Embracing Chaos and Complexity: A Quantum Change for Public Health

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Public health research and practice have been guided by a cognitive, rational paradigm where inputs produce linear, predictable changes in outputs. However, the conceptual and statistical assumptions underlying this paradigm may be flawed. In particular, this perspective does not adequately account for nonlinear and quantum influences on human behavior. We propose that health behavior change is better understood through the lens of chaos theory and complex adaptive systems. Key relevant principles include that behavior change (1) is often a quantum event; (2) can resemble a chaotic process that is sensitive to initial conditions, highly variable, and difficult to predict; and (3) occurs within a complex adaptive system with multiple components, where results are often greater than the sum of their parts. (*Am J Public Health.* 2008;98:1382–1389. doi:10.2105/AJPH.2007.129460)

The understanding and modification of behavior within public health research and practice generally has been guided by a linear, reductionistic paradigm. That is, we assume small inputs produce proportionally small outputs and that the whole equals the simple sum of its parts. Across the dominant theoretical models used by researchers and practitioners, the key determinants of behavior typically involve some variation of knowledge, attitude, belief, self-efficacy, and intention.[1,2] Change is usually conceptualized as rational and as a deterministic process in which individuals obtain information, consider pros and cons, make a behavioral decision, and then plan a course of action. An implicit assumption within this perspective is that the change process is largely under conscious control. Consistent with this perspective, our public health statistical models have almost exclusively assumed a linear relationship between psychosocial predictors and behavior (change); that is, greater increases in knowledge, attitudes, and intentions will lead to greater (and proportional) changes in behavior.[3] In other words, small inputs create small outputs.

The conceptual and statistical assumptions underlying this rational, linear paradigm may be seriously flawed and might limit our ability to both explain and modify health behaviors. In particular, such a perspective fails to account for nonlinear, quantum influences on human thought and action.[3] The limitations of a rational-linear conceptualization of behavior change may, in addition to measurement error, explain in part the modest proportion of behavioral variance accounted for in the literature (typically 10%–20% and rarely higher than 50%).[4–13]

We propose that our conceptual and statistical understanding of the behavior change process can be informed by nonlinear paradigms, most notably chaos theory and complex adaptive systems. Key principles from these perspectives relevant to understanding health behavior change are that it (1) is often a quantum event rather than a linear one; (2) can resemble a chaotic process that is sensitive to initial conditions, highly variable, and difficult to predict; and (3) occurs within a complex adaptive system that involves multiple component parts that interact in a nonlinear fashion, and the results of their interaction are often greater than the sum of their parts.

A key statistical implication that flows from this conceptualization is that patterns of change can be mathematically modeled. However, such patterns usually involve nonlinear terms and multiple levels of interaction.

A QUANTUM VERSUS LINEAR MODEL OF BEHAVIOR CHANGE

An alternative view to the planned, rational model of human motivation is that decisions to initiate behavior change are often quantum rather than linear events.[14] In quantum mechanics, light, sound, and other phenomena are conceived as having properties of both wave and particle. As a wave, these entities appear as a collective frequency. Yet under some conditions they behave as individual particles. A similar duality may also be evident in human motivation. For example, behavioral decisions can result from a wave of motivation or inspiration rather than a linear, additive sequence or gradual calculation of pros and cons. It is not so much a planned decision, but something that arrives beyond cognition. Psychologist William R. Miller described the essence of this process:

> Buried in the statement "I just decided," however, can be another kind of experience that has been confused with ordinary decision making. It is the insightful type of quantum change. When people talk about such experiences in shorthand, they may say "It just happened" or "I just decided." Inquire a little more closely, however, and it becomes apparent that the process is somewhat more complex.[15(p37)]

Miller delineated 2 primary types of quantum change, a dramatic, mystical experience and a sudden insight or sense of finding one's truth. Common to both pathways is that they occur outside of conscious reasoning; they happen to the person rather than by the person.[14] Both types propel the individual toward self-actualization, leaving an indelible impact and often pervasive change in how people perceive themselves, others, and the world. These changes may occur with little or no new input of information into the system. Yet something dramatic can occur.

Although the cases described by Miller—as well as by others who have written about quantum change—tend to involve an overwhelming transformation, we propose that less dramatic, less mystical "mini-epiphanies" may contribute to many behavior change decisions.[14–17] Whereas much of the previous thought on quantum change in public health has focused on problem drug use, our proposed "mini-epiphanies" may also apply to other health behaviors, outside the realm of classic addictions, albeit perhaps in a more subtle manner.

BEHAVIOR CHANGE SENSITIVE TO INITIAL CONDITIONS

The origins of modern chaos theory are often linked to a meteorologist named Edward Lorenz. In the 1960s he was developing computer models of weather prediction, and one day after an initial run of a predictive equation, he decided to run the model a second time. But to save time he started the calculation in the middle of the sequence, manually plugging in some key numbers. To his surprise, the predicted output diverged sharply from the original. He eventually discerned that in the original computation the number used was 0.506127 but in the simulation he had only entered the first 3 significant digits, 0.506.[18] This phenomenon, eventually labeled "extreme sensitivity to initial conditions," posits that a minor change at the beginning (or at various points) of a sequence of events can dramatically alter the long-term outcome of the system. This phenomenon is also referred to as the butterfly effect.

The flapping of a single butterfly's wings today could produce a tiny change (i.e., small input) in the state of the atmosphere. Over a period of time, what ultimately happens meteorologically diverges from what would have happened had the butterfly not flapped its wings. So, in a month's time, a tornado that would have devastated the Indonesian coast may not occur. Or maybe a tornado that was not going to happen does occur (i.e., large output).[19]

Another metaphor for sensitivity to initial conditions involves rolling 2 identical balls down a craggy mountain. Starting the balls even a few millimeters apart atop the mountain could result in the balls traversing vastly different courses and coming to rest hundreds of feet apart. Small changes in a starting point can lead to dramatic differences in the final pathway taken or the final outcome in the case of a system that attains equilibrium.

Examples of systems that can exhibit chaos and are sensitive to initial conditions include the weather, warfare, population dynamics, fluid dynamics, health epidemics, and stock market prices. Here, we suggest that chaos may also arise in human motivation and behavior. In the case of health behavior change, initial conditions could include knowledge level; current attitudes and mood states; frequency, duration, and intensity of the target behavior; social support; social norms; genetics; and a myriad of other intrapsychic and environmental states and traits. The potential permutations in initial conditions are virtually infinite, which suggests that the potential pathways to change are too.

Chaotic systems are not synonymous with complete randomness; nonetheless, random events, because of sensitivity to initial conditions, can significantly affect complex systems. Consider why, after years of false starts and failed attempts, a person succeeds at ending an addiction, increasing his or her physical activity, eating healthier, or losing weight. Or why, after years of success, a person relapses into substance use. The precipitating event may be external, such as hearing about someone they knew who lost weight, quit smoking, started drinking again, or passed away. Or the individual may be exposed to a random public service announcement or a newspaper article. This concept of external stimuli affecting motivation is similar to the cues concept in the health belief model.[20,21] The random event may also be intrapsychic. Resident chunks of knowledge or attitude may unexpectedly coalesce to form a perfect motivational storm. For some inexplicable reason, despite no new information or persuasive appeal, the person changes his or her behavior. Motivation arrives as opposed to being planned.[3] Such inspiration might occur while driving a car, lying in bed unable to sleep, or even when not consciously focusing on the issue at all.

The concept of fractal patterns, a central concept of chaos theory, may also be relevant to the study of health behavior change. Fractals, which have been identified in natural science in such places as the microvascular system, brachial trees, and snowflakes, are recurring patterns within larger systems that are self-similar; that is, a shape or pattern appears similar at all scales of magnification. Although similar, the derivative is slightly variant. Although behavior change may unfold in almost infinite permutations of knowledge, attitude, norms, efficacy, and intention, there may be recurrent patterns of change within individuals as well as between individuals. These common patterns, if identified, could be helpful in identifying response styles within individuals or audience segments across individuals that unique interventions could target. There may be, for example, individuals predisposed to cognitive, rational change, whereas others may be predisposed to quantum, intuitive change.[3]

BEHAVIOR CHANGE AS A COMPLEX ADAPTIVE SYSTEM

Health behavior change may mirror other complex systems found in nature that involve multiple component parts that interact in a nonlinear fashion. Factors such as knowledge, attitude, belief, and efficacy no doubt exert influence on health behavior change. They may be thought of as the particle components of the motivational quantum. However, the interaction of these factors resembles a complex system. For example, which particular bits of knowledge, attitude, belief, and environmental constraints and the amount of each required to tip the system for a particular individual or a particular behavior is virtually impossible to predict.

In part, the complexity of human motivation relates to its sensitivity to initial conditions. In addition to differences in starting points, there may be key vectors along the pathway that propel the individual into a dramatically different space. These events may be thought of as trigger points that lead to large changes in direction or location (i.e., an epiphany). In complex systems this potential for the sequence of events to alter the course of a dynamical system is sometimes referred to as path dependence.[22] In systems that exhibit path dependence, actions at certain times, called "lever points" or "tipping points," can have large effects on outcomes. For public health research and practice, efforts to identify and "hit" such lever points require that we adopt a complex systems approach and recognize that small behavioral changes can have large system-level effects. Adopting a complex systems approach requires statistical approaches that consider the timing of interventions as well as the relevant initial conditions at the time of the intervention, such as mood states. Second, we must see behavior as probabilistic (i.e., quantum) and recognize that particular realizations may not be the result of rational thinking so much as they are the occurrence of unpredictable external and intrapsychic events.

Tipping points on the macrolevel are dramatic changes in social behavior that arise quickly and usually unexpectedly.[23] Whether it is a jingle or slogan, a political idea or mass purchase of a faddish product, such tipping points are virtually impossible to predict, yet retrospectively coherent explanations for the "stickiness" of the phenomena are routinely offered. Threshold effects or tipping points are not a new idea in the health sciences. For example, cutpoints for obesity, hyperlipidemia, and blood pressure are in part based on nonlinear thresholds at which disease risk begins to rise at a faster rate.[24] In behavioral terms, the tipping point can refer to the threshold at which individuals or groups adopt a particular idea or practice. Relating tipping points to the obesity epidemic, for example, there may be a societal tipping point at which a large percentage of the population decides to alter their diet and activity patterns. A recent tipping point may have occurred in 2004 to 2005 when as much as 15% of the US population had tried the Atkins diet or some other low-carbohydrate regimen[25] despite little scientific evidence demonstrating effectiveness.[26–28] Such nonlinear shifts have also occurred in the prevalence of smoking and illicit drug use.[29,30] However, they are difficult to predict let alone cause. On an individual level, the tipping point may be similar to the breaking or boiling points described in mathematician Rene Thom's catastrophe theory.[3]

The stock market provides an excellent example of system-level unpredictability. Even though each individual actor in the system pursues his or her own strategy, the collective behavior produces a random walk of prices.[31] At times, these behavioral rules produce large fluctuations (i.e., tipping points). Although predicting tipping points may be impossible, interventions that reduce their likelihoods, such as reductions in program trading, can constrain the boundaries of the chaotic system. For health behavior, consider taxes and other legislative constraints as efforts to prevent public health "crashes." For public health, a relevant question is whether we can identify intrapsychic patterns, initial conditions, or behavioral paths within and across individuals that increase the likelihood of tipping into healthy behavior, a point discussed in more detail below. And consistent with social cognitive theory, the action of individuals interact with social norms and other collective phenomena.

In the complex systems approach, an individual's decisionmaking process may be analogous to the spinning of ping pong balls in a lottery machine.[32] Each ping pong ball could represent a chunk of knowledge, attitude, efficacy, or intention. On each ball lay a few strips of Velcro hooks; the human psyche has strips of Velcro loops, which serve as potential motivational "receptors." Some of the motivational ping pong balls may have resided in the system for years, whereas others may have been more recently implanted through a health education program, clinical counseling encounter, or health communication campaign. Additionally, some "barrier" balls may have been deactivated (stripped of their Velcro) by allowing the person to express their fears and dread about change or to resolve their own obstacles. Rather than attempting to predict which piece or pieces of motivation may tip the individual to change or not, the role of the health professional (from the chaotic perspective) is to ensure the balls are kept spinning at various intervals, with varying air flow velocities to maximize the chances that they adhere to their receptors. From a complex systems perspective, when the right number or combination of balls has adhered, a tipping point becomes possible.

An example of complexity in behavior change may help clarify our point. Suppose that there exist 5 key pieces of information, denoted by the numbers 1 through 5, that might motivate a particular behavior change (e.g., smoking cessation), and suppose that each person has 7 mood states, denoted by the letters A through G. The latter may range from strongly positive affect to strongly negative affect. A person is only capable of becoming motivated to change his or her behavior while in mood states C, D, or E. Think of mood values A and B as being "too hot" and F and G as being "too cold" to accept an intervention. To capture the phenomenon that an individual's mood state changes over time, assume that the letter value of the person's mood states follow an unbiased random walk over time. The model can be thought of as follows: each day, a person has a value associated with his or her psychological state and each day the value is reset. This random walk of psyche values implies that only every so often will a person be susceptible to an intervention.

To complete the model, suppose that the person is participating in a Web-based intervention, which he or she logs onto daily for a week. The Web intervention contains the 5 key facts about his or her health behavior (1–5). The individual can attend to these facts in any order. Suppose that the intervention only succeeds if 2 conditions are satisfied: the person's mood is at letter C, D, or E at the time of the intervention and the exposure to the information occurs in the order 5-2-1-3-4-1-2. The sequence 5-2-1-3-4-1-2 will be a rare event. And the occurrence of that sequence on a day when the person's psyche has the correct mood state is even more unlikely. Nevertheless, given the nature of random walks, with enough time, every person could eventually experience a successful intervention. Interaction terms and path analyses may help elucidate these relationships, but fundamentally this approach requires that we embrace the chaotic and complex nature of behavior change. Imagine the complexity if every individual requires a unique combination of numbers and letters to achieve change.

The metaphorical model that we have sketched suggests 3 sources of unpredictability. First, the combinations of balls that prove necessary or sufficient to produce change may vary across individuals and be unknowable to the interventionist. Second, even if we did know which balls stuck, we might not be able to discern the order in which they adhered. If, as we suspect, behavior exhibits path dependency, this order will matter and may vary across individuals. Finally, the process of when and why particular balls may stick could involve chaotic events that defy accurate prediction. These 3 sources of uncertainty and their nonlinear effects suggest that the goal of behavior change interventionists may be to encourage wing flapping—that is, encouraging the subcomponents of the complex system to interact and hopefully produce a large output. Mediation and other statistical analyses to predict subsequent change may be a dicey endeavor, however.

The fact that many health promotion interventions produce significant positive effects may at first blush suggest that our current paradigm is working and that no major shift in thought or action are required. However, that current intervention strategies produce modest improvements is no more a proof of concept than it is to say that the average 6% to 7% annual rise in the stock market proves that stockbrokers are able to predict the market. In both cases, there may be underlying human dynamics that predispose systems to moving in a particular direction.[3] The former example may be because of an inherent will to live, and the latter from the inherent optimism of investors.

EMPIRICAL EVIDENCE

The results of at least 2 studies provide some support for the existence and power of quantum motivational change. West and Sohal reported an analysis of how smokers decided to quit.[33] Approximately half of the ex- and current smokers in their sample reported that their most recent quit attempt was unplanned (i.e., a quantum change), and those who did quit this way were more likely to remain nonsmokers than those who made a specific plan to quit. At least 1 other study of smokers found that more than half of quit attempts were spontaneous as opposed to planned.[34] The other study supporting quantum motivational change involved problem drinkers.[35] Matzger et al. found that problem drinkers whose decision to quit arose from a transformational experience (e.g., a negative or traumatic event such as hitting rock bottom or having a spiritual awakening) were significantly more likely to be non–problem drinkers at long-term follow-up than were those who reported weighing the pros and cons of drinking or who were encouraged by an outside other to quit. The cognitive (i.e., weighing of pros and cons) approach to behavior change in this study was associated with worse outcomes. Not only do there appear to be different pathways to change, but these different processes may affect behavioral outcomes differentially.

An interesting observation gleaned from physiology is that some degree of complexity can actually be desirable for certain systems.[36] A good example is heart rate variability. As Goldberger et al. have shown, within-individual variation in heart rate (as well as in other physiological functions such as breathing rate and sleep patterns) form complex yet self-similar patterns when mapped over time.[36–39] Analyses of these patterns indicate that there is an optimal degree of what they term "correlated variability," that is, optimal levels of complexity. Among congestive heart failure patients this correlated variability is too large (i.e., there is insufficient variability or complexity), but on the other end of the spectrum lies ventricular fibrillation, wherein the correlated variability is too small (i.e., there is too much variability). Goldberger and others have also noted that there is a pattern of gradual decomplexification of some physiological functions across the life span. For example, the walking gait of an infant is overly complex, whereas that of a senior citizen may be insufficiently complex. Ability to adapt to new psychological stimuli may also follow this pattern.[36–39] How these principles might apply to human behavior and motivation is an intriguing proposition. For example, addiction, obsessive-compulsive behavior, depression, or inability to change any health behavior could be conceptualized as a lack of optimal variability in emotional or behavioral response. Interventions, therefore, may aim to increase the complexity and variability of response rather than simply find a single substitute or coping behavior.

STATISTICAL IMPLICATIONS

Typically, because of the number of moving parts they include, complex systems models are often implemented with agent-based techniques. Agent-based modeling is a simulation technique that has been used to explain complex patterns of behavior at the individual and group level, such as evacuation patterns during crises, economic fads, and other group behaviors.[40] An agent-based model consists of individual entities—agents—that follow rules. The agents are situated in place and time and interact with one another according to their behavioral rules. In many models, the agents evolve their behavioral rules on the basis of feedback from the model.

Although they do not give closed-form solutions, agent-based models still can produce testable hypothesis. Testing these models often entails moving away from a linear conceptualization of behavior change. Adopting an agent-based approach almost surely would lead to a de-emphasis on finding the magic-bullet main effect or a specific structural model that accounts for dramatic amounts of variance. Agent-based models enable researchers to include inter-individual variability in the pathway to change. This level of conceptual and analytic complexity is a blessing and a curse. It accounts for complexity but may substantially limit our ability to develop generalizable statistical models of change.

In the linear framework, unaccounted-for variance is generally relegated to the catch-all "error" term, when in fact such an "error" may represent the chaotic component of the outcome. Stated otherwise, "error" may be the result of imposing a linear model on a nonlinear phenomenon. Additionally, in complex dynamic systems the interaction of factors can yield almost infinite potential patterns. In regression models, this degree of complexity may be analogous to higher-order interaction terms that could involve 5-, 10-, or 15-way interactions. Although linear methods can be used to model such interactions, they are limited statistically and conceptually.

First, the ability to detect such interactions would typically be underpowered, so unless

Linear	Quantum
Cognitive-rational	Intuitive
Motivation is arrived at	Motivation arrives
Planned	Epiphany
Cortical	Limbic
Left brain	Right brain
Particle	Wave
Maintenance of change	Initiation of change
Engineers/physicists	Artists

FIGURE 1—Continuum of motivational processes.

the magnitudes of these interactions are prespecified so that the study could be adequately powered, these analyses would generally lead one to assume, perhaps falsely, that no interaction exists. Second, untangling a 3-way or higher-order interaction generally extends beyond our ability to map and interpret such a finding. In complex systems, the levels of interactions are copious. Next, because many of the interactions are themselves nonlinear, standard interaction terms may be unable to detect these relationships, although quadratic and other nonlinear models could help in this regard. Finally, from a chaotic perspective, the confluence of interactions both within and between individuals is highly variable, and the system is sensitive to initial conditions making robust prediction of such complex interactions virtually impossible. Linear models of behavior change may then be both conceptually inappropriate and statistically futile. In traditional statistical terms, this approach would equate to analyzing and reporting separate main effects for multiple independent variables when there are known interactions (nonlinear in nature) of these variables. The solution does not do justice to the complexity of the phenomena.[3]

Given these observations, it may be useful to address why our linear models are able to account for even the modest amount of variance typically reported. There are several reasons. First, not all change is quantum. A significant proportion of change is caused by cognitive-rational processes. Quantum factors are only part of the change landscape, and their relative influence may depend on individual differences (both state and trait) as well as the factors unique to the target behavior. Secondly, if the true relationship between 2 variables is nonlinear, mapping linear models on such a relationship can still yield statistically significant effects. The linear solution simply misses potential curves and thresholds, which would be like drawing a straight line through a parabola. Our models are only detecting weak signals because we cannot differentiate noise from complexity.

Embracing the chaotic and complex nature of behavior change may conflict with innate human tendency to infer causality (i.e., determinism) as well as a need for predictability. For example, many individuals will assume that a lottery winner used some replicable strategy that led to them “earning” their prize or that some higher-order karma deemed the winner worthy. Allowing elements of chaos to be part of the public health picture requires that we relinquish the faith that reward and punishment or fortune and misfortune are doled out in an orderly, just fashion. Perhaps not surprisingly, chaos theory and nonlinear dynamics have met considerable resistance within the scientific community.[18] In fact, we would not be surprised if our article evokes some resistance. For public health professionals, adopting a complex systems approach may require reconceptualizing how and why we influence change.

UNIFYING LINEAR AND CHAOTIC PARADIGMS

The linear and quantum paradigms are not necessarily mutually exclusive. Our view of behavior change can include both complex and chaotic processes as well as those that are more linear and rational. As shown in Figure 1, the cognitive-planned and chaotic-quantum aspects of motivation can be placed along a continuum. Specifically, some behavior change events may best be explained as simple linear phenomena, whereas others may be highly complex and nonlinear. This distinction between types of motivation may hold both within and across individuals.

Some individuals may, by their nature, be prone to employ linear or rational decision-making processes typically associated with left-hemispheric functioning. Others may be predisposed to complex or quantum processes in which change is more unpredictable, dramatic, and less planned. Most individuals are likely influenced by both linear and quantum processes, perhaps depending on innate predispositions (traits), transient cognitive-emotional states, or characteristics of the target behavior.

We have focused on the process of initiating change, specifically the decision to attempt change. Quantum processes may be more influential at this stage, whereas cognitive, behavioral, and physiological processes may be more relevant to maintaining change. For example, whereas the decision to quit smoking may represent a quantum phenomenon, success at quitting may be determined more by the behavioral strategies employed, whether appropriate pharmacologic treatment is used, habit strength, and the extent to which the individual is cognitively prepared for the pitfalls of cessation and relapse. Conversely, some aspects of the postdecision cessation process may also be influenced by chaotic processes such as the efficacy to persist or the motivation to retry if initial attempts fail.

It is important to note that our chaotic and complex perspective of behavior change focuses mostly on the individual intrapsychic dimension. Environmental factors such as cost, availability, and legal restrictions also interact with intrapsychic determinants. In some cases, environmental determinants can overwhelm system constraints, and individual-level factors may have less impact on behavior. For example, raising cigarette taxes by several dollars per pack has a suppressing impact on individual smoking behaviors,[41] and lack of availability of fruits and vegetables can constrain dietary choices. In cases in which there is little volitional input (e.g., we hold a gun to the person's head and tell them they cannot smoke, or there are no healthy foods available in the environment), the system can become highly linear and predictable. Similarly, for diseases that are driven primarily by biological or genetic factors, individual volition may have little impact on outcome. On the other hand, as the degree of volition increases, these environmental and biological factors merely represent other components of the complex and chaotic system.

PRACTICE IMPLICATIONS

The complex and chaotic components of health behavior change, although difficult to predict or control, can nonetheless be incorporated into public health interventions. For example, with the "perfect storm" analogy, it may be important to provide individuals with periodic interventions that are delivered under varying "atmospheric" (i.e., psychological or life states) conditions. Periodic exposure is consistent with the approach many chronic disease management programs use. From this perspective, such programs can be viewed as providing repeated opportunities to produce the motivational storm. An example of periodic exposure can be found in the work of Cupertino et al.[42] in which smokers were engaged to participate in a smoking cessation intervention multiple times over 2 years. The idea of repeated exposures is also consistent with counseling models such as motivational interviewing, which provide clients with repeated opportunity to consider life with and without their risk behavior—that is, to spin the balls and possibly hit a lever point.[43,44] A goal in motivational interviewing is to help participants experience epiphany for change. Perhaps health promotion interventions should also devote more effort to understanding the role of mood states as a factor in intervention receptivity, and eventually strategically vary the states in which individuals are exposed to health messages and programs.

There are also statistical implications. The potential variance in behavior accounted for by traditional cognitive factors perhaps should be assumed to have an upper limit far below 100%. Given previous studies, a reasonable upper limit may be in the 50% range. And rather than assuming unaccounted-for variance simply reflects error, nonlinear models could be used to explore alternative mathematical relationships.

POTENTIAL AREAS OF RESEARCH

The proposition that a significant proportion of human behavior operates in quantum and chaotic terms, at first blush, may appear to defy empirical verification. However, as noted in 2 recent commentaries by Baranowski and Brug, it is important that the suppositions described herein be subjected to rigorous scientific inquiry.[45,46] Broadly, established qualitative and quantitative research methodologies can be applied to examine the extent to which chaotic and quantum process influence health behavior changes.

Qualitative Methods

Qualitative methods such as structured interviewing can be used to explore how and why individuals change their behavior. Although researchers have used these techniques for many years to elucidate the behavior change process, specifically framing the inquiry around quantum versus planned change and the experience of motivational epiphanies may yield important insights that have not heretofore been addressed. Quantum change researchers have already initiated some such research.[14–17] Specifically, it may be useful to explore the extent to which motivation arrived as opposed to was planned among individuals who changed either on their own or after exposure to an intervention. Similarly, rather than focusing on large, "main effects" of motivational variables, explorations from this perspective would focus on the complex nonlinear interactions between these variables. Such research could help inform the development of quantitative methods for assessing quantum versus planned change as well as the associated processes.

Quantitative Studies

Quantitative studies can be used to explore the correlates of quantum versus planned change as well as how these processes may differ across different health behaviors and individuals. For example, whereas quantum process may be more operative for addictive behaviors, rational process may be relevant to changing chronic disease behaviors or obtaining screening tests. The use of these processes may also differ by gender, age, or ethnicity. Individual psychological states may also serve as important initial conditions.

Physiological Mechanism Studies

With the advent of technologies such as functional magnetic resonance imaging, eye tracking, and momentary ecologic assessment, it may be possible to examine the neurologic basis for different types of motivation and even to predict when, how, and why quantum transformations occur. With functional magnetic resonance imaging, for example, neurologic markers of motivational types can be mapped, and individuals experiencing different types of neurocognitive motivation could be tracked to see how initial types of motivation may differentially affect long-term behavioral outcomes.

Agent-Based and Computational Modeling

Modern computing power has made it possible for researchers to construct agent-based models of phenomena ranging from global climate change to biological epidemics and behavioral contagion. Agent-based models allow for flexibility but maintain consistency through logical operation of the computer code. For processes with multiple, interacting forces they can help identify patterns and potential trajectories of success.[47,48] With an agent-based model, we could construct an artificial world populated with people who possess mental states that make them more or less open to an intervention.

CONCLUSION

We are not proposing that linear statistical models and cognitive, rational health promotion interventions be jettisoned in their entirety. To the contrary, we are proposing a complementary approach. By introducing a different way of looking at the successes and failures of interventions, we may be more likely to develop effective interventions.[49] There is a vast scientific base indicating that our interventions can successfully change behavior. What we are proposing, however, is that we begin to rethink why and how our interventions work so that we can improve those interventions. We propose that many large-scale interventions work because they have spun the balls of motivation in a large group of individuals, and for a subset of these individuals, the balls hit the necessary trigger point, arrived in the proper order, arrived while the person was in the right state, and fit and stuck to their motivational receptors. Interventions may then be reconceptualized as providing opportunities for individuals to hit a motivational lever. Perhaps, then, we should place greater emphasis on the periodicity of intervention rather than intensity—that is, provide multiple opportunities to experience the perfect storm as well as understand the psychological states that predispose one to experience stickiness. It is important to note that current theories and communication methodologies can inform which balls we select to highlight in our interventions, even if it may be difficult to predict if and how they may stick or whether the order in which they stick makes a difference.

Rather than advocate a wholesale change in practice, we have a more modest goal. We hope to encourage public health practitioners and researchers to incorporate nonlinear concepts into the design and analysis of their interventions. This goal may require adjusting our expectations for how well we can predict and quantify the change process; this means embracing these concepts rather than wrestling with them. ■

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