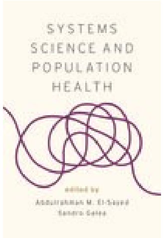

Systems Science and Population Health

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CHAPTER

14 Systems of Behavior and Population Health

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Abstract

The purpose of this chapter is to bring meaning to the idea of systems of behavior in the context of population health. Systems of behavior are the mental apparatus (thoughts, beliefs, memory, emotion, motivation, etc.) that drive behavior. The emphasis on systems is decisive because it bounds the nature of explanations, mechanisms and factors under consideration to dynamic processing models of behavior. Furthermore, the chapter considers systems of behavior in the service of systems of populations, a topic that is rarely covered within either population health or the behavioral and neural sciences. Thus, ultimately, this chapter aims to provoke thinking about how to embed systems in systems, where behavior is nested within populations.

Keywords: psychology health behavior, mechanisms, neural science, psychology

Subject: Public Health, Epidemiology

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1. Introduction

The purpose of this chapter is to bring meaning to the idea of systems of behavior in the context of population health. Systems of behavior are the mental apparatus (thoughts, beliefs, memory, emotion, motivation, etc.) that drive behavior. The emphasis on systems is decisive because it bounds the nature of explanations, mechanisms, and factors under consideration to dynamic processing models of behavior. Furthermore, we consider systems of behavior in the service of systems of populations, a topic that is rarely covered within either population health or the behavioral and neural sciences. Thus, ultimately, this chapter aims to provoke thinking about how to embed systems in systems, where behavior is nested within populations.

One approach to building systems of behavior might be to co-opt the mental apparatus from related fields such as behavioral medicine, health behavior, and health education—fields that have adopted theories of behavior to drive intervention and prevention approaches. However, this is not fully satisfactory because the theoretical approaches are less oriented toward a systems approach of behavior (we will describe what we mean by systems of behavior in detail below) than toward serving as frameworks for choosing measures of interest (for intervention) and capturing risk factors (for study). In a similar way, the addiction literature is limited in what it offers for building systems of behavior.

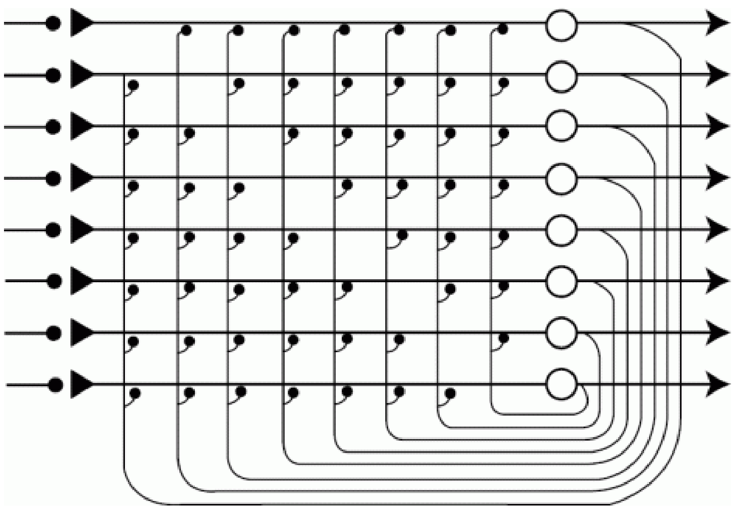
In what follows, we start with defining what we mean by systems of behavior and put forth a set of minimal criteria to help define it. Our approach reflects our training in cognitive science, a field that has specialized in building systems of p. 168 ↳ human behavior since the 1950s [1], and is thus ultimately constrained by what is known about humans (as opposed to any computation that solves a particular task). Then we provide an example from our recent work of a systems model of health behavior along with a critique of the model and some preliminary attempts to embed this system into a system of a population. Finally, we provide some thoughts and suggestions on the practicalities of embedding behavioral systems within population systems, thus addressing to some extent how to move forward.

We cannot emphasize strongly enough that what is presented below is about systems of populations, not developing systems of behavior for the purpose of informing intervention or prevention needs at the level of the individual. We will save the latter topic, an important one, for another discussion.

2. Systems of Behavior

Figure 14.1 is a schematic of a well-known and influential system of behavior—a model of an individual human's memory—whereby the circles represent mental constructs and the solid lines represent interactions among them [2]. Underlying this schematic is a set of detailed, formal assumptions, some capturing learning and some dictating the processing of information—all of which were implemented in a computer program. The conceptual development of this model was in response to a large body of experimental evidence on the nature of human memory. Equally important, the criteria for judging confidence in the model was determined by virtue of the matching between experimental data and data generated by the model during simulations. The similarities to agent-based modeling are obvious; the differences are only of scale—the interacting parts are mental constructs in place of people. p. 169 ↳

Figure 14.1



A classic system of behavior (from [2]; adapted with permission). See the text for a description of its components and operations.

We will not venture to rigorously define what is and is not a system of behavior but will instead explore three broad classes of criteria for gauging the extent to which a model of behavior represents a system. Table 14.1 describes these classes in detail. Operations is a class referring to the parts of a system: how they interact internally, the potential interactions external to the system, and how the system adapts over time via learning mechanisms. Variation captures the notion of differences in behavior across implementations of the system as a function of values of the parameters that define the operations of the system. A simple example would be the speed at which new information is learned—the operation of learning is not changed, just its rate. Development focuses on how the model was conceptualized, how it is compared to empirical findings, and the degree to which the system is implemented in a usable computational formalism. Ideally, this last criterion satisfies the need for embedding the system of behavior into a system of the population.

Table 14.1. Criteria for Qualifying as a System of Behavior

Criterion	Description	Class
Process-Oriented/Mechanistic	Postulates mental constructs and their interactions	Operations
Dynamic	Representation of change over time and, potentially, interfaces dynamically with social contexts and environment	
Learning	Aspects of the model can change permanently over time	
Individual Differences	Has the capacity to represents systematic and theoretically important variation in behavior across individuals	Variation
Theoretical Grounding	Processes and constructs are grounded and constrained by neuroscientific, psychological, or behavior economic theory	Development
Empirical Grounding	Proper comparison to empirical (most likely experimental) data to include testing of novel predictions. Ideally, a wide variety of experimental conditions would be considered	
Computational Implementation	A formal model of the operations and drivers of variation that also represents its theoretical basis in a way that is empirically comparable to human experiment and observation	

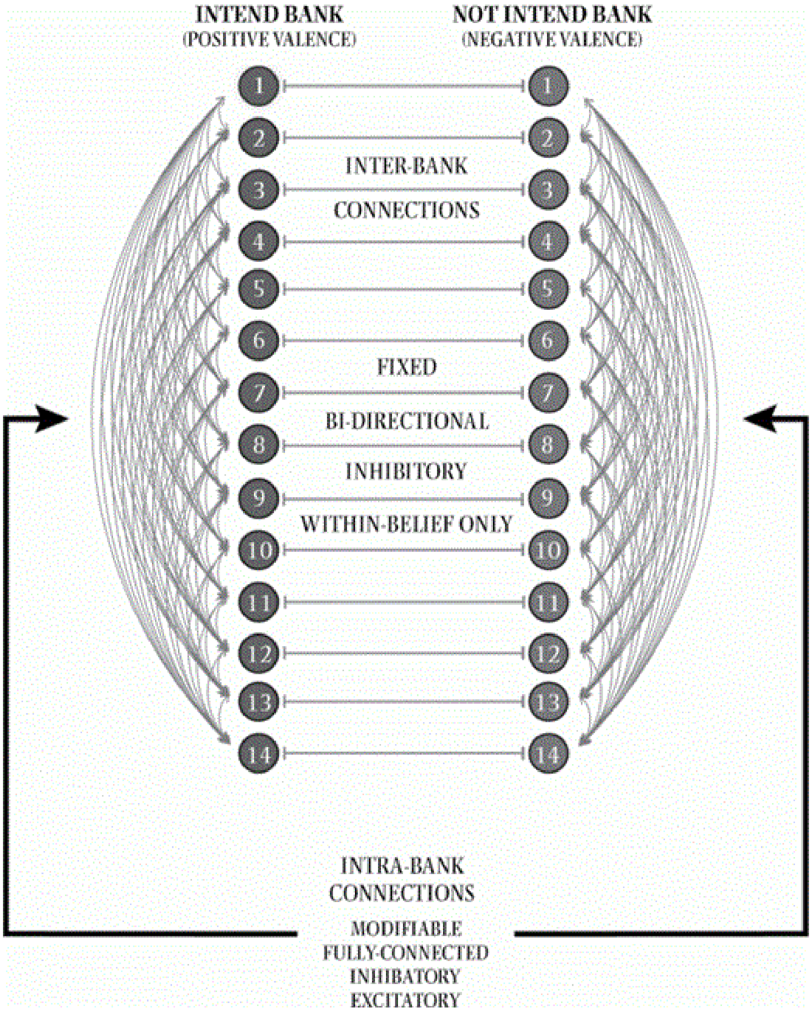
An issue that is not represented in Table 14.1 is how to define what counts as behavior. For the purposes of
p. 170 this discussion, overt behavior is not required for a ↳ model of behavior (e.g., picking up a cup of coffee). Thoughts and other mental processes alone qualify as behavior (e.g., recognizing that one wants coffee and planning to get it are both behaviors).

3. A System of Health Behavior

We now show a system of health behavior—derived from some of our recent work [3, 4]—based on a well-understood formalism used extensively in cognitive science called "artificial neural networks" (henceforth "neural networks"). This formalism has been used repeatedly to represent important perceptual, cognitive, and social phenomena (see [5] for a review; [6] for more recent work). The import for population health is the natural analogy between the socio-cognitive aspects of health behavior (e.g., beliefs, attitudes, intention, and social learning) and the kinds of mental processes that neural networks are good at representing (see [7] for a review). Specifically, neural networks are able to capture social processes that can be conceptualized as a dynamic human memory process, both taking into account what has been learned from past experience and the potential for more immediate influences such as current social and environmental contexts [2, 8, 9, 10].

It is precisely these features that make neural networks useful for modeling health behavior—to capture the simultaneous influence of prior learning from past social contexts and the more current (or immediate) social context. For illustration, Figure 14.2 shows one of our systems models of the Theory of Reasoned Action [11] using the neural network formalization [4]. This model conceptualizes intention toward a behavior as driven by a dynamic, on-the-fly memory process called "constraint satisfaction"—the set of beliefs, cued by the social context external to the model, become activated, and then the system settles into a state (the intention state in this case) that has maximized how well it has satisfied the many constraints in the model. The constraints are the positive and negative relations between beliefs that encode belief structures from past experience via learning (e.g., exposure to peers' beliefs over the past year).

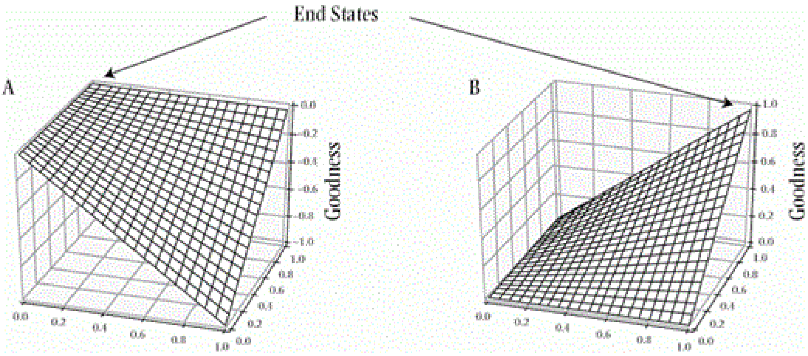
Figure 14.2



A schematic of an artificial-neural network implementation of the Theory of Reasoned Action [11] (borrowed from [4]; adapted with permission). Each belief is constructed from two processing units, one of which represents positive valence and the other negative valence (see the numbered circles; number indexes the belief). Within bank constraints (shown as curved arrows on the left and right of the belief units) capture the relations among beliefs and are modifiable via learning. Between bank constraints are fixed and represent the theoretical construct that beliefs are uni-dimensional, and thus valence units should be mutually inhibitory. The operation of the model proceeds from an exposure to beliefs in its external social context and results in a stable intention state via a constraint satisfaction process.

The constraint satisfaction process used in the model is a hill-climbing algorithm. That is, the final state of the model, once cued by a social context, is the end path of a trajectory on a goodness surface that seeks increased goodness (larger goodness means more constraints were satisfied). Figure 14.3 is an idealized representation of the goodness surfaces for two instantiations of the model (given a cue from the social context). Panel A suggests that the model will settle in a separate state compared to Panel B (the highest point on the goodness surface is the settling point).

Figure 14.3



A stylized goodness surface across possible states of a hypothesized neural network that uses constraint satisfaction as a settling mechanism. The x- and y-axes represent the full range of values for two units in the neural network (the full goodness surface for the model in Figure 2 is 28 dimensions, one per network node). See text for interpretation and comparison of Panels A & B and for additional details.

The differences between the two panels in Figure 14.3 represent three distinct scenarios: (1) the difference
p. 171 between two people given an identical social ↳

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context, where the differences are driven by variable social histories or different past exposures to social context features, or (2) the difference between two social contexts for the same person, or (3) the same context, the same person, but before and after the model had significant time to learn from past contexts. In short, end states, driven by hill climbing, vary because of learning (changes in the constraints) or differences in current social context.

Our prior work with this model, some of it using human data, illustrated the following via a series of simulations: (1) its predictive power with respect to intentions toward behavior and (2) a formalization that accounts, simultaneously, for both past experience via learning and a person's more immediate social contexts [3, 4].

How does this example model fair against the criteria presented in Table 14.1? Is it a system of behavior? The operations of the model are clearly mechanistic (beliefs and their attendant constraints serve as the mental constructs and their interactions), dynamic (through the constraint satisfaction process), and enable learning over time from exposure to social contexts. Although variation in the model across individuals was not explicitly explored to date, it is something that the model could easily afford. For example, the rate of learning in the system (slower, faster) and the degree to which positive and negative valences inhibit one another (see [12, 13] regarding ambivalence in attitudes) might serve as explanations of variation across individuals. Finally, the development of the model was grounded in the Theory of Reasoned Action [11] (a highly influential theory both in health behavior and in social psychology), was tested against empirical data, and was formalized using a well-understood computational formalism. Thus, all of the criteria in Table 14.1 were met.

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4. Systems of Behavior in a System of a Population

A fundamental goal for population health is to have a clear understanding of the relation between models of individuals and models of populations, both in the service of scientific understanding and intervention/prevention needs. Under the i.i.d. (independent and identically distributed) assumption, statistical models offer an appropriate realization of this goal, especially when data are longitudinal in nature. Multilevel hierarchical modeling can accommodate non–i.i.d. conditions within a statistical framework but do not capture bi-directional feedback across levels of a system. Agent-based modeling addresses the question of bi-directional feedback in a flexible dynamic way, but has yet to incorporate systems of behavior, instead relying on extra-simple assumptions regarding individuals' behavior [14, 15, 16, 17]. Little, if any, work approaches this goal in the context of systems of behavior.

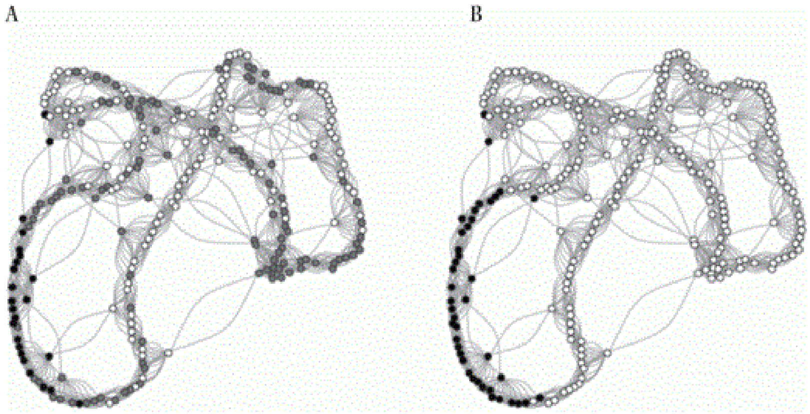
Next, we will present new preliminary work of our own that begins to explore questions about the relation between individuals and populations using a systems of behavior approach. Specifically, we address the following question: to what degree do the parameters of a model of intention within individuals affect the diffusion of intention across a population? This question aligns with work over the past decade on the diffusion of health behaviors on social networks [18, 19, 20, 21, 22, 23, 24, 25] in that it is primarily concerned with diffusion dynamics of behavior. The difference lies in how the individual is represented.

Using our newly developed modeling platform called MANN (Multi-Agent Neural Networks, see https://github.com/chendaniely/multi-agent-neural-network accessed 3/25/16) we explored the diffusion of intention toward a behavior on a social network as a function of two parameters related to how intention operates within the individual. That is, over a large set of simulations, we varied the parameters of a neural network representing the Theory of Reasoned Action [11] while fixing the social network parameters, thus providing an experimental test, in-silico, of whether variation in the neural network parameters affected the diffusion dynamics of intention on the social network.

Specifically, the parameterization of the neural network focused on two competing aspects, illustrated in Figure 14.2, that are dictated by the nature of the constraints built into the model. The within-bank constraints represent the degree of excitation within intention units (or not intention units) such that as these constraints become stronger in magnitude, the likelihood is increased that a small degree of activation within each bank will lead to amplification within the same bank. The between-bank constraints are similar but inverse, so as these increase in magnitude, each bank inhibits more the degree to which the
p. 174 other ↳ bank will become activated. Both of these constraints are reflected in the hill-climbing procedure that is described above and illustrated in Figure 14.3.

A single simulation consisted of instantiating a small world network (specified in [26]; our parameter values for the social network were 250 vertices, 10 nearest neighbors and a 0.02 probability of rewiring per each network edge, using bidirectional edges) in which each vertex was represented as a neural network (similar to Figure 14.2) that had the within-bank and between-bank constraints set to a value dictated by the experimental design (described below). A simulation was initialized so that all vertices were identical in terms of the value of the within and between bank constraints (with some purposeful random noise added). After initialization, five of the vertices were exposed randomly to one of three social contexts (high intention, high not intend, or ambivalence). Then, the simulation ran for 100 time steps. During each time step all vertices were updated in a random sequential order. A vertex was updated by using one of its neighbors' last intention states, a portion of which was directly accessible to the updating vertex and thus served as a constraint on the updating vertex. In this way, intention states had the chance to propagate through the social network. Figure 14.4 compares an early to later state of a single simulation.

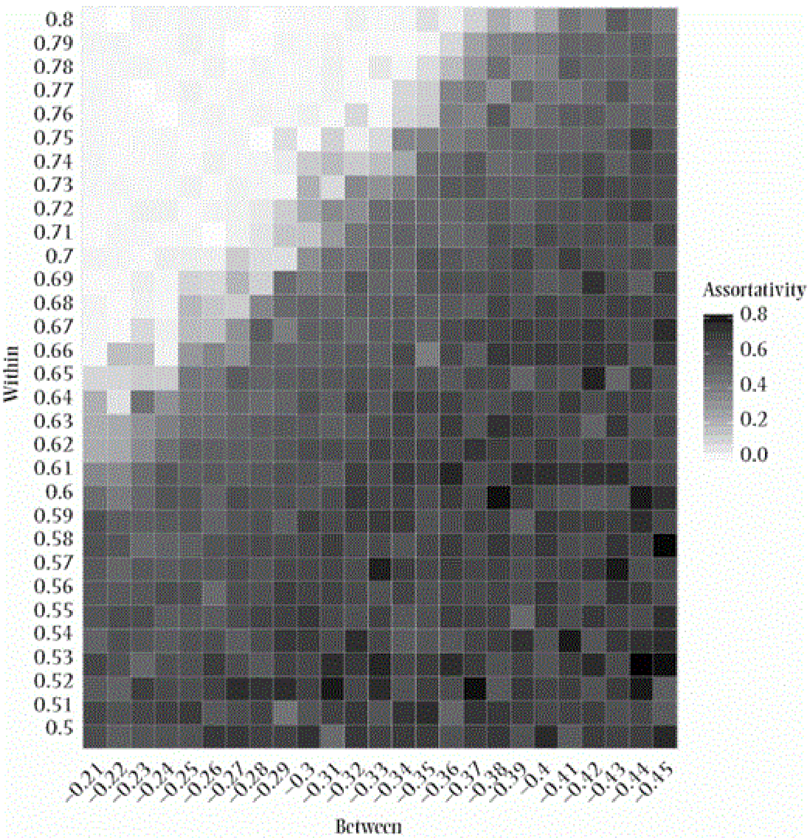
Figure 14.4



Example of the time course of the diffusion of intention on a small-world graph with 250 vertices. Each vertex represents a recurrent neural network instantiation of the Theory of Reasoned Action [11]. The black vertices represent a state of not intending, the white intending, and the gray, ambivalent. Panels A & B illustrate the state of the network early and late in the diffusion process, respectively.

Figure 14.5, a heat map, presents the full results of the simulations across the neural network parameter space (there were 25 levels of the between bank constraints and 31 levels of the within-bank constraints totaling 775 points in parameter space). Each cell in the heat map, representing one point in parameter space, is the average over approximately 10 simulations. (Figure 14.5, thus, captures p. 175 ↳ approximately 7750 simulations.) The metric represented in Figure 14.5 is the average amount of assortativity with respect to intention state at the final time step (t = 100) of each simulation. That is, roughly, it captures how much clustering of intention is present on the social network at the end of the simulation. As a point of reference, Figure 14.4, Panel B shows a high degree of clustering on intention.

Figure 14.5



A heat map representing 7750 diffusion of intention simulations (Figure 4 represents one of these). The axes represent two parameters of the recurrent neural network instantiation of the Theory of Reasoned Action [11]. The value of each cell in the heat map represents the average network assortativity (on the small-world graph) on intention of approximately 10 simulations for one point in the parameter space. See text for further details.

The pattern shown in Figure 14.5 suggests that, although there are two regions of the parameter space in which changes in the neural network parameters have little consequence, the two regions are very distinct—one exhibits a large degree of assortativity with respect to the intention state; the other does not. This type of phase transition is characteristic of complex systems.

In sum, by constructing a simulation environment in which systems of behavior were nested within a population, we illustrated, experimentally, that the ↳ parameters of the system of behavior affected the population dynamics, even when holding the social network parameters constant.

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5. Looking Forward

Thus far we have (1) suggested criteria for a system of behavior, coming largely from work in cognitive science and computational psychology (see Table 14.1), and (2) provided an example of a system of health behavior and a glimpse of what insights might be gleaned when implementing said system into a system of a population. We will now focus on some core issues to consider as we move forward with further development of the systems of behavior approach in the domain of population health.

The most basic consideration is to recognize the conditions under which a system of behavior model is desirable, while appreciating that much work using systems science has yielded useful insights into population health phenomena without implementing systems of behavior [15, 16, 17, 18, 27]. In some cases, the research question itself will require a systems of behavior approach, like the work shown above in which we explored the effect of variation in the parameters of a system of behavior on the diffusion dynamics in a population. Beyond such obvious cases, however, the need for a systems of behavior model will be less clear.

One unmistakable situation in which systems of behavior will be desirable is when intervention/prevention levers under question implicate a set of complex mental processes such as those described in Table 14.1 (e.g., changes in dietary habits). By implementing a system of behavior in a model of a population, the insights will be in terms of the actual mental processes that should be targeted in order to see changes in the population. To date, however, there is a dearth of work, if any, that addresses interventions using a system of behavior (as outlined in Table 14.1) embedded in a system of a population. Although Figure 14.5 represents this notion directly, it is only in the abstract as proof-of-concept.

Another core consideration is feasibility. Although there exist many systems of behavior already in computational form, covering many aspects of human behavior [28], it is uncertain to what extent these are directly applicable to population health needs. To gauge this will require both exploration of existing models and, most likely, extension of existing theory (computational or not) to include processes that are yet postulated but relevant for population health. Consider the system of behavior for the Theory of Reasoned Action [11] presented in Figure 14.2. We co-opted a general model used for attitude formation and reconceptualized the Theory of Reasoned Action to fit. In the process, we extended the Theory of Reasoned Action by implementing p. 177 ↳ additional mechanisms (e.g., how beliefs of one person are communicated to another, learning, and constraint satisfaction), none of which were empirically grounded. Only now are we in the process of developing social experiments to provide empirical grounding.

One intriguing idea is to leverage the extensive work on what are called architectures in cognitive science [29, 30, 31]. Architectures attempt to capture several core aspects of human behavior that are general across tasks and can account for individual differences. This might serve as a useful approach for understanding difficult issues such as behavioral comorbidity (e.g., smoking and unhealthy diet behavior) and could incorporate a general set of individual difference mechanisms that are directly related to health behaviors (e.g., delayed discounting [32]; self-regulation [33]).

A final consideration is the appreciation that common risk factors (e.g., gender, age, race/ethnicity, geography, socioeconomic status) cannot be represented in a direct way in a system of behavior. It is not that these factors are negligible, only that they are placeholders for the direct processes represented in Table 14.1—e.g., differences in attitudes between two genders/racial ethnic groups can only be explained by the operations and individual difference parameters of a system of attitude formation. A useful heuristic is this: to the extent that a risk factor can be conceptualized in terms of Table 14.1, it can be considered as a system of behavior or a part thereof.

6. Conclusion

The main point of this work was to introduce the feasibility of integrating systems of behavior with systems of populations for further understanding, practice, and policy in population health. Paradoxically, this notion is not only foreign to those in population health but also to those who focus on human behavior. In part, the latter group doesn't see the purpose; studying individuals is sufficient. However, it is the former group for whom this chapter is targeted.

In any event, it is clear that much work is to be done in such a novel enterprise. Mostly, this work will require highly interdisciplinary teams, the generation of novel theory for application, and mostly, evidence and buy-in that this effort will, in fact, help to drive improvements in population health. We are hopeful that the work in this chapter begins a fruitful discussion.

Acknowledgments

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