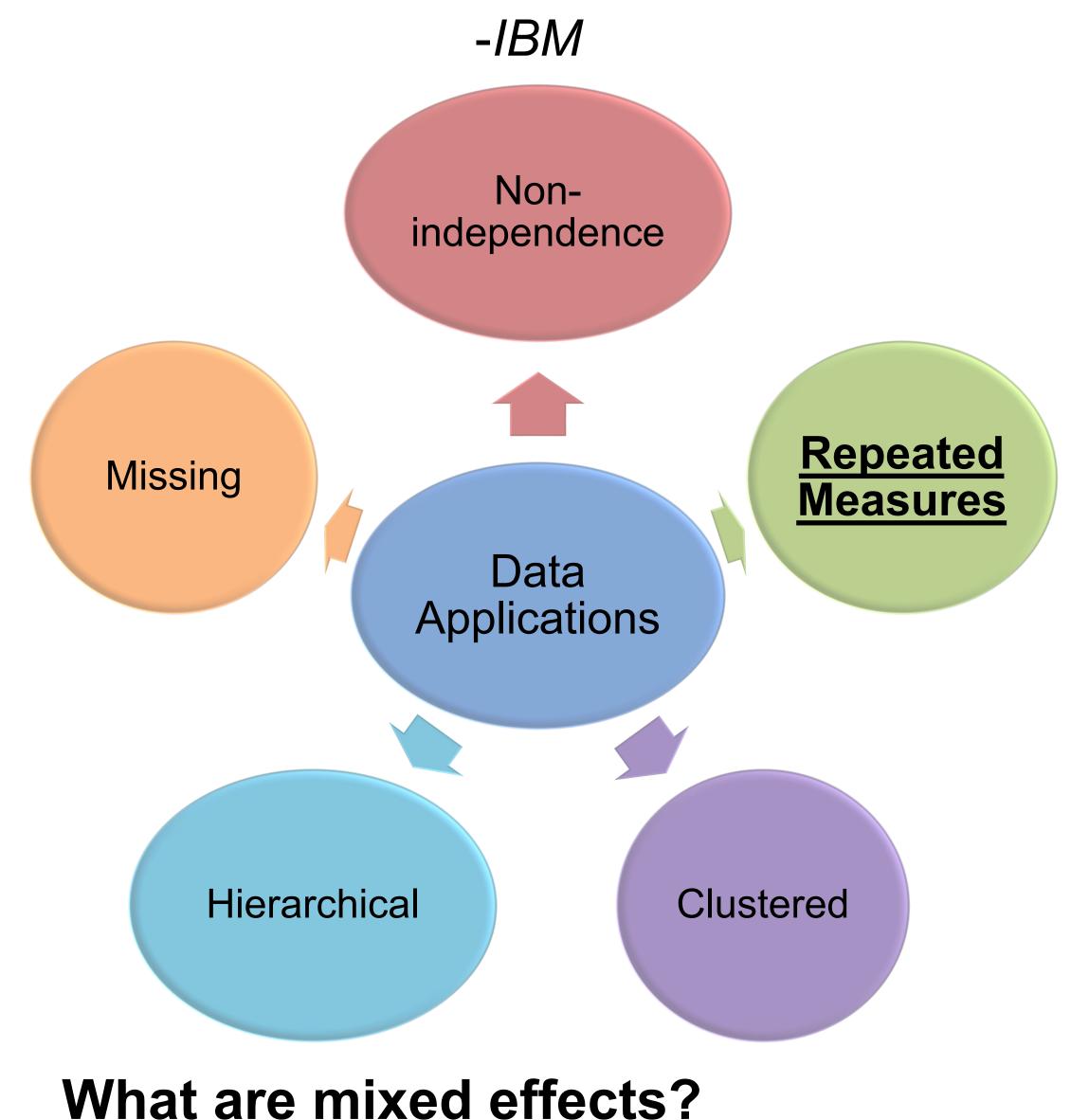
# From Classroom to Clinic: Applying Linear Mixed **Models to Understand Real-World Medical Research** Data

University of West Florida (UWF) - STA 6257 (Advanced Statistical Modeling)

### INTRODUCTION

#### Defining a **linear mixed model** (LMM):

*"advanced statistical tools designed to* analyze data that exhibit complex structures, such as hierarchical organization, repeated measures, and random effects"



#### • Fixed effects – the variable of interest and controlled variables (*i.e., those that* are directly)

• Random effects – measured random variability between individuals, clusters, or hierarchies (*i.e., those that are not* typically measured directly)

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### MATHEMATICAL FOUNDATIONS

**Mathematical Foundations:** Linear Algebra

Simple LMMs can be defined by:

### $y = X\beta + Zu + \epsilon$

•Y is the response vector. •X is the design matrix for fixed effects. •**β** is the <u>vector</u> of **fixed effect**s •Z is the design matrix for random effects. •*u* is the vector of **random effects** •ε is the <u>vector</u> of **residual errors**.

#### **An Example:**

•2-level longitudinal structure •100 students (*random effect*) •10 test scores (*dependent variable – fixed effect*) Associated study time each (independent variable fixed effect)  $\bullet N = 1000$  (students \* tests)  $\bullet J = 10$  (scores per student) •P = 2 (random intercept + fixed effect) •This LMM can be **defined** by:

 $Y_{1000 imes 1} = X_{1000 imes 2} \ eta_{2 imes 1} + Z_{1000 imes 10} \ u_{10 imes 1} + \epsilon_{1000 imes 10}$ 

Level 1 (Time):

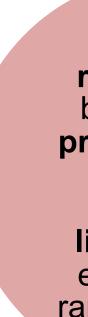
 $Y_{ti} = \beta_{0j} + \beta_{1j} \cdot \text{StudyTime}_{ti} + e_{ti}$ 

Level 2 (Student):

$$eta_{0j}=\gamma_{00}+u_{0j}$$

 $\cdot \gamma_{00}$  is the grand intercept mean. •**u**<sub>0i</sub> is the deviation of the **j**<sub>th</sub> **group** 





•14 measured variables (fixed effects)

•2 grouping variables (*random effects*)

•4 of the fixed effects are *dependent variables* representing airway resistance.

 Data required winsorization to satisfy LMM assumption of normality. All other assumptions were met.

#### **The Final Model:**

 $Y_{ijk} = (\beta_0 + u_{0j} + u_{1j} \times Observation\_number2_{ijk} + \ldots + u_{5j} \times Observation\_number6_{ijk})$  $+ \beta_1(BMI_{ijk}) + \beta_2(AsthmaYes_{ijk}) + \beta_3(ICSYes_{ijk}) + \beta_4(LABA_{ijk})$  $+\beta_{5}(Gender_{ijk})+\beta_{6}(Age\_months_{ijk})+\beta_{7}(Height\_cm_{ijk})+\beta_{8}(Weight\_Kg_{ijk})$  $+ \beta_9(Group_{ijk}) + \epsilon_{ijk}$ 

•Fixed effects: Diagnosis (C-SCD or C-Asthma) and all demographic and co-morbidity variables.

•Random effects: Subject and observation number.

•Adding observation number increased AIC, but these effects were kept in the final model due to the goal of the research project (predicting airway resistance). •All assumptions satisfied.

•Akaike Information Criterion (AIC) = 1801.60. •Smaller Mean Squared Error (41.95 v. 117.1 and 270.60) and Mean Absolute Error (5.07 v. 8.48 and 12.15) than previous models.

### ASSUMPTIONS

1. The relationship between the predictors and response variable is linear, within each level of random effects

2. Random effects (u) are assumed to be independent and normal with mean zero and variancecovariance matrix G.

3. Residual errors (c) are assumed to be independent and normal with mean zero and variancecovariance matrix R.

Homoscedastic **ity** is **assumed** for the residuals across all levels of the independent variable.

### THE CAPSTONE PROJECT

#### The Dataset:

•Longitudinal, retrospective study.

•Impact of BMI on airway resistance and reactance in children with Sickle Cell Disease (C-SCD) and asthma (C-Asthma).

•Same patients (n=85), multiple (repeated) measurements over time (6 visits total).





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### **CONCLUSION AND** ADDITIONAL RESOURCES

#### **Conclusion:**

- LMM's are versatile tools for modeling complex relations with multiple effects (fixed and random), as well as missing and non-independent data.
- For the given capstone dataset, the generated LMM can reliably predict measures of airway resistance and reactance given demographic and co-morbidity data.
- This model can be reliably used for **both children with Sickle Cell Disease and those with asthma.**

View our FULL literature, report, and slides for the capstone project:







Bates, D., Mächler, M., Bolker, B., and Walker, S. (2015), "Fitting Linear Mixed-Effects Models Using Ime4," Journal of Statistical Software, 67, 1– 48. https://doi.org/10.18637/jss.v067.i01. Galecki, A. T., Kathleen B. Welch (2014), Linear Mixed Models: A Practical Guide Using Statistical Software, Second Edition, New York: Chapman; Hall/CRC. https://doi.org/10.1201/b17198.

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