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ESSAY

Building new computational models to support health behavior change and maintenance: new opportunities in behavioral research

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Abstract
Adverse and suboptimal health behaviors and habits are responsible for approximately 40 % of preventable deaths, in addition to their unfavorable effects on quality of life and economics. Our current understanding of human behavior is largely based on static "snapshots" of human behavior, rather than ongoing, dynamic feedback loops of behavior in response to ever-changing biological, social, personal, and environmental states. This paper first discusses how new technologies (i.e., mobile sensors, smartphones, ubiquitous computing, and cloud-enabled processing/computing) and emerging systems modeling techniques enable the development of new, dynamic, and empirical models of human behavior that could facilitate just-in-time adaptive, scalable interventions. The paper then describes concrete steps to the creation of robust dynamic mathematical models of behavior including: (1) establishing "gold standard" measures, (2) the creation of a behavioral ontology for shared language and understanding tools that both enable dynamic theorizing across disciplines, (3) the development of data sharing resources, and (4) facilitating improved sharing of mathematical models and tools to support rapid aggregation of the models. We conclude with the discussion of what might be incorporated into a "knowledge commons," which could help to bring together these disparate activities into a unified system and structure for organizing knowledge about behavior.

Keywords

Mobile health, mHealth, Connected health, Health-related behavior, Just-in-time adaptive interventions, Real-time interventions, Computational models of behavior

INTRODUCTION

Adverse and suboptimal heath behaviors and habits are responsible for approximately 40 % of preventable deaths, in addition to their undesirable effects on quality of life and the global economy [1–4]. Although a solid empirical base exists for the effectiveness of interventions in initiating some behavior change [5–8], much less support exists for interventions that sustain behavior change or change some of the most challenging, yet prevalent, behaviors (e.g., smoking [9], poor diet and lack of physical activity [10, 11], and unsafe sex [7]). This may be due to the fact that current understanding of human behavior is largely based on static "snapshots" of human behavior [12], rather than ongoing, dynamic feedback loops of behavior in response to ever-changing biological, social, personal, and environmental states [13, 14]. Traditionally, the study of human behavior has postulated a set of concepts, definitions, and propositions that are meant to explain behavior by assuming the relationships between variables [15], often in terms of linear functions, and then subjecting parts of the theory to empirical testing. However, rich streams of continuous data are now becoming available through new and emerging technologies, including wearable and deployable sensors [16–19] and mobile phones [20–22]. This data, along with sophisticated modeling techniques, provide unprecedented opportunities to understand real-time behavior in context [12, 13, 23, 24]. The challenge to 21st health behavior change research is to move toward computational, dynamic modeling of behavior [25] that can capture complex and rapid changes in behavioral state and related influencing factors. To accomplish this challenge, we need to: (1) establish "gold standard" measures, (2) develop ontologies for current behavioral constructs, (3) facilitate improved sharing of mathematical models and tools to improve theory falsification and more rapid aggregation of models, and (4) create a "knowledge commons" that could help to bring together these disparate activities into a unified system and structure for organizing knowledge about behavior. This paper gives examples of a computational behavioral framework and highlights steps for the field to reach this potential and create new opportunities including development of new just-in-time interventions that are personalized, predictive, and responsive to moment-by-moment context, and drive bold changes in health promotion, disease prevention, and healthcare delivery in the next decades.

THE IMPERATIVE AND THE OPPORTUNITY: UNDERSTA NDING HUMAN BEHAVIOR IN REAL TIME

Observing and inferring behavior

What falls under the rubric of behavior, and what falls outside that rubric? This question continues to be a topic of hot debate [26–30]. Some behaviors are agreed upon and directly observable, such as (but not limited to) utterances, facial expressions, diet, smoking, safe sexual practices, sun safety, and exercise, although there are divergent opinions on methods for observation and measurement of these behaviors. However, focusing solely on these observable, proximal behaviors does not give the full picture of human behavior, nor does this narrow focus give us information on what we need in order to influence or change these behaviors [31]. The numerous influences upon behaviors are difficult to observe, and depend upon the behavior and situation at hand, including such factors as feelings, mental states, values, and motivations. Thus, we need to take into account the full range of *behaviors* and *influences upon these behaviors through real-time measurements of overt behavior, the environment (both social and physical) and self-report. Combined, these measurements will allow us to develop real-time measures and inferences of behavior, context, and internal states.* As a simple example, consider "Joe"–a 48-year-old, divorced man whose doctor has told him that he needs to lose weight because he is at risk for developing multiple health issues. Joe works long hours at a desk job in an environment where the closest food is at a fast food restaurant in the lobby of his building. Joe usually gets home from work late and generally does not feel he has the time or energy to engage in any physical activities. In the past, we would enroll Joe in a study that used the same intervention for all of the participants and that targeted changes in his activity behavior either directly (enrolling him in a physical activity program) or indirectly, such as by enhancing his perceived self-competence or motivation to exercise. But Joe's activity level is affected by many variables, the effects of which we (or he) may not even be fully aware. What used to be measureable only by resource-intensive direct observation or self report can now be "automated," allowing us to know what the individual is doing and in what context without having live coders watching their every move or having to ask repeatedly. Data streams from a broad variety of sources–mobile phones, sensors, social media, pictures and videos, location, purchase transactions, apps, internet use, and self-report, just to name a few, can, when aggregated [32, 33], provide an in-depth view of the person as they interact with the world around them. For example, using new technologies, internal events, or states (for instance increased stress) can be inferred from physiological measures [34] to augment self-report. Context, which includes external events, activity cues (such as, having his bicycle near the doorway to his garage), and social behavior, can be observed unobtrusively using a range of mobile devices and sensors [35–37]. Physical activity can be assessed using various sensors [38, 39]. By including all of these variables in real-time, we can develop a model of Joe's activity behavior (see Fig. 1) over time that can guide the development of a personalized intervention that is sensitive to his skills and environment in a way that has not been possible in the past. Further, by aggregating data from multiple sources, we can now develop computational models that can precisely specify the relationships between variables. These models can be subjected to rigorous mathematical testing, which opens new opportunities for empirically driven and computationally derived behavioral models that can be further tested, refined, and generalized.

The promise of dynamic mathematical models of behavior[1]

The development of computational models of behavioral change is now a key objective of many researchers to explain the mechanisms of behavior and actions of various behavioral interventions [13, 24, 41–43]. The goal is not to propose many models that are independent of one another, but rather to propose multiscale models that can be incrementally improved, expanded, and integrated. The ultimate goal is to have testable models of behavior with interoperable subcomponents that capture the complexity of behavior in the real world. The models can be developed ideographically and then validated against the behavior of large numbers of people in a wide variety of circumstances. Such models would be developed incrementally, with initial models only responding to small amounts of input capturing only certain aspects of behavior and interactions. Eventually, through

[1] It is important to note the difference in what is being described as a model. The term "theory" has been defined variously across various disciplines, but is defined here as a formalized set of concepts that organize observations and inferences, and is meant to predict phenomena (41. Graziano, A. and M. Raulin, *Research is a process of inquiry.* Research methods: a process of inquiry, 4th Edition. Allyn & Bacon, Needham Heights, MA, 2000: p. 28–53. The term "model", on the other hand, has been used by different disciplines to mean different things. There are conceptual models, conceived of as proposed causal linkages between a set of concepts believed to be related to a specific outcome (42. Eime, R.M., et al., *A systematic review of the psychological and social benefits of participation in sport for children and adolescents: informing development of a conceptual model of health through sport.* Int J Behav Nutr Phys Act, 2013. 10: p. 98.which is very similar to the definition of theory given here. There are statistical models, such as Structural Equation Models, a family of multivariate statistical techniques that incorporate factor analysis and path analysis (43. Weston, R. and P.A. Gore, *A brief guide to structural equation modeling.* The Counseling Psychologist, 2006. 34(5): p. 719–751. This paper proposes the development of computational models of behavior.

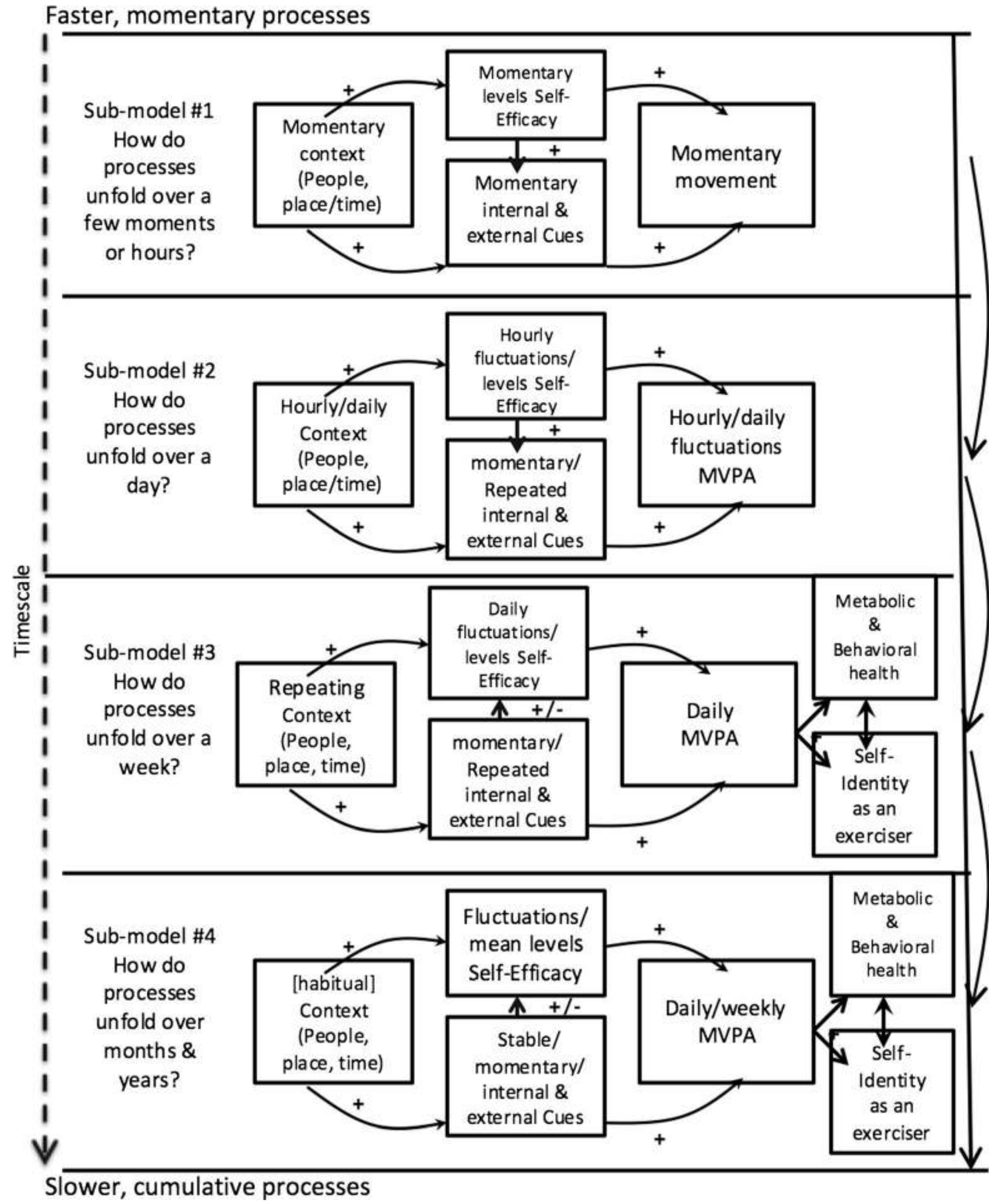

Fig. 1 | Faster to slower processes, adapted from [40]

validation and the addition of new processes and parameters, the models can develop to become better representations of behavior and behavior change.

Development of computational models of behavior will require a clear explication not only on *If* there is a relationship between constructs (e.g., does access to walking paths influence walking), but exactly *How* the constructs interact at different timescales [44]. This stronger emphasis on how interactions occur places strain on inferential statistics that have been traditionally used to develop static models of understanding behavior (e.g., structure equation modeling). Often, these models do not provide an easy process for modeling all of the plausible inter-relationships between constructs, especially non-linear effects like habituation to interventions [45]. A quantifiable representation of such inputs on behavior and decision-making would permit the selection of interventions that are optimal and tailored to both long-term and short-term behavior and contextual situations [46].

There are numerous modeling methodologies to choose from, ranging from system identification complemented with model-predictive control [47–50], to agent-based modeling [51–54], and dynamic Bayesian network analysis [55], such as Markov modeling [56] or related machine-learning approaches [57, 58]. A full discussion on how each of these methods could conceivably be applied to into a behavioral context is beyond the scope of this paper. However, we provide an illustrative example as it relates to Joe's need to increase his physical activity, whereby social cognitive theory [59] and control systems modeling [48] allows us to quantify behavioral theory and guides us in the development of personalized adaptive interventions.

For example, co-authors, Hekler and Rivera, and colleagues [45, 60] have been working on developing a dynamic model of social cognitive theory (SCT). SCT was chosen for several reasons including that it is an extensively used conceptual framework for behavioral interventions [61] and postulates a number of dynamic feedback loops between an individual's thoughts, environment, and behavior ("triadic reciprocal determinism") that lend themselves well to a dynamical model [62–65]. The first step in translating SCT from a relatively static to more dynamic model is to establish a "fluid-analogy" (see Fig. 2) to start to articulate a general model structure. The use of a fluid analogy (e.g., with representations of various inputs in the model as values and the use of "reservoirs" to represent accumulation of a factor, particularly across timescales) provides a starting framework for mapping path diagrams (a common practice within behavioral science) to control systems methods for mathematically specifying the model. For this initial theorizing, the goal was to articulate the inter-relationships occurring at a daily timescale [66, 67] and Just-In-Time, Mobile Adaptive Intervention (JITAMI) pathways.

This fluid analogy of SCT provides a general model structure and also provides insights on which factors are likely more transient (i.e., represented as values) versus those that might have a more of an accumulating affect (i.e., represented as reservoirs) across a daily timescale. The model illustrates, for instance, how the "reservoir" of Joe's physical activity behavior can be influenced by inflows, outflows and feedback loops from various constructs.

While this dynamic model version of SCT highlights the complexity and feedback loops implied by SCT, this model is only focused on the daily timescale for understanding inter-relationships. A second step is to start to articulate a timescale-separated model that can articulate the "nested" effects and inter-relationships that function at different timescales. Figure 3 illustrates a draft visualization of a dynamic theory that builds on SCT [68], but now with an emphasis placed on understanding how timescale impacts constructs. As can be seen from this visualization, it is feasible that constructs have varying meaning, measurement strategies, and intended purposes depending on the aggregation method. Take, for example, the central pathway that delineates the proximal outcomes from the perspective of Joe's physical activity that ultimately lead to the target distal outcome of preventing atherosclerotic plaque formation. At the minute timescale, the construct under study is Joe's specific body movements. This construct is nested within the construct of bouts of moderate to vigorous intensity physical activity (MVPA) at the hour timescale, which is nested within the minutes per day of MVPA at the daily timescale, which is nested within minutes per week of MVPA (the focus of the national guidelines) at the weekly timescale, and so on. These nested effects can be observed with other more psychological constructs as well. For example, the operant

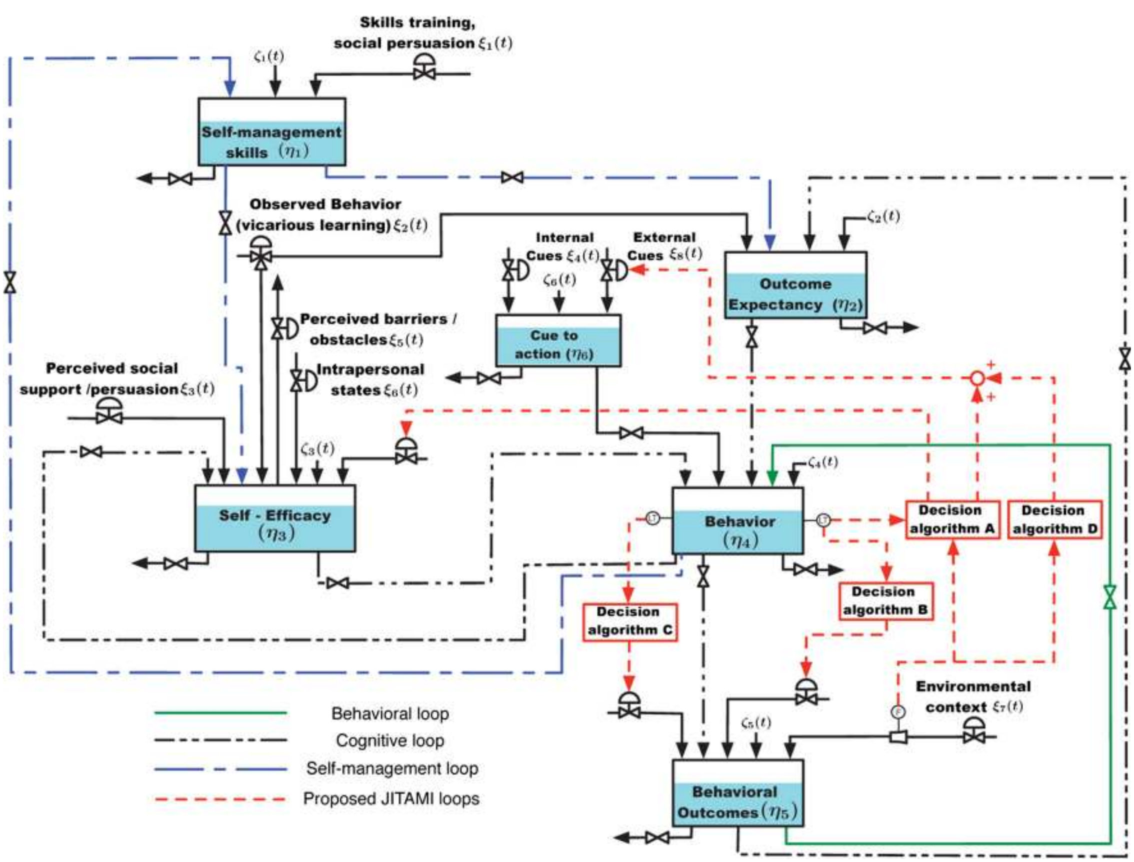

Fig. 2 | Fluid analogy of social cognitive theory, adapted from [60]

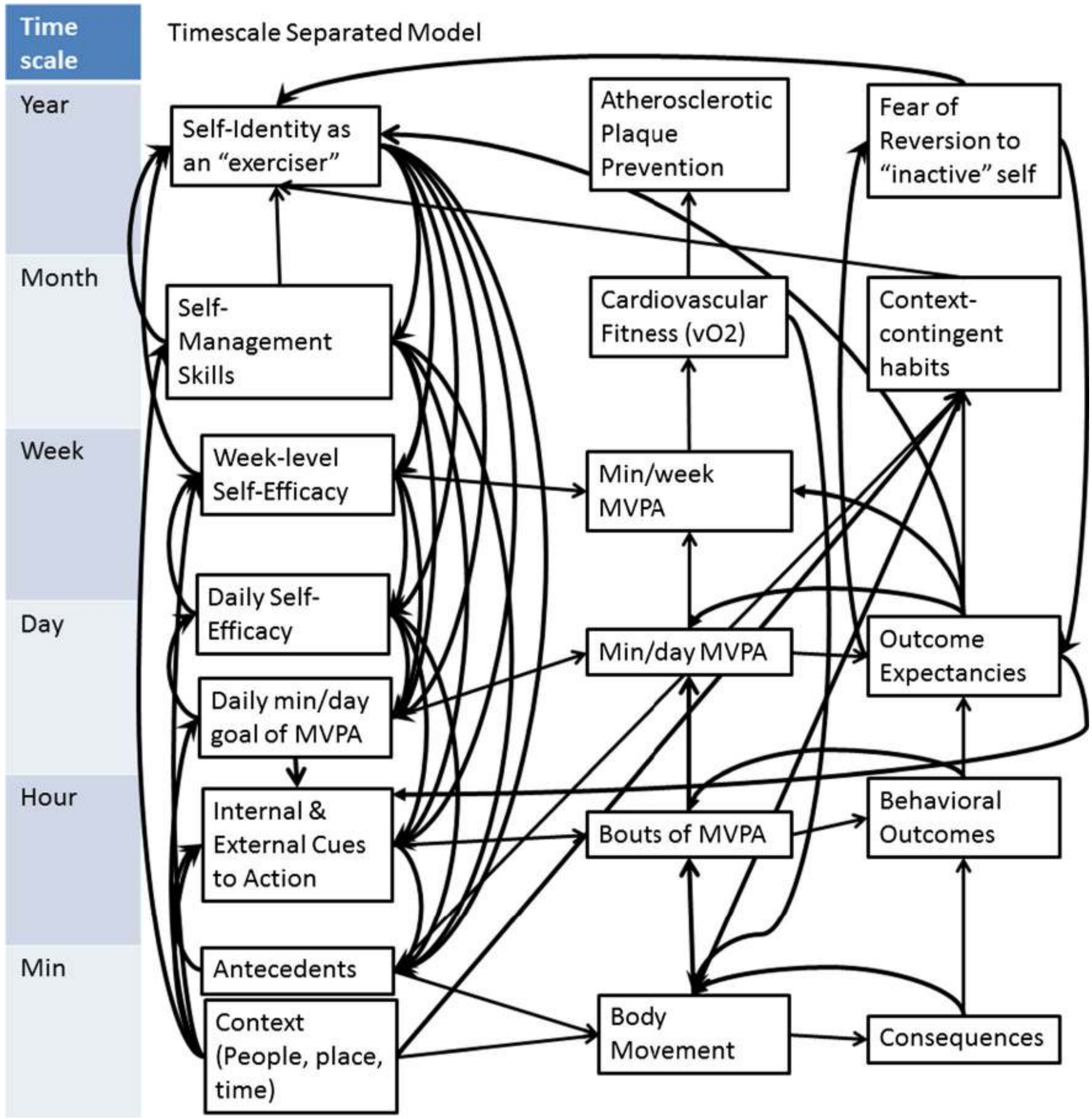

Fig. 3 | Timescale separate model that builds on SCT fluid analogy

conditioning construct of consequences at the minute timescale is conceivably nested as a factor that influences Joe's behavioral outcomes at an hourly timescale, which is a nested component of Joe's outcome expectancies. As can be seen from this, when accumulation across timescales occurs, it is quite plausible that new emergent properties (e.g., moving from a behavioral construct such as outcomes to a cognitive construct such as outcome expectancies) can emerge. We highlight this timescale segmented model not to suggest that the structure and inter-relationships are correct (as, indeed, a core point of this paper is that we do not have enough data to develop these sorts of models yet) but to help provide a more concrete example of how timescale quickly highlights how to think more dynamically.

Articulating the dynamics can be further explicated via a better articulation of the inter-relationship between constructs implied by this separated timescale model. Take for example the concept of setting a recommended daily step goal for Joe as a specific instance of daily goal-setting. Previous clinical experience and theory [69] highlights the likelihood that establishing an appropriate recommended step goal for any given day is a dynamic problem. If a step goal is too low, it is likely not challenging enough to be useful for promoting behavior change, but if it is too high, it is possible that it will be demotivating, particularly over repeated instances whereby the goals is consistently not achieved as lack of success would diminish self-efficacy [70]. Not only that, but the optimal step goal for any given day is going to be influenced by time-varying moderators such as previous instances of meeting or not meeting the goal, current location, day of the week, stress-levels for the day, or impact of others. Based on this, articulation of an algorithm for setting a daily step goal number requires a non-linear dynamic model representation. While there is some work highlighting strategies for developing a dynamic algorithm for setting a step goal (e.g.

[71]), much more work is still need to explore a variety of algorithms or "decision rules [40]." From a control systems perspective, setting an appropriate step goal is akin to an equilibrium curve within a dynamic model and thus can provide some insights on how to mathematically specify this model as well as provide insights on how an experiment might be designed to help parse out and identify the right goal-number at any given moment. This is only one example of a potential dynamic relationship between two constructs. Based on the how many plausible inter-relationships are possible (as indicated in Fig. 3), mapping out dynamics is truly a complex and nested problem.

This example provides a transdisciplinary example of lessons being melded from disciplines. In this case, the behavioral scientists in the team established meaningful behavioral goals, a conceptual framework to work from, and plausible behavioral strategies to use. The process involved a great deal of specifications on each of the variables, as well as "learning the language" of the other discipline, i.e., control systems engineering. It is this sort of interactive, iterative collaboration and melding of skills that will likely be required for each of the methods described above. This is a major challenge to development as it is often difficult to foster the appropriate "team science" model [72] to allow this melding of lessons from disciplines to emerge. These challenges are discussed in more detail below and include actionable steps that the field could take to help alleviate this problem.

CHALLENGES AND RESEARCH OPPORTUNITIES IMPLIED BY DYNAMIC BEHAVIORAL MODELING

While these techniques from engineering and computer science can be used to generate dynamic, empirically supported, mathematical models of behavior, there is much work required to realize this potential beyond the few cases where the work is being done now (e.g.,[73, 74]). We contend that there are four core challenges if behavioral modeling is to become used as a mainstay in behavioral research. First, we lack appropriate gold-standard metrics, particularly for constructs measured at a rapid timescale. Second, behavioral research is plagued with a veritable "Tower of Babel" problem, whereby there is an over-abundance of similar concepts that use different terms [75], which makes quantitatively specifying them in computational models challenging. Third, and related to the second issue, is that data that are collected now, in the "Tower of Babel" scenario, lacks consistent data tags or code, which makes it hard to compare, share, or pool. Fourth, even if dynamic behavioral models are developed, it is quite plausible for the research community to follow the "Tower of Babel" problem into mathematically specified models by creating segmented and disjointed knowledge. As such, a core long-term challenge is ensuring the computational behavioral models created are developed incrementally, hierarchically, and modularly such that they can be incorporated and linked to one another. In the remainder of the paper, we will provide suggestions on research agendas that could be accomplished to resolve these four domain issues.

Enabling dynamic mathematical models via improved measures

We lack appropriate gold-standard metrics for important constructs, especially those measured at a rapid timescale. Thus, recent work on variables such as stress, which has traditionally been measured in a static fashion, suggests that it can be measured much more frequently through the use of physiological sensing [76]. While this advance is critical to understanding stress in the real world, how do we validate it? New measures need to be compared against the gold standard, but with the understanding that the real-time measures will likely not map easily on existing static measures [42]. This is expected because we are measuring these constructs in real-time with the goal of capturing what should be significant variability when compared to static measures, otherwise why increase the measurement frequency? Unfortunately, it challenges conventional ideas of reliability and validity and will require innovation throughout the validation process.

Further, we often have many different measures of the same behavioral construct. While this is the case in many other areas of science, other disciplines have "pruned" their measures so as to get consistency across the field. While this is a long-term goal, the first step might be to come up with a set of shared measurement tools and to encourage reuse of the same tools in different data collection efforts. This is reflected in multiple initiatives funded by the National Institutes of Health, such as PhenX [77] (consensus measures for phenotypes and exposures), the Neuroscience Toolbox for cognitive functioning [78], and PROMIS [79] for patient reported outcomes. Although created to address a series of specific research issues, each of these efforts allows researchers to use common tools to measure prevalent constructs. These projects aim to provide researchers with common tools and acknowledge that, while no measurement tool is perfect, when large numbers of researchers use the same tools in different studies it may accelerate scientific discovery. Further, common tools may actually lead to more innovation in measurement because there can be comparisons and patterns identified, which cannot be done when every research team is using a different instrument. As well, new tools, especially those with a rapid timescale, can be developed with accepted benchmarks.

Developing a behavioral ontology

Tower of Babel: Even more challenging than measures is the unique issue in health behavior research, where many constructs that are theorized to be important are not yet directly observable or represented in a quantitative fashion. Current theories of behavior have introduced many key constructs representing aspects of an individual's state, such as "belief," "attitude," "intention," and "motivation." These are high-level abstractions that are not directly observable and may have to be inferred from multiple data streams and signals including momentary self-report. This point is only reinforced by the recently published book by Michie et al. which highlights 88 behavioral theories related to behavior change [80]. The over-abundance of theories and constructs poses a huge barrier to entry for other disciplines to engage and build on these behavioral theories. Based on this, far more work on culling through and organizing this "Tower of Babel" is required by behavioral scientists and the increased use of ontologies is likely a very important target.

An ontology, within the information sciences, is a well-specified structuring of knowledge that provides key building blocks for shared knowledge including a common vocabulary and a mapping of the inter-relationships of different concepts within a given domain. At the current stage of the science, a shared ontology of cross-cutting variables that can be measured unobtrusively, reliably, objectively, longitudinally, and in context is needed. Health-relevant data requires insights from across a growing number of disciplines as new technologies become increasingly woven into our lives, including (but not limited to) behavior sciences, geographical sciences, medicine, computer science, and engineering disciplines. Thus, to build this shared inventory, discipline-specific understandings and vocabularies for behavior need to be "de-siloed", so that data sources can be effectively meshed and shared.

Such an ontology or inventory should be amenable to easy and rapid update, and can highlight those variables that are currently easily accessed passively (e.g., on-body and environmental sensors), those that may have to be inferred (e.g., diet data from grocery loyalty cards and from digital footprints) and those that will come from self-report (which has considerable value, but which has a high user burden and which will need to be employed strategically).

There is a great deal of work both within behavioral science and outside focused on creating the structures to support such ontologies. With regard to behavioral theories, co-author Michie has been using expert-consensus processes (e.g., Delphi methods) to attempt to tackle the "Tower of Babel" problem within behavioral theories. In particular, she and her colleagues have been organizing the behavioral theories via strategies such as the Theoretical Domains Framework, the Behavior Change Wheel [81], a behavior change techniques taxonomy [82], and currently, in collaboration with Larry An, the development of an ontology that links the theoretical domains to likely mechanisms of change, to specific techniques to use. All of this is being generated with an expert-consensus process. These efforts are pivotal toward providing a common language and structure for progressing the field.

Enhancing data sharing

Clearly defined and shared constructs from an ontology, along with common data labels to be used across a wide range of studies, will facilitate pooling and sharing, as well as empirical comparison of studies. Further, as new datasets are acquired, raw data from multiple sources can be merged to create rich longitudinal data sets. The framework that is developed for data sharing must accommodate (or encourage) a shared understanding of what we mean by "behavior," how behavior can be changed and how behavior change can be maintained. The framework must also accommodate the complexity of capturing and modeling the (social and built) environments, using a variety of methods and sensing systems and allow collaboration among model developers. In this way, distributed research teams can collectively improve and validate the computational models and document new challenges. Only in this way will we be able to effectively learn from successes and mistakes and to move the research front forward.

Beyond this, there are a variety of strategies being explored for fostering improved sharing and facilitation of common resources. For example, the main mission of the Big Data to Knowledge (BD2K) [83] initiative of the National Institutes of Health is to enable biomedical scientists to capitalize more fully on the Big Data being generated by various research communities, and they are poised to announce several major new initiatives around data modeling. All of these efforts are in alignment with the overall goal of fostering desiloed knowledge via better definitions of terms and constructs.

Enabling model development that is iterative, hierarchical, and modular

Modeling behaviors requires balancing complexity, accuracy (i.e., a model's ability to depict accurately what is being modeled), generalizability (i.e., a models' ability to adapt to different situations or individuals), and model fitting (i.e., estimating model parameters to best fit experimental data). For instance, extremely rich conceptual models, such as Hovell et al's Behavioral Ecological Model [84], are extremely complex and usually not amenable to full measurement. Conceptually, if a model is too complex, it will not be useful as it will mirror the real-world and offer no additional insight, while if it is too simple a model will not capture important aspects of behaviors. However, a very complex model might be hard to understand but perform well, just as a very simple model may be easy to interpret but perform poorly. Ideally, models are observable, controllable but also trainable and interpretable. A model that does not generalize to a variety of situations or across individuals is also of limited utility. Research teams will need to build models incrementally and/or hierarchically, and deploy these models in different well-specified contexts for testing and revision. For example, dynamic models can be developed by first focusing on one time scale, such as a day, and building toward "faster" and "slower" models incrementally [40].

Beyond incremental growth, a second facet that will enable this work to happen more rapidly is via an emphasis on modularity. Specifically, a possible approach, informed by system theory, is to start small and build and validate modular models in well-defined contexts with available datasets, gradually linking modules to enhance the feature understood and complexity to facilitate the adaption of the overall models to new contexts and/or individuals. This incremental, hierarchical, and modular approach, which is long standing in fields such as aviation and network systems, would result in a series of experimentally validated behavioral models, which may be directly compared against large datasets for performance, complexity, and generalizability beyond initial context.

TYING IT ALL TOGETHER—A KNOWLEDGE COMMONS

To encourage an ongoing dialectic process between theories that are inevitably developed in the course of science, and computational validation of these ideas, we propose a knowledge commons. A knowledge commons is comprised of three elements: (1) access to an organized data warehouse; (2) tools and methods for data cleaning, signal fusion (combining data or "signals" from various sensors), and data mining; and (3) a library of computational models of behavior and behavioral decision-making and tools for experimental evaluation of those models. We will delineate strategies for moving forward on each of these tasks below.

Access to an organized data warehouse

The research community will need to become more creative at systematically collecting data and more open to approaches where the volume of data acquired overcomes the limitations of any single measurement. Instead of using only traditional measures, which may be high burden for both the participant and experimenter, these new data may be acquired via a variety of passive methods, such as the sensors, inference algorithms, related data that is collected in the course of daily life (e.g., loyalty cards) described above, or could be developed especially for a database by incentivizing participants for more burdensome measures, such as have been used in behavioral economics [85]. Data may also be generated using interactive game interfaces that also infer function [41]. Some data may be collected by mining data from devices or data services used by individuals that are intrinsically rewarding, such as social networking services. Mobile phones provide several data collection opportunities, including usage data, location data, contacts, social networks, and voice recognition, which has recently been used for understanding such things as social interactions [37] or depression. Sometimes we may recruit specific target populations and deploy sensors specifically to generate a large, robust data set. At other times, we may opportunistically study data contributed by large convenience samples of people willing to contribute data as citizen scientists. Both types of data will allow scientists to generate new and more accurate models that will allow for greater, more reliable behavior measurement and modeling of behavior change. With the help of technology, these same models should permit a new class of real-time, tailored interventions to be created.

These datasets could be made available to the entire research community in virtual data warehouses, although this would require agreements between researchers and technology companies on data sharing and costs that are equitable for all involved. New models derived from such data could be evaluated against well-known and well-understood baseline datasets. Similar activities have taken place in other fields and have accelerated progress. For example, in the field of astronomy, the Strasbourg Astronomical Data Center (CDS), a data warehouse developed in 1972, has allowed a whole generation of scientists to study the stars without the time and expense of doing independent data collection. Instead, these scientists benefit from a few massive data collection sites that are deposited at the CDS to feed the needs of the field economically and efficiently. Data warehouses of real-time health-related behavior with shared labels and common coding schemes would not only help all researchers working in mobile health, but also could fill the needs of other fields in which behavior is a factor (e.g., sustainability, human-computer interaction, security).

Access to a data warehouse and knowledge commons built on open standards that all developers contribute to and share is key to creating and maintaining a network of model developers. Precedent exists today in the USA for some federally funded research (http://www.nlm.nih.gov/NIHbmic/nih_data_sharing_repositories.html) and in Europe, for instance in the Virtual Physiological Human research frontier known as VPH-Share [86]. VPH-Share aims to develop the organizational fabric (the infrastructure) and integrate the optimized services to expose and share data and knowledge, jointly develop multi-scale models for the composition of new VPH workflows and facilitate collaborations within the VPH community. A similar knowledge commons for understanding human behavior in real-time and in context–a Virtual Behavioral Human Share–would allow developers to expose and share data and knowledge (including models) in a structured way. Further, the various entities listed above are also striving toward this type of goal.

Ideally, with proper consent systems in place, data collection for a warehouse could be facilitated by the deployment of sensor toolkits that begin data collection on a cohort. These data could also be complimented by simulated behavior data from games and other digital "traces" left as people use their devices to navigate their world. These digital traces include posts, e-mails, messages, GPS tracks, and web usage. Data can be augmented with the immense amount of real-time data available in the environment, such as GIS-mapped crime data, weather data from NOAA, or the Environmental Protection Agency's (EPA) ongoing air and water data collection. Data could also be merged with epidemiological work and other studies using common ontologies and data standards. These rich data can be fused to generate complex models that predict behavior in real time.

Data may be collected from specific cohorts of people of interest due to health disparities, as is common in much health behavior change research, but data could also be collected from citizen scientist convenience samples. This may enable very large datasets to be acquired rapidly, at low cost.

Tools and methods for data cleaning, signal fusion, and data mining

A challenge in creating a knowledge commons lies in the fact that the data that will be collected and stored will need to be "harmonized" and structured in order that it can be reused by other projects. Scaling the datasets to the size needed to develop fully functional computational models will require that the data in the repository be quite heterogeneous, with many different types of sensors and only modest overlap between them, where data are acquired from totally different people and environments. Tools must therefore be developed for not only data cleaning, but also data harmonization.

Technically, this means that we need an ontology that covers all data types in the data commons. For some data types, special ontologies exist already and can be shared. Further, research such as that being done within Open mHealth, are focused on trying to build these common structures, although much work needs to be done. The approach must be sensor/device independent, which means that the ontology must be able to support the full range of devices for a given measurement, such as pedometers and their variants for walking. Some behavioral medicine ontologies have been created to describe relationships between theoretical constructs, intervention methods, goals, and actions that follow certain preconditions, but so far they have a limited scope and few practical implementations [87, 88]. Tools are needed that would permit crowdsourcing this activity.

The challenge that data cleaning and harmonization create is advantageous because it will force model developers to focus on harmonizing the data. In other words, instead of developing specific algorithms for each device, developers will need to agree on how to make data acquired from different devices comparable.

The engineering communities are already developing algorithms for inference and sensor fusion that take relatively low-level sensor data, such as accelerometer data, and use these data to infer higher-level behavioral constructs, such as specific types of physical activity. These techniques are typically based on statistical models that incorporate uncertainty in both the input data and the outputs. Higher-level behavioral models must also be developed to optimize inferences based on this uncertain information. And for all of these endeavors, multiple disciplines need to be brought to the table to include the full spectrum of expertise needed to address any specific measurement, from hardware developers through software and algorithm developers to content specialists.

A library of computational models of behavior and behavioral decision-making and tools for experimental evaluation of those models

The sophisticated computational models of behavior and behavioral decision-making discussed throughout this paper would use the latent variables inferred from self-report or using sensor fusion to provide insight into (and predictions of) behavior. These models would incorporate the uncertainty from the latent variables as well as the uncertainty due to the complexity of human decision-making and behavior. Therefore, an inventory of tools for analyzing and evaluating complex data and models needs to be developed. Complex concepts such as goals and plans and desires would be computationally modeled, and models would be connected to available data. This inventory will require partnerships between the behavior science, computer science, and engineering disciplines and new research methods to generate and analyze data, as well as to evaluate dynamic models, especially longitudinally and in real-world settings.

In the data warehouse, the coded definition of each model must be provided. This ensures that models are (1) well defined and (2) reusable. In addition, the models must be immediately "runnable" over the existing datasets in the repository so that modifications to the models can be immediately evaluated. Ideally, new investigators trained in modeling as well as behavior and behavior change would be able to run several models on multiple (potentially huge) datasets and compare results with only a modest learning curve. The comparison will require yet another innovation: development of new tools for visualization of the behavioral datasets and the predictions of the behavioral models.

Knowledge commons structure: practical issues

Acquisition of real time data on a 24/7 basis of individuals living their lives in dynamic contexts entails several practical issues that need to be considered. One is technical, and deals with the storage capacity of the data commons. For model identification, it is essential to have access to quality data in enough quantity to be able to analyze and mine it. What we end up with is "big data" [89] where data are generated at the person scale. Computing power and storage capacity today can accommodate massive datasets of raw data. Raw data is preferable to data that has been reduced a priori, often using proprietary algorithms, because it more easily allows reuse of data as better algorithms are developed.

Another important practical issue is privacy and security of data. These issues require important consideration, especially if personal "big data" are acquired for commercial systems, as opposed to research projects where all participants will have given informed consent. Protecting privacy and data security is especially important in the context of behavior change and modeling the decision-making of individuals. Data from individual sensors that are not considered invasive, when combined with the models, may require heightened security. As products result from research, society needs to make certain that legal and ethical requirements are satisfied both in the design of systems and interventions. Researchers conducting studies and individuals and researchers contributing data to the knowledge commons must also be cognizant of privacy and security considerations.

CONCLUSIONS

The gaps in our understanding of human health-related behavior make it challenging to change and maintain healthy behaviors, thus hindering progress in alleviating the high cost in resources and human suffering caused by chronic disease. New technologies now enable users to access, store, transmit, and manipulate information in real time, anywhere, at any time. We can now monitor a host of health-related behaviors, states, social interactions, and health indices, as well as a host of other physiological, behavioral, and contextual signals in real time. Much of this observation can be done unobtrusively, although some observations still require user input. Data from mobile and environmental sensors and systems must now be exploited to understand human behavior in real time by using emerging computational methodologies such as systems modeling. Modeling behavior can move the field away from testing theories to build a knowledge base, toward compiling data to develop complex models of behavior that can be computationally evaluated and refined. However, there are several steps that need to be taken to harness new technologies and the data that they provide to develop new dynamic, personalizable, adaptable, contextualized models of health behavior and behavior change.

We have described here five concrete steps to the creation of robust dynamic mathematical models of behavior including: (1) establishing the appropriate "gold standard" measures for important constructs; (2) the creation of tools, resources, and other tutorials that both enable dynamic theorizing and "lower the bar" for using modeling techniques by other disciplines; (3) the development of ontologies and other strategies of specification of current behavioral theories to make them more accessible; and (4) facilitating improved sharing as well as inter-operability of mathematical models and tools to support improved theory falsification as well as more rapid aggregation of the models, particularly those that are developed. We conclude with the discussion of what might be incorporated into what we have labeled a "knowledge commons," which could help to bring together these disparate activities into a unified system and structure for organizing knowledge about behavior. These steps will enable the development of dynamic computational models of behavior that facilitate incremental model verification, improvement, and expansion. These models will move the field of health behavior change to a new level, where quantitative, testable models of behavior can provide ongoing adaptive interventions that are integrated into daily life that will help individuals move toward health behavior change and maintenance.

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