Intensive Longitudinal Data: Applications to Real-Time Health Data Collection

Summer G. Frank-Pearce, PhD, MPH
Trent L. Lalonde, PhD
APHS Breakfast Club
November 11, 2018

APHA | APPLIED PUBLIC HEALTH STATISTICS SECTION

- Founded in 1908 – Longest Continuously Running APHA Section!
- Webinars, Workshops, Scientific Sessions, Networking, Section Awards, . . .
- Chair: Lei Zhang (lei.zhang@msdh.state.ms.us)
- Membership: Wei Pan (wei.pan@duke.edu)

APHA | APPLIED PUBLIC HEALTH STATISTICS SECTION

- APHA 2018 Highlights:
  - Tuesday, 10:30 AM: APHS Student Poster Competition
  - Tuesday, 12:30 PM: APHS Luncheon, Awards Ceremony, and Lowell Reed Lecture
  - Tuesday, 3:00 PM: Current and Future: Student Finalist Presentations and Spiegelman Awardee Presentation
  - Tuesday, 6:30 PM: Section Social

About the instructors

Summer G. Frank-Pearce
Assistant Professor of Research
University of Oklahoma HSC
Summer-FrankPearce@ouhsc.edu

Trent L. Lalonde
Associate Professor
University of Northern Colorado
Trent.Lalonde@unco.edu

Github site: https://github.com/lalondetl/APHSWorkshop

Motivating Studies

- Marijuana Use, Co-Use, and Motivation

Marijuana Study

- Aims to quantify the momentary relationships among motivation, social context, marijuana craving, and marijuana use.
- Aims to describe daily co-use of alcohol and marijuana

Marijuana Study

- Use momentary behaviors such as craving, anxiety, and mood to predict upcoming marijuana use (frequency and time)
- Identify personality traits (impulsivity, volatility of mood, self-control) and contextual factors (with others, studying) associated with co-use of alcohol and MJ.
- In addition, traditional longitudinal goals of evaluating academic performance

Marijuana Study

Recruiting and Baseline Procedure:

- Convenience Sample
- Brief screening call
- Use survey and urinalysis
- Extensive baseline interview
- Training with LifeData App

Marijuana Study

ILD Data Collection:

- Participants prompted 3 times per day for 14 consecutive days (two weekends, random start)
- Prompts scheduled randomly within windows selected so as not to interfere with work, classes, etc.
- Identical questions, some skip logic
- Momentary: “Please rate your mood in the current moment.”
- Interval: “Since the last time you were prompted, how many times have you used?”
- Time Stamp: “Please provide the date(s) and time(s) of your marijuana use.”

Motivating Studies

- Smart-T2

Smart-T2 Cessation Study

- Aims to compare the effects of three treatment approaches on smoking cessation outcomes.
- Aims to identify contextual factors and treatment mechanisms associated with cessation.

Smart-T2

NCI QuitGuide

Usual Care

Smart-T2 Cessation Study

Weighted algorithm predicts smoking lapse based on risk factors:

- Urge to smoke
- Stress
- Cigarette availability
- Low motivation to quit
- Alcohol Use
- Interacting with others smoking

Businelle et al. (2016)

Smart-T2 Cessation Study

- Study Procedure
  - Participants (n=90) followed for 5 weeks
    - 1 week before quit date
    - 4 weeks after quit date
  - All participants
    - Receive smartphone with Insight™ app and nicotine replacement therapy
    - Complete 5 EMAs per day (1 Daily Diary and 4 Random Assessments)
    - Compensated for in-person visits and percentage of EMAs completed

Smart-T2 Cessation Study

- In Smart-T intervention group only
  - Algorithm identifies level of risk using
    - EMA responses
    - Self-reported interest in quitting
  - Risk level dictates appropriate tailored message
  - Automatically pushed for just-in-time intervention

Smart-T2 Cessation Study

Condition	Themes	Example Messages
Participant not interested in quitting	▪ Benefits of quitting ▪ General motivation ▪ Planning for quit attempt	On average, non-smokers live 12 years longer than smokers AND ex-smokers live up to 10 years longer than smokers who don't quit.
Low Risk of Imminent Lapse	▪ General cessation advice ▪ Maintaining abstinence	Remember: Every day without cigarettes is a success. The first few hours and days are the hardest. It gets easier as time goes by. HANG IN THERE! You're doing it!
High Risk of Imminent Lapse	▪ Tailored to highest risk factor (e.g., urge, stress)	Don't let negative emotions keep you from a healthier life! When you feel stressed or angry, distract yourself, go for a walk, get out of the situation for a few minutes, try deep breathing exercises.

Goals for this workshop

About this workshop

- Today's Workshop Goals
  - Provide an overview of ILD using contemporary examples
  - Provide foundations of ILD
- Ongoing Workshop Goals
  - Provide materials to facilitate the analysis of ILD
    - Not proficiency in data analysis

Today's Workshop Goals

- Identify goals, hypotheses and research questions for studies using intensive longitudinal data (ILD)
- Explain strengths and limitations of ILD methods
- Distinguish between basic designs for ILD
- Discuss basic models for ILD
- Briefly describe advanced models for ILD
- Summarize real-world examples of research projects using ILD

Ongoing Workshop Goals

- Utilize workshop materials as a guide to
  - Manipulate the format/structure of ILD
  - Visualize and summarize/describe ILD
  - Apply multilevel models to ILD with continuous and binary outcomes
  - Apply variance modeling of ILD
  - Interpret results from ILD models
  - Determine when a more advanced modeling approach is appropriate

Define ILD

- Data from repeated measurements on same individual
  - ~30 or more measurements
  - In real-time
  - In natural environment
- Collection aided by modern technology
  - Historically pen and paper daily diaries used
- Common terms for method of collecting ILD
  - Experience Sampling
  - Ecological Momentary Assessments (EMA)

Types of ILD

Researcher Initiated

- Time-based – assessment prompts based on a defined schedule
  - Once per day or week
    - Participant asked to aggregate data by summarizing their experience over a day
      - Provide average measure (intensity of craving)
      - Summarize event measures (number of cigarettes smoked)
      - Asked to do both (number and intensity of headaches)
      - Less salient (or more ordinary) events may be remembered less accurately resulting in bias

Researcher Initiated

- Time-based – assessment prompts based on a defined schedule
  - Multiple times per day
    - Fixed-intervals
      - Evenly spaced
      - Helpful for modeling correlation among outcomes
      - Potential bias from participant anticipating assessment

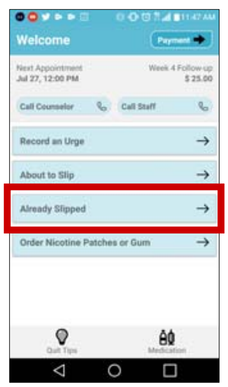
Researcher Initiated

- Time-based – assessment prompts based on a defined schedule
  - Multiple times per day
    - Randomly within time interval
      - Unevenly spaced
      - “Random sample from an individual’s experience” similar to “Random sample from population”
      - Sampling randomly inside blocks of time
      - Helpful for capturing dynamic behaviors that change over time
      - Element of “surprise” may reduce potential for bias

Researcher Initiated

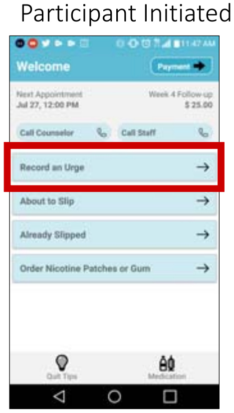
- Event-based – assessment prompts occur when an event detected by study device
  - Location detected
    - Device detects participant has entered a tobacco retail building
  - Characteristic detected
    - Device detects participant has high heart rate

Participant Initiated



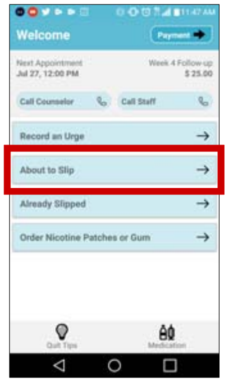
- Event-based - participant chooses to interact with study staff/device without being prompted
  - Record completed action or event

Participant Initiated



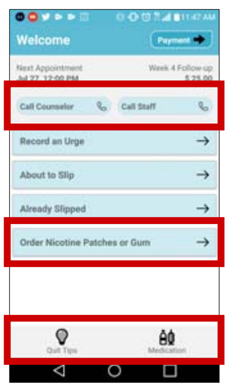
- Event-based - participant chooses to interact with study staff/device without being prompted
  - Record current emotional state or behavior

Participant Initiated



- Event-based - participant chooses to interact with study staff/device without being prompted
  - Record intended or future action or event

Participant Initiated



- Event-based - participant chooses to interact with study staff/device without being prompted
  - Contact study staff
  - Access resources on study device

Event-based EMAs

- For both researcher and participant initiated
  - Must have clear definition of event
- For participant initiated
  - Train individuals to identify event
  - Participants will still fail to report events
    - Cannot know when “missing event” occurred
    - Cannot assess compliance

Passive/Incidental

- Data that is automatically collected on a study device without a specific prompt by researcher or initiation by participants
  - Smart devices that collect GPS coordinates
  - Accelerometers that track physical activity or sedentary behavior
  - Technology-enhanced pill bottles that track when bottle opened (medication compliance)

Strengths and Limitations of ILD

Strengths of ILD

- Behaviors/measures observed in natural environment
- Measurement in “near real-time” reduces recall bias
- Identify relationships between variables within a subject/participant
- Directly observe processes of change in relationship among variables
  - Within subject changes across time
  - Between subject differences

Limitations of ILD

- Participant burden
  - 4 random assessments per day for 5 weeks
    - 4 X 7 X 5 = 140 observations per person
  - 1 daily diary per day for 5 weeks
    - 1 X 7 X 5 = 35 observations per person
  - All 5 daily assessments
    - 5 X 7 X 5 = 175 observations per person
  - Over course of study
    - 2 minute EMA -> more than 5 hours
    - 3 minute EMA -> more than 8 hours

Limitations of ILD

- Large amount of data produced
  - All 5 daily assessments (n=150)
    - 175 X 150 = 26,250 total observations
  - Only daily diary (n=150)
    - Daily diaries = 35 X 500 = 5,250
  - Passive data i.e. accelerometer
    - X total observations
- Storing capacity, server space
- Data processing and manipulation slower

Limitations of ILD

- Requires complex models which are more difficult to interpret
- Not appropriate for rare events
- Requires alternative method of assessing measurement reliability
- Reactivity

Goals of ILD

Goals of ILD Studies

- Estimation of relationships that change over time both among individuals and within them
  - Distinguish between-subject and within-subject effects
  - Allow for variability in within-subject process (random effects)
  - Identify differences based on person-level baseline predictors

Goals of ILD Studies

- Estimate associations with cyclic or periodic patterns
- Estimate impact of predictor on outcome
  - Actual value or change in value
  - Synchronous or sequential
- Estimate variability or volatility
  - Identify differences based on person-level baseline predictors
  - Identify difference before versus after an event

Format and Structure of ILD

Format and Structure of ILD

- “Wide” format
  - Each column includes one measurement time of a variable
  - Each row contain only one participant
- “Long” format
  - Each column contains a variable
  - Each row includes one measurement time for a participant

Format and Structure of ILD

- “Wide” format
  - Each column includes one measurement time of a variable
  - Each row contain only one participant

Wide format

ID	X at Time 1	X at Time 2	Y at Time 1	Y at Time 2	Z at Time 1	Z at Time 2
1	5	3	1	0	2	2
2	4	4	1	1	1	1

Format and Structure of ILD

- "Long" format
  - Each column contains a variable
  - Each row includes one measurement time for a participant

Long format

ID	Time	X	Y	Z
1	1	5	1	2
1	2	3	0	2
2	1	4	1	1
2	2	4	1	1

Format and Structure of ILD

Long format

ID	Time	X	Y	Z
1	1	5	1	2
1	2	3	0	2
2	1	4	1	1
2	2	4	1	1

Wide format

ID	X at Time 1	X at Time 2	Y at Time 1	Y at Time 2	Z at Time 1	Z at Time 2
1	5	3	1	0	2	2
2	4	4	1	1	1	1

Format and Structure of ILD

ID	Time	X	Y	Z
1	1	5	1	2
1	2	3	0	2
1	3	4	0	2
1	4	2	0	2
1	5	4	0	2
2	1	4	1	1
2	2	4	1	1
2	3	3	0	1
2	4	4	0	1
2	5	3	1	1

<u>Simplified example data</u>

- ID – study ID
- Time – time point
- X – stress level
  - Likert scale
  - 1= very low to 7= very high

Format and Structure of ILD

ID	Time	X	Y	Z
1	1	5	1	2
1	2	3	0	2
1	3	4	0	2
1	4	2	0	2
1	5	4	0	2
2	1	4	1	1
2	2	4	1	1
2	3	3	0	1
2	4	4	0	1
2	5	3	1	1

Simplified example data

- Y – smoked since last contact
  - Binary/dichotomous
  - 1= Yes or 0= No
- Z – Treatment group
  - Binary/dichotomous
  - 1= Intervention or 0= Control

Format and Structure of ILD

ID	Time	X	Y	Z
1	1	5	1	2
1	2	3	0	2
1	3	4	0	2
1	4	2	0	2
1	5	4	0	2
2	1	4	1	1
2	2	4	1	1
2	3	3	0	1
2	4	4	0	1
2	5	3	1	1

Simplified example data

- Long format
  - Multiple rows per subject
- Static variables
  - Z (Treatment Group)
- Time varying variables
  - X (Stress)
  - Y (Smoke)

Format and Structure of ILD

ID	Time	X	Y	Z
1	1	5	1	2
1	2	3	0	2
1	3	4	0	2
1	4	2	0	2
1	5	4	0	2
2	1	4	1	1
2	2	4	1	1
2	3	3	0	1
2	4	4	0	1
2	5	3	1	1

Simplified example data

- Time varying variables
  - Can vary within subject
  - Within subject variability can differ across subjects
- Each row represents a specific time or time frame

Temporality in ILD

ID	Time	X	Y	Z
1	1	5	1	2
1	2	3	0	2
1	3	4	0	2
1	4	2	0	2
1	5	4	0	2
2	1	4	1	1
2	2	4	1	1
2	3	3	0	1
2	4	4	0	1
2	5	3	1	1

How can we assess the relationship between X and Y?

- Data can be used "as is" when current contextual or environmental cues are of interest
- Example: interest in immediate effect of cigarette ad on intention to quit smoking

Temporality in ILD

ID	Time	X	Y	Z
1	1	5	1	2
1	2	3	0	2
1	3	4	0	2
1	4	2	0	2
1	5	4	0	2
2	1	4	1	1
2	2	4	1	1
2	3	3	0	1
2	4	4	0	1
2	5	3	1	1

How can we assess the relationship between X and Y?

- Data must be manipulated when exposure must precede outcome
- Example, interest in effect of stress on subsequent smoking behavior

Lagging data in ILD

ID	Time	X	Y	W
1	1	5	1	[illegible]
1	2	3	0	[illegible]
1	3	4	0	[illegible]
1	4	2	0	[illegible]
1	5	4	0	2
2	1	4	1	1
2	2	4	1	[illegible]
2	3	3	0	[illegible]
2	4	4	0	[illegible]
2	5	3	1	1

ID	Time	X	Y	W
1	1	5	.	2
1	2	[illegible]	1	2
1	3	[illegible]	0	2
1	4	[illegible]	0	2
1	5	[illegible]	0	2
2	1	4	.	1
2	2	[illegible]	1	1
2	3	[illegible]	1	1
2	4	[illegible]	0	1
2	5	[illegible]	0	1

Lagging data in ILD

ID	Time	X	Y	Z
1	1	5	1	2
1	2	3	0	2
1	3	4	0	2
1	4	2	0	2
1	5	4	0	2
2	1	4	1	1
2	2	4	1	1
2	3	3	0	1
2	4	4	0	1
2	5	3	1	1

ID	Time	X	Y	Z
1	1	5	.	2
1	2	3	.	2
1	3	4	1	2
1	4	2	0	2
1	5	4	0	2
2	1	4	.	1
2	2	4	.	1
[illegible]	3	3	1	1
[illegible]	4	4	1	1
2	5	3	0	1

Lagging data in ILD

- Depends on research question and variables of interest
  - Determine how far before the event of interest an exposure must occur
  - Determine types of ILD to include
    - Researcher or participant initiated
    - Fixed or random interval
- May require further manipulation of data
  - Limiting dataset to relevant observations

Basic Description of ILD

Basic Description of ILD

- Individual variable and pairwise relationships
  - Central tendency for continuous data
  - Distribution for categorical data
- Aggregated within person
  - Total or mean number of events
    - Throughout study
    - In certain time periods
- Important to minimize aggregating across individuals -> ignores repeated observations on individuals

Basic Description of ILD

- Exploring your data:
  - **NOT** intended to inform hypotheses tested
  - Intended to **provide context** for conclusions
  - Intended to describe sample
  - Can identify potential issues with proposed models

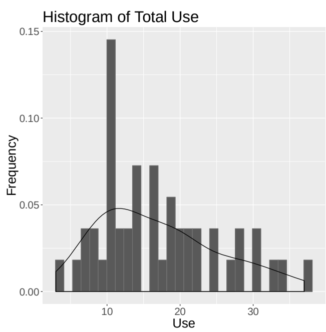
Visualization of ILD

Visualization of ILD

While not often published, visualization is a crucial component of exploring ILD

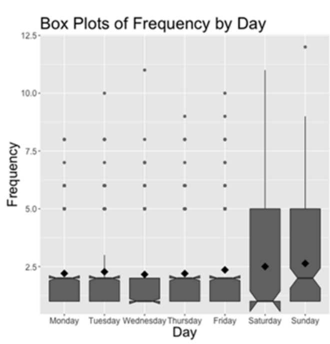
- Summary Statistics and Raw Data: Distributions by Participant
  - Histogram
  - Box Plot

Visualization: Histogram



- Typical Use
- Lease Use
- Greatest Use
- Shape

Visualization: Box Plots



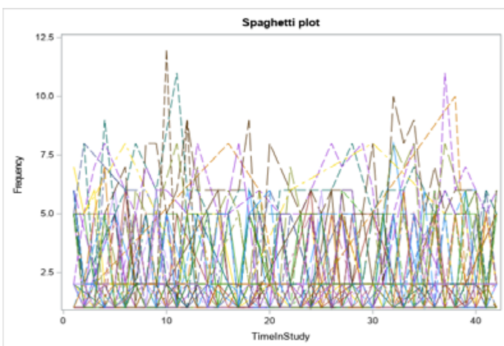
- Typical Use
- Heaviest Use Days
- Periodic Use Patterns

Visualization of ILD

While not often published, visualization is a crucial component of exploring ILD

- Raw Data: Relationships and Time Trends
  - Interaction Plots
  - Time Plots
  - Spaghetti Plots

Visualization: Spaghetti Plots



Visualization: Spaghetti Plots

Important Information from Spaghetti Plots:

- <u>Time Trends:</u> Do participants appear to show a discernible increase, decrease, periodic trend?
- <u>Interactions:</u> Do the time trends appear to change for different sub-populations?
- <u>Variation:</u>
  - Do participants show similar fluctuations over time?
  - Is the volatility consistent across the study?
  - How does variation between subjects compare to variation within subjects?

Multilevel Modeling of ILD

Multilevel Modeling (MLM)

- MLM used when observations correlated
  - Natural grouping
    - Students in a classroom
    - Clinics in a hospital
    - Members in a family
  - Repeated measures (longitudinal data)
    - Before and after intervention
    - Follow-up time points after intervention
  - Intensive longitudinal data

Multilevel Modeling of ILD

- Two-level model
  - Single equation describes relationship between predictors and outcome
  - Conceptualized as two separate equations
    - Level 1
    - Level 2

Two-level Modeling of ILD

- Level 1
  - Describes within person relationship of predictor and outcome
  - Models momentary predictors of momentary outcomes (occasion level)
  - Regression coefficients (intercepts, slopes) estimated for each moment level predictor variable
  - Intercepts and slopes can vary randomly across persons (random effect)

Two-Level Modeling of ILD

- Level 2
  - Regression coefficients (intercept, slope) from level 1 treated as dependent variable
  - Describes individual differences in the effect of momentary variable on the outcome
  - Person-level predictors modelled (not expected to change across time points)
  - Residual term accounts for portion of individual differences in coefficients not accounted for by person-level predictors

Multilevel Modeling of ILD

- Fixed effects
  - Assume effect of predictor on outcome constant across people
    - Or that person-level variables account for all differences in effect of predictor on outcome
- Random effects
  - Allows effect of predictor on outcome to vary across people (Level 1)
    - In other words, allow people to differ in their within-person relationships

Multilevel Modeling (MLM)

- Why use MLM?
  - Correctly accounts for clustering in data
  - Allows variability across participants and groups
    - Group treated as random sample from population of groups
    - Thus, can generalize to the population of groups
  - Robust to missing data
    - Participants do not need same number or timing of observations

MLM of ILD

- Models the dependent variable in terms of baseline and ILD variables and time

Dependent Variable = Baseline Variables + ILD Variables + Time Trends + Variation ***Across*** Individuals + Variation ***Within*** Individuals

MLM of ILD

- Models the dependent variable in terms of baseline and ILD variables and time

Dependent Variable = Baseline Variables + ILD Variables + Time Trends + Variation ***Across*** Individuals + Variation ***Within*** Individuals

- For ILD Variables, can decompose effects
- Allows for direct interpretation of effects *between* people and effects *across time*
- We will focus on this method in these slides

Neuhaus and Kalbfleisch, 1998

MLM of continuous ILD

- Models the mean of an outcome, in terms of

Dependent Variable = Baseline Variables + ILD Variables + Time Trends + Variation ***Across*** Individuals + Variation ***Within*** Individuals

$$Y_{it} = \beta_0 + \beta_1 Z_i + \beta_{2B}\bar{\chi}_{i.} + \beta_{2W}(\bar{\chi}_{i.} - \chi_{it}) + \beta_t t_{it} + \upsilon_i + \varepsilon_{it}$$

MLM of continuous ILD

- Models the mean of an outcome

$$Y_{it} = \beta_0 + \beta_1 Z_i + \beta_{2B}\bar{\chi}_{i.} + \beta_{2W}(\bar{\chi}_{i.} - \chi_{it}) + \beta_t t_{it} + \upsilon_i + \varepsilon_{it}$$

- β_0 is intercept term
- Z_i is a baseline, time-independent predictor with effect β_1

MLM of continuous ILD

- Models the mean of an outcome

$$Y_{it} = \beta_0 + \beta_1 Z_i + \beta_{2B}\bar{\chi}_{i.} + \beta_{2W}(\bar{\chi}_{i.} - \chi_{it}) + \beta_t t_{it} + \upsilon_i + \varepsilon_{it}$$

- χ_{it} is an ILD, time-dependent predictor with,
  - Between effect β_{2B}, and
  - Within effect β_{2W}

MLM of continuous ILD

- Models the mean of an outcome

$$Y_{it} = \beta_0 + \beta_1 Z_i + \beta_{2B}\bar{\chi}_{i.} + \beta_{2W}(\bar{\chi}_{i.} - \chi_{it}) + \beta_t t_{it} + \upsilon_i + \varepsilon_{it}$$

- t_{it} is the time in the study with effect β_t
- υ_i is the random individual effect
- ε_{it} is the random variation over time

MLM of continuous ILD

- Consider the following model
  - Alcohol craving as outcome, Y_{it}
  - Age as time-independent baseline predictor, Z_i
  - Mood as time-dependent ILD predictor, χ_{it}

$$Y_{it} = \beta_0 + \beta_1 Z_i + \beta_{2B}\bar{\chi}_{i.} + \beta_{2W}(\bar{\chi}_{i.} - \chi_{it}) + \beta_t t_{it} + \upsilon_i + \varepsilon_{it}$$

- β_1 represents the expected difference in the mean alcohol craving across populations that differ, on average, by one year in age

MLM of continuous ILD

- Consider the following model
  - Alcohol craving as outcome, Y_{it}
  - Age as time-independent baseline predictor, Z_i
  - Mood as time-dependent ILD predictor, χ_{it}

$$Y_{it} = \beta_0 + \beta_1 Z_i + \beta_{2B}\bar{\chi}_{i.} + \beta_{2W}(\bar{\chi}_{i.} - \chi_{it}) + \beta_t t_{it} + \upsilon_i + \varepsilon_{it}$$

- β_{2B} represents the expected difference in the mean alcohol craving across populations that differ by one unit of average mood reported

MLM of continuous ILD

- Consider the following model
  - Alcohol craving as outcome, Y_{it}
  - Age as time-independent baseline predictor, Z_i
  - Mood as time-dependent ILD predictor, χ_{it}

$$Y_{it} = \beta_0 + \beta_1 Z_i + \beta_{2B}\bar{\chi}_{i.} + \beta_{2W}(\bar{\chi}_{i.} - \chi_{it}) + \beta_t t_{it} + \upsilon_i + \varepsilon_{it}$$

- β_{2W} represents the expected change over time for an individual in their mean alcohol craving as their mood changes

MLM of continuous ILD

- Consider the following model
  - Alcohol craving as outcome, Y_{it}
  - Age as time-independent baseline predictor, Z_i
  - Mood as time-dependent ILD predictor, χ_{it}

$$Y_{it} = \beta_0 + \beta_1 Z_i + \beta_{2B}\bar{\chi}_{i.} + \beta_{2W}(\bar{\chi}_{i.} - \chi_{it}) + \beta_t t_{it} + \upsilon_i + \varepsilon_{it}$$

- υ_i represents the variation in individual alcohol craving among the population of individuals

MLM of continuous ILD

Consider an example:

- Model the outcome of desire to use marijuana in terms of
  - Momentary indicator of whether individual is with others, time-dependent variable
  - Energy level, decomposed into
    - Average energy level, a person-level, time-independent variable
    - Momentary energy level, a lagged, time-dependent variable

MLM of continuous ILD

Example: Model "Desire" in terms of "With Others" and "Energy Level"

- With Others: $\beta = -3.43$, p=0.038
  - Expect populations with others to show lower Desire (by about 3.43), all other factors equivalent
- Energy (Between): $\beta = -0.09$, p=0.502
  - Expect populations with greater energy to show lower Desire (by about 0.09)
- Energy (Within): $\beta = 0.02$, p=0.371
  - Expect individuals to show an increase in Desire over time with increased energy (by about 0.02)

MLM of Binary ILD

- Models the **probability** of an outcome, in terms of

Outcome Probability ~ Baseline Variables **+** ILD Variables **+** Time Trends **+** Variation ***Across*** Individuals **+** Variation ***Within*** Individuals

$$\text{logit}(\pi_{it}) = \beta_0 + \beta_1 Z_i + \beta_{2B}\bar{\chi}_{i.} + \beta_{2W}(\bar{\chi}_{i.} - \chi_{it}) + \beta_t t_{it} + \upsilon_i + \varepsilon_{it}$$

MLM of Binary ILD

Consider an example:

- Model the outcome of use of marijuana in terms of
  - Momentary indicator of whether individual is with others, time-dependent variable
  - Energy level, decomposed into
    - Average energy level, a person-level, time-independent variable
    - Momentary energy level, a lagged, time-dependent variable

MLM of Binary ILD

Example: Model Likelihood of "Use" in terms of "With Others" and "Energy Level"

- With Others: $\theta > 7.9e10$, p=0.865
  - Expect odds of use for populations with others to increase by a multiple of 7.9e10, all other factors remaining constant
- Energy (Between): $\theta = 0.98$, p=0.279
  - Expect odds of use for populations with greater energy to decrease by a multiple of 0.98
- Energy (Within): $\theta = 1.004$, p=0.156
  - Expect odds of use to show an increase over time by a multiple of 1.004 with increased energy

Additional ILD Considerations

Some Recent Methods in ILD

- Hurdle models for zero-inflated data
- Recurrent survival models for recurrent time-to event outcomes
- Time-varying effect models to estimate if and how effect changes over time
- Just-in-time adaptive interventions (JITAI)

JITAI

- Intervention based on decision rules
- Aim to provide the right amount of intervention or support at the right time
  - No intervention when not needed
- Uses dynamically changing information
- Identifies opportunities to provide intervention in the natural environment
- Four key components to consider

JITAI

- Examples
  - Alert participant after 30 continuous minutes of sedentary behavior
  - Alert participant when technology-enhanced pill bottle not opened 30 minutes past scheduled medication time
  - Provide message or video intervention after assessment indicates participant who has quit smoking is at risk of smoking a cigarette

Missingness in ILD

- Can be due to the usual suspects
  - Loss to follow up
  - Sporadic missing
    - MCAR, MAR, or NMAR
- Can be due to technology specific issues
  - Phone
  - Cell tower
  - Server

  Communication across technologies
- Develop a plan for dealing with both in staff procedures and in analyses

Acknowledgements

- Funding agencies that support our work
  - Oklahoma Tobacco Settlement Endowment Trust (092-016-0002l)
  - NIH R15 Program Grant Number 1R15DA041656-01
  - UNC FRPB PAT 10414-40610-2300-QT605