# Hype or Revolution? How M-Health is finding its way into Mental Health mainstream research and clinical care

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Executive Lead,
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University of Toronto

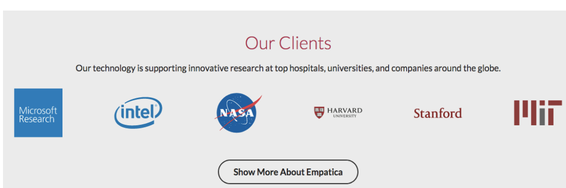

M. Scott Brauer

The story behind embrace…

In 2007, Prof. Picard's team at the MIT Affective Computing Lab was working on a wearable device that could measure skin conductance  and stress….  to help children with autism spectrum

empatica


embrace
HELPS PEOPLE LIVING
WITH EPILEPSY.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E4
Battery life
Streaming Mode: 20+hrs
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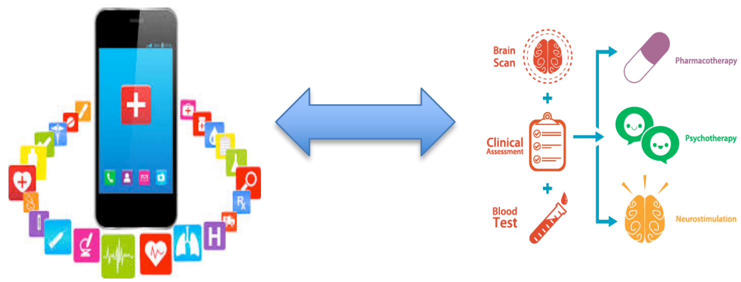
Data Management
Flash memory
Bluetooth LE (Smart)
Form Factor
Small and comfortable
Case: 44 mm x 40mm, height 16 mm
Weight: 25 gr
Event Mark Button
Certification
CE certification
FCC certification
Sensors
Photoplethysmography (PPG)
Continuous Heart Rate (HRV, Stress, Relaxation)
3-axis Accelerometer
Movement, Activity
Temperature + Heat flux
Activity, Context
Electrodermal Activity (EDA)
Skin conductance (Arousal, Excitement)
Measure both branches of the autonomic nervous system.
Electrodermal Activity
Continuous Heart Rate


YOUR
embrace
STORIES

# What Can We Expect from M-Health?




- ○ **Info gathering**
- ○ community and clinic data
- ○ **Delivery & management of health care**
  - ○ Guidance for & enhancement of measurement-based care
- ○ **Real-time monitoring**
  - ○ Ecological momentary assessments (EMA)
  - ○ Passive, behavioral or context-sensing

# Digital Health (FDA, 2017)

*Any mobile health, health information technology, wearable devices, telehealth, telemedicine and personalized medicine.*

Digital medicine devices either touch the surface of a person's body, or are ingested, inserted or implanted into the body. They also record information that can be stored, tracked, and shared.

- Data collection, management and analysis
- Emerging forms combine device technology with medication

FDA U.S. FOOD & DRUG ADMINISTRATION

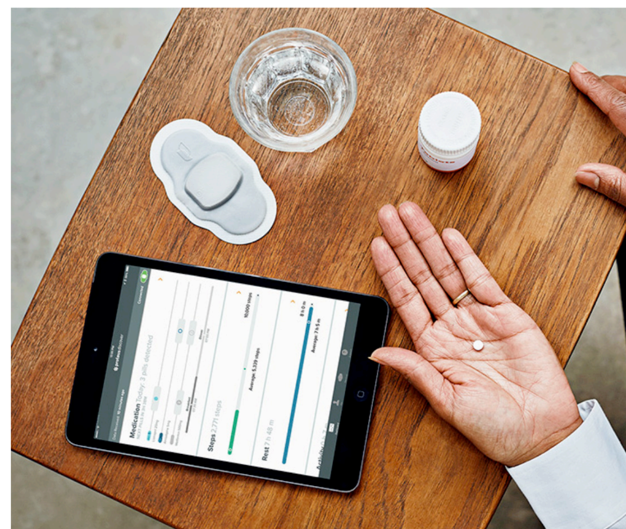
FDA NEWS RELEASE

# FDA approves pill with sensor that digitally tracks if patients have ingested their medication

ABILIFY MYCITE® is a drug -device combination of aripiprazole embedded with Proteus' ingestible sensor that communicates with Proteus' wearable sensor patch, and a smartphone application. The product measures ingestion of ABILIFY MYCITE® and patient activity, rest and mood.

## How does Proteus Discover work?

Proteus Discover consists of an ingestible sensor the size of a grain of sand, a small wearable sensor patch, an application on a mobile device and a provider portal. The patient activates Proteus Discover by taking medication with an ingestible sensor. Once the ingestible sensor reaches the stomach, it transmits a signal to the patch worn on the torso. A digital record is sent to the patient's mobile device and then to the Proteus cloud where with the patient's permission, healthcare providers and caregivers can access it via their portal. The patch also measures and shares patient activity and rest.



# Digital Phenotyping

- **Definition -** "Moment-by-moment quantification of the individual-level human phenotype using data from personal digital devices"

- **Rationale** Individuals might leave behind a footprint of their health status through use of technology

Activities through Social media
Online communities
Wearable technologies
Mobile devices

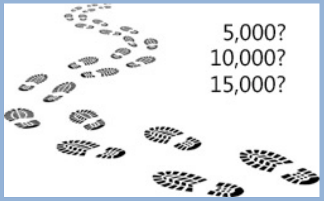
# Potential Advantages of Incorporating Digital Phenotyping into 'mainstream' Clinical Care and Research

- DP allows a better capture of the lived experiences of subjects, and their interactions with the surrounding world...

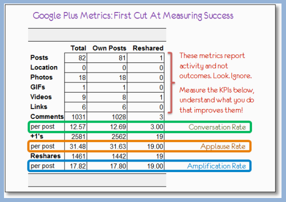
  - With minimal interference
  - Documenting experiences leading to/following key events
  - Active and passive data

# Behavioral Sensing Measures

Number of steps




Number, type of communications



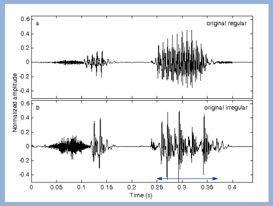
Google Plus Metrics: First Cut At Measuring Success

| | Total | Own Posts | Reshared | |
|---|---|---|---|---|
| Posts | 82 | 81 | 1 | |
| Location | 0 | 0 | 0 | |
| Photos | 18 | 18 | 0 | |
| GIFs | 1 | 1 | 0 | |
| Videos | 9 | 8 | 1 | |
| Links | 6 | 6 | 0 | |
| Comments | 1031 | 1028 | 3 | |
| per post | 12.57 | 12.69 | 3.00 | Conversation Rate |
| +1's | 2581 | 2562 | 19 | |
| per post | 31.48 | 31.63 | 19.00 | Applause Rate |
| Reshares | 1461 | 1442 | 19 | |
| per post | 17.82 | 17.80 | 19.00 | Amplification Rate |

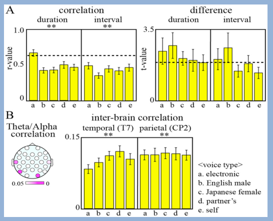
These metrics report activity and not outcomes. Look. Ignore.

Measure the KPIs below, understand what you do that improves them!

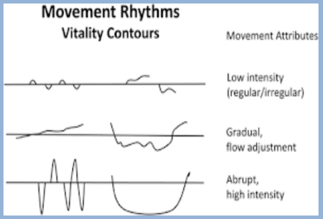
Duration of Speech



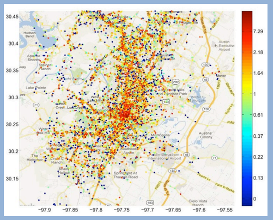

Rhythms of voice




Rhythms of Movement




Location Entropy



# Incorporating Digital Phenotyping into 'Mainstream Research'

## Challenges

- Skepticism - health researchers are 'laggards', not early adopters…
- Concerns around privacy and confidentiality
- Ethical concerns, reinforcing inequalities
- What are the appropriate metrics? Novel endpoints?
- Customizable? Scalable?
- Statistical methods for analyzing, modeling data
- Reliability of mobile apps


the
APPS
market

# CAN-BIND Integrated Platforms

## Clinical Outcomes

- Clinician administered scales
- Patient-reported outcomes
- Electronic data capture

## Molecular Profiling

- Gene expression
- SNP analysis
- GWAS
- SRM-MS
- Whole genome miRNA
- Redox, methylation

## Preclinical

- Rodent anhedonia models
- Zebrafish high-throughput
- Pharmacology & electrophysiology

## M-Health

- Behavioural Sensing
- Ecological momentary assessments

## EEG

- Resting state, eyes open
- Resting state, eyes closed
- Various functional tasks

## Neuroimaging

- T1-weighted anatomical scan
- DTI series
- T2-weighted BOLD EPI series
- BOLD EPI series during tasks

## Data Science

- Statistical tools coupled with machine learning tools to create biomarker models

## Knowledge Translation

- Public and provider education
- Patient Advisory Committee
- Social media strategy
- Implementation science

## CAN-BIND and HealthRhythms Program for Research

Ultimately, we hope to be able to:

- **Quantify prodromal symptoms prior to relapse** versus sustained wellness
- **Measure patient behavior** in the context of interventions
- **Characterize digital biomarkers** across patient segments
- **Cross validate novel endpoints** against traditional markers - clinical, imaging, molecular

| Prediction Score | Subj01 | Subj02 | Subj03 | Subj04 | Subj05 | Subj06 | Subj07 | Subj08 | Subj09 | Subj10 | Subj11 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| MAE - RF | 0.62 | 1.37 | 1.1 | 1.36 | 1.32 | 0.74 | 2.6 | 0.9 | 1.11 | 1.83 | 1.1 |
| % Error | 12.4 | 15 | 12.1 | 15 | 13.2 | 20 | 23.6 | 18 | 10.5 | 9.9 | 10 |

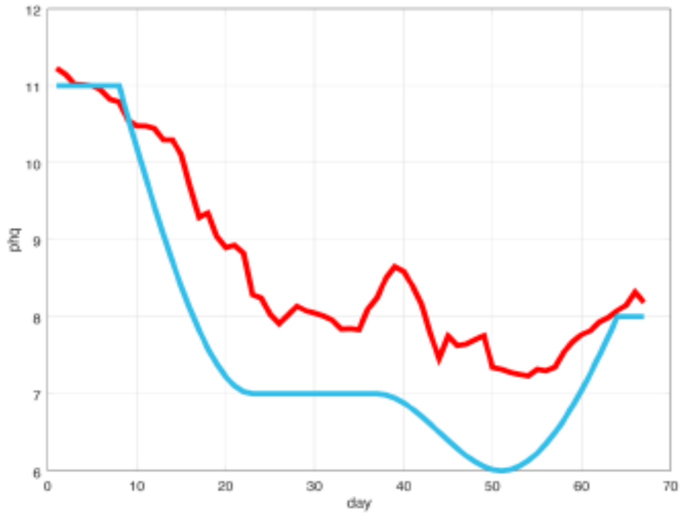



**Figure 3. Predicted (Red) vs. Actual PHQ Scores (Blue): Participant 01**

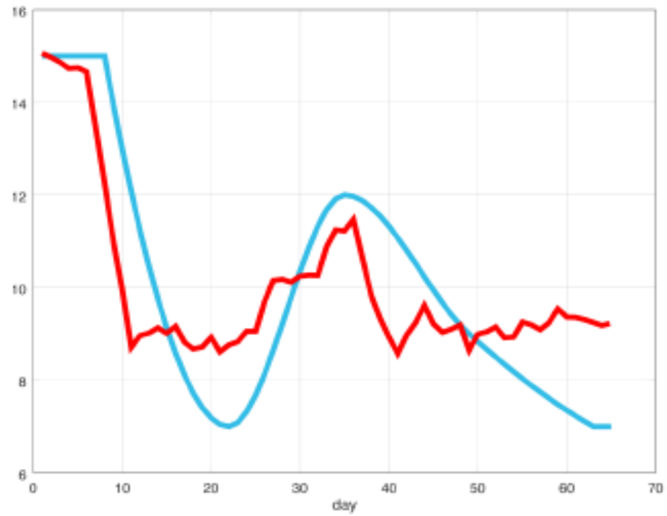



**Figure 4. Predicted (Red) vs. Actual PHQ Scores (Blue): Participant 04**

ARTICLE

# Relapse prediction in schizophrenia through digital phenotyping: a pilot study

Ian Barnett[1], John Torous[2,3], Patrick Staples[4], Luis Sandoval[2], Matcheri Keshavan[2] and Jukka-Pekka Onnela[4]

- 17 subjects with schizophrenia in active treatment at a state mental health clinic in Boston
- Active and passive data
- Beiwe app on their personal smartphone for up to 3 months

Anomalous breaks from a patient's usual trend in self-reported outcomes, sociability or mobility may be indicative of broader behavioral changes, could precede adverse events such as relapse

*Neuropsychopharmacology* (2018) 43:1660–1666; https://doi.org/10.1038/s41386-018-0030-z

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**Table 2.** Listing of 6 survey question categories, 15 mobility features, and 16 sociability features

| Survey question categories | Mobility features | Sociability features |
|---|---|---|
| 1. Depression | 1. Time spent at home | 1. Number of outgoing texts |
| 2. Sleep quality | 2. Distance traveled | 2. Total outgoing text length |
| 3. Psychosis | 3. Radius of gyration | 3. Texting out-degree |
| 4. Warning symptoms scale | 4. Maximum diameter | 4. Number of incoming texts |
| 5. Taking medication | 5. Maximum distance from home | 5. Total incoming text length |
| 6. Anxiety | 6. Number of significant locations | 6. Texting in-degree |
| | 7. Average flight length | 7. Texting reciprocity |
| | 8. Standard deviation of flight length | 8. Texting responsiveness |
| | 9. Average flight duration | 9. Number of outgoing calls |
| | 10. Standard deviation of flight duration | 10. Total outgoing call duration |
| | 11. Fraction of the day spent stationary | 11. Call out-degree |
| | 12. Significant location entropy | 12. Number of incoming calls |
| | 13. Minutes of GPS data missing | 13. Total incoming call durations |
| | 14. Physical circadian rhythm | 14. Call in-degree |
| | 15. Physical circadian rhythm stratified | 15. Call reciprocity |
| | | 16. Call responsiveness |

Each mobility and sociability feature is calculated each day for each patient. For each survey question category, a category score is produced for each day the surveys were administered by averaging the score across all questions answered from that category, where each survey question is scored from 0 to 3. Mobility feature 15 is stratified by weekend day vs. week day. Detailed descriptions of mobility feature definitions can be found in Canzian and Musolesi [35]. In sociability features, text length is quantified as the number of characters in the text messages, so for example, sociability feature 2 is the sum of the number of characters in text messages over each day. Further, we use the social network term "degree" to refer to the number of distinct communication partners. For example, sociability feature 6, texting in-degree, corresponds to the number of individuals who have sent a text message to the subject on the given day.

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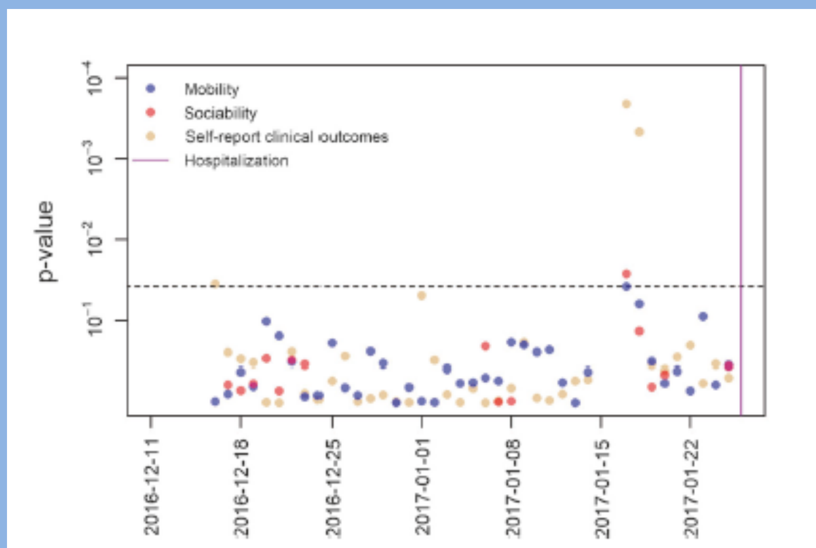


Of the **3 subjects who experienced relapse** with sufficient data, **the rate of anomalies detected in the 2 weeks prior to relapse** was **71% higher** than the rate of anomalies detected in dates further away from relapse

Draft for Body Sensor Networks 2015

Recognizing Academic Performance, Sleep Quality, Stress Level, and Mental Health using Personality Traits, Wearable Sensors and Mobile Phones

Akane Sano*1, Andrew J. Phillips*2, Amy Z. Yu*1, Andrew W. McHill*2, Sara Taylor*1, Natasha Jaques*1, Charles A. Czeisler*2, Elizabeth B. Klerman*2, Rosalind W. Picard*1

**Machine Learning of Sleep and Wake Behaviors to Classify Self-Reported Evening Mood**

Sara Taylor[1], Natasha Jaques[1], Akane Sano[1], Asaph Azaria[1], Asma Ghandeharioun[1], Rosalind Picard[1]

mit media lab

[1] Media Lab, Massachusetts Institute of Technology, Cambridge, MA, USA
*(sataylor,jaquesn,akanes,azaria,asma_gh,picard)@media.mit.edu*

**Introduction**

The SNAPSHOT Study is a large-scale and long-term study that seeks to measure: Sleep, Networks, Affect, Performance, Stress, and Health using Objective Techniques.

This study investigates:
(1) how daily behaviors influence sleep, stress, mood, and other wellbeing-related factors
(2) how accurately we can recognize/predict stress, mood and wellbeing
(3) how interactions in a social network influence sleep behaviors.

In this work we investigate the use of machine learning methods, using sleep and wake data, to predict mood.

We seek to model behavioral patterns to predict these downturns in mood and begin to understand what will help build resilience to depression.

**Data Collection**

68 Undergraduate Students
Age 18-25, 47 males
~30 day study [1]

Data collected from:
- Wearable Sensors
- SMS and Call Logs
- Smartphone Use
- Smartphone Location
- Self-reported daily activities and behaviors

snapshot.media.mit.edu

**Results**

Many features were computed and evaluated over sleep and wake, including:
- Skin Conductance metrics (median, st.dev., area under the curve)

*Fig 1: Skin conductance signal*

- Smartphone Screen-on durations
- Number of SMS and Calls sent and received

*Fig 2: Number of SMS messages colored according to evening mood*

- Time Spent Indoors
- Normality of the day

*Fig 3: Probability distribution of one participant's locations. Blue areas are more likely.*

Combinations of these features achieved 68% accuracy for classifying evening happiness

This happiness classification accuracy is improved to 72% when we multi-task over several labels [2]

**Conclusions**

- Features between midnight and 8am were particularly informative for classifying evening mood.
- Automated machine learning, applied to nightly data from sensors and smartphones, shows value for predicting college student's mood the following evening.
- There is potential value in using objective sleep hygiene data for understanding mood progression.

**Future Work**

- Integrate more data. We have now collected data from over 200 students.
- Account for individual differences. Currently, our models group all participants together during classification. We now have new methods where we can leverage data from across the population and account for individual differences at the same time.

**Support**

Thanks to Dr. Charles Czeisler, Dr. Elizabeth Klerman, Dr. Cesar Hidalgo, Dr. Andrew Phillips, Dr. Andrew McHill, Dr. Laura Barger, Amy Yu, Conor O'Brien, Justin Buie and Salim Qadri for their help in running the SNAPSHOT study. This work was supported by the MIT Media Lab Consortium, NIH Grant R01GM105018, Samsung, and Canada's NSERC program.

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Can we recognize or predict stress, mood, and wellbeing and how interactions in a social network influence sleep behaviors?

# Results from SNAPSHOT

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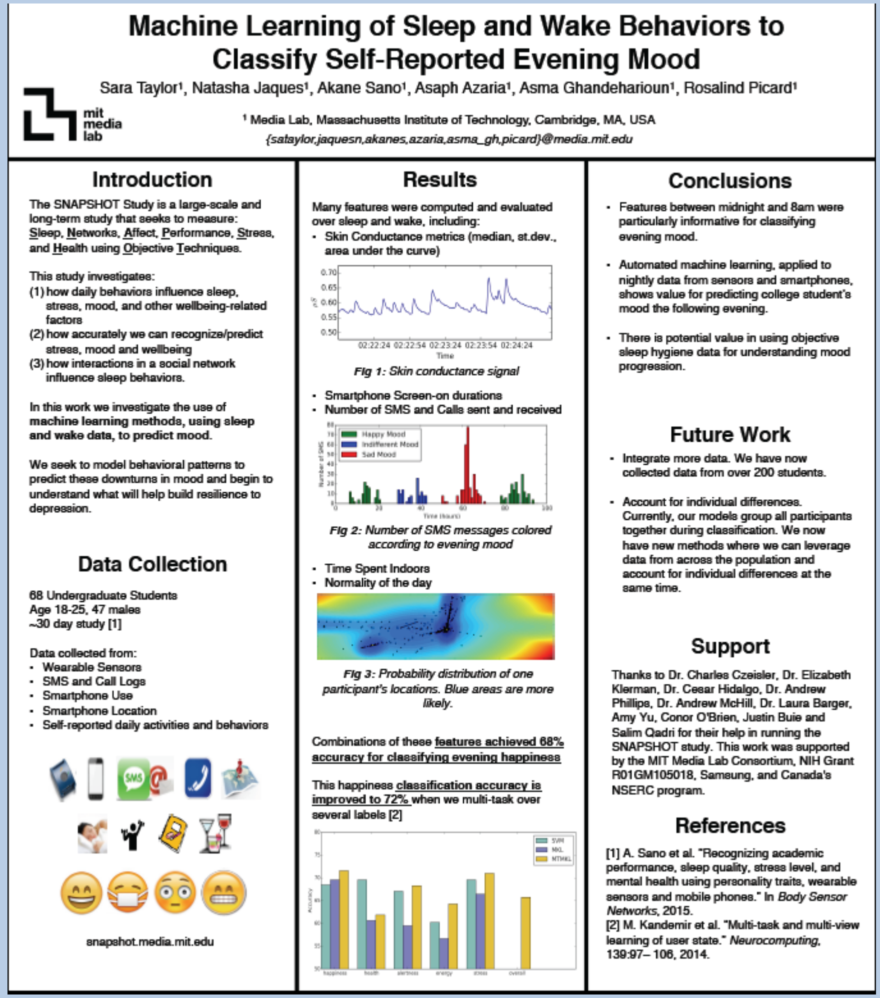

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# Integrating digital phenotyping in clinical characterization of individuals with mood disorders

Elisa Brietzke[a], Emily R. Hawken[a], Maia Idzikowski[a], Janice Pong[b], Sidney H. Kennedy[c], Claudio N. Soares[a,d,*]

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**Table 1**
Main applications of digital phenotypes to be explored in research in mood disorders.

| Objective | Inter-individual variability | Intra-individual variability |
|---|---|---|
| Diagnosis | Comparison with healthy controls and between diagnoses | Detect mild and subsyndromal manic/depressive symptoms |
| Clinical characterization | Assessment of RDoC dimensions | Detection of nuances, symptoms variability and granularity |
| Course of illness | Detection of subgroups of patients (sample stratification) | Prediction of critical outcomes in illness course (relapse, recurrence, resilience) |
| Treatment response | Prediction of response, non-response and remission | Early detection of response, non-response and remission |
| Treatment tolerance | Identification of predictors of side effects (e.g. use of sedative agents and patients with hypersomnia) | Early, objective and reliable identification of side-effects. |
| Prevention | Identification of high-risk groups | Prediction and prevention of chronic and multi-episodic presentations versus wellness |
| Biomarkers approach | Traits | States |

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# Research project(s)

- Digital phenotyping incorporated into clinical trials
  - Early changes that could identify/predict poor/good response
  - Variability/sustainability of treatment response over time – predictors of resilience or sustained wellness
  - New outcome measures - high correlation with standard measures…but within the context of participant's daily routine

- Digital phenotyping incorporated into biomarker validation studies
  - Composite/algorithm to understand intra-individual variability over time
  - Better understand response, relapse, sustained wellness

# The Division of Digital Psychiatry

AT THE BETH ISRAEL DEACONESS MEDICAL CENTER

PROJECTS

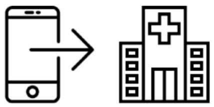
# Digital Clinic

John Torous, MD MBI
DIRECTOR

The Digital Clinic represents direct implementation and service delivery of digital mental health. In the learning healthcare system model, our team constantly collects feedback and works to improve our implementation with the goal of increasing quality of care as well as access.

# The Division of Digital Psychiatry

AT THE BETH ISRAEL DEACONESS MEDICAL CENTER



Digital Clinic

Digital Relapse Prediction

Digital Opportunities for Outcomes in Recovery Services

# Funding support from

- Ontario Research Fund, Research of Excellence (ORF-RE)
- Queen's University
- SEAMO Innovation Research Awards
- Ontario Brain Institute (OBI)

Ontario
Research Fund

Queen's
UNIVERSITY

SEAMO
Southeastern Academic Medical Organization

ONTARIO BRAIN INSTITUTE
INSTITUT ONTARIEN DU CERVEAU