases from a real study of suicidal individuals who were assessed on various factors relating to affect and suicidal ideation four times per day for 28 days (Kleiman et al., 2017).

Structuring multilevel data

Analysis of real-time monitoring data is difficult because even the most basic studies (e.g., 4 measurements per day, for 28 days) have a complex “multilevel” structure. Thus, it is important to first understand what a multi-level structure is and why data structured this way cannot be analyzed using traditional linear regression models. In real-time monitoring studies,

the same person answers the same questions multiple times across the study. This means that responses are not independent. In other words, responses given by the same person would likely be more strongly related than responses given by two different people. Moreover, any two responses given on the same day by the same person separated by a few hours might be more strongly related than any two responses by the same person on different days, especially if these two observations come one right after another (and are thus “autocorrelated”). This non-independence of responses presents a challenge for ordinary least squares (OLS) regression models that assume data are not related in this manner. Accordingly, multilevel modeling is a category of analyses that extend traditional OLS regression to accommodate the non-independence of responses in multilevel data, such as data collected in a real-time monitoring study (NB: the same is true for daily diary studies, and much of what is discussed here would apply to these studies as well).

Before going into the actual analyses, **Figure 1** shows a visual description of common multilevel models. The top panel shows a two-level model, which is the simplest multilevel model. In this example, a set of i observations (i referring to the total number of observations) at level 1 are nested within j participants at level 2. This would mean that there would be a maximum of $i * j$ responses to analyze, if all participants completed 100% of the required prompts (which is rarely the case, and multilevel modeling is robust to missing data like this). Within multilevel modeling, there can be (but there does not have to be) observations at any level. For example, current affect could be assessed at each observation (i.e., at level 1). A within-person average could be aggregated from these responses, to represent someone’s average level of affect. This variable would be at the participant level in this example, since there would be only one measurement per person. This would be the case for any other person-level (i.e.,

level 2) variable such as age, sex, level of trait impulsivity, current psychiatric diagnostic status, etc. The bottom panel of **Figure 1** shows an example of a three-level model where i observations are nested within j days, nested within k participants. Like two-level models, variables can (but do not have to be) assessed at each level. These specific three-level models, where observations are nested within days within people are particularly useful for examining both between-day (e.g., does average daily stress today predict average daily suicidal ideation tomorrow?) and within-day (e.g., is hopelessness stronger in the morning than at night?) questions. A three-level model would also be useful in cases where participants complete observations randomly throughout the day in real-time as well as once-per-day assessments (e.g., a nightly diary about stressors that occurred that day).

Figure 2 shows an annotated example of how to structure multilevel data in the “long” format, where each observation is on a separate row. This can be contrasted with the “wide” format where each participant is a separate row, and each observation is its own column. The long format is preferable since it presents an easier to manage dataset when there are hundreds or thousands of observations per participant.

Analyzing and interpreting multilevel data

In the following sections, readers are first walked through the explanation, analysis, and interpretation of a multilevel model with two levels. Next, readers are walked through a multilevel model with three levels in a way that builds on the two-level model. The final section covers the difference between fixed and random effects and shows how to integrate random effects into the models already learned. Throughout these sections, the basic conceptual framework for multilevel modelling and the basic steps for conducting these analyses are addressed simultaneously. The R packages required for all analyses are shown in **Table 1**. The

first few lines of the included R code will help readers install these packages if they are not already installed. A brief summary of all R commands used in this paper is shown in **Table 2** with more detailed, annotated commands presented in figures during the appropriate steps.

Analyzing data with two levels (e.g., observations within person)

Step 1: Unconditional model. The first step in conducting multilevel modelling is to make sure multilevel modelling is appropriate in the first place. This is done through testing an “unconditional model” (also called an “intercept only” model). In the unconditional model, only the dependent variable and the grouping variable(s) (e.g., subject ID) are entered. No predictors are entered, thus the model is not “conditioned” upon any predictor variables.

Analysis. Analyzing this model requires a slightly different procedure than the next few steps because *sjPlot* does not work with models that do not have any predictors. **Figure 3** shows the code to run and interpret the model, along with annotations for what each part of the code means. The first line of code in the figure tests the unconditional model and the second line produces the results for interpretation.

Interpretation. The second line of code will print several columns of results. The most relevant for evaluating an unconditional model is the p-value. If it is $< .05$ (or whatever predetermined cutoff for significance is being used), the model can be interpreted as showing significant between-participant variation and thus supporting the use of multilevel modeling. It is important to note that there are alternate ways to assess suitability for using a multilevel model, including evaluation of the intra-class correlation (ICC) which is described later. It is difficult to use the *ICC* to determinate the suitability of a multilevel model because there is no agreed upon *ICC* values to do so.

Step 2: Model with level-1 effects. After determining that a multilevel model is appropriate, the next step is to begin to add level-1 predictors. Within multilevel modeling of real-time monitoring data, level-1 is almost always the “observation” level.

Analysis. **Figure 4** shows the code to run and interpret the model, along with annotations for what each part of the code means. The first part of the code that runs the actual model is very similar to the unconditional model, except the “1” placeholder for independent variables is replaced with the names of the actual independent variables.

Interpretation and explanation of the intra-class correlation. **Figure 5** shows the sjPlot output of an lme4 model. The “fixed parts” section of this output can be interpreted in a similar manner to OLS regression. The information in the “random parts” section helps researchers *partition the variance* in the dependent variable. Partitioning the variance refers to identifying how much variance in the dependent variable is due to within-person (σ^2) and between-person (τ_{00}) variance. Although the *ICC* can refer to different aspects of multilevel data, it is most useful within this context to refer to what proportion of variance is due to between-person differences. Accordingly, it is calculated from the within-person and between-person variance statistics and is thus in some ways redundant with these values. For example, in **Figure 5**, the *ICC* is .436, which is calculated by dividing between-person variance and the sum of between- and within-person variance (i.e., $ICC = \tau_{00} / (\sigma^2 + \tau_{00})$, or $0.436 = 2.695 / (2.695 + 3.429)$). The *ICC* in this example would be interpreted as meaning that 46.4% of the variance in suicidal ideation scores are due to person-to-person variation, whereas 53.6% (i.e., $1 - 0.464$) of the variance is due to within-person observation-to-observation variation. As noted above, there are no strong guidelines for interpreting an *ICC*, however scores approaching 1.0 would indicate that nearly all variation is occurring at the highest level (in this case, person-level) and could mean that multilevel

modeling is not appropriate. It should be noted that *ICCs* can also be calculated in unconditional models, which partition the variance of the dependent variable outside of the influence of any independent variables.

Step 3: Model with level-2 effects. The next step involves entering level-2 effects, although it is not always necessary to take this piecewise approach testing a level-1-effects-only model first. It is also not necessary that all models have level-2 effects. In fact, including level-2 effects may not always be desirable since doing so can neutralize some of the power benefits of repeated measures at lower levels, since there would be only one observation per level-2 unit in a two-level model (Maas & Hox, 2005). A model with level-2 variables should only be used when the theoretical conceptualization of the model necessitates it and there is sufficient power to do so. For example, if researchers are interested in adjusting for the effect of gender, entering gender as a level-2 term would be appropriate.

Analysis and interpretation. The code for an lme4 model that includes level-2 effects is identical to the code for a model that does not include level-2 effects. All independent variables are specified the same way and lme4 is able to determine which variables are at which level. The interpretation for analyses with level-2 effects is also nearly identical to analyses with level-1 effects only.

Analyzing data with three levels (e.g., observations within days within people)

Three-level models are useful when assessing factors at an intermediate level between observation and participant (e.g., observations within days within participant) or assessing factors at a level above participants (e.g., observations within participants within experimental/control group). As in the other model structures, it is not necessary to have measurements at every level.

Code. If not done by automatically when exporting real-time monitoring data, a new “level” variable must be created before testing a three-level multilevel model. For example, if the model includes days nested within participants, lme4 will not be able to determine the nesting structure automatically because each participant would have many of the same “day” values (see **Figure 2**). Accordingly, a new variable must be created that combines or “concatenates” (using the paste()) command the subject variable and the day variable to create a unique variable that shows both subject and day at the same time (e.g., day 1 for subject 1001 would become 10011). By doing this, lme4 can identify that days are nested within participants. An example of this formula is shown in **Table 2** (“three level model with fixed effects”). Once the new variable is created, three-level models follow the same general form as a two-level model, but with the addition of another random term (i.e., (1|level)), which is also shown in **Table 2**.

Interpretation. **Figure 6** shows the output from a three-level model. This output looks very similar to the two-level models, except for the addition of more variance partitioning information. Now that the variance is partitioned into three levels, we can see that 41.9% of the variance is at the subject level, 20.2% is at the day level, and 37.9% remains at the observation level.

Random slopes models

A regression line (or any plotted line for that matter) has two components: (1) the y-intercept (usually referred to as “intercept” or “constant”), which is the mean of the dependent variable when all independent variables equal 0 (if variables are scaled such that they include 0) and (2) the slope, which is the relationship between an independent variable(s) and the outcome. In multilevel modelling, intercepts and slopes can be either “fixed” or “random”. “Random” in this context refers to allowing the intercept and/or slope to vary randomly across higher-level

units (indeed, this is why multilevel modeling is also called “random coefficients modelling” in some contexts). “Fixed” means that the same value is given for all higher-level units. All multilevel models have at least one random effect. All examples thus far have used random intercepts and fixed slopes (this is the most basic multilevel model). The interpretation of random intercept/fixed slopes models is that each higher-level unit (e.g., person-level) has a different intercept, reflecting different mean levels of the dependent variable, but the relationship between independent and dependent variables is assumed to be the same across all people. In other words, an intercept is calculated for each person, but the slope is calculated for the entire sample. In random slopes models, it is assumed that the relationship between independent and dependent variables differs across the higher-level unit (e.g., people). In other words, an intercept and slope is calculated for each person. This can be compared to traditional OLS regression, where (because there is only one level of data to be analyzed), the intercept and slope is calculated for the entire sample. **Figure 7** shows how the interpretation and visualization of predicated values from OLS regression (fixed intercept/slope), models with fixed slopes, and models with random slopes differ.

The decision between fixed and random slopes depends upon the theoretical context of the hypothesis being tested. Random effects are most useful when the researcher is interested in differences among higher-level units (e.g., person-level). For example, random slopes models could ask questions about whether there are differences in regard to the strength of the association between two variables. Although beyond the scope of this tutorial, random slopes models are also useful for testing interactions which could answer questions regarding whether certain level-2 variables predict level-1 slopes (often called a “slopes-as-outcomes model”).

For example, researchers might be interested in whether people high in trait self-criticism have a stronger relationship between hopelessness and suicidal ideation.

Code. Specifying random slopes in lme4 is not much different than models that use fixed slopes. All that is involved is replacing the “1” placeholder in the grouping statement (e.g., (1|subject)) with the names of the independent variables whose slopes should be random. **Table 2** shows an example of this code.

Interpretation. The use of random or fixed effects does not change the way the models are interpreted, since it is recommended to interpret the model based on the fixed effects (Nezlek, 2008). Random slopes, do, however, produce several additional random effects terms that can be useful for understanding how much slopes vary across participants. First, the slope-intercept correlation (also referred to as ρ_{01}) refers to how random intercepts and random slopes are related. For example, a positive slope-intercept correlation would indicate that those at higher mean levels of the dependent variable exhibit a stronger relationship between the independent variable(s) and the dependent variable. Second, the re_var() command (see **Table 2**), produces the random-slope variance (also referred to as τ_{11}) that can be interpreted as between-participant variance in slopes attributed to each variable. It also produces the slope-intercept covariance (also called τ_{01}), which is conceptually similar to the slope-intercept correlation but is arguably less useful than it since the covariance is not adjusted for potential differences in scales like a correlation is.

Multilevel modeling with logistic regression

Just as in traditional one-level models, logistic regression in multilevel modeling used when the outcome variable is binary (e.g., whether or not someone had suicidal thoughts).

Code. The code for multilevel logistic models in lme4 builds directly off of the code for linear models. As shown in **Table 2**, there are two differences between linear and logistic models. The first difference is instead of using the lmer() command, logistic models use the glmer() command. The glmer() command refers to generalized linear mixed models, which (also as in single-level regression), refers to a category of analyses. Thus, the second difference between logistic models and linear multilevel models is that *family=binomial(link="logit")* must also be added to the command. Although beyond the scope of this tutorial, other types (or families) of generalized linear models (e.g., Poisson) can also be specified through this command.

Interpretation. The interpretation of logistic models is very similar to one-level logistic regression and linear multilevel modeling. The output produces odds ratios and confidence intervals (like most logistic regression models) and variance partitioning statistics (like most multilevel linear models).

Advanced Topics: Centering and Leading/Lagging

Centering

There are some differences between centering in OLS regression and centering in multilevel modelling. First, although centering is commonly recommended only when testing interactions in OLS regression (Aiken & West, 1991), centering is recommended for all multilevel modelling. Centering in multilevel modeling changes the interpretation of the model in ways that centering in OLS regression does not. These differences in interpretation are discussed below. Second, in OLS regression, when there is only one measurement per person, there is one option for centering (i.e., subtracting a constant like the mean score from each response). In multilevel modeling, there are multiple responses per person and thus there are several options for centering (e.g., centering on the entire sample's mean or centering on each

individual's mean). What makes this even more complicated is that there is no clear correct decision between these options because each option asks of the data a different question and should thus be chosen based upon the theoretical context of the study (Enders & Tofighi, 2007; Kreft, Leeuw, & Aiken, 1995). **Table 3** summarizes the differences between types of centering and the text below provides more detail on each option.

Grand-mean centering. Grand-mean centering involves subtracting a constant (typically the entire sample's mean) from each individual response and is identical to the centering performed in OLS regression. Grand-mean centered variables are interpreted as deviation from the overall sample's mean. This implicitly assumes that all participants have generally the same mean and deviations from that mean have the same impact across participants. For example, grand-mean centering the variables included in the sample data, it is implicitly assumed that all participants have generally similar "average" levels of hopelessness, etc. and that a one-unit increase in hopelessness would lead to the same increase in suicidal ideation across all participants. Thus, grand-mean centering is most useful when it can be assumed that means and deviations from the mean are relatively consistent across participants (although such an assumption can be hard to make).

Participant-mean centering. Participant-mean centering (also called group mean centering and centering within clusters) involves subtracting each participant's mean from each of their individual responses. For example, if participant A's mean level of hopelessness is a 6 out of 10 and participant B's mean level of hopelessness is a 4 out of 10, 6 would be subtracted from all of participant A's responses and 4 would be subtracted from all of participant B's responses. Participant-mean centered variables are thus interpreted as deviation from each participants' individual mean. This removes all between-person variance in the centered data,

making the mean score across participants comparable, since each person's mean would be 0. Participant-mean centering is useful any time participants' means are suspected to differ meaningfully, or if variations from a participant's average or baseline are theoretically-important to the model being tested.

Participant mean centering while including participant means in model. An option that builds on participant-mean centering involves specifying the participant-centered observations as a level-1 variable and individual participants' means as a level-2 (or whichever level is the person-level) variable. This allows comparison of between-person and within-person variability. For example, the level 1 effect of hopelessness on suicidal ideation can be interpreted as the effect of how much that individual observation differs from the participant's mean. The level-2 effect would be interpreted as the effect of someone experiencing more or less hopelessness on average. This would be most useful when both the variation from observation to observation and from person to person is relevant to the theoretical model being tested.

Three-level models. Although the text in this section referred to two level models, centering can occur at any level of analysis. In a three-level model that has, for example, observations within days within people, researches could center within participants or grand mean center, but could also center on each day's mean. Like the options discussed below, deciding to center on an intermediate level between observation and person should be made based on the data and hypotheses being tested.

Leading (and lagging) variables for prospective analyses

Up until this point, all of the analyses that have been discussed are cross sectional (i.e., all independent and dependent variables are assessed at the same time). However, one of the most useful applications of real-time monitoring data is using short-term prospective analyses see

whether factors at time T predict other factors at time $T+I$ a few hours later. Such applications require leading or lagging of variables. This refers to bringing up the assessment of the dependent variable from $T+1$ to the row of data containing measurements at T (i.e., leading) or bringing down the assessment of the independent variable from time T to the row of data containing measurements at $T+1$ (i.e., lagging). Both leading and lagging can be used to conduct prospective analyses. Leading is generally simpler because it involves creating only one new variable (i.e., because there is only one dependent variable in a model), whereas lagging requires new variables for every independent variable.

Code. The code for leading and lagging variables is shown in **Table 2**. An annotated version of the code is shown in **Figure 8**.

Interpretation. These analyses and their interpretation are nearly identical to cross-sectional models. When the independent variables are assessed at time T (e.g., hopelessness and burdensomeness at 2:12pm) and the dependent variable is assessed at time $T+I$ (e.g., suicidal ideation at 6:48pm), the model is assessing whether variables at time T predict outcomes at time $T+I$. When the measure of the dependent variable at time T is also included in the model, the model is now assessing whether the independent variables at time T predict change in the outcome variable between time T and time $T+I$.

Conclusion and a final note on decision-making in multilevel modeling

The goal of this tutorial was to provide an accessible introduction to analyzing the multilevel data that are produced in studies that use real-time monitoring to assess factors of interest.

Although further, more advanced tutorials are needed for more advanced multilevel modeling of real-time monitoring data (e.g., interactions, growth curve modeling), the information provided here should give researchers the tools necessary to test many basic hypotheses. Although true of

essentially all inferential statistics, there are several different options for data and model manipulation (e.g., grand mean or participant mean centering, using fixed or random slopes). Unlike other types of analyses, there is not always a clear answer for which option is best for which context. This provides several options for each analysis that are usually equally defensible but may have different impacts on the interpretation of the results. A lack of understanding of these decisions and their impact can lead to a high potential for false positives. Of course, this is not an issue unique to multi-level modelling, since the idea of “researcher degrees of freedom” has been well known across other areas of psychological science (see Simmons, Nelson, & Simonsohn, 2011). Nevertheless, because multilevel modeling is less commonly understood than simpler models, it is important for researchers to fully understand and explain what the implications are for each decision that is made.

References

- Aiken, L. S., & West, S. G. (1991). *Multiple regression: Testing and interpreting interactions*. Milton Keynes: SAGE Publications, Inc.
- Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, 67(1), 1–48.
<https://doi.org/10.18637/jss.v067.i01>
- Enders, C. K., & Tofighi, D. (2007). Centering predictor variables in cross-sectional multilevel models: A new look at an old issue. *Psychological Methods*, 12(2), 121–138.
<https://doi.org/10.1037/1082-989X.12.2.121>
- Gandrud, C. (2016). *Datacombine: Tools for easily combining and cleaning data sets*. Retrieved from <https://CRAN.R-project.org/package=DataCombine>
- Hayes, A. F. (2006). A primer on multilevel modeling. *Human Communication Research*, 32(4), 385–410. <https://doi.org/10.1111/j.1468-2958.2006.00281.x>
- Kleiman, E. M. (2017). *EMAtools: Data management tools for real-time monitoring/ecological momentary assessment data*. Retrieved from <https://CRAN.R-project.org/package=EMAtools>
- Kleiman, E. M., Turner, B. J., Fedor, S., Beale, E. E., Huffman, J. C., & Nock, M. K. (2017). Examination of real-time fluctuations in suicidal ideation and its risk factors: Results from two ecological momentary assessment studies. *Journal of Abnormal Psychology*.
<https://doi.org/10.1037/abn0000273>
- Kreft, I. G. G., Leeuw, J. de, & Aiken, L. S. (1995). The Effect of Different Forms of Centering in Hierarchical Linear Models. *Multivariate Behavioral Research*, 30(1), 1–21.
https://doi.org/10.1207/s15327906mbr3001_1

- Lüdtke, D. (2016). *SjPlot: Data visualization for statistics in social science*. Retrieved from <http://CRAN.R-project.org/package=sjPlot>
- Lüdtke, D. (2017). *sjStats: statistical functions for regression models*. Retrieved from <https://CRAN.R-project.org/package=sjstats>
- Maas, C. J. M., & Hox, J. J. (2005). Sufficient sample sizes for multilevel modeling. *Methodology*, 1(3), 86–92. <https://doi.org/10.1027/1614-2241.1.3.86>
- Nezlek, J. B. (2001). Multilevel Random Coefficient Analyses of Event- and Interval-Contingent Data in Social and Personality Psychology Research. *Personality and Social Psychology Bulletin*, 27(7), 771–785. <https://doi.org/10.1177/0146167201277001>
- Nezlek, J. B. (2008). An introduction to multilevel modeling for social and personality psychology. *Social and Personality Psychology Compass*, 2(2), 842–860. <https://doi.org/10.1111/j.1751-9004.2007.00059.x>
- Pew Research Center. (2017). *Mobile phone ownership over time*. Washington, DC: Pew Research Center. Retrieved from <http://www.pewinternet.org/fact-sheet/mobile/>
- Rexer, K., Gearan, P., & Allen, H. (2015). *2015 Data Science Survey*. Winchester, MA: Rexer Analytics. Retrieved from http://www.rexeranalytics.com/assets/rexer_analytics_2015_data_miner_survey_summary_report.pdf
- Shiffman, S., Stone, A. A., & Hufford, M. R. (2008). Ecological momentary assessment. *Annual Review of Clinical Psychology*, 4, 1–32. <https://doi.org/10.1146/annurev.clinpsy.3.022806.091415>

Simmons, J. P., Nelson, L. D., & Simonsohn, U. (2011). False-positive psychology undisclosed flexibility in data collection and analysis allows presenting anything as significant.

Psychological Science, 22(11), 1359–1366. <https://doi.org/10.1177/0956797611417632>

Woltman, H., Feldstain, A., MacKay, J. C., & Rocchi, M. (2012). An introduction to hierarchical linear modeling. *Tutorials in Quantitative Methods for Psychology*, 8(1), 52–69.

<https://doi.org/10.20982/tqmp.08.1.p052>

Table 1. R packages used in this tutorial.

Package	Use in this tutorial
DataCombine (Gandrud, 2016)	Used to create leads in data.
EMAtools (Kleiman, 2017)	Used for structuring and centering data.
lme4 (Bates, Mächler, Bolker, & Walker, 2015)	Conducts all multilevel models.
sjPlot (Lüdecke, 2016)	Used to create APA-style tables from lme4 analyses that can be easily understood.
sjStats (Lüdecke, 2017)	Used for extracting fit statistics.
Note: Other R packages such as nlme can also conduct multilevel modeling.	

Table 2. R commands used in this tutorial

Description of analysis/code	Code
1. Unconditional Model	<pre>MODEL <- lmer(DV~1+(1 subject), data=DATA) get_model_pval(MODEL, p.kr=TRUE)</pre>
2. Model with level-1 fixed effects	<pre>MODEL<-lmer(DV~IV1+IV2+(1 subject), data=DATA) sjt.lmer(MODEL)</pre>
3. Model with level-1 and level-2 fixed effects	<pre>MODEL<-lmer(DV~IV1+IV2+IV3+(1 subject), data=DATA) sjt.lmer(MODEL)</pre> <p>Note: At least one of the IVs should be a level-2 variable (lme4 will automatically identify this).</p>
4. Three level model (w/fixed effects) (plus subject*day variable creation)	<pre>DATA\$Subj_Day<-paste(DATA\$subject, DATA\$day, sep=" ") MODEL<-lmer(DV~IV1+IV2+(1 Subj_Day)+(1 subject), data=DATA) sjt.lmer(MODEL)</pre>
5. Model with level-1 random effects	<pre>MODEL<-lmer(DV~IV1+IV2+(IV1+IV2 subject), data=DATA) sjt.lmer(MODEL) re_var(MODEL)</pre>
6. Multilevel logistic regression	<pre>MODEL<-glmer(DV~IV1+IV2+(1 subject), data=DATA, family=binomial(link="logit")) sjt.glmer(MODEL)</pre> <p>Note: DV must be a factor with two levels (e.g., 0/1).</p>
7. Creating leads in data	<pre>DATA<-slide(data=DATA, Var="Variable", TimeVar="ObsNumb", GroupVar = "Subject", NewVar="Var_Lead", slideBy=1)</pre>

Note: Number next to analysis correspond to examples included in the demonstration R code.

Table 3. Centering options for multilevel modeling

Centering type	Interpretation of centered value	Interpretation of intercept	Formula	R command
Grand mean	How much each individual score differs from the average score for <i>the entire sample</i> .	Expected value of DV when IV is at the overall sample mean.	$X_{ij} - \bar{X}$ (Response i for participant j – overall sample mean)	<code>data\$var_gmcent<-gcenter(data\$var)</code>
Participant mean	How much each individual score differs from the average score for <i>that individual</i> .	Expected value of DV when the IV is at each participants' mean.	$X_{ij} - \bar{X}_j$ (Response i for participant j – mean for participant j)	<code>data\$var_pcent<-pcenter(data\$ID,data\$var)</code>

Figure 1. Example two- and three-level multilevel models.

Figure 2. Overview of data structure for multilevel analysis.

Figure 3. R code for an unconditional model.

Figure 4. R code for a model with level-1 effects.

Figure 5. Annotated output for a model with level-1 effects.

	B	CI	<i>p</i>
Fixed Parts			
(Intercept)	-0.80	-1.33 – -0.28	.009
Hopeless	0.81	0.72 – 0.89	<.001
Burdensome	0.38	0.30 – 0.47	<.001
Random Parts			
σ^2		3.493	
$\tau_{00, \text{subject}}$		2.695	
N_{subject}		54	
ICC_{subject}		0.436	
Observations		2168	
R^2 / Ω_0^2		.639 / .639	

Within-person residual variance

Between-person variance
Refers to the variation in intercepts across people.

Level 2 units
In this case, it is the number of participants.

Between-group ICC
Proportion of variance explained by between-person differences. Calculated using σ^2 and τ_{00} .

Number of level 1 observations

Effect size measures
 R^2 is an approximation of R^2 in OLS regression. It represents the correlation between fitted and observed values. Ω_0^2 is an estimate of the proportion of variance in the response variable (DV) accounted for by the explanatory variables (IVs). See Nakagawa & Schielzeth, (2013) for technical details.

Figure 6. Annotated output for a three-level model.

	B	CI	<i>p</i>
Fixed Parts			
(Intercept)	-0.68	-1.12 – -0.16	.012
Hopeless	0.80	0.70 – 0.88	<.001
Burdensome	0.36	0.28 – 0.44	<.001
Random Parts			
σ^2		2.346	
$\tau_{00, \text{Subj_Day}}$		1.249	
$\tau_{00, \text{subject}}$		2.591	
$N_{\text{Subj_Day}}$		1053	
N_{subject}		54	
ICC _{Subj_Day}		0.202	
ICC _{subject}		0.419	
Observations		2168	
R^2 / Ω_0^2		.819 / .814	

Within-person residual variance (level-1)

Between-day variance (level-2)

Between-person variance (level-3)

Variance attributable to between-day variation
 $\tau_{00, \text{Subj_day}} / (\tau_{00, \text{subject}} + \tau_{00, \text{Subj_day}} + \sigma^2)$

Variance attributable to between-person variation
 $\tau_{00, \text{subject}} / (\tau_{00, \text{subject}} + \tau_{00, \text{Subj_day}} + \sigma^2)$

Figure 7. Comparison of predicted values from OLS regression, multilevel modeling with fixed slopes, and multilevel modeling with random slopes.

Note. Colored lines = different participants.

Figure 8. Code for leading and lagging variables.