Toward mobile behavioral biomarkers

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Biomarker:
A specific physical trait used to measure or indicate the effects or progress of a disease, illness, or condition.
Goal: optimize treatment using mobile behavioral biomarkers

Participant self-care
How is this new medication working for me?

Clinical care
How is the patient responding to new care plan?

open mHealth

patient apps: personal-evidence and clinically-informed tools to engage and support healthy behaviors

‘relevant-time’ clinical dashboards: summarizing and correlating symptoms, side effects, meds, and health behaviors

Research evidence
What works best in different contexts?

mhealth-enabled n-of-1 studies: systematic, individualized studies of treatment alternatives

mHealth evidence-base: which mHealth techniques are effective, and for whom

w/ Ida Sim, Open mHealth
mHealth applications as source of data

Patient/Participant

Self Report
- symptoms
- side effects
- behaviors

Internet

End-User Dashboards

Passive Monitoring
- GPS, Wifi, Accel
- sms, calls, calendar, social media
- actigraphy, mobility, comm

Apps/activities
- interventions
- games, tools, assessments
Transform continuous passive traces into behavioral biomarkers

Low-level state classification: create time series of states after data cleaning
- sedentary/ambulatory
- at home/work
- interacting with app, people...
- ‘standard’ ML techniques

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w/ Ramanathan, Longstaff, Alquaddoomi, et al
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Mid-level semantic features:
calculate domain-specific features
• daily minutes ambulatory, sedentary durations, walking speed
• sleep times, social interactions
• time spent before leaving house, “diameter of day”...

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- **Higher level individual markers:**
  - fuse features, metrics into ‘marker’
  - assessing persons state, variations
  - fatigue, pain, depression, insomnia, cognitive function...
  - in-person variance, patterns, correlations

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Estimate personally- and clinically-useful information:
- modular layered processing
- ranging from simple functions to machine learning classifiers

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from phones to fitbits...
from chronic pain to depression...
from mobility to text...

w/ Ramanathan, Longstaff, Alquaddoomi, et al
Example biomarkers for chronic pain medication management

**Minutes ambulatory per day**

![Graph showing minutes ambulatory per day](image)

**Walking periods > 6 minutes per day**

![Graph showing walking periods > 6 minutes per day](image)

**Hours spent at home per day**

![Graph showing hours spent at home per day](image)

**Time left home (AM)**

![Graph showing time left home (AM)](image)
rephrasing ‘does it work?’

(Complexes of) Exposures
sertraline

strength of association?
individual

Outcome
depression

population
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‘does it work on average?’ (RCT)

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Depression (PHQ-9)

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N-of-1 study design: ‘does it work for Mr. Jones?’

Effexor

PHQ-9

Zoloft

Effexor

Zoloft

Effexor

Sim, Kravitz

Broad potential use of activity based behavioral biomarkers
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By patient

• to inform behavior change apps/social media
• in quantified self/PEA exercises around “what causes this change”, is this helping, self-administered medication dosage
• to drive just in time tool apps like PTSD coach
• as context stream for adaptive UI
Broad potential use of activity based behavioral biomarkers

By the clinician
- to inform treatment progress
- detect relapse/recovery, etc;
- clinical research evidence (trials, outcomes, ...)

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Across a range of use cases
- depression, adhd, insomnia, trauma
- chronic pain, IBD, asthma, migraines
- integrative medicine effectiveness
- behavior change for physical activity, substance use
Role in personalized medicine?

discovery (phenotype data) and delivery (data for patient and clinician)
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Technology side is ready to start

• Hardware is available and already in peoples hands and budgets.
• Software has been prototyped, and its not *rocket science*.
• Algorithms can iteratively (and rapidly) improve with use
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- how to use the data
  - look for each individuals relevant patterns/correlations/etc)
  - collect evidence on effectiveness (clinical-outcomes and behavior)
Open architecture and community modularity, shared architecture, analytics-driven iterative design

non-profit with seed funding from RWJF (project of Tides center, incubator)

Estrin, Sim, et al

http://openmhealth.org
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- no one (group/research or commercial entity) can do it all well, now and over time

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