

Measuring and Modeling Intensive Longitudinal Health Behaviors: Overview of Projects in the Intensive Longitudinal Health Behavior Network (ILHBN), Part I

Northeastern

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Overview of the ILHBN

The ILHBN is a cooperative agreement network consisting of 7 U01 projects and 1 U24 Research Coordinating Center to study health behavior changes such as the prevention of suicidal thoughts and behaviors, smoking, drug use, and alcohol use; and the promotion of mental health, sleep, and physical activities, and decreases in sedentary behavior. The overarching mission of the ILHBN is to:

- Introduce innovations into longstanding health behavioral theories
- Advance the field of theory-driven behavior change interventions
- Provide a framework to guide future intensive longitudinal studies of health behaviors

Snapshot of Modeling Approaches

Studies	Supervised	Unsupervised/Hybrid	
Study I	Dynamic factor analysis	Deep learning models	
	Multilevel time series models	Concurrent fusion	
	Mixed Markov models	Temporal fusion	
Study II	Hazard modeling	Change point analysis	
ý	Time series models		
Study III	SVM, Naive Bayes	Anomaly Detection	
Study IV	Meta-analysis of dynamic models, graphical tools to		
•	overlapping dynamic concepts		

Study I

- Title: Mobile Assessment for the Prediction of Suicide (MAPS)
- Scientists: Nicholas Allen¹, Randy Auerbach² (MPIs), David Brent³, Jeff Cohn^{3,4} & Louis-Philippe Morency⁴; ¹ U of Oregon; ² Columbia U; ³ U of Pitt; ⁴ Carnegie Melon U
- Goal: Prediction of suicidal thoughts and behaviors in youth
- Theoretical framework: Psychache Theory; Interpersonal Theory of Suicide; Diasthesis Stress Theory
- Measurement: Over 6 months, ongoing smartphone and mobile sensor data; daily ecological momentary assessment (EMA) with clinical follow-up at 1, 3, and 6 months

Figure 1: Overview of Study Design



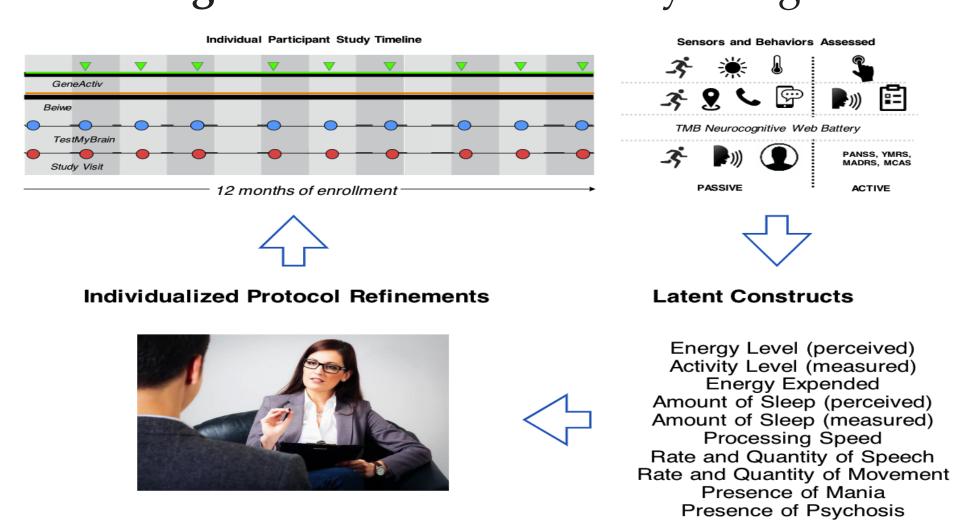
Figure 2: Examples of Continuous Mobile Sensing Variables

Feature	Andriod	iOS
In-call voice sample	_	
All typed text		-
Facial expressions	_	~
Geographic Location GPS		-
Music choice	~	✓ *
Accelerometer.Gyro		-
Ambient light	~	
Charging time		-
Screen-on time	~	
App usage		
Screen touch events	_	
SMS frequency		
SMS transcripts	_	
Call frequency		_
Video diary	_	_
Audio diary	_	-
EMA	_	_
Barometer		-
Wearables	~	~
		*=ITunes only

Study II

- Title: Robust predictors of mania and psychosis
- Scientists: Justin Baker¹, Scott Rauch¹ (MPIs), Ian Barnett² et al; ¹ McLean Hospital and Harvard Medical School; ²U of Pennsylvania
- Goal: Predict the occurrence of mania/psychosis from preceding behavioral changes
- Theoretical framework: Energy Balance Abnormality (Processing Speed); Cognitive Control
- Measurement: Over 1 year, ongoing smartphone and mobile sensor data, and up to 10 study visits (w/actigraphy data)

Figure 3: Overview of Study Design



One possible analysis: Change point analysis to represent a p-variate process on day j with change point at k as:

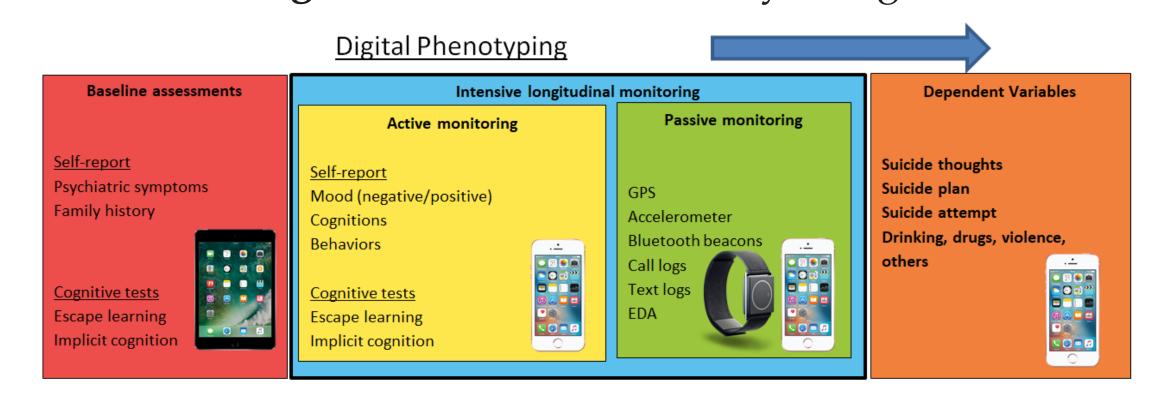
 $Y_j = \mu_j + I(j \ge k)\beta_j + \epsilon_j; \ \epsilon_j \sim \text{MVN}(\mathbf{0}, \Sigma); \ \mu_j = \alpha + \gamma_j;$ $\beta_j = \text{shifts after change point } k; \ \gamma_j = \text{day of week effects,}$

Likelihood ratio tests for H_0 : $\beta = 0$, with derivations of asymptotic distribution of test statistic

Study III

- Title: Intensive Longitudinal Monitoring of Suicidal and Related Behaviors
- Scientists: Matthew Nock (PI)¹, Evan Kleiman¹, John Torous², et al; ¹Harvard U and ²Medical School
- Goal: Identify digital phenotype of suicidal individuals, dynamic trajectories of suicidal thoughts and behaviors over time, and objective/subjective markers of risk

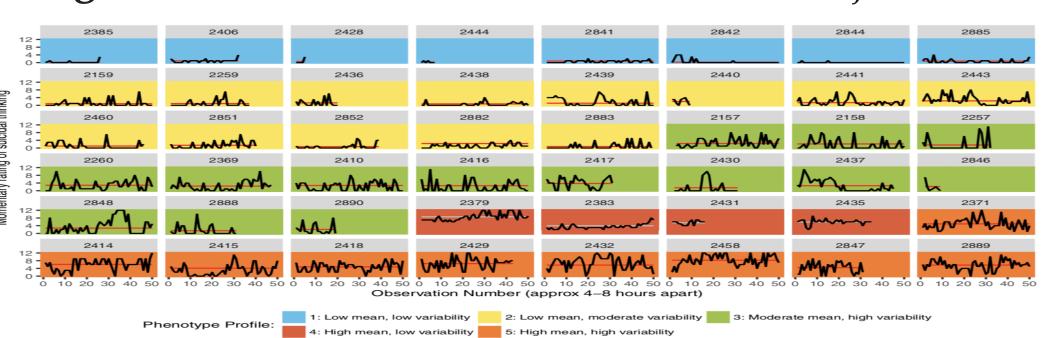
Figure 4: Overview of Study Design



Study III (Contd.)

- Theoretical framework: Data-driven
- Measurement: Over 6 months, ongoing smartphone and mobile sensor data; daily and weekly EMA

Figure 5: Time Series Plots of Individual Trajectories



Study IV

- Study title: An Ontology for the Study of Affective Dynamics
- Scientists: Sy-Miin Chow¹, Nilam Ram¹, Akhil Kumar¹, Timothy Brick¹, Zita Oravecz¹, Peter Molenaar¹, Kai Larsen²; ¹ Penn State U; ²U of Colorado Boulder
- Goal: Develop a shared knowledge base to define methods, models, and time scales for studying affective dynamics, and their correlates with selected health behaviors.
- Affect is a central component of many of the U01 studies either as a predictor, or the dependent variable
- Distinct methods and models have been used to study affective dynamics different terms to describe the same modeling parameter; different parameters are coined the same name

<u>Univariate, discrete-time</u> : $Sad_{i,t} = \rho Sad_{i,t-1} + noise_{it}$

Univariate, continuous-time : $dSad_i(t) = \beta(Base - Sad_i(t))dt + \sigma d$ noise $_i(t)$: Vector AR, regime-switching VAR and SDEs etc.

Table 1: Reported Time Scales for Selected Dynamic Features of Affect

Concepts/Measures	Time Scales	Selected References	
Emotional variability (iSD) @ Emotional reactivity @ Transitions & durations	Macro, micro Meso, macro		
from state-space grids @ Dynamic flexibility @ Inertia @Centralizing tendency	Micro Micro Micro (secs, hrs) Micro (hours)	Hollenstein (2015) Hollenstein (2015) Kuppens et al. (2010, 2015) Oravecz et al. (2011)	

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