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Mixed Model Analysis With Intensive Longitudinal Data

A New Freeware Program for Multilevel Statistical Modeling of Intensive Longitudinal Data

Donald Hedeker, Ph.D., University of Chicago
Genevieve F. Dunton, Ph.D., University of Southern California
Eldin Dzubur, Ph.D., Cedars-Sinai Medical Center

Speakers

- Donald Hedeker, Ph.D., University of Chicago
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Workshop Outline

- **3:15-3:25pm** Introduction/Overview (Dunton)
- **3:25-4:00pm** Conceptual/Research Background and Applications (Dunton)
- **4:00-4:30pm** Modeling of Between-Subject and Within-Subject Variances (Hedeker)
- **4:30-4:45pm Break**
- **4:45-5:45pm** MixWild Demonstration/Tutorial (Dzubur)
- **5:45-6:00pm** Closing/Q&A

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How to Download MixWild

- Please visit: https://reach-lab.github.io/MixWildGUI/

- Please submit your email prior to downloading the application in the web page so we can notify you of major software updates.

- Click on macOS or Windows to download the program.

- Select your directory to save the program.

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Overview of MixWild Capabilities

- One stage standard multilevel model (MLM)
  -time-varying predictors and outcomes nested within people

- Two stage mixed effects location scale—linear/logistic regression model
  -subject-level means, variances, slopes predicting subject-level outcomes

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Random Effects Comprised of Time-varying Variables

1. Subject-level means (i.e., random location effect)

How happy is a subject, on average, across occasions?

2. Subject-level variances (i.e., random scale effect)

How erratic is a subject's mood across occasions?

3. Subject-level slopes (i.e., random slope effect)

How strongly is a subject's mood related to activity across occasions?

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Brief History of MixWild

- MIXREGLS (Hedeker & Nordgren, 2013)

  -Fortran standalone program; accessible via R and Stata

  -Estimates random effects of mean and variance structure

- MixWild (Hedeker & Dunton, 2018)

  -Standalone program with GUI

  -Funded through **R01HL121330**

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Conceptual and Research Applications of Intensive Longitudinal Data (ILD)

Genevieve F. Dunton, PhD, MPH
University of Southern California

Limited vs. Repeated Occurrence Health Behaviors

<u>Repeated Occurrence Health Behaviors</u> (e.g., phy. act.)

- High frequency (daily) sustained over a lifetime
- Time-varying explanatory factors
- Past behavior very important

<u>Limited Occurrence Health Behaviors</u> (e.g., screenings)

- Low frequency (annually)
- Time-invariant explanatory factors
- Past behavior less important

Criticisms of Health Behavior Theories

- Cognitive (versus affective or contextual)
- Nomethetic (versus idiographic)
- Interindividual (versus intraindividual)
- Static (versus dynamic)

Intensive Longitudinal Data (ILD)

- Data with many measurements collected over a time

- Often collected over a micro-timescale (seconds, minutes, hours)

Intensive Longitudinal Data (ILD) Capture Methods

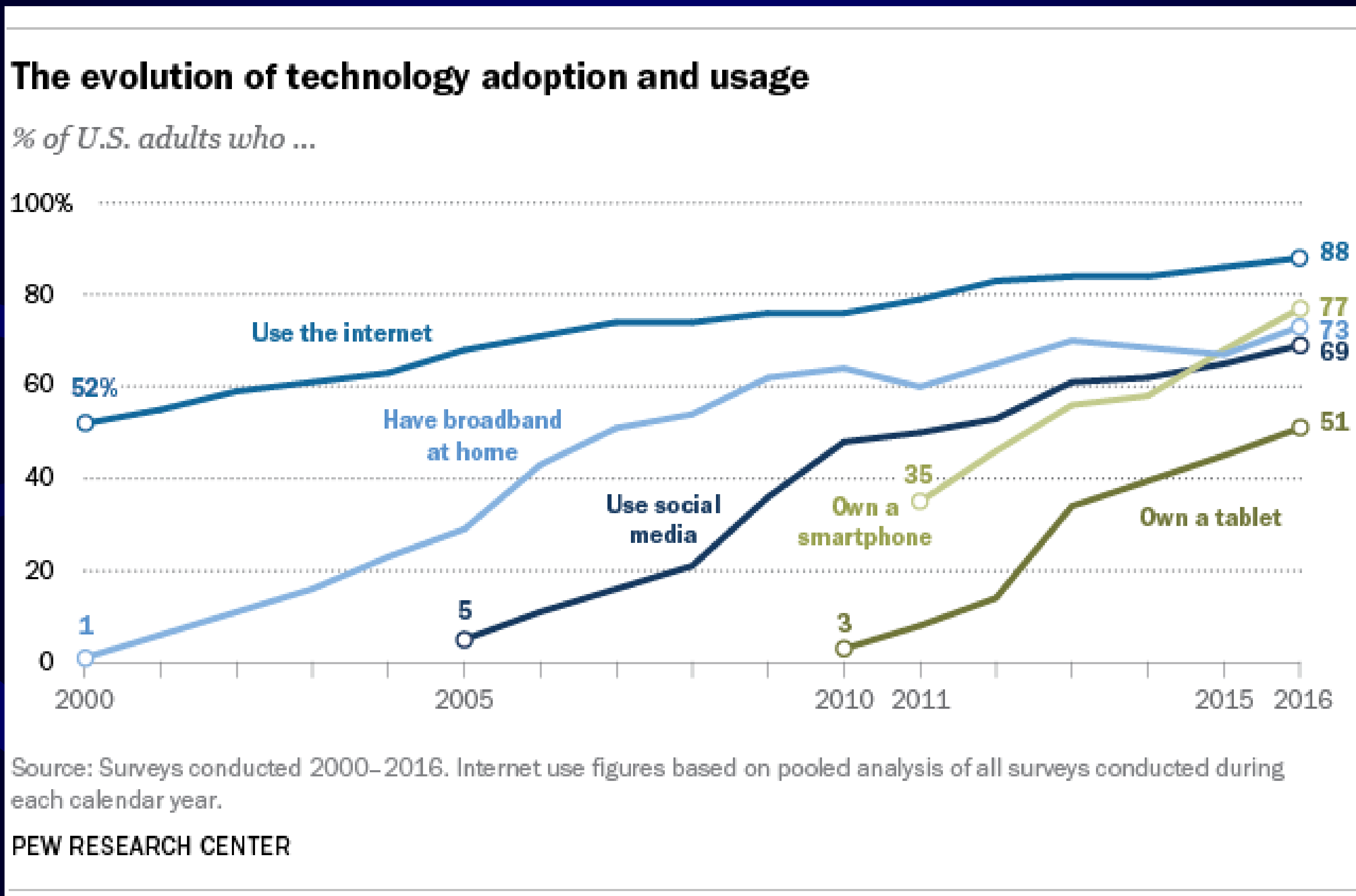
Examples: Ecological Momentary Assessment (EMA), accelerometry, heart rate monitoring, galvonic skin response , Global Positioning System (GPS), other sensors

- Real-world environments
- Real-time assessments
- Repeated measures (intensive longitudinal data)

Advantages of ILD Capture Methods

- Limited recall bias
- Ecological validity
- Capture daily and within-daily variation
- Assess time-varying effects
- Identify bidirectional processes and feedback loops

mHealth Technologies



mHealth Technologies

- As of 2016, 77% of U.S. adults own a smartphone
- Smartphones have been adopted across SES groups and in developing countries
- "Apps" can deliver real-time surveys
- Smart phones have built-in accelerometer, location monitoring, camera, and video
- Able to synch with other ambulatory sensors via bluetooth (e.g., heart rate, asthma inhalers, air pollution, UV)

Pew, 2015; Riley et al., 2011.

Ecological Momentary Assessment (EMA)

Ecological
- Real-world environments & experiences
- Provides ecological validity

Momentary
- Real-time assessment
- Avoids recall bias

Assessment
- Self-report (subjective)
- Multiple repeated measures

Stone & Shiffman, 1994

How ILD Methods can Advance Understanding of Health Behavior

1. *Synchronicity*—the extent to which explanatory factors and behavior co-occur

2. *Sequentiality*—the sequence of antecedents to and consequences of behaviors

3. *Instability*—patterns of fluctuation and change in explanatory factors, associations, behavior

Dunton, G. F. (2017). Ecological Momentary Assessment in physical activity research. Exercise and Sports Sciences Reviews, 45(1), 48-54.

How EMA Methods can Advance Understanding of Health Behavior

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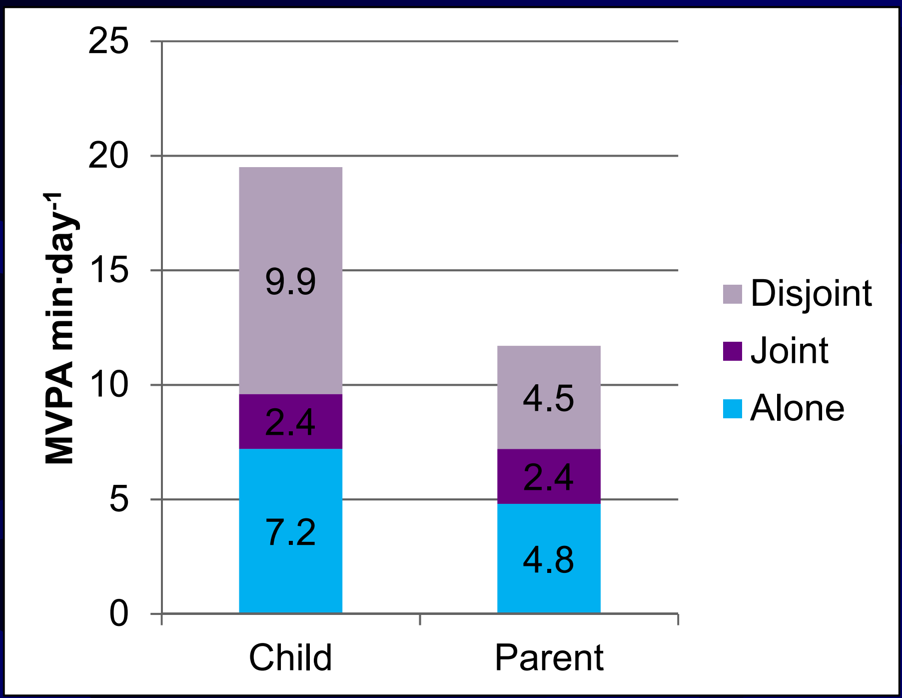
Synchronicity

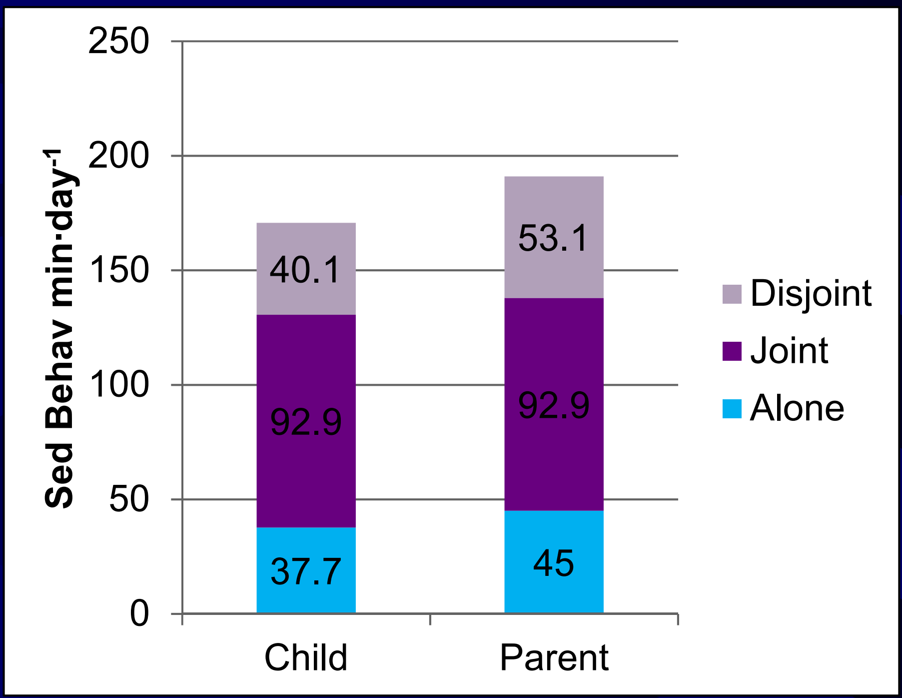
ILD Can Address Problems such as…..

- Ecological Fallacy- inferences about lower-level unit of analysis are based on statistics collected for a higher-level unit of analysis (lack of temporal synchronicity)

- Uncertain Geographic Context Problem- uncertainty about the exact setting that has a direct causal influence on the behavior (lack of spatial synchronicity)

Temporal Synchronicity:
Joint Parent-Child Physical Activity



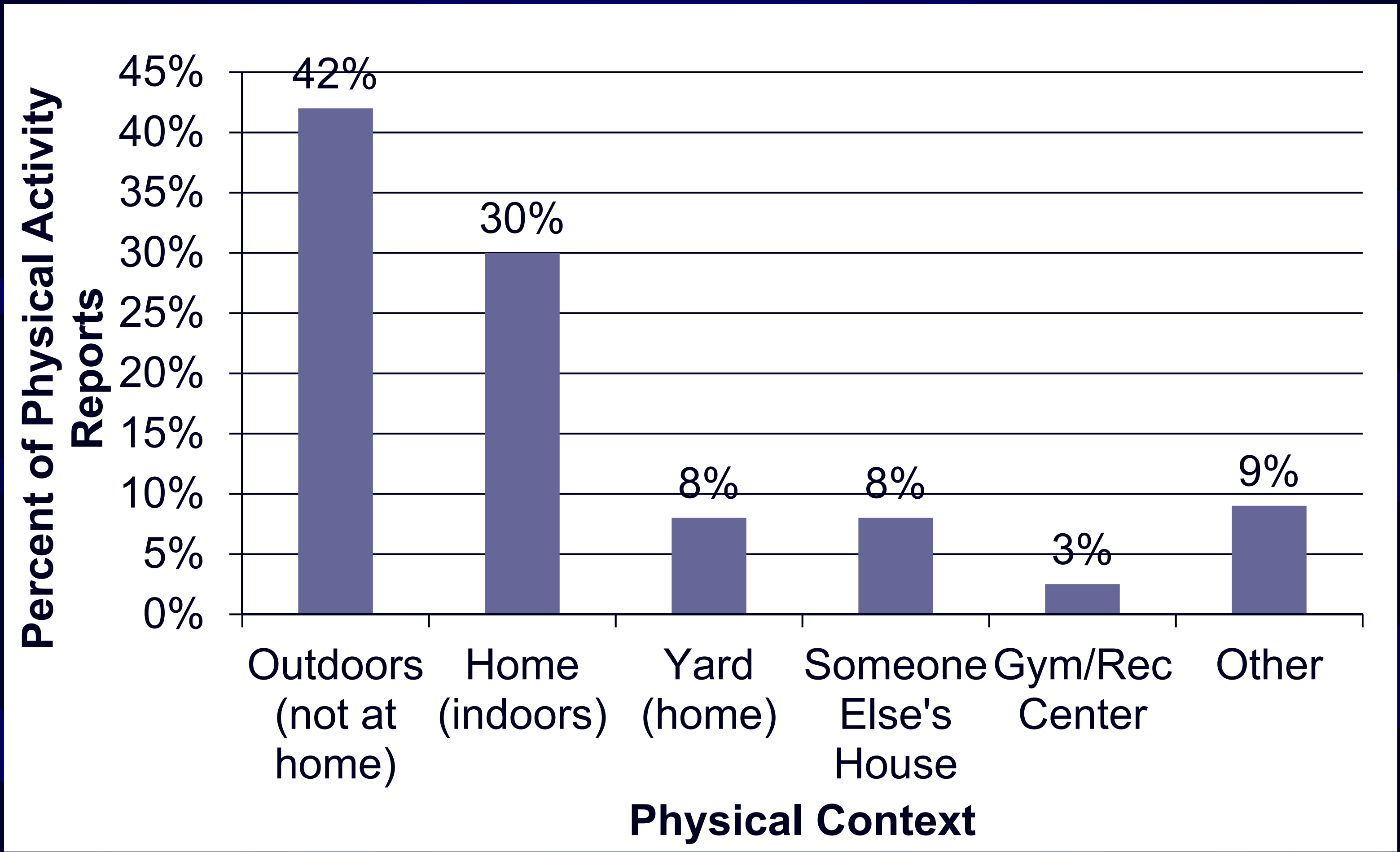


Measured through 7 days of accelerometer and GPS monitoring.

Dunton, G. F., Almanzo, E., Liao, Y., Jerrett, M., Spruijt-Metz, D., Chou, C., & Pentz, M. (2012). Joint physical activity and sedentary behavior in parent-child pairs. Medicine & Science in Sports & Exercise, 44, 1473-1480.

Spatial Synchronicity:

Physical Contexts of Children’s Physical Activity



Dunton, G. F., Kawabata, K., Intille, S., Wolch, J., & Pentz, M. A. (2012). Assessing the social and physical contexts of children's leisure-time physical activity: an ecological momentary assessment study. American Journal of Health Promotion, 26(3), 135-142.

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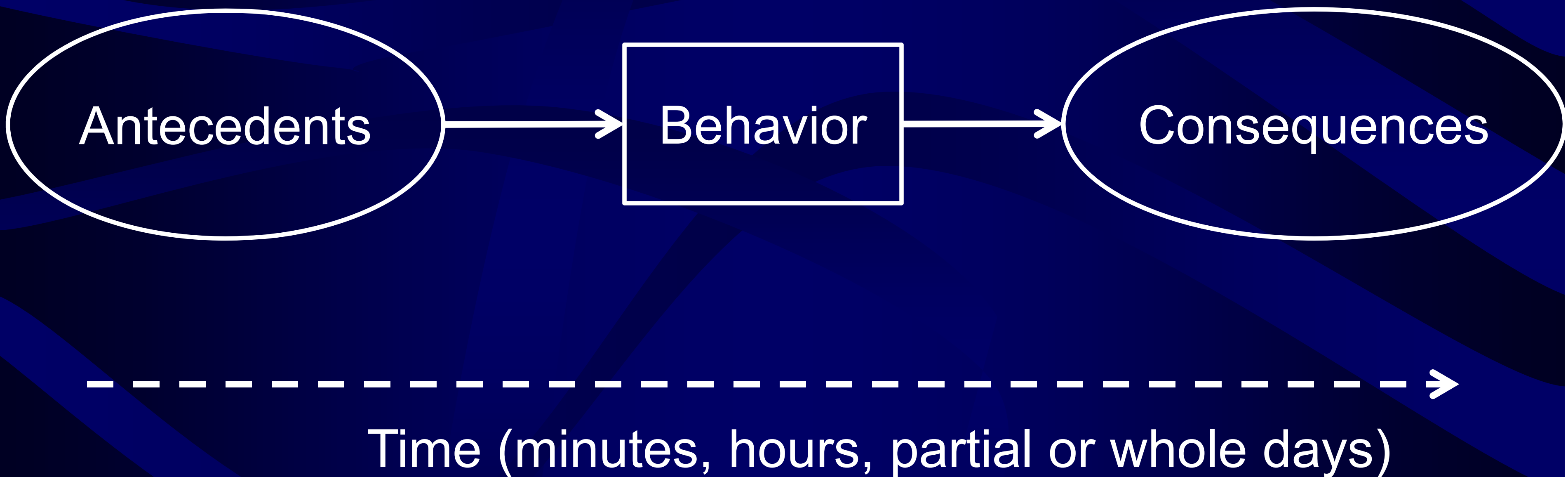
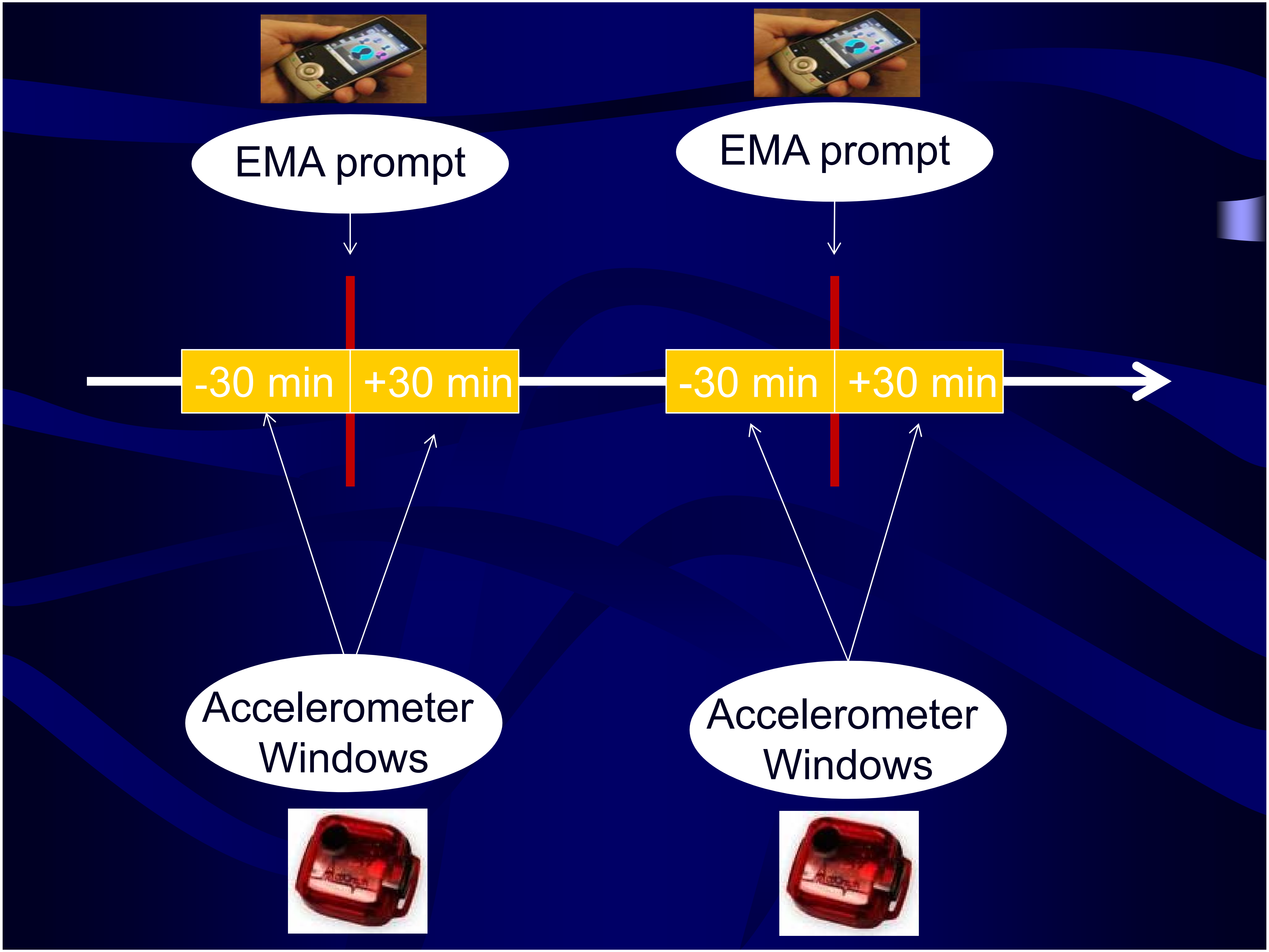
Sequentiality




EMA prompt
EMA prompt
-30 min
+30 min
-30 min
+30 min
Accelerometer Windows
Accelerometer Windows

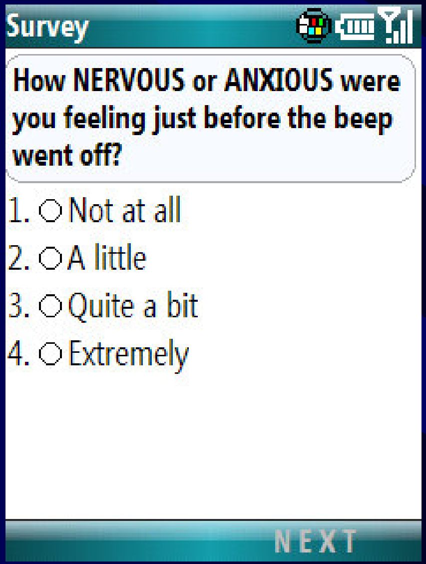
Affective Antecedents to Physical Activity in Children

Table 2

The Association of Affective and Physical Feeling States With MVPA Minutes Occurring in the 30 Minutes After the EMA Prompt

	MVPA	
Variable	β (*SE*)	*p*
Positive affect (PA; *n* = 113)		
Intercept	1.23 (0.11)	<.001
BS	0.22 (0.19)	.248
WS	0.17 (0.11)	.136
Negative affect (NA; *n* = 116)		
Intercept	1.33 (0.13)	<.001
BS	−0.38 (0.34)	.260
WS	0.41 (0.22)	.060
Feeling energetic (*n* = 114)		
Intercept	1.05 (0.09)	<.001
BS	0.21 (0.17)	.235
WS	0.46 (0.06)	<.001
Feeling tired (*n* = 115)		
Intercept	1.03 (0.08)	<.001
BS	−0.38 (0.19)	.040
WS	−0.03 (0.07)	.686

Note. MVPA = moderate-to-vigorous physical activity; EMA = Ecological Momentary Assessment; BS = between-subjects; WS = within-subjects. Each variable was tested in a separate model.



Dunton G. F., Huh, J., Leventhal, A., Riggs, N. Hedeker, D., Spruijt-Metz, D., & Pentz, M. (2013). Momentary assessment of affect, physical feeling states, and physical activity in children. Health Psychology, 33(3):255-63.

Affective Consequences of Physical Activity in Children

Table 3

The Association of MVPA Minutes Occurring in the 30 Minutes Before The EMA Prompt With Affective and Physical Feeling States

	Positive affect (PA; n = 115)		Negative affect (NA; n = 117)		Feeling energetic (n = 113)		Feeling tired (n = 113)	
MVPA	β (SE)	p	β (SE)	p	β (SE)	p	β (SE)	p
Intercept	1.80 (0.06)	<.001	0.35 (0.04)	<.001	1.36 (0.05)	<.001	0.80 (0.04)	<.001
BS	0.05 (0.06)	.481	−0.08 (0.04)	.035	0.10 (0.05)	.060	−0.06 (0.05)	.190
WS	0.02 (0.01)	.049	0.00 (0.01)	.853	0.07 (0.01)	<.001	−0.00 (0.01)	.593

Note. MVPA = moderate-to-vigorous physical activity; EMA = Ecological Momentary Assessment; BS = between-subjects; WS = within-subjects. Each column represents a separate model.

Dunton G. F., Huh, J., Leventhal, A., Riggs, N. Hedeker, D., Spruijt-Metz, D., & Pentz, M. (2013). Momentary assessment of affect, physical feeling states, and physical activity in children. Health Psychology, 33(3):255-63.

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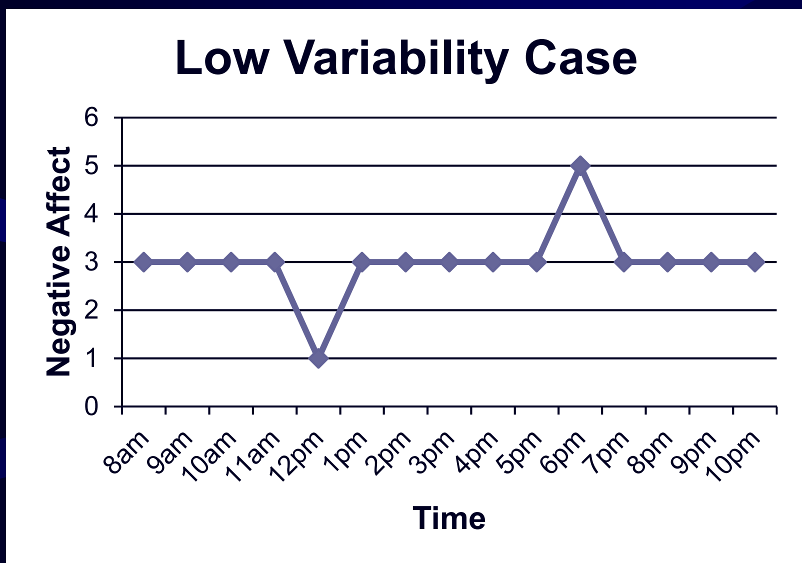
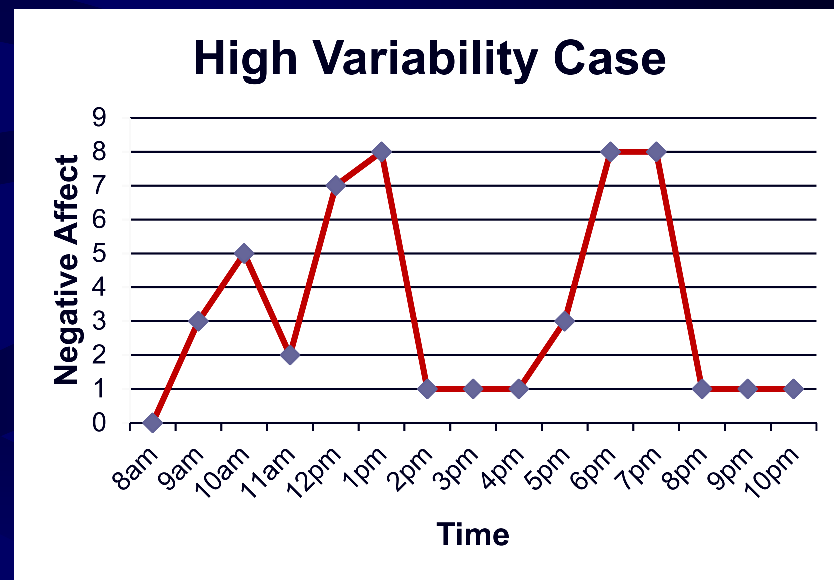
Within-Subject Instability as a Predictor of Behavior





Emerging evidence that greater emotional instability may be related to worse physical health (e.g., Hedeker et al.., 2012, Hedeker et al., 2008)

Putting it all together-- MixWild

How do….

Synchronicity (i.e., subject-level slopes)

Sequentiality (i.e., subject-level slopes)

Instability (i.e., subject-level variances)

....predict subject-level behavioral and health outcomes?

Subject-level Slopes Comprised of Time-varying Variables Associated with Subject-Level Physical Activity Outcome

Table 1. Results from linear regression model testing associations between affective response during physical activity and future physical activity level

	Change in MVPA Minutes between Baseline and 6 Month		Change in MVPA Minutes between Baseline and 12 Month	
	Standardized Coefficient	*p*	Standardized Coefficient	*p*
Model 1				
Positive affect during active EMA prompts	0.14	0.46	0.10	0.59
Positive affect during non-active EMA prompts	-0.05	0.80	-0.12	0.29
Model 2				
Negative affect during active EMA prompts	-0.37	0.11	**-0.51**	**0.02**
Negative affect during non-active EMA prompts	0.34	0.13	0.57	0.01
Model 3				
Energy during active EMA prompts	**0.34**	**0.03**	**0.30**	**0.04**
Energy during non-active EMA prompts	-0.08	0.62	-0.22	0.16
Model 4				
Fatigue during active EMA prompts	0.08	0.69	0.15	0.43
Fatigue during non-active EMA prompts	-0.10	0.62	-0.06	0.77

Liao, Y., Chou, C. P., Leventhal, A., & Dunton, G. F. Associations of affective responses during free-living physical activity and future physical activity levels: An Ecological Momentary Assessment study. International Journal of Behavioral Medicine, 2016, 1-7.

Subject-level Variances Comprised of Time-varying Variables Associated with Subject-Level Physical Activity Outcome

Table 4

Mixed-Effects Location-Scale Model for Affect and Physical Feeling State Variables and Mean Hourly Leisure-Time Moderate-to-Vigorous Physical Activity (MVPA) in Minutes—Maximum Likelihood Estimates and SEs

Parameter	Mean β (*SE*)	*p*	BS var. α (*SE*)	*p*	WS var. τ (*SE*)	*p*
Positive affect (PA)						
Intercept	1.74 (0.10)	<.001	−1.10 (0.15)	<.001	−0.48 (0.14)	.001
Mean hourly leisure-time MVPA	0.01 (0.03)	.621			−0.09 (0.04)	.018
BS var. in scale					0.42 (0.14)	.003
Covariance (mean and WS var)					−0.15 (0.06)	.009
Negative Affect (NA)						
Intercept	0.42 (0.05)	<.001	−2.44 (0.16)	<.001	−1.50 (0.09)	<.001
Mean hourly leisure-time MVPA	−0.03 (0.01)	.057			−0.06 (0.02)	.011
BS var. in scale[a]						
Covariance (mean and WS var)[a]						
Feeling energetic						
Intercept	1.32 (0.09)	<.001	−1.48 (0.16)	<.001	−0.19 (0.08)	.014
Mean hourly leisure-time MVPA	0.01 (0.02)	.535			−0.002(0.02)	.909
BS var. in scale					0.08 (0.03)	.011
Covariance (mean and WS var)					−0.01 (0.02)	.743
Feeling tired						
Intercept	0.82 (0.06)	<.001	−2.10 (0.17)	<.001	−0.56 (0.14)	<.001
Mean hourly leisure-time MVPA	−0.01 (0.02)	.687			−0.02(0.03)	.489
BS var. in scale					0.53 (0.13)	<.001
Covariance (mean and WS var)					0.20(0.04)	<.001

Note. $N = 119$. BS = between-subjects. WS = within-subjects.
[a] The model with the addition of the random scale estimate (BS var. in scale) and estimate of covariance between random scale and location (mean and WS var) did not converge because of a lack of variance in the dependent variable.

Dunton G. F., Huh, J., Leventhal, A., Riggs, N. Hedeker, D., Spruijt-Metz, D., & Pentz, M. (2013). Momentary assessment of affect, physical feeling states, and physical activity in children. Health Psychology, 33(3):255-63.

Subject-level Variances Comprised of Time-varying Variables Associated with Subject-Level Physical Activity Outcome

Parameter	Mean (β)	BS var (α)	WS var (τ)
Self-efficacy			
Intercept	2.84 (0.48)**	-0.64 (0.17)**	-0.47 (0.45)
MVPA (x10min, centered)	-0.01 (0.04)		0.13 (0.04)**
Between person var. in scale			0.27 (0.08)**
Covariance (mean and WS var.)			-0.02 (0.06)
Outcome expectancy			
Intercept	4.35 (0.32)**	-1.45 (0.17)**	-1.41 (0.47)**
MVPA (x10min, centered)	0.00 (0.03)		0.01 (0.04)
Between person var. in scale			0.31 (0.08)**
Covariance (mean and WS var.)			-0.09 (0.04)*
Intentions			
Intercept	2.49 (0.45)**	-0.87 (0.18)**	-0.19 (0.40)
MVPA (x10min, centered)	0.01 (0.04)		0.07 (0.03)*
Between person var. in scale			0.15 (0.06)*
Covariance (mean and WS var.)			-0.04 (0.05)

Note: Models include mean and WS variance terms for age, gender, BMI, ethnicity, household income, day of week, and time of day (reported in text).**p<.01, *p<.05

Pickering, T., Liao, Y., Huh, J., Dunton, G. F. (2016). Physical activity and variation in momentary behavioral cognitions: An ecological momentary assessment study, Journal of Physical Activity and Health, 13(3).

Other Research Applications
(just a few examples among many, many)

- Is emotional stability related to other health behaviors (e.g., smoking, eating), mental health, and health outcomes (e.g., BMI, inflammation)?

- How do interventions increase/decrease stability in psychosocial mediators of health and behavior change?

- How do psychosocial determinants of behavior (i.e., time-varying predictors) influence future behavior change?

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Symposium 55: Novel Analytic Approaches to Variance Modeling in Ecological Momentary Assessment Studies of Physical Activity

Friday April 13, 2:00-3:15pm Salon 10

Presenters:

Jaclyn P. Maher, PhD, University of North Carolina at Greensboro
Chih-Hsiang (Jason) Yang, PhD, University of Southern California
Genevieve F. Dunton, PhD, MPH, University of Southern California

Discussant:

David Williams

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  Gayla Margolin, Ph.D (USC)
  Stephen Intille, Ph.D (Northeastern)
  Don Hedeker, Ph.D (Univ. of Chicago)
- Project Manager: Lissette Ramirez, MPH
- PhD Students: Yue Liao, PhD; Eldin Dzubur, MS; Eleanor Tate, PhD; Sydney O'Connor, B.S.

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- NHLBI 1R01HL121330 (Dunton & Hedeker, PIs)
- NHLBI 1R21HL108018 (Dunton & Intille, PIs)
- NIEHS P50ES026086 (Dunton, PI on Project 2)
- NCI 1R01CA123243 (Pentz, PI)

USC REACH Lab website:
http://reach.usc.edu/

REACH
The Real-Time Eating Activity and Children's Health Lab

Thank You