The Science of Behavior Change

Applying Novel Technologies and Methods to Understand Trans-Behavioral Self-Regulation

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Targets of Behavior Change

• Health risk behavior -- including poor diet, physical inactivity, tobacco and other substance use, non-adherence to medical regimens -- causes as much as 40% of the illness, suffering, and early death related to chronic diseases.

• Interventions targeting health behavior may have a robust impact on health outcomes – including associated morbidity and mortality

• Although an array of interventions has been shown to be effective in promoting health behavior change, much of this work has been siloed (e.g., one disease/disorder/behavior at a time).
Targets of Behavior Change

• Many interventions are intended to engage multiple mechanisms of behavior change, although mechanisms are infrequently examined.

• Mechanisms refer to intervention-induced changes in psychological, behavioral, and/or biological factors, which are in turn responsible for health behavior change.
The need to alter health behavior is ubiquitous across medicine.

Understanding the extent to which the principles of effective health behavior change are similar or different across health conditions and settings is an important area of scientific inquiry.

This will aid in an understanding of the conditions under which intervention effects are vs. are not replicable.
Targets of Behavior Change

• One particularly promising explanatory construct related to health behavior across many populations and types of health behavior is that of self-regulation.

• Self-regulation refers to a person’s ability to manage cognitive, motivational, and emotional resources to act in accordance with his/her long-term goals – Impacted by many intrapersonal and contextual (e.g., social) factors.

• A large literature has identified self-regulation as a potential causal mechanism in health behavior (and deficient regulation as a potential mechanism in health risk behavior)
**Targets of Behavior Change**

- Interventions designed to promote self-regulation have shown tremendous promise across diverse populations.
  - Offer tools to aid in identifying and engaging in goal-directed behavior
  - Learning new skills and lifestyle changes consistent with one’s goals
  - Reinforcing successes in behavior change
The scientific literature has shown that science-based approaches to health behavior change often transcend many areas of health.

Common “trans-disease” processes in self-regulation are also evident in neuro-behavioral research reflecting commonalities in underlying brain circuitry and circuit dysfunction associated with an array of health disorders.

(e.g., circuits related to inhibition of actions; value systems in risk taking)
Challenges

Despite the promise of this line of research, many opportunities exist in this line of scientific inquiry.

• **Challenge 1.** A broad set of constructs of self-regulation have been studied across multiple siloed literatures with little crosstalk.

  - Psychological constructs such as impulsivity; cognitive homeostasis
  - Affective/social psychology constructs such as emotion regulation processes and resource models
  - Health psychology/behavioral medicine constructs of self-efficacy/outcome expectancy
  - Behavioral measures of behavioral disinhibition and temporal discounting
  - Neural constructs of top-down control (from frontal-parietal networks) vs. impulsive drives (from subcortical and ventromedial prefrontal regions)
Challenges

- **Challenge 2.** Research examining mechanisms has tended to examine a small set of potential mechanisms at a specific level of analysis (e.g., brain or behavior) – may oversimplify our understanding of behavior.

- **Challenge 3.** Many models of self-regulation have regarded human behavior as linear and static and haven’t recognized behavior is dynamic and responsive to diverse social, biological and environmental contexts.
Towards a Data-Driven Ontology of Self-Regulation

• We are using a systematic, empirical process to integrate concepts across the divergent self-regulation literatures to develop an overarching “ontology” of self-regulatory processes.

• Goals:

  ➢ Demonstrate that self-regulatory function can be measured at psychological, behavioral, and neural levels

  ➢ Identify empirically-derived relationships between resulting data sets and from these levels of analysis

  ➢ Create an ontological framework of self-regulation and tasks used to measure self-regulatory function
Towards a Data-Driven Ontology of Self-Regulation

- 522 participants completed 38 tasks, 23 surveys, and a number of "real world outcome" surveys on Mechanical Turk - 10 hour battery

- Included measures of self-regulatory domains related to risk-taking, temporal discounting, impulsivity, emotion regulation, etc.

- Also extended into more generic cognitive domains like working memory, processing speed, learning, and others

(Eisenberg et al., 2017; Under Review)
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<td>19. Kirby delay-discounting task</td>
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Participant Characteristics

- 50.1% male
- 85% white
- Mean age 33.6 (range 20-59 years)
- 24.5% have children
- 34% report lifetime psychiatric history
- 19% depression
- 5% anxiety
- 3% ADHD

- 30% with BMI>30 (obese)
- 27% current smokers
- Cannabis use:
  - 15% (at least once/month)
  - 10% (daily)
- Alcohol use:
  - 20% (+1 times/week)
  - 5% heavy drinkers
  - (3+drinks, 4+ times/wk)
Analyses

• This project allowed us to evaluate constructs arising from diverse research domains within the same analytic space -- allowing for theoretical synthesis and distillation.

• We first defined a “cognitive space” that provides a parsimonious low-dimensional representation of the task and survey data using exploratory factor analysis (EFA).

• This provides a quantitative notion of psychological distance, affords clustering across measures, and provides a consistent vocabulary to describe disparate behavioral measurements.
Results

• Using model selection based on Bayesian information criterion (BIC), we found 5 and 12 factors were the optimal dimensionalities for the decomposition of tasks and surveys, respectively.

• The sub-metrics we derived from tasks loaded into 5 dimensions (factors) that define the complete task space:

  1. **Caution** (a factor denoting how much one trades speed vs. accuracy)
  2. **Perception/Response** (a factor denoting time to complete tasks that are not decision-making tasks)
  3. **Speeded Information Processing** (a factor denoting performance when making quick decisions)
  4. **Discounting** (a factor that largely denotes discounting of delayed rewards)
  5. **Strategic Information Processing** (a factor that captures working memory, intelligence, etc.).
Twelve factors emerged from the survey data and reflect our empirically informed categorization schema for all surveys:

(1) Sensation Seeking  
(2) Mindfulness  
(3) Impulsivity  
(4) Emotional Control  
(5) Reward Sensitivity  
(6) Goal-directedness  
(7) Risk Perception  
(8) Eating Control  
(9) Ethical Risk-taking  
(10) Social Risk-taking  
(11) Financial Risk-taking  
(12) Agreeableness
Overall, self-regulation does not appear to be comprised of 61 distinct constructs (as measured by the 38 distinct tasks and 23 distinct surveys) but can be reduced into many fewer empirically-derived dimensions (5 for tasks; 12 for surveys).

Hierarchical clustering on the factor loadings revealed:

- **For Survey Factors**: A self-control branch composed of two separate clusters: one primarily related to **impulsivity** and the other reflecting **long-term goal attitudes/time perspective**.

- **For Task Factors**: Two clusters composed of “**strategic information processing**” vs. “**speeded information processing**”
Results

• Behavioral tasks and self-report surveys are entirely independent.
  
  ➢ Cross-validated prediction of one from the other is no better than chance
  ➢ The largest task-survey correlation is ~.2

• Measures thought to have mechanistic specificity in the literature may have low predictive validity and weak psychometrics and/or may tap into similar constructs as other measures.
We predicted individual real-world health behavior (e.g., alcohol use, mental health), with factor scores derived from the task and survey EFA solutions as our input features.

Surveys performed much better, predicting about 30% of the variance in mental health, 14% of variance in obesity, and 12% of variance in binge drinking.

Thus, these putative targets of self-regulation predicted multiple types of health behavior.

In contrast, tasks had almost no predictive ability (except for the temporal discounting tasks, which only predicted ~2% of the variance on 3 target factors).
Ontology of Self-Regulation

• The ontology does more than provide a parsimonious description underlying self-regulation and a large-scale "behavioral geometry" of the mind.

• We are assessing:
  
  ➢ which assays are optimal measures of self-regulation  
    (http://scienceofbehaviorchange.org/measures)
  
  ➢ what their neural underpinnings are  
    (to have an ontology that is behaviorally and neurally valid)
  
  ➢ how increasing self-regulation impacts health behavior across populations
Towards a Data-Driven, Contextual Model of Self-Regulation

• Yet, this work alone only provides a snapshot of self-regulatory processes.

• Health behavior is dynamic and responsive to diverse social, biological and environmental contexts (across and within individuals)

• Choices we make about health behavior are made in every day life.

• More frequent and longer assessment of moderators, mediators, and outcome(s) are necessary to elucidate the temporal dynamics between changes in specific mechanisms and behavior.
Advances in digital technologies and data analytics have created unprecedented opportunities to assess and modify health behavior and thus accelerate the ability of science to understand and contribute to improved health.

New opportunities to examine within-person differences in health behavior via:

- intensive collection of individual-level data using mobile devices
- wearable sensors
- continuous monitoring
- mapping digital footprints of online social media activities
- digital phenotyping
Promise of Digital Technology

• These rich physiological, behavioral, intrapersonal and social data can be collected on a longitudinal basis, in many contexts, and as individuals move through their daily lives.

• Increasingly sophisticated data analytics can turn these rich data into meaningful insights about individual health:

  ➢ **Network analysis** (topology and structure of social media networks)
  ➢ **Natural language processing** (social communications that may influence intrapersonal context and other features that impact health/risk behavior)
  ➢ **Dynamic structural equation models** (time-varying relationships among intensive longitudinal data and enable integration of multiple types and sources of digital health data analytic methods to glean new insights into dynamic factors that influence health behavior)
Digital Health can inform a data-driven
Contextual model of self-regulation

• Virtually any population you can think of has access to mobile technology.

• There are more mobile phone subscriptions in the world than there are people in the world.

• Digital health refers to the use of mobile technology to both understand people’s health related behavior and provide personalized health care resources in unprecedented ways.
Theoretical Contextual Model of Self-Regulation

Broader Context

Person-Level Dispositions and Characteristics
- Severity of risk behavior
- Cognitive functioning
- Motivation to change risk behavior
- Stage of change
- Average frequency/quantity of risk behavior
- Physical and mental health conditions
- Self-regulation styles
- Race, ethnicity, age, gender
- Past trauma

Immediate Situational Context

Fluctuating Internal States
- Urges to perform risk behavior, motivation to perform risk behavior, motivation to avoid risk behavior, intention to perform risk behavior, guilt, perceived stress, positive/negative affect

Momentary Self-Regulatory Behavior

Fluctuating Features of External Environment
- Location, exposure to negative behavior cues, access to cigarettes/alcohol/food, barriers and facilitators to engage in risk behavior, day of week, time of day

Environmental Conditions
- Access and exposure to treatment resources
- Social support
- Socioeconomic status

Major Life Events
- Death of a loved one
- Divorce
- Physical, sexual, or emotional abuse
- Serious accident or illness
- Other traumatic events

Roos & Witkiewitz, 2017
Digital technologies enable an entirely new offering of tools for:

- Collecting rich data about people’s behavior, health, and environment
- Providing personalized interventions and resources based on individuals’ needs and preferences
- Enabling dynamic computational models to predict and respond to people’s changing needs, goals, and health trajectories over time.

Digital Health can inform a data-driven Contextual model of self-regulation
The Center for Technology and Behavioral Health (CTBH) is a national research center designed to use science to inform the development, evaluation, and sustainable implementation of a wide array of digital technology-based tools for substance use disorders and related issues (including mental health, HIV, chronic pain), as well as health behavior broadly (including obesity, diabetes, etc.).
Research with many populations, including children, adolescents, young adults, chronic substance users, smokers, chronic pain patients, veterans, persons with co-occurring addiction and mental illness, persons living with HIV, prescription opioid abusers, and persons with chronic physical health conditions (e.g., obesity, diabetes, hypertension)

In many contexts, including addiction and mental health specialty programs, medical specialty programs, hospitals, schools, criminal justice settings, primary care, and direct to consumer online
CTBH’s research is guided by the stage model for technology-based intervention development and evaluation, (e.g., basic research; tests of feasibility, acceptability, comprehensibility; efficacy trials in research systems; “real world” effectiveness trials, including multi-site effectiveness and cost-effectiveness trials; and implementation research projects)

Basic science is infused through every stage focused on mechanisms of action.

Designed to create maximally potent and implementable interventions

Stage Model of Intervention Development

Developed a novel “momentary self-regulation” scale, which measures self-regulation on a momentary basis as individuals move through their lives (administered via mobile devices).

We used item-response theory to reduce 594 self-regulation items from our large Mturk study to 116 items.

We then performed exploratory factor analyses to narrow the set to 20.

Confirmatory factor analysis revealed a 4-factor solution:

(1) perseverance/impulsivity
(2) sensation seeking
(3) emotion regulation
(4) mindfulness/acting with awareness

(Kim et al: Under Review)
Momentary Self-Regulation Measure

• We modified 20 items for momentary use (e.g., “I usually think carefully before doing anything” to “Since the last prompt, I have thought carefully before doing anything”.)

• We enrolled n=60 in a pilot momentary self-regulation study via MTurk.

  We collected 14 day micro-surveys through text message prompts (42 timepoints per participant of repeated self-regulation survey items)

• We conducted psychometric analyses to finalize survey items, comprised of 12 items (four 3-item subscales)

(Kim et al: Under Review)
• In a separate study (with n=50 heavy smokers and n=50 obese individuals with binge eating disorder), we demonstrated the momentary self-regulation measure is sensitive to capturing within-individual temporal dynamics in self-regulation (in contexts that promote/fail to promote self-regulation) and related to multiple health domains.

(Scherer et al., In Preparation)

• This empirically-derived, momentary self-regulation assessment is the first of its kind.

This novel metric practically operationalizes and empirically examines self-regulatory processes and dynamics in a naturalistic setting and can be implemented through mobile devices for EMA.
Digital Therapeutics

- ↓ Drug use
- ↑ Retention in Addiction Treatment
- ↓ Aberrant opioid use
- ↓ Pain-related ED Visits

Transform healthcare
Service delivery models

Healthcare
Reform
Laddr® Self-Regulation
Mobile Platform

• Laddr is the only mobile platform that employs the fundamental principles behind the science of behavior change to apply to a broad array of interrelated health/life domains based on individuals’ goals and needs.

• Laddr® offers science-based health behavior change tools via an integrated platform to target a wide range of behavioral problems, including smoking, binge eating, alcohol use, drug use, depression, panic, anxiety, etc.

• Laddr is informed by over 20 years of NIH-funded research and dozens of randomized trials.

Square2 Systems, Inc.
Active Ingredients

**Future Orientation**
Exercises establish the user’s core values and high level goals to improve motivation and decision making.

**Trigger Identification**
Users learn about behavior chains. They identify triggers for relapse using functional analysis.

**Trigger Remapping**
Users remap default trigger responses (i.e. substance use) to healthy responses recommended by Laddr.

**Tracking Activities**
Users cultivate healthy, rewarding activities critical to Behavioral Activation and CRA.

**Goal Setting & Problem Solving**
Users learn to set goals and problem solve using techniques laid out in PST and CBT.

**Challenging Negative Thoughts**
Users employ techniques from CBT to challenge cognitive distortions and dispel maladaptive beliefs.

**Coping Skills**
Users learn refusal skills, relaxation skills and relationship skills.

**Exposure Therapy**
Imaginal, in vivo and Interoceptive exposure therapy tools help users manage anxiety and panic.
Summary/Next Steps

• Tremendous opportunity to address systemic obstacles in delivering science-based approaches to healthcare that transcend disease/behavior, population, and context, enabling a generalizable, replicable, and scalable solution

• Digital health approaches are providing a new understanding of trans-behavioral self-regulation across many populations and contexts.

• Self-regulation tools offered on mobile platforms enable widespread reach and scalability of effective interventions (with goal of being maximally potent and implementable).

• This line of research may allow us to make great strides in crafting “precision medicine” approaches for a wide array of populations.
Thank you!

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