Moving Behavioral Theories into the 21st Century

By Wendy J. Nilsen and Misha Pavel

Data on health and wellness from around the world reveal a pattern of less than optimal outcomes for the young and old alike. These results are not limited to the developing world. In fact, a recent report showed that Americans die sooner and experience higher rates of disease and injury than people in other high-income countries [1]. Although the precise causes of these disparities are not fully elucidated, chronic diseases, including obesity, heart disease, diabetes, and lung disease, are increasing in the Western world. Similarly, in the low- and middle-income countries, chronic disease is increasingly being cited as an emerging problem and a major component of disease burden [2]. It is widely suspected that the increased prevalence of unhealthy behaviors plays a significant role in overall health and in chronic disease. Indeed, it has been estimated that approximately 40% of all premature deaths are due to behavioral patterns that are potentially modifiable [3]. Further, in patients suffering from chronic disease, self-management of health behaviors (e.g., eating well, exercising as indicated, and taking medication as directed) has been shown to have a significant effect on symptom reduction and quality of life, as well as reducing costs in the health-care system [4]. Finally, enhancing health behavior to prevent disease has been consistently shown to decrease adverse health events over time. Thus, the dangerous effects of inactivity, poor diet, smoking, drug and alcohol use, lack of sleep, and chronically stressful environments are now widely appreciated to be associated with not only the quality of life but also with mortality and health-care and disability costs.

Technological Advancements for Improving Quality of Life

The role of behavioral science in the prevention and treatment of disease and reducing future rates of disability is often underestimated, and many behavioral change interventions for health have shown positive results. More specifically, behavioral interventions have demonstrated favorable health outcomes alone or in combination with biomedical treatments, as well as often having a more agreeable side-effect profile. For example, the Diabetes Prevention Program trial showed that a lifestyle intervention reducing body weight by 7% and increasing physical activity by only 2.5 h per week reduced the risk of developing type 2 diabetes in overweight individuals by 58% [5]. The reduction in risk was significantly higher for those receiving the behavioral treatment than patients who were given medication to delay diabetes onset. These positive effects were seen over a three-year follow up [6]. Similar positive health effects have been reported in other chronic diseases (e.g., high blood pressure) as well as the treatment and prevention of smoking, drug dependence, and depression.

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Despite these benefits, behavior change programs have not been well integrated into public health or the health-care system. Although an empirical base exists for many behavior change interventions, much less support exists for interventions that sustain behavioral change or prevent the onset of disease or other health problems. Even when effective behavior change programs are reported, the cost, staff, and time

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involved in delivering them present major challenges in scaling up these approaches. Also, effective programs developed in one community (e.g., an urban area) may not generalize to new settings (e.g., rural environments) or to new populations.

Also complicating behavior change research is that, in many cases, the active ingredients of behavior change interventions are not known, making it difficult to reproduce or optimize them. Thus, there is limited understanding of the psychological, social, behavioral, neurobiological genetic and/or contextual mechanisms of behavior initiation, change, and maintenance or even whether mechanisms governing these periods of behavioral change are even the same. Loosely defined constructs such as motivation, stress, and self-control are considered key drivers of behavior change, but their assessment as well as the mechanisms underlying these concepts is not clear. Other candidate mechanisms of behavior change include, but are not limited to, aspects of executive functioning (cognitive processes managing planning, memory, attention, perception, and decision making), emotional self-regulation (managing emotion in response to experience and the social environment), and metacognition (thinking about one's thoughts and knowing about one's knowledge). Not only is the understanding of underlying drivers of behavior limited, most health-behavior change occurs outside the context of professional settings and one-on-one interventions, posing a challenge for behavioral change in the real world.

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Our current understanding of human behavior is largely based on limited static measures rather than ongoing, dynamic indices of behavior in response to ever-changing biological, social, personal, and environmental contexts and states. Because experimentation with human subjects carries important ethical implications, experimental designs that directly manipulate many of these factors are challenging, if not impossible, to achieve. This leaves much of the mechanisms and drivers of behavior in a scientific black box. Thus, despite the value of behavior change both for health and wellness, the field has been beset by challenges and has not yielded the effect on public health and health care that would be expected given its potential.

Moving Behavioral Change Research into the 21st Century

The study of human behavior has traditionally been theory based, deriving a set of concepts, definitions, and proposed relationships between variables to explain or predict behavior, and then subjecting aspects of the theory to empirical testing. These approaches presupposed a limited number of static data points, which may or may not have been based on objective measures of health or behavior. These measures were traditionally augmented with participant self-reports of unobservable constructs that were thought to drive behavior, such as motivation or self-efficacy. Mathematically assessing or modeling behavior was daunting because of the lack of available data on the multiple influences affecting behavior and the way these influences change over time. To address behavior change in the current digital world, new empirically based theories that can better explain the just-in-time dynamics of behavior are required [7]. Mobile sensors and smartphones, cloud-computing, and other emerging technologies are fundamental to the development of these theories. Specifically, these new technologies provide us the data and the tools to describe and predict behavior and, hopefully, to help individuals to acquire and maintain health behaviors that will decrease mortality, improve the quality of life, and reduce the costs of health care.

Thus, new technologies provide us opportunities for measuring and mathematically modeling behavior and decision making in ways that were simply impossible before. We can now monitor physical activity; biomarkers (e.g., glucose, sodium, cortisol); heart rate; blood pressure; indicators of stress; smoking; social interactions; geographical location; and a host of other internal, external, personal, social, and contextual factors in real time. Much of this observation can now be done through unobtrusive and passive sensing, yielding intensive, longitudinal measurements of behavior that are time stamped, transmittable, and immediately available for analysis. These data will support the science of behavior change by providing insight into how multiple feedback loops among moment-to-moment events, states, and environments interact in real time to impact behavior. These data can thus be used to build computational models of human behavior, and, ultimately, human health. These computational models can, in turn, be used to optimize intervention that can be accomplished in real time and adaptively, and in this way to design better prevention and health-care delivery systems.

Predictive Computational Models of Behaviors

The ability to make accurate predictions is the hallmark of the engineering models that are used to design and realize complex systems ranging from prescription glasses to automobiles and supercomputers. To the greatest extent possible, these models are based on first principles, but frequently enhanced by functional generalization of empirical evidence, for example, friction in mechanical engineering. The point is that these computational models enable designers and practitioners to optimize functionality by adjusting the design parameters and estimating the results using the computational models. Such models are typically simplifications of the actual phenomena, but they are accurate enough for the optimization of the design processes.

These models are also needed to characterize human behaviors and the underlying processes influencing behavior to design optimal interventions for behavioral change and maintenance. Such models need to embody the effects of psychological, social, behavioral, neurobiological genetic and/or contextual variables on individual behavior initiation, change, and maintenance. Using empirical evidence, the predictive nature of the models can be used to anticipate outcomes of interventions before the treatment is ever deployed. In addition to their utility in optimizing intervention, computational models provide a multitude of additional benefits. From the theoretical point of view, computational models force theories to comprise quantitative assertions of the underlying principles and thereby provide explanations. In a similar manner, computational predictive models also

challenge the robustness of prevailing theory through perturbations. As such, they can be used to guide data collection and even generate new research questions.

Computational models are often forced to incorporate uncertainties and explicate their effect. These are perhaps the only way to use the evidence arising from the many sources of big data: complex, longitudinal personal data, including genetic and epigenetic data, outcomes of randomized controlled trials and results from laboratory experiments. For the same reasons, they improve statistical efficiency of empirical data by reducing the degrees of freedom. The emergence of new technologies (sensors, devices, phones, apps, and cloud) and computational methodologies (such as systems modeling) could be used to build dynamic, personalizable, adaptable, contextualized models of health behavior and behavior change. These tools would transform behavior change research and provide useful guidance to intervention developers tackling behavior change and maintenance problems at the personal, family, community, national, and global scales. In summary, an important aspect of this approach is that the computational models must be individual-specific so as to capture the significant heterogeneity across individuals and support individual-specific, precision medicine-like approaches.

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Optimizing Intervention: System-Theoretic Approach

A key question concerns the design and delivery of the intervention that would be the most effective for any particular individual, taking into account his particular state and environment to maximize the likelihood or the intensity of the desired, perhaps new, behaviors. Assuming that the behaviors and the state of an individual can be defined and measured sufficiently accurately, the problem of behavior change can then be cast within an optimal control-theoretical framework.

Within such a framework, it is necessary to define the inputs and outputs and then characterize the system dynamics and its evolution over time as a function of its inputs. The system output is a quantitative representation of behaviors, for example, total expended calories per day, number of calories consumed per day, and number of cigarettes smoked per day. The inputs comprise a set of variables that represent the environment, context, social interactions, and any interventions, as shown in Figure 1. Once the input and output variables are defined, it is then necessary to specify the dynamics of the system, i.e., how the system's state and outputs evolve over time in response to the inputs. In a classical control-theoretic framework, the system—often referred to as a plant—is typically described in terms of differential equations, and the control signals are computed by considering the difference between the desired and the actual outputs. In those cases where the plant and the controller can be described by a set of linear differential equations as a time-invariant linear system, it is possible to derive optimal control laws analytically.

An illustrative early example of such an approach was proposed by Rivera and his colleagues [8]. In that approach, the authors made assumptions that enabled them to convert a regression-based model of behavior change, derived from a theory of health behavior, to a set of linear differential equations and show how an optimal control can be implemented. We note this example to illustrate a number of the theoretical and empirical issues that need to be addressed in the process of developing models to optimize interventions for behavior change.

The first step in computational modeling comprises a definition of the state, inputs, and outputs of the system—in this case, the individual to be represented by the computational model. These model components must be defined so that they can be quantified and measured. Until recently, measurement in this domain was the purview of psychologists and social scientists equipped with a limited set of tools, typically implemented as questionnaires administered in a laboratory, a classroom, or perhaps over the Internet via computer. The data consisted of the subjective answers that were analyzed to derive a formulation of latent variables, psychological constructs such as perceived behavioral control, subjective norm (perceived social influence), intention, readiness to change, self-efficacy, knowledge, and perceived barriers to change—depending on the assumed theoretical framework.

The resulting theoretical representations of the system states have typically been realized in terms of regression equations and the relationships among variables have been characterized in terms of correlation or, more recently, in terms of structural equations. In some theoretical frameworks, the state of the individual is represented in terms of continuous variables or in terms of discrete states, such as the stages of changes articulated in the Transtheoretical Model [9]. The inputs include, but are not limited to, social connectedness, social support, educational resources, access to facilities, interactions with coaches, genetic liability, and availability of feedback. The outputs include performance: intensity and frequency of desired activities or likelihood of desirable decisions.

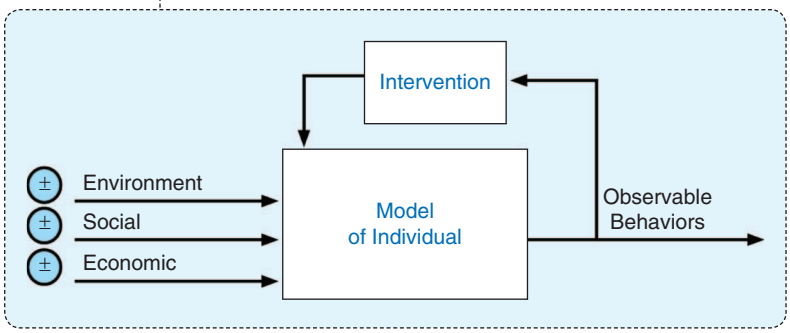

FIGURE 1 A schematic diagram of the control-theoretic framework for optimal behavioral change is shown.

New mobile and wearable technologies afford us new types of data that are continuous, captured in real life rather than in a laboratory situation, and time stamped. To build on existing social science knowledge and empirical evidence concerning intervention, the starting point for development of computational models of behavior may take advantage of the existing data and theoretical constructs and then move to new constructs as they emerge.

As noted earlier, recent advances in technology enable unprecedented approaches to sensing and inference of behaviors and individual state variables. At the output, it is possible to measure activity, including specific movements. At the input, it is now possible to use social network analysis, semantic analysis, natural language processing, and other techniques to represent the inputs in ways that they can be measured and quantified. Along the same lines, assessment of the individual can be aided by measuring a host of physiological variables and biomarkers including those related to the emotion and stress states. Many of these measurements can be done effectively, economically, and continuously using mobile and wearable technologies.

The next step in modeling requires the description of the state dynamics: how the state changes as a result of a combination of the current state and the inputs. In system-theoretical terms, this roughly corresponds to system identification. Currently, this part of the modeling process is likely to be challenging because of a paucity of data regarding the actual state changes in real time as a result of specific inputs. The computational model would, for example, have to incorporate the change in the state variable corresponding to self-efficacy in response to an intervention by a human or virtual coach. The most challenging aspect is the idiosyncratic aspect of the individuals' goals and objectives. For example, one individual would not want to quit smoking until he realized the devastating effect on his teeth, while another may be motivated by the effect of second-hand smoke on their child. Thus, variables as diverse as concerns about appearance and family are examples of individual motivating factors, without which the individual may seem immune to change.

For the sake of completion, we need to note that in addition to the standard control-theoretic approaches, it is likely that the development of the computational models will require more advanced techniques. For example, because of the possibility of discrete states in conjunction with continuous variables, the models will involve hybrid control techniques. Moreover, the complexity of the environments and context may require more recently developed robust control-theoretic representation.

Room for Improvement

The science of behavior change has come a long way over the past decades, and we now know much more about human behavior, motivation, and cognition than ever before. We have effective interventions that can change behavior in at least some of the population. That said, we still have considerable room for improvement. By using continuous-longitudinal data from ubiquitous sensors and smartphones and leveraging existing data as well as developing real-time feedback systems, we can begin developing behavior change programs that are optimized for the individual and that adapt to the individual's changing behaviors. These programs will eventually be assessed before they are deployed and enhanced in real time in the field. These techniques will improve human health by preventing disease, reducing the damage of chronic diseases, and ensuring that all people live a long life with a high quality of life.

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