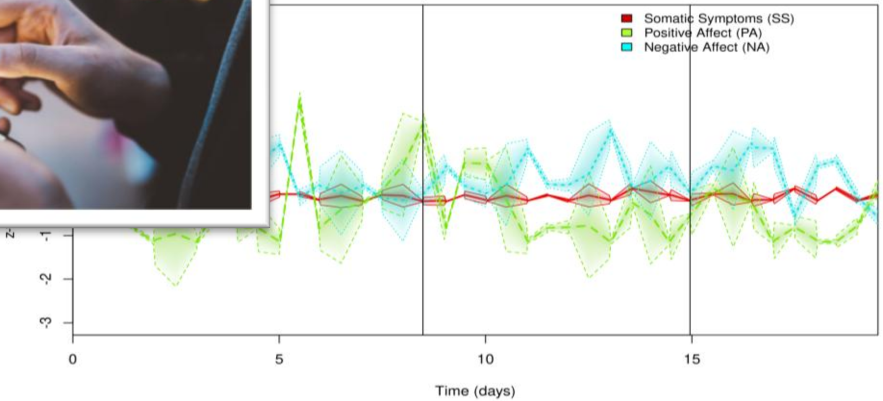
Project Group eHealth



Introduction to Ecological Momentary Assessment in Research & Clinical Practice

David Gosar

Contents

Basics of EMA

Basics of Ecological Momentary Assessment

Basics & History

- **EMA involves repeated sampling of subjects' current behaviors and experiences in real time, in a persons' natural environments**[2]

- **Major Advantages**
  - avoids retrospective bias (prior beliefs, recent & salient events, mood congruent memory effects, duration neglect…)
  - ecological validity (conclusions about real behavior in real environments)
  - intense longitudinal data allows assessment of dynamics (microprocessees, potential for causal modeling…)
  - current tech supports integration with other sources of data (sensor, wearables…)[3]

- **Disadvantages**[3]
  - choosing & maintaining tech (servers, software…)
  - tech support required for patients/participants
  - privacy & data issues (GDPR, informed consent for data storage, size of data, passive sensing…)
  - intrusion on personal time & space (user engagement)

MINI-SERIES

ECOLOGICAL MOMENTARY ASSESSMENT (EMA) IN BEHAVIORAL MEDICINE

Arthur A. Stone, Ph.D. and Saul Shiffman, Ph.D.[1]
State University of New York at Stony Brook and University of Pittsburgh

WHAT ARE ECOLOGICAL MOMENTARY ASSESSMENTS?

There are four qualities that define EMA methods:

EMA Assesses Phenomena at the Moment They Occur

The rationale for this is that behavioral and medical scientists overestimate the fidelity of information obtained with

Ecological Momentary Assessment

Saul Shiffman,[1] Arthur A. Stone,[2] and Michael R. Hufford[3]

[1]Department of Psychology, University of Pittsburgh, Pittsburgh, Pennsylvania 15260; email: Shiffman@pitt.edu

[2]Psychiatry and Behavioral Sciences Department, State University of New York, Stony Brook, Stony Brook, New York 11794-8790; email: Arthur.stone@sunysb.edu

[3]Cypress Bioscience, Inc., San Diego, California 92121; email: mhufford@cypressbio.com

Annu. Rev. Clin. Psychol. 2008. 4:1–32

First published online as a Review in Advance on November 28, 2007

The *Annual Review of Clinical Psychology* is online at http://clinpsy.annualreviews.org

Abstract

Assessment in clinical psychology typically relies on global retrospective self-reports collected at research or clinic visits, which are limited by recall bias and are not well suited to address how behavior changes over time and across contexts. Ecological momentary assessment (EMA) involves repeated sampling of subjects' current behaviors and experiences in real time, in subjects' natural environments. EMA aims to minimize recall bias, maximize ecological validity, and allow study of microprocesses that influence behavior in real-world contexts. EMA studies assess particular events in subjects' lives or assess subjects at periodic intervals, often by random time sampling, using technologies ranging from written diaries and telephones to electronic diaries and physiological sensors. We discuss the rationale for EMA, EMA designs, methodological and practical issues, and comparisons of EMA and recall data. EMA holds unique promise to advance the science and practice of clinical psychology by shedding light on the dynamics of behavior in real-world settings.

[1]Stone & Shiffman (1994),
[2]Shiffman, Stone & Hufford (2008),
[3]Doherty et al. (2020)

Basics of Ecological Momentary Assessment

Basics & History

- Related methods grouped under the term EMA developed before onset of smartphones
  - Experience Sampling Method (ESM), Ambulatory Assessment (AA), Diary Methods, Living Labs…

- ESM present since 80s[1], but gained greater adoption with digital devices (SMS, PDA), especially smartphones[2]
  - omnipresent, unintrusive, gather intimate data, able to sense, computational powerful & remotely accessible
  - gathers exact, dense, ecologically valid & "objective" data
  - computational power & ability of presentation of stimuli via multimedia exceeds earlier lab equipment

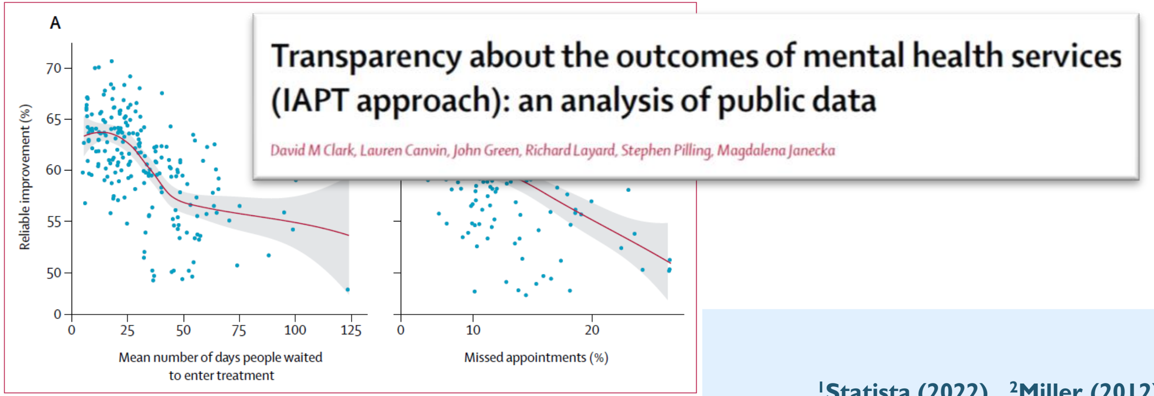
[1]Larson & Csikszentmihalyi (1983), [2]Miller (2012)

Basics of Ecological Momentary Assessment

Basics & History

- **Two major catalysts for uptake**:
  - **wide adoption of smartphones**
    - in 2012 Miller wrote in his Psychology Smartphone Manifesto that it would *"border on scientific malpractice" if by 2025, "when more than 5 billion people will have smartphones" we were "still giving paper-and-pencil questionnaires to a few hundred local college students."*
    - example Slovenia projections of mobile internet user penetration from 2016 to 2026 expected to increase from 46.9% to 81.1% in 2026[1]

  - **COVID-19 pandemic & recognition of unmet mental health needs**
    - increased appreciation for the potential of e-Health to tackle underserved population dealing with mental health issues (importance of providing timely interventions)
    - EU efforts in e-mental health



[1]Statista (2022), [2]Miller (2012)

Basics of Ecological Momentary Assessment
Dynamic Concepts in Psychology

- Dynamic concepts have often been part of psychological theory
  - dynamical concepts, but often static measurement (questionnaires, (semi)-structured interviews…)
  - social learning, defense mechanism, emotion regulation,…
  - variability of affect as an indicator of psychopathology[1]…
- Great need to develop explicit theoretical models of psychological micro-processes, how they interact & unfold in time
  - no clear conventions on sampling in different time-based design, due to the fact that "the temporal dynamics of emotional & cognitive processes are largely unknown"[2]
  - some key theoretical & practical questions:
    - how often & under what circumstance is the construct(s) in questions to be measured?
    - what are possible contingent variables and reporting mechanisms?
    - how does sensor data map onto behavior, symptoms and diagnoses?[3]

[1]DSM-5-TR (2022), [2]Miller (2012)
[3]Frank et al. (2017)

Basics of Ecological Momentary Assessment
Dynamic Concepts in Research of Affect & Emotion

- Affect dynamics in the context of psychopathology [I]
  - **emotional (in)stability**
    - extent of variability of emotion in time (squared successive differences - *SSD*)
    - "borderline" personality disorder, anxiety, depression, bulimia, PTSD
  - **emotional inertia**
    - self-sustaining quality of emotion & moment to moment predictability (auto-correlation - *AR*)
    - neuroticism, low self-esteem, rumination, subclinical depression
    - changes during transitions into psychotic or depressive episodes ("critical slowing")
  - **emotional differentiation (granularity)**
    - ability to differentiate emotional states, perceive complex emotion (interclass *r* - *ICC*)
    - "borderline" personality disorder, major depression (for negative affect), schizophrenia

[I] Trull, Lane, Koval & Ebner-Priemer (2015)

nature human behaviour

LETTERS

https://doi.org/10.1038/s41562-019-0555-0

Complex affect dynamics add limited information to the prediction of psychological well-being

Egon Dejonckheere[1,2*], Merijn Mestdagh[1,2*], Marlies Houben[1], Isa Rutten[1], Laura Sels[1], Peter Kuppens[1] and Francis Tuerlinckx[1]

representativeness of the population?

easures

			Mathematical description	Mathematical equation	Composite score?	Time related?	Example references
			The sum of all affect intensity ratings divided by the total number of completed measurement occasions.	$M_{PAj} = \frac{1}{T_j}\sum_{t=1}^{T_j} PA_{tj}$	Yes	No	22,23,80
			The sum of all squared differences between a particular affect intensity rating and the mean level of that affective state, divided by the total number of completed measurement occasions minus one. The square root of the variance produces an s.d. for that affective state.	$s.d._{PAj} = \sqrt{\frac{\sum_{t=1}^{T_j}(PA_{tj} - M_{PAj})^2}{T_j - 1}}$	Yes	No	23,81
3. Relative variance or standard deviation PA and NA (s.d.*)	Relative emotional variability	Captures the average emotional deviation from one's mean levels of positive or negative affect, taking into account the maximum possible variability given the mean of that affective state.	The s.d. of an affective state divided by the maximum possible s.d. of that affective state, given a certain mean level of that affective state.	$s.d.^{*}_{PAj} = \frac{s.d._{PAj}}{\max(s.d._{PAj} \mid M_{PAj})}$	Yes	No	20,82,83
4. MSSD PA and NA (MSSD)	Emotional instability	Captures the average change in emotional intensity between two successive measurement occasions for positive or negative affect.	The mean of all squared differences between two successive intensity ratings of an affective state. The square root of this measure produces the MSSD for that affective state.	$MSSD_{PAj} = \sqrt{\frac{\sum_{t=2}^{T_j}(PA_{tj} - PA_{t-1j})^2}{T_j - 1}}$	Yes	Yes	16,34,84
5. Auto-regression PA and NA (AR)	Emotional inertia	Captures the degree to which positive or negative affect carries over from one moment to the next, is self-predictive, and resistant to change.	The person-specific (within-person centred) auto-regressive slope in a multilevel AR(1) model, in which the intensity rating of an affective state at time $t-1$ predicts the intensity rating of that state at time t.	$PA^{c}_{tj} = (b^{g} + b^{r}_{j}) + (AR^{g}_{PA} + AR^{r}_{PAj})PA^{c}_{t-1j} + \varepsilon_{tj}$ $AR_{PAj} = AR^{g}_{PA} + AR^{r}_{PAj}$	Yes	Yes	8–10
6. Emotion-network density (*D*)	Emotional interdependency across time	Captures the degree to which various positive and negative emotions predict each other over time, reflecting how one's entire emotional system is resistant to change.	The mean of all absolute person-specific (within-person centred) auto- and cross-regressive slopes in a series of multilevel VAR(1) models. In each model, the intensity of one emotion rating at time t is predicted once by the intensity ratings of all other emotions at time $t-1$, including the intensity rating of that emotion itself.	$\mathbf{E}^{c}_{tj} = (\mathbf{b}^{g} + \mathbf{b}^{r}_{j}) + (\mathbf{VAR}^{g} + \mathbf{VAR}^{r}_{j})\mathbf{E}^{c}_{t-1j} + \boldsymbol{\varepsilon}_{tj}$ $\mathbf{VAR}_{j} = \mathbf{VAR}^{g} + \mathbf{VAR}^{r}_{j}$ $D_j = \sum_{k=1}^{K}\sum_{l=1}^{K} \lvert \mathbf{VAR}_{jkl} \rvert$	No, discrete emotions	Yes	45,64
7. ICC PA and NA (ICC)	Emotional granularity or differentiation	Captures one's ability to differentiate between various positive or negative discrete emotions.	The intra-class correlation between various same-valenced emotion intensity ratings. This measure reflects the degree to which different emotion intensity ratings converge. A low ICC reflects high emotion differentiation.	$PA_{tkj} = E_{PAkj} + PA_{tj} - M_{PAj} + \varepsilon_{tkj}$ $MSE_{PAj} = \frac{\sum_{t}^{T_j}\sum_{k}^{K_{PA}} \varepsilon_{tkj}^2}{(T_j - 1)(K - 1)}$ $MSR_{PAj} = \frac{\sum_{t}^{T_j}\sum_{k}^{K_{PA}} (PA_{tj} - M_{PAj})^2}{(T_j - 1)}$ $ICC_{PAj} = \frac{MSR_{PAj} - MSE_{PAj}}{MSR_{PAj}}$	No, discrete same-valenced emotions	No	43,85,86
8. PA–NA correlation (*ρ*)	Affective bipolarity, valence focus, or emotional dialecticism	Captures the degree to which one experiences positive and negative affect independently, or as bipolar opposites.	The within-person correlation between positive and negative affect.	$\rho_j = \frac{\sum_{t=1}^{T_j}[(PA_{tj} - M_{PAj})(NA_{tj} - M_{NAj})]}{s.d._{PA}s.d._{NA}}$	Yes	No	14,42,87
9. Gini coefficient PA and NA (*G*)	Emodiversity	Captures the variety of one's emotional repertoire for positive and negative emotions.	The weighted sum of the frequencies of various same-valenced emotions (with the weight being the order of the emotion frequencies), divided by the product of the total frequency of all same-valenced emotions and the total number of emotion categories. A low Gini coefficient reflects a high emodiversity.	$G_{PAj} = \frac{2\sum_{k}^{K_{PA}} k c_{kj}}{\sum_{k}^{K_{PA}} c_{kj}} - \frac{K_{PA} + 1}{K_{PA}}$	No, discrete same-valenced emotions	No	21,46,88

PA, positive affect; NA, negative affect; ICC, intra-class correlation; *E*, discrete emotion; **E**, vector of discrete emotions; *T*, total number of time points, with *t*, specific time point; *N*, total number of people, with *j*, specific person; *b*, intercept; **b**, vector of intercepts; ^{c}, within-person centred undefined variable; ^{g}, fixed effect; ^{r}, random effect; ε, residuals; $\boldsymbol{\varepsilon}$, vector of residuals; AR, auto-regressive component; **VAR**, vector auto-regressive matrix; *K*, number of emotions, with *k* and *l*, indices of specific emotions; E_{PAkj}, the mean of positive affect ... for person *j*; c_{kj}, the number of times an emotion *k* is bigger than a threshold for person *j* (for example, 10% of the measurement scale), with $c_{kj} \leq c_{k+1j}$.

M and SD more parsimonious

Statistical Methodology for Intense Longitudinal Data

Statistical Methodology for Intense Longitudinal Data

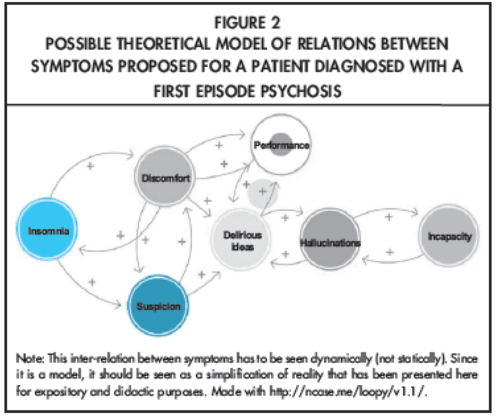
Time Series Analysis, Multi-level Models

- Time-series Analysis
  - calculation of SSD, AR & ICC[1]
  - calculations based on multi-levels models[2]
    - mean squared successive differences (MSSD)
    - probability of acute change (PAC)
  - vector autoregressive modeling (VAR)
    - inherently multivariate, each variable is a predictor & outcome
    - can use Granger Causality to find direction of effects, establish networks
    - R-packages *AutoVAR*[3] & *qgraph*[4]
    - R-packages for graph comparisons *NetworkComparisonTest*[5], for simulations *IsingSampler*[6] & *IsingFit*[7]

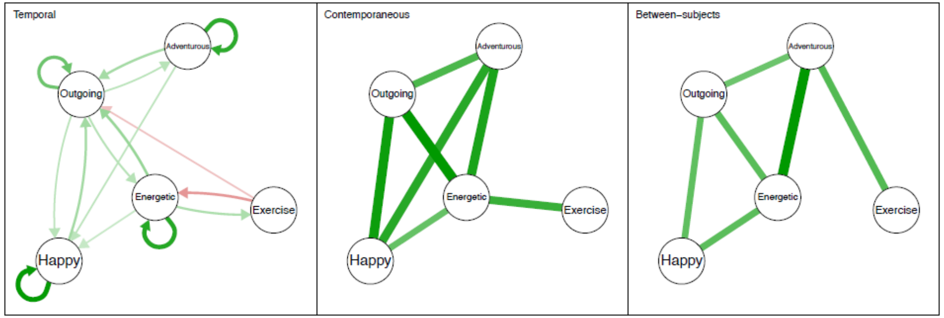
[1]Trull, Lane, Koval & Ebner-Priemer (2015), [2]Jahng et al. (2008)
[3]van der Krieke et al. (2015), [4]Epskamp et al. (2012), [5]van Borkulo (2013)

Statistical Methodology for Intense Longitudinal Data

Network Analysis



- Network models of psychopathology
  - latent factor models – symptoms are an expression of a latent mental (brain) disorder
  - network models – disorder are a consequence of interactions among symptoms and forming of feedback loops which maintain stable states[1,2]
    - ie. psychotic symptoms & disordered sleep[3]
  - hybrid models (FA & network models for residuals[4,5])



[1]Borsboom & Cramer(2013), [2]Fonseca-Pedrero (2018), [3]Borsboom (2017), [4]Fried & Kramer (2017), Epskamp et al. (2017)

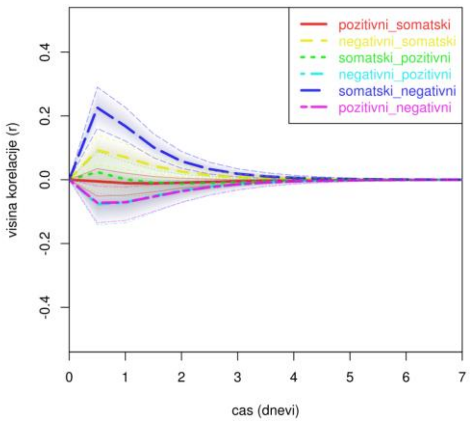
Statistical Methodology for Intense Longitudinal Data

Dynamic Structural Modeling

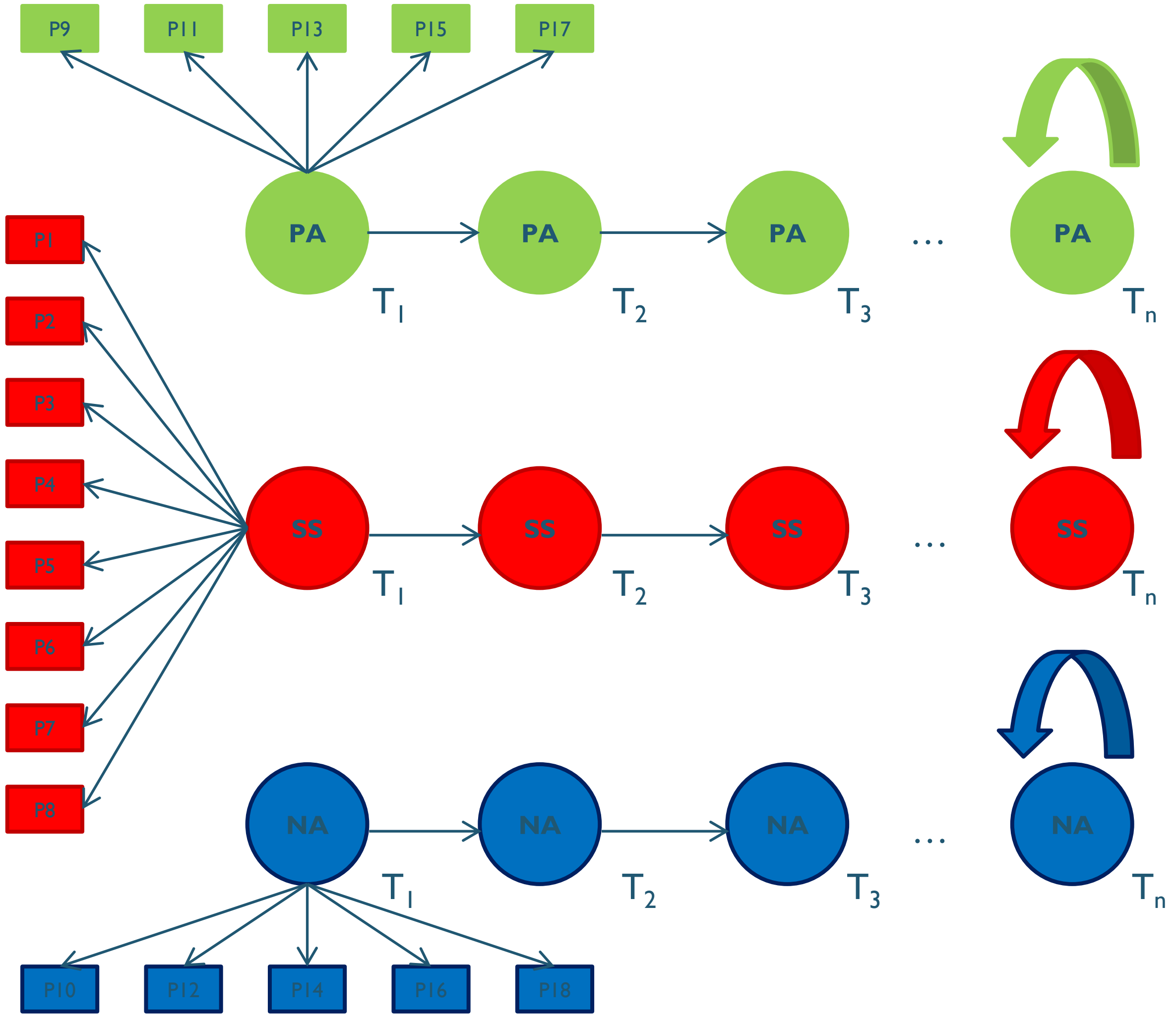
- VAR network models difficult to replicate with different data
- **Assumptions**: equispaced measurement of static processes
  - In psychology!? Not really (reporting intervals rarely equispaced, missing values, effects of interventions – not static, white noise…)

- **Structural Equation Modeling in continuous time (CTSEM)**[1] available in R-package CTSEM
  - dynamics of latent factors in time
  - time-independent & time-dependent predictors
  - dynamic measures such as inertia (similar to AR), diffusion (similar to SSD) & cross-correlation (useful for causal modeling) + Bayesian Estimation
  - other nonlinear dynamic approaches to studying temporal fluctuations in psychological constructs[2]
  - regime switching models for abrupt changes in dynamics[3]

Time as a continuous variable

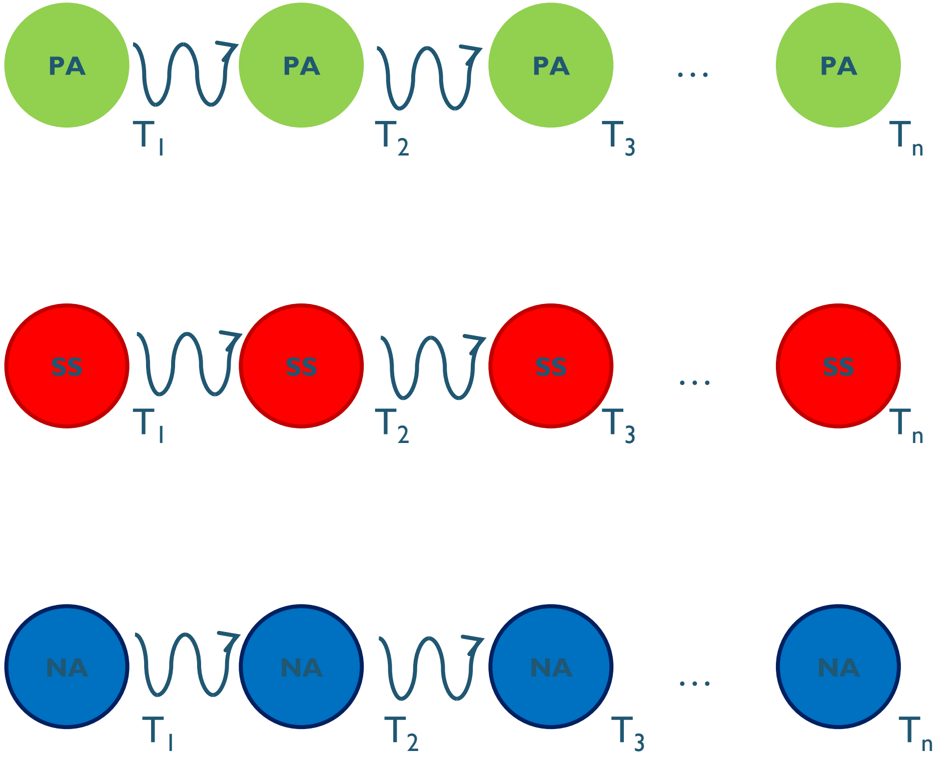


[1]Driver et al. (2022), [2]Gori et al., (2022), [3]Schneider et al. (2018)



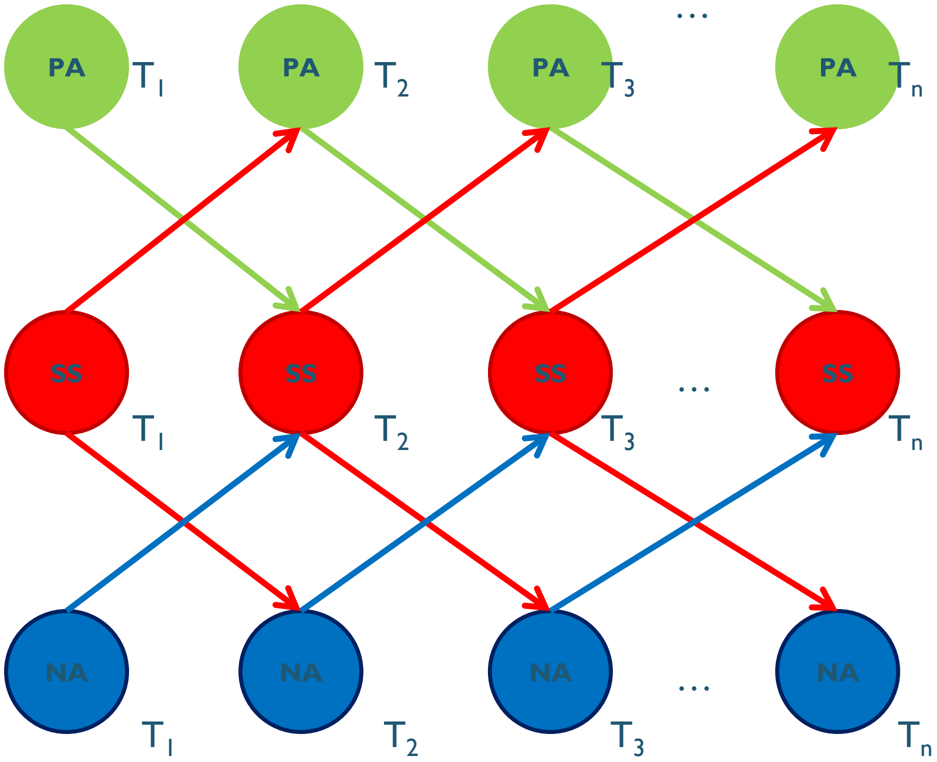
INERTIA (AR)

autocorrelation or persistence of process



DIFUSSION (W)

degree of randomness in the variability of a process in an individual

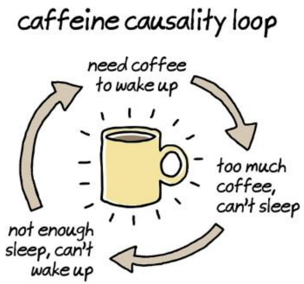


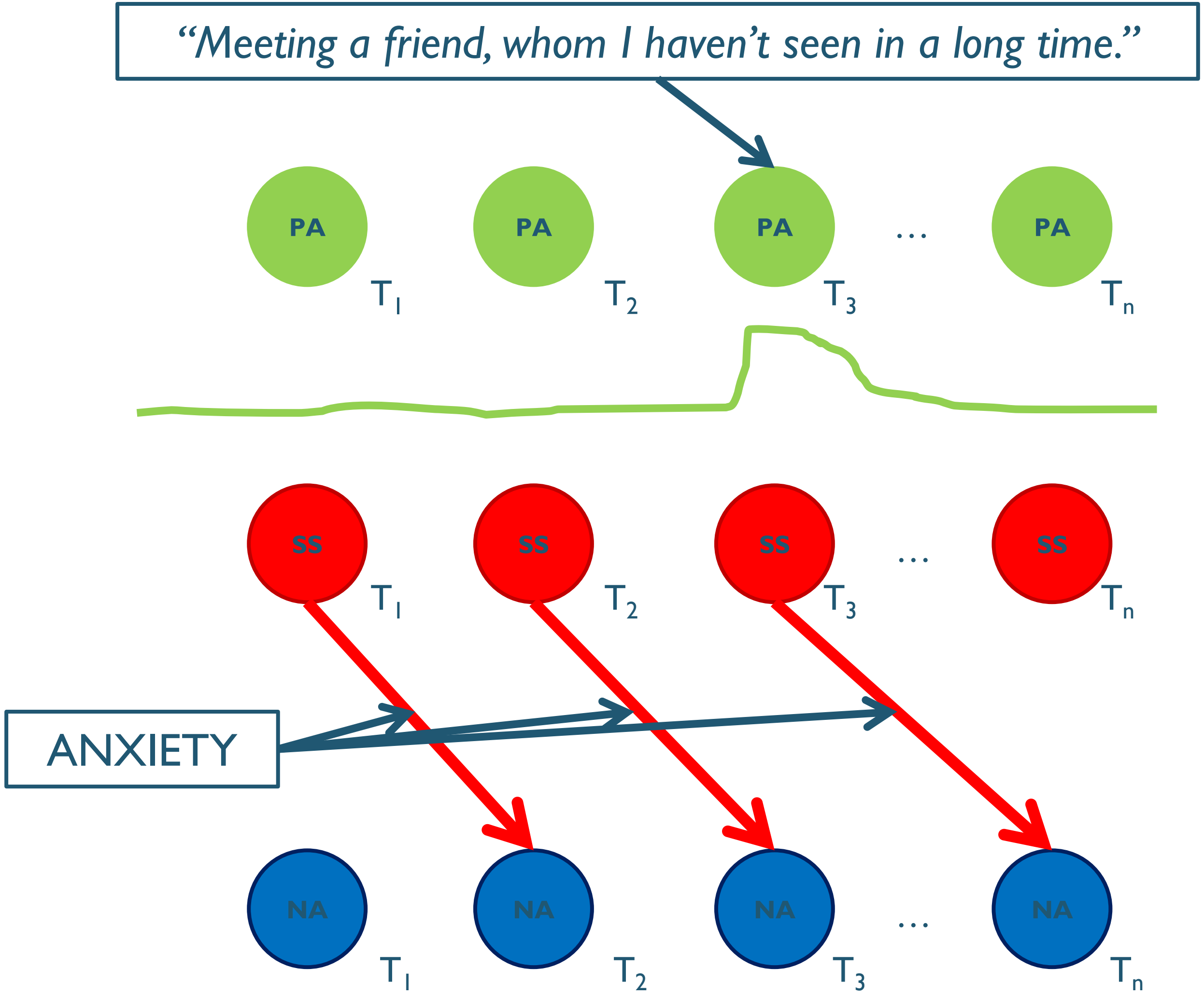
impact of one process on the future state of another

CROSS CORRELATION

(CR)

modeling lagged effects - an attempt to model causality





time dependent
(e.g. pleasant meeting)

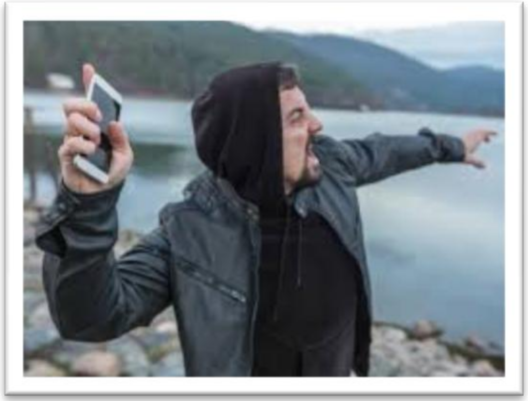
PREDICTOR VARIABLES

time independent
(e.g. anxiety)

Statistical Methodology for Intense Longitudinal Data

Missing Data

- missing data common in EMA studies
  - **meta-analysis in adults**[1]
    - 126 studies (1-9 prompts per day, 3-730 days)
    - pooled rate of missing data: **24.9%**
    - predictors:
      - ☐ neither prompt frequency nor study length
      - ☐ psychopathology (substance abuse)
      - ☐ age x day of study interaction [3]
  - **meta-analysis in children & adolescents**[2]
    - 42 studies (2-9 prompts per day, 2-42 days)
    - pooled rate of missing data: **21.7%**
    - predictors of missing data:
      - ☐ clinical studies (<6 prompts per day)
      - ☐ nonclinical studies (>2-3 prompts per day)



MISSING DATA

[1]Jones et al. (2018), [2]Wen, Schneide, Stone & Spruijt-Metz (2017), [3]Ono et al. (2019)

Statistical Methodology for Intense Longitudinal Data

Missing Data & Modeling in Continuous Time

Do missing values exist? Incomplete data handling in cross-national longitudinal studies by means of continuous time modeling

Johan H. L. Oud · Manuel C. Voelkle

onal longitudinal studies it is often impossible to administer the same
nts at the same occasions to all sample units in all participating coun-
lts in large quantities of missing data, due to (a) missing measurement
untries, (b) missing assessment waves within or across countries, (c)
lual sample units. As compared to cross-sectional studies, the problem of missing values is further aggravated by the fact that missing values are always associated with different time intervals between repeated observations. In the past, this has often been dealt with by the use of phantom-variables, but this approach is limited to simple designs with few missing value patters. In the present paper we propose a new way to think of, and deal with, missing values in longitudinal studies. Instead of conceiving of a longitudinal study as a study with T discrete time points of which some are missing, we propose to conceive of a longitudinal study as a way to measure an underlying process that develops continuously over time, but is only observed at some selected discrete time points. This transforms the problem of missing values into a problem of unequal time intervals. After a quick introduction to the basic idea of continuous time modeling, we demonstrate how this approach provides a straightforward solution to missing measurement instruments in some countries, missing assessment waves within or across countries, and missing data for individual sample units.

Turning the problem on its head →

instead of missing values, just sampling of a continuous, process at different time points

Statistical Methodology for Intense Longitudinal Data
Integration with Data from Sensors & Wearables

- Example: Do people have the same physiological reactions when experiencing the same emotions[1]
  - EMA reporting triggered by significant change in physiology (substantial changes in cardiac activity occurred in the absence of movement)
  - 52 participants, extensive physiology (ECG, ICG), accelerometric data
  - EMA free descriptions + rating scales
  - finding – guess not, people label the same physiological reactions with different emotions in relation to context

Context-aware experience sampling reveals the scale of variation in affective experience

Katie Hoemann[1,6], Zulqarnain Khan[1,6], Mallory J. Feldman[2], Catie Nielson[1], Madeleine Devlin[1], Jennifer Dy[1], Lisa Feldman Barrett[1,3], Jolie B. Wormwood[4,5,7] & Karen S. Quigley[1,5,7]

Other Forms of Context Awareness
(EMA using GPS sensors, accelerometers…)

[1]Hoemann et al. (2020)

EUROPEAN MEDICINES AGENCY
SCIENCE MEDICINES HEALTH

15 February 2016
EMA/CHMP/SAWP/513571/2015
Committee for Medicinal Products for Human Use (CHMP)

Qualification opinion on ingestible sensor system for medication adherence as biomarker for measuring patient adherence to medication in clinical trials

Contemporary Research Applications

Contemporary Research Applications

Common Topics of Research 2015 to 2020

Reference	Review topic	Number of papers
Wen *et al.* (2017)	Children and adolescents	42
Baltasar-Tello *et al.* (2018)	Mood disorders in children and adolescents	13
Heron *et al.* (2017)	Youth	24
Serre *et al.* (2015)	Craving and substance use	91
Liao *et al.* (2016)	Diet and physical activity in youth	13
Engel *et al.* (2016)	Eating disorder and obesity research	Not reported
Chun (2016)	Post-traumatic stress symptoms	15
Raugh *et al.* (2019)	Psychiatric populations	128
Lui *et al.* (2017)	Psychotherapy	21
Bos *et al.* (2015)	Psychopharmacology	18
May *et al.* (2018)	Chronic pain research	105
Miguelez-Fernandez *et al.* (2018)	Attention-deficit/hyperactivity disorder	23
Liu *et al.* (2018)	Social interactions	23
Schembre *et al.* (2018)	Behavioral research	20
Rodríguez-Blanco *et al.* (2018)	Non-suicidal self-injury	23
Singh & Björling (2019)	Craving and substance use	56
van Berkel *et al.* (2017a)	Mobile devices	110

- review of reviews by Doherty, Balaskas & Doherty (2020)

Contemporary Research Applications
Emotion Dynamics & Mental Health

- Some interesting topics in mental health research
  - the role of binge eating in regulating negative affect revisited – EMA meta-analysis[1]
  - comparing models of day to day fluctuations in mood in bipolar disorder (AR, ARIMA, Marko model, Markov AR)[2]
  - identifying potential pediatric chronic abdominal pain triggers using ecological momentary assessment[3]
  - EMA in clinical psychopharmacology to assess the evolution of adverse effects of psychiatric treatment in time [4]

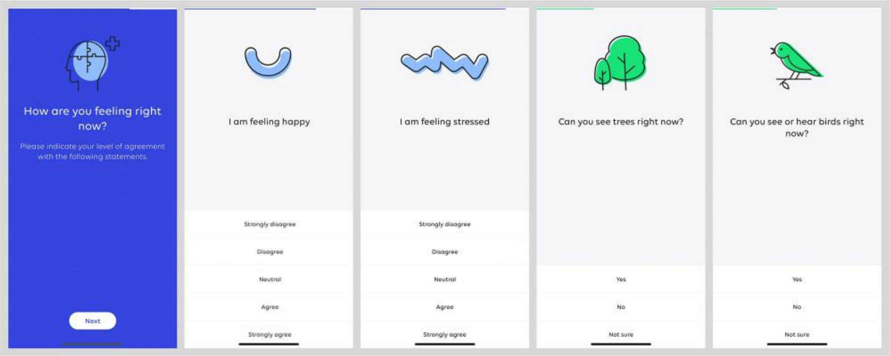


Figure 1. Screenshots of the Urban Mind app interface.

www.nature.com/scientificreports

scientific reports

Check for updates

OPEN **Smartphone-based ecological momentary assessment reveals mental health benefits of birdlife**

Ryan Hammoud[1✉], Stefania Tognin[1], Lucie Burgess[1], Nicol Bergou[1], Michael Smythe[2], Johanna Gibbons[3], Neil Davidson[3], Alia Afifi[1], Ioannis Bakolis[4,5] & Andrea Mechelli[1]

[1]Haedt-Matt & Keel (2011), [2]Hamaker et al. (2016), [3]Verrill Schurman & Friesen (2015), [4]Bos et al. (2015), [5]Hammoud et al. (2022)

Contemporary Research Applications
Interpersonal Dynamics

- Just two interesting examples
  - Couples Therapy
    - emotional inertia & romantic partners experience of emotional responsiveness
    - two studies (N = 44, 4x/day, 4 weeks; N=103, 4x/day, 10 days)
    - partners of individuals with high (inert) or low (erratic) emotional inertia perceived them to be less responsive → steeper declines in relationship satisfaction across 12 months
  - How depressed parents dish-up food
    - identifying how parental stress & depressive mood influence parent food-related parenting practices (preassuring to eat, homemade food)
    - 150 children age 5 to 7 years, 10 days
    - high stress & depressive mood earlier in day → pressure-to-eat feeding & less homemade meals that day

[1]Berge et al. (2017), [2]Luginbuehl & Schoebi (2019)

Contemporary Research Applications
Cognition in Daily Life

Reliability and Validity of Ambulatory Cognitive Assessments

Martin J. Sliwinski[1], Jacqueline A. Mogle[1], Jinshil Hyun[1], Elizabeth Munoz[1], Joshua M. Smyth[1], and Richard B. Lipton[2]

ARTICLE OPEN

Smartphone-based symbol-digit modalities test reliably captures brain damage in multiple sclerosis

Linh Pham[1], Thomas Harris[1], Mihael Varosanec[1], Vanessa Morgan[1], Peter Kosa[1] and Bibiana Bielekova[1]

Bridging the Gap between Performance-based Assessment and Self-reported Everyday Functioning: An Ecological Momentary Assessment Approach

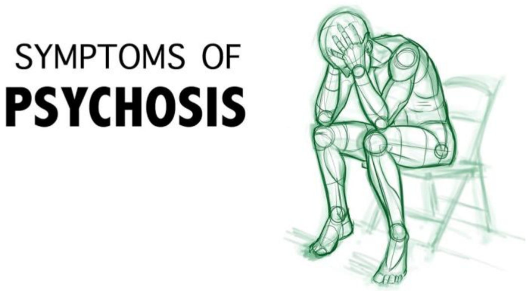
Maureen Schmitter-Edgecombe[1], Catherine Sumida[1], Diane J. Cook[2]
[1]Department of Psychology, Washington State University, Pullman, WA
[2]School of Electrical Engineering and Computer Science, Washington State University, Pullman, WA

- Assessment of cognition via EMA
  - Assessing Working Memory & Speed of Information Processing
    - good between person reliability (>.97) & within person variability (~.40 to .50)[1]
    - convergent & discriminant validity with lab measures[1]
    - adapted task (SMDT) predictive of deterioration on MRI in MS[2]
    - variability in working memory in EMA N-back predicts self-reported functional status and cognitive failures beyond mean levels & lab measures[3]

[1] Sliwinski et al. (2018), [2]Pham et al. (2021), [3]Schmitter-Edgecombe et al. (2020)

Contemporary Research Applications
Predicting Critical Events

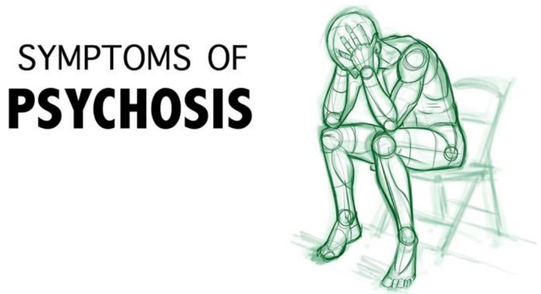
- **Identifying psychosis spectrum disorder from ESM using Machine Learning (ML) approaches**
  - 260 psychosis spectrum patients & 212 healthy controls
  - filled out questionnaire with 10-items 10x per day
    - three positive (cheerful, relaxed and satisfied)
    - six negative (anxious, down, guilty, insecure, irritated, lonely)
    - one psychosis specific item (suspicious)
  - Support Vector Machines indicated key features:
    - anxious and insecure levels
    - dynamically accelerating anxiety & insecurity
    - capturing successive "up-and-downs" rather than individual "ups" or "downs" important

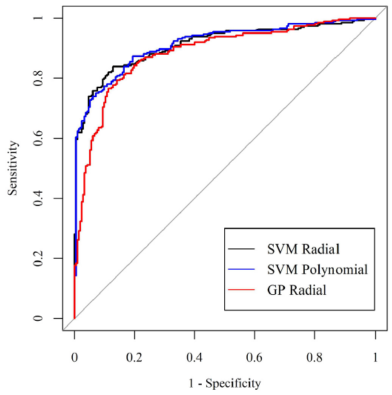


- **Identifying psychosis spectrum disorder from ESM using Machine Learning approaches**

Rank	varImp(LVQ)	RFE	ReliefF
1	acc.anxious.interq	cheerful.q0.1	cheerful.q0.1
2	insecure.q0.9	Age	relaxed.med
3	acc.anxious.q0.9	acc.anxious.interq	velo.guilty.q0.1
4	down.q0.9	satisfied.q0.1	relaxed.q0.9
5	lonely.q0.9	lonely.q0.9	velo.irritated.q0.9
6	cheerful.q0.1	acc.satisfied.inter	down.q0.9
7	anxious.q0.9	suspicious.q0.9	insecure.q0.9
8	acc.insecure.interq	acc.anxious.q0.9	velo.suspicious.interq
9	insecure.interq	acc.insecure.interq	suspicious.q0.9
10	down.interq	lonely.interq	velo.suspicious.q0.1
Common in top 20: cheerful.q0.1, insecure.q0.9			

Variable rank with Learning Vector Quantization (LVQ), Recursive Feature Elimination (RFE) and ReliefF feature selection methods applied on the dataset including base, velocity and acceleration data in normal values, with V2 aggregation applied. Abbreviations in variable names are as follows: acc: acceleration, interq: interquartile, q: quantile, velo: velocity, med: median.





Contemporary Research Applications
Predicting Critical Events

- Is ESM be helpful in predicting suicide risk?
  - findings of a review of 23 studies
    - suicidal ideation fluctuates substantially over time (hours, days) & individuals with higher mean ideation have more fluctuations
    - higher suicidal ideation instability a phenotypic indicator for increased suicide risk
    - negative affect, hopelessness and burdensomeness to predict increased ideation within-day
    - more individuals reported through EMA than traditional measures, no reactivity effect

Don't Miss the Moment: A Systematic Review of Ecological Momentary Assessment in Suicide Research

Liia Kivelä[1], Willem A. J. van der Does[1,2], Harriëtte Riese[3] and Niki Antypa[1*]

No studies of overt outcome (attempt, completed suicide)

[1]Berge et al. (2022)

Contemporary Research Applications
EMA Specific Ethical Issues

- Safety measures & consent for emergency interventions
  - i.e. suicide risk[1], psychotic episode, manic episode
- Other ethics issues
  - adverse effects of EMA (increased phone use[2], trigger in drug-injecting participants[3], …)
  - data privacy & safety[4]
  - autonomy & common data standards[5]
  - service providers & bus factor[5]
  - explainable AI & prevention of bias[4]
  - engagement in design & execution

Consensus Statement on Ethical & Safety Practices for Conducting Digital Monitoring Studies with People at Risk of Suicide and Related Behaviors

Matthew K. Nock, Ph.D., Evan M. Kleiman, Ph.D., Melissa Abraham, Ph.D., Kate H. Bentley, Ph.D., David A. Brent, M.D., Ralph J. Buonopane, Ph.D., Franckie Castro-Ramirez, A.M., Christine B. Cha, Ph.D., Walter Dempsey, Ph.D., John Draper, Ph.D., Catherine R. Glenn, Ph.D., Jill Harkavy-Friedman, Ph.D., Michael R. Hollander, Ph.D., Jeffrey C. Huffman, M.D., Hye In S. Lee, B.S., Alexander J. Millner, Ph.D., David Mou, M.D., Jukka-Pekka Onnela, Ph.D., Rosalind W. Picard, Ph.D., Heather M. Quay, J.D., Osiris Rankin, A.M., Shannon Sewards, M.A., John Torous, M.D., Joan Wheelis, M.D., Ursula Whiteside, Ph.D., Galia Siegel, Ph.D., Anna E. Ordóñez, M.D., Jane L. Pearson, Ph.D.

1. Not exclude participants soley on the basis of elevated clinical severity or suicide risk.
2. Not exclude or remove participants who are not willing or able to meet pre-specified conditions for participant or help-seeking (e.g., remaining in treatment or calling a hotline when at high risk).
3. Provide participants with explicit information about key elements of study procedures during the informed consent process.
4. Collect and retain (during the real-time monitoring period) contact information (phone, email, and home address) from both the participant and at least one collateral to facilitate contacting participants during periods of perceived elevated risk.
5. Address key aspects of technology use and participant safety before proceeding with data collection.
6. Review participant survey responses at least once every weekday.
7. Respond to those determined to be at "imminent risk" for suicide within 12 h of learning of this risk.
8. Collect data about suicidal desire, intent, plan to determine participants' level of risk.
9. Respond to participants determined to be at high or "imminent" risk for suicide with automated risk assessments, safety plans, and human outreach (depending on risk and type of study) as soon as possible.
10. Store data in de-identified form, in secure servers, and in compliance with HIPAA guidelines. In cases in which data safety and monitoring boards are used they should include at least one person with expertise managing suicide risk.

[1]Nock et al. (2021), [2]Heron et al. (2017), [3]Roth et al. (2017), [4]Rubeis (2022), [5]Van Daele et al. (2020)

Current & Future Clinical Implications

Current & Future Clinical Implications
Using EMA in the Clinic

Original Paper

App-Based Ecological Momentary Assessment to Enhance Clinical Care for Postpartum Depression: Pilot Acceptability Study

Holly Krohn, MPH; Jerry Guintivano, PhD; Rachel Frische, MPH, MBA, MD; Jamie Steed, BSc; Hannah Rackers, MPH; Samantha Meltzer-Brody, MPH, MD

Department of Psychiatry, University of North Carolina at Chapel Hill, Chapel Hill, NC, United States

- Postpartum depression - the most commonly diagnosed complication of childbirth
  - 6 week study with 27 mothers who completed questionnaires & EMA, also provided passive sensing measures (HR, steps, sleep)
  - increased insight into mental health status (impact or reduced sleep, better support from partners, increased desire for activities when less active)

Current & Future Clinical Implications

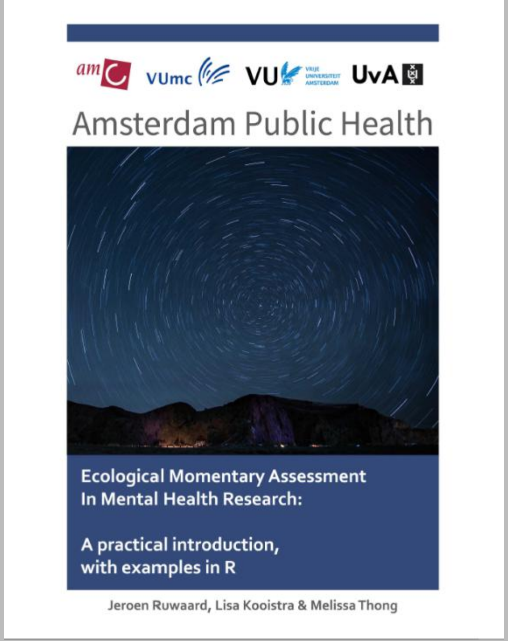
Just-in-time Treatment

- Just-in-time Ecological Momentary Intervention (EMI)
  - hot topic, but small empirical base of data, lower quality research
    - EMI's based on EMA to Promote Health Behaviors[1]
      - 17 studies (47% mental health, 24% diet, weight loss, physical activity, 18% substance abuse, 12% smoking)
      - small sample sizes, and great heterogeneity in intervention designs and measurements
      - 4 randomized trials n.s., 4 quasi-experimental improvement for depression, psychosis, alcohol abuse & eating patterns
    - 14 EMI's for promoting physical activity (poor quality, underpowered)[2]
      - use of goal setting, prompts , feedback on behavior and action planning

[1]Dao et al. (2021), [2]Hardeman et al. (2019)

Resources for EMA

Some other EMA resources



m-Path: An easy-to-use and flexible platform for ecological momentary assessment and intervention in behavioral research and clinical practice

Merijn Mestdagh[1]*, PhD

Stijn Verdonck[1]*, PhD

Maarten Piot[1], MSc

Koen Niemeijer[1], MSc

Francis Tuerlinckx[1], Prof

Peter Kuppens[1], Prof

Egon Dejonckheere[1,2], PhD

a user-friendly and flexible framework for implementing smartphone-based ecological momentary assessment (EMA) and intervention (EMI) in both research and clinical practice in the context of blended care.

Resources for EMA

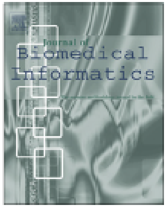
Looking to integrate wearables into your EMA research

ELSEVIER

Contents lists available at ScienceDirect

Journal of Biomedical Informatics

journal homepage: www.elsevier.com/locate/yjbin



Let's get Physiqual – An intuitive and generic method to combine sensor technology with ecological momentary assessments

CrossMark

F.J. Blaauw [a,b,*], H.M. Schenk [a], B.F. Jeronimus [a,c], L. van der Krieke [a], P. de Jonge [a,c], M. Aiello [b], A.C. Emerencia [a]

[a] *University of Groningen, University Medical Center Groningen, University Center for Psychiatry, Interdisciplinary Center Psychopathology and Emotion Regulation (ICPE), The Netherlands*
[b] *University of Groningen, Johann Bernoulli Institute for Mathematics and Computer Science (JBI), Distributed Systems Group, The Netherlands*
[c] *University of Groningen, Department of Developmental Psychology, The Netherlands*

Resources for EMA

Kudos to the Competition – APA Webinars on Intensive Longitudinal Data

Intensive Longitudinal Data: Methodological Challenges and Opportunities

WATCH RECORDING

Download: Presentation Slides | Transcript

Intensive Longitudinal Data: A Multilevel Modeling Perspective

WATCH RECORDING

Download: Presentation Slides | Transcript

Intensive Longitudinal Data: A Dynamic Structural Equation Modeling Perspective

WATCH RECORDING

Resources for EMA

So you're writing up an EMA study?

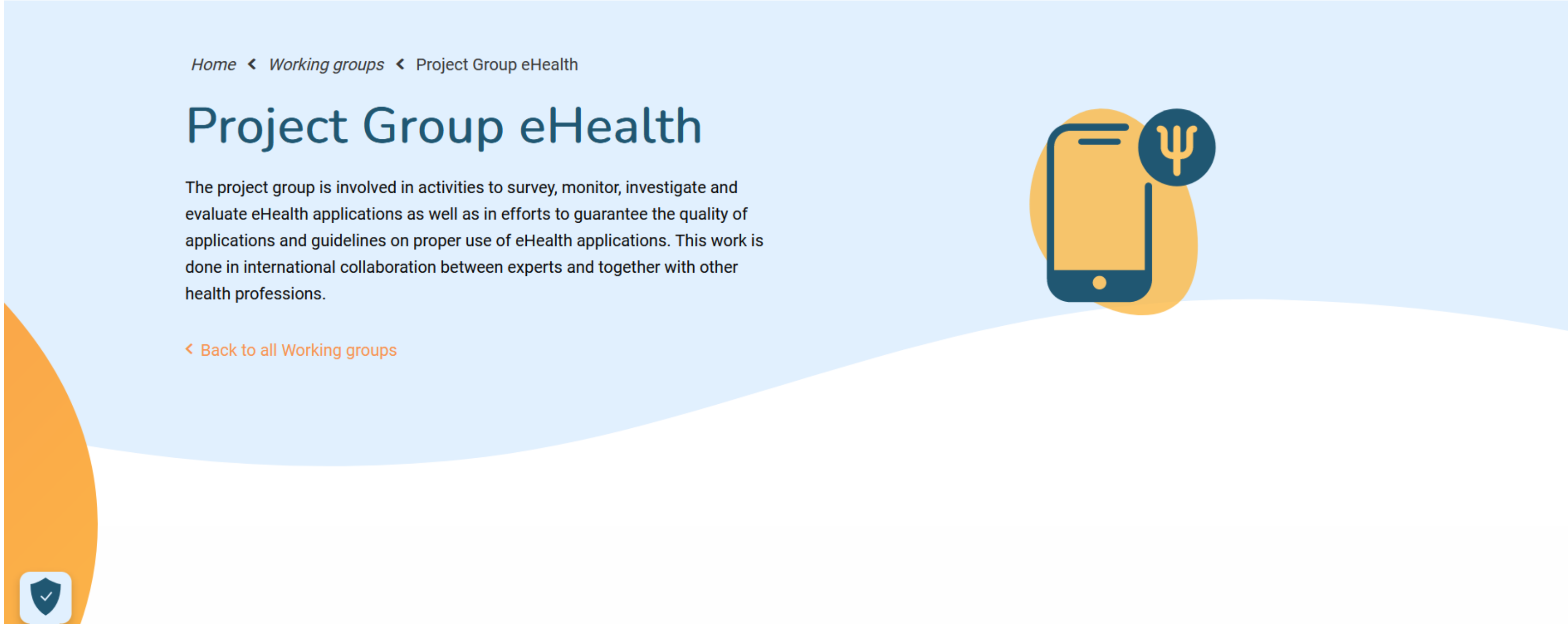
Ambulatory Assessment in Psychopathology Research: A Review of Recommended Reporting Guidelines and Current Practices

Recommended reporting criterion	Psychology (n = 37)[a]	Sciences (n = 16)[a]	Medicine (n = 10)[a]	Total (n = 63)
Justify sample size (e.g., using a multilevel power analysis)	3	0	0	2
Explain rationale for the sampling design (e.g., random, event-based)	19	19	10	17
Explain rationale for sampling density (e.g., assessments per day) and scheduling (i.e., when the assessments are scheduled)	16	25	10	17
Provide technical details of sampling (e.g., prompting and recording practices; procedures for event-based entries; ability to suspend/delay responses; branching details, triggering assessments, follow-ups, or dense sampling of events or experiences)	38	25	20	32
Report full text of items, rating time frames, response options or scaling	78	75	80	78
Report psychometric properties of items in the current EMA study (between- and within-subject), as well as the origin of the items	38	31	0	30
Fully describe hardware and software used	73	75	90	76
Define valid and missing data (for participants broadly, and specific to individual EMA reports); report descriptive analyses regarding valid data (e.g., mean per person, range, % participants above and below 80% threshold)	65	62	70	65
Describe the procedures used to enhance compliance and participation (e.g., remuneration schedule, participant training)	78	69	60	73
Describe the final data set: number of reports (total; person average; group average), days in study and retention rates, and rates of delayed or suspended responding (if applicable)	49	50	30	46
Describe preparation for data analyses centering of predictor variables and at what level; report covariates included in the models	68	50	50	60
Describe levels of analysis (momentary, day, person); explain how time is taken into account in analyses; specify and justify choices of random versus fixed effects in models; describe analytic modeling used as well as statistical software used	95	81	90	90

Trull & Ebner-Priemer (2020)

Resources for EMA

History & Basic of Technology



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Project Group eHealth

The project group is involved in activities to survey, monitor, investigate and evaluate eHealth applications as well as in efforts to guarantee the quality of applications and guidelines on proper use of eHealth applications. This work is done in international collaboration between experts and together with other health professions.

< Back to all Working groups

- https://www.efpa.eu/working-groups/ehealth

- EFPA Project Group eHealth members
- Collaborating students
  - Lea Kopač, Beti Kovač, Sara Seršen
- Psychologist colleagues at department
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University Medical Center Ljubljana

Slovenian Psychological Association

EFPA Project Group eHealth