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A Multi-scale Paradigm to Design Policy Options for Obesity Prevention: Exploring the Integration of Individual-Based Modeling and System Dynamics

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Complex adaptive systems-of-systems are inherently multi-scale across several dimensions, including temporal, geographical, and organizational. We present a multi-model paradigm integrating a community-scale individual-based model (IBM) to investigate the immediate effects of interventions with a population-scale system dynamics (SD) model to analyze long-term results of those interventions. The IBM incorporates actors embedded in a social network to simulate the spread of opinions relating to nutrition and physical activity (N&PA) behaviors such as dieting and exercise, and the effects of these opinions on individual actions and consequential body weights. The IBM network structure is composed of a mixture of scale-free and uniformly random connections to represent a social network of relationships and interactions within a community: opinions regarding obesogenic behaviors propagate among individuals on the network, or are influenced by media sources via advertising, public health campaigns, and counter-marketing. We analyze and compare effects of possible policy interventions, and illustrate a policy cocktail that addresses multiple aspects of the obesity problem, resulting in amplification of desirable results and a strong uncertainty reduction. The outputs of the IBM, seen as changes in obesogenic behaviors, are used by the SD model to calculate the resulting changes in mortality and morbidity over ensuing decades.

Keywords: multi-scale modeling, obesity, opinion formation, spread of health behaviors, network effects, policy analysis, virtual populations, multi-method.

1. Introduction

As the incidence of overweight and obesity increases throughout the world, obesity is being recognized as a global epidemic (Kumanyika et. al., 2002). The overall percentage of obese adults in the US increased from 13.6% in the 1970s to almost 30% in 2000 (Bray, Bouchard and James 2003). As of 2006, fully two-thirds of Americans were classified as overweight (Ogden 2006). A recent study predicts that the US obesity epidemic will not plateau until at least 42% of adults are obese (Hill, et al. 2010). The obesity problem is not limited to the US; its prevalence has tripled in many countries since the 1980s.

One of the greatest contributors to chronic disease, excessive body weight is associated with various health conditions, most notably with diabetes and heart disease but also with asthma, orthopedic problems, certain forms of cancer, psychosocial adversity, and mental disorders including depression (Must and Strauss, 1999).

In addition to its role in increased mortality/ morbidity, obesity is also a major contributor to medical expenditures (Finkelstein et al, 2005) such that governments recognize the need to take action to mitigate the increasing health care costs of obesity. Estimates suggest that obesity related expenditures accounted for as much as 9% of total US medical expenditures in 1998 (roughly $78.5 billion), a proportion that is expected to increase (Finkelstein, Fiebelkorn, and Wang 2003).

To date, obesity has presented a challenge to public health researchers at many levels; part of the impediment to definitive analysis has been the multiplicity of complex factors influencing the development of obesity among individuals within a population, and those factors influencing the success/failure of prevention efforts. It is recognized that the systems approach needed to address these issues is interdisciplinary, requiring the collaboration of epidemiologists, statisticians, physicians, mathematicians, behavioral sociologists, and other related scientists (Levy, Mabry, and Gortmaker et al. 2010).

As emphasized in a recently released Institute of Medicine report (2010), systems-oriented models can be especially useful for considering the potential impact of an array of policies required to tackle the obesity problem. Huang et al. (2009) and Hammond (2009) have argued that "the attributes of the obesity epidemic as socio-ecological, multi-factoral, and multi-scale, demand analysis that is systems-oriented and uses a multi-level framework with a holistic perspective in order to describe the complex and dynamic nature of the forces at play." Increasingly, systems-oriented frameworks and multi-scale modeling approaches are being utilized in obesity prevention research.

In this study, we present a multi-model paradigm to integrate a community-scale individual-based model (IBM) with a population-scale system dynamics (SD) model to analyze possible long term results of policy interventions for obesity prevention. The purpose of the IBM is to investigate the consequences of local interactions of members of a population, influences by media sources, and the effects of policy interventions. Towards this goal, the IBM uses a randomly generated population embedded in a social network to simulate the spread of opinions, and, by extension, the spread of health behaviors among individuals in a representative community. Behaviors related to nutrition and physical activity (N&PA), such as dieting and exercise, are investigated.

In recent years, inter-personal health effects have been the focus of many researchers (Burke and Heiland, 2006; Hammond and Epstein, 2007; Cutler and Glaeser 2007). The influence of these health effects are shown to extend to health conditions such as obesity (Christakis and Fowler, 2007), and smoking (Cutler and Glaeser, 2007; Fowler and Christakis, 2008).

Using an opinion dynamics algorithm for opinion contagion within a network, the IBM explores the effects of an individual's opinions regarding obesogenic behaviors on that individual's health behaviors. The IBM calculates changes in behavior at the individual level due to changes in opinion resulting from influences in the social network: individuals adopt or cease obesogenic behaviors based on their opinions passing certain initiation or cessation thresholds. Outputs of the IBM, seen as changes in obesity rates, are used as inputs to an SD model which calculates the resulting changes in mortality and morbidity over ensuing decades. Designed to work collaboratively, this multi-model approach provides analysis and comparison of the effects of possible policy interventions or combinations of policies ("policy cocktails") in conjunction with probable requirements for health care into the future.

2. Individual Based Model (IBM)

2. 1. Agent/Individual-Based Modeling

Individual based models (IBMs) are commonly used to look at consequences of individual or local interactions of members of a population. The notion of the IBM was first introduced by Reynolds, who has primarily used agent-based methods to model and analyze social systems, such as people in crowds, colonies of honey bees, or fish flocks (Reynolds, 1999). In agent-based models, a number of (possibly) heterogeneous individual agents are defined in terms of their *behaviors* (procedural rules) and characteristic *parameters*, which typically interact in a given space.

IBMs are a subset of multi-agent systems designed as a collection of interacting parts, but are distinguished by the fact that each "agent" corresponds to an autonomous individual in the simulated domain (Reynolds, 1999). This modeling approach is also termed as *entity*- or *agent*-based models, and as individual/entity/agent-based *simulations* (Reynolds, http://www.red3d.com/cwr/ibm.html). IBMs also have an overlap with cellular automata, and their emergent dynamic behaviors are known to be linked with those of other models to form a higher degree of complexity and emerging behaviors.

2.2. Network Topology

IBM's typically consist of an environment or framework in which agents and interactions are embedded. The structure of interactions within this framework, i.e. the network topology, illustrates who is interacting with whom and at what frequency. It has been demonstrated that social networks substantially differ from other types of networks, including biological and technological networks, in that they are often divided into groups or communities (Newman and Park, 2003).

Random networks with scale-free topologies form the basis for our individual-based simulations using opinion dynamics to model N&PA related health behavior. Scale-free networks are often created using the method of preferential attachment, which generates network topologies with a power law distribution of node degree (Barabasi, 1999). This network topology has been commonly observed in a wide variety of real-life phenomena, including social networks representing friendships, advice-seeking, and sexual relations (Albert and Barabasi, 2002). Preferential attachment, however, fails to explain some of the underlying topology observed in real friendship networks and, consequentially, the likelihood of the spread of health behaviors and obesity through social ties.

In this study, we modify a scale-free network to include a proportion of edges between randomly selected nodes, resulting in a network that is predominantly constructed using the Barabasi-Albert model of scale-free network construction, with a smaller proportion of edges determined by an Erdos-Renyi random process.

2.3. Opinion Dynamics Model

Opinion formation as a social process has been of interest to researchers of social phenomena for decades, motivating some of the earliest work in social network analysis and yielding classical components of the field such as structural balance theory (Scott, 2000). More recently, a family of models has been developed based on techniques arising from the field of statistical physics. The variant we employ here falls under bounded confidence models, where an opinion is represented as a real value on the interval [0, 1] (Castellano et al. 2009). In contrast to discrete opinion dynamics models, all agents start with different (and randomly assigned) opinions allowing opinion clusters to emerge at final steady-state, such as consensus (one cluster), polarization (two clusters), or fragmentation (more than two clusters). Individuals update their opinions based on the opinions of those they contact in the network, according to a discounting equation and subject to bounds of confidence. These confidence bounds (often referred to as "tolerance") integrate the realistic notion that individuals are more willing to alter their opinions to ones more closely resembling their own, and that strongly different opinions are more likely to be avoided or ignored. As the tolerance value ε_i gets smaller, more clusters emerge.

This model is grounded in the work of Deffuant, Weisbuch, and their collaborators (Weisbuch et al., 2002). They presented a model in which random, undirected interactions take place in a well-mixed or locally-connected population, resulting in the formation of opinion clusters – distinct, homogeneous groups of similar opinions – with the number of clusters inversely proportional to the tolerance values of the nodes (Weisbuch et al., 2002). We extend their original model of randomized interactions to more appropriately capture the dynamics relating to the obesity problem.

Recent studies investigating the importance of social networks to obesity have indicated that friendship relations relevant to the phenomenon should be considered as directed (Christakis and Fowler, 2007). This means that if Person B lists Person A as a friend, but A does not nominate B, we expect that A will influence B, but not vice versa. Directionality in such social networks represents directionality in friendship nominations. For the relationship example here, a single directed line would be drawn from B to A. Because the opinion we are modeling is an aggregation of many underlying beliefs and opinions relating to lifestyle choices, we also introduce a smoothing, or an averaging function to replace the randomized interactions developed in the Deffuant model, similar to that proposed by Hegselmann and Krause (2002). In this model, an individual will gradually adjust their opinion by using the average value of the opinions of those neighbors falling within the threshold defined by their tolerance value.

The equation for the updated opinion of an individual at time t+1 is:

$$x_i(t+1) = x_i(t) + \frac{1}{n}\sum_{j=1}^{n} \mu_{ij}(x_j - x_i)$$

where x_i is the opinion of the individual under consideration, and x_j is the neighbor's opinion. μ_{ij} is referred to as the plasticity value and can be considered to represent the strength of the relationship from i to j. The algorithm iterates over the n out-degree neighbors of i whose opinions fall within the tolerance thresholds:

$$|x_i - x_j| \le \varepsilon_i$$

where ε_i is the tolerance limit of the individual under consideration.

2.4. Opinion-Behavior Mapping

Our model also employs a function for individuals to derive their behavior based on their opinion value. In our application, we are particularly interested in N&PA related behaviors affecting an individual's body weight and obesity, and more specifically, increased consumption of caloricdense foods, such as fast food and soft drinks containing large quantities of sugars. In our model, we specify an initiation threshold for these behaviors. If an individual's opinion increases above this threshold, they are considered to have increased their consumption of these products to the point of significant increase in their body weight. For simplicity in this analysis, we use a simple step function, although a sloped, stepped, or sigmoid function could also be used depending on the physiological model under investigation.

We also introduce hysteresis into the opinion to behavior mapping function. which incorporates the nonlinear etiology of obesity. Existing literature provides evidence that once obesity establishes itself, both the habituated behaviors and similarly tenacious physiological processes resist weight loss (Leibel, 2008). Evolutionary considerations which account for reproductive efficiency and survival suggest that body energy stores are readily sensed and regulated, but this regulation is not symmetrical on both sides of the energy equation. Physiological and behavioral responses defending our energy storages are stronger than responses to excess gains of storage. On the physiological level, lower levels of the leptin hormone at birth appear to result in more rapid weight gain (Parker, 2010) which in turn may cause higher leptin concentrations, thereby a leptin resistance, more weight gain, and eventually resistance to weight loss (Monteiro and Victora 2005, Singhal et al. 2003) .

Childhood obesity studies suggest that even by the age of 5 years, many aspects of obesity appear relatively resistant to change (Gardner, Hosking and Metcalf et. al., 2009). Recent findings also indicate that obesity is more persistent than other common chronic conditions in children (Van Cleave, Gortmaker and Perrin, 2010). On the other hand, these findings do not imply that obesity is permanent at these, or even at later ages in life. The downflow rates of obesity, i.e. people moving from obese to non-obese categories, ranges between 20-30% per year for children, and 10-20% per year for adults.

Obesity shows a similarly resistant nature on other levels including cultural norms and behaviors. In a simple computational experiment, Hammond (2008) demonstrated that changing norms of body weight themselves could propagate obesity in itself, as the population becomes increasingly obese over time. Similarly, research indicates that as the population body mass index (BMI) has increased, cultural norms shift such as parents or caregivers do not recognize child obesity as readily (Carnel et al. 2005) therefore "normalizing" obesity and making behavior change more difficult (Ross and Mirowsky, 1983; Neumark-Sztainer et al. 2008). On the behavioral level, increased screen time may cause children to get less sleep (Owens et al.) thereby causing hormonal changes that make them more likely to get less physically active, eat more, and watch more TV (Taveras et al, 2006, 2008)

Initiation and cessation thresholds are represented as opinion values, where the units of opinion are simply the degree to which an individual has a favorable association to the subject (e.g., consumption of calorie-dense soft drinks and fast food, a preference for sedentary forms of entertainment, and other obesogenic behaviors). As indicated, thresholds are aggregate across a large number of individual ideas and opinions (fast food tastes good; fast food is inexpensive and convenient, etc.). The initiation threshold sets the bar for the level of favorable disposition necessary to give rise to a behavioral regime leading to health consequences (the level of "overindulgence").

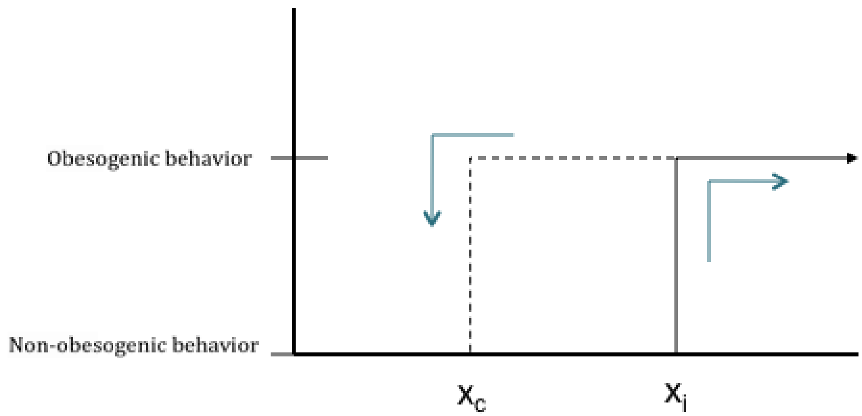

Figure 1: Behavioral change resulting from opinions passing initiation and cessation thresholds. If an individual's opinion passes the initiation threshold, x_i, that individual will adopt obesogenic behaviors. Once adopted, the individual will continue those behaviors until their opinion passes the cessation threshold, x_c.

In addition to the opinions and behaviors of individuals in the social network, we consider the activity of advertising and health-related education and counter-marketing efforts. Existing literature suggests that the availability, accessibility, and marketing of foods all contribute to our food consumption patterns, either directly by enabling or constraining our choices, or indirectly by changing physiological processes to affect food intake. In the US, the availability and accessibility of healthy foods such as fresh produce are often limited, particularly in poor or rural communities (White, 2007). Marketing of high-calorie foods to children through packaging, retail, and media is found to have increased purchase and consumption of those foods (Committee on Food Marketing and the Diets of Children and Youth, 2006).

The media sources are represented as nodes in the network with only in-bound links, indicating that these messages have the ability to influence the network without being influenced by its members. Advertising, counter-marketing, and educational nodes attempt to promote an opinion value in the network favorable to their own position.

3. Simulation Experiments

3.1. Design of the Scenarios: Policy Cocktail Example

Many classes of medically important diseases demonstrate significant robustness to treatment. This robustness can be due to heterogeneity in the causal chain of biochemical events, and in the evolutionary dynamics resulting from partial treatment successes. The medical community has developed a practice of treating some of these diseases with “drug cocktails,” combinations of drugs with multiple avenues of effect or multiple targets within the system. Many problems in public policy can exhibit analogous characteristics – adaptive and dynamic components in the system can respond to policy interventions in ways that counteract the original intent, attenuating or even reversing desired changes. This is sometimes referred to as the policy resistance problem of complex dynamical systems.

Here, we illustrate an example of the design of a policy cocktail to address the obesity problem in adolescent populations using the individual based model. The application of multiple policies with different targets can achieve two results – an amplification of effects resulting from a complementary combination of policies, and a reduction in outcome uncertainty, which demonstrates increased robustness against variability across model community structures.

In this scenario, we consider a local community in an abstract form, representing an individual high school. The model community consists of 250 individuals originally seeded with random opinions drawn from a uniform distribution. We apply the opinion dynamics algorithm on the network until it reaches steady state and opinion values cease to change. At this point, each person either shares the same opinion as their neighbors (i.e., they reach consensus), or their opinions differ by more than the tolerance value (creating clusters of similar opinions and behaviors).

From this steady state, we analyze these individuals’ changes in opinions and behaviors in response to a series of proposed policy interventions. We model these interventions both singly and in combination. The policies under consideration are targeted to different aspects of the obesity problem, mapped to various components of the individual-based model.

Policy Intervention 1: Elimination of soft drinks from schools

In addition to first order effects that are the direct consequences of policies, interventions in complex adaptive systems can also result in second and higher order effects. These additional effects sometimes result in unintended consequences, which can attenuate or even reverse the original policy goals. However, the intentional integration of second order effects can allow the design of more elaborate and potentially more effective policies. This observation suggests that policy can craft interventions as perturbations, such that the intended consequences of the intervention is not restricted to the first order consequences – the first order consequences might even be considered as being of secondary importance. Rather, the goal of an intervention as perturbation policy is to induce a systemic disruption that opens an opportunity for follow-on policies to have increased efficacy.

We first introduce an elimination-oriented policy, which includes any intervention that strongly restricts or eliminates the availability of a product. Existing literature provides evidence that product elimination can be useful as an organizational intervention tool, especially concerning the consumption of sugar-sweetened drinks (Wang et al. 2009, Bleich et al. 2008, Ludwig et al. 2001), which is seen as a major contributor to increased obesity among youth and adults in the US and elsewhere.

Accordingly, we chose our initial policy intervention as the elimination of soft drink machines in schools. In our model, this elimination results in a psychological and behavioral dislocation on the part of individuals habituated to the purchase, forcing reconsideration and a deliberate behavioral choice. We model this as an increase in tolerance for individuals who have adopted a set of behaviors leading to overweight and obesity. Although the intended, first order effect of such a policy might be a reduction in availability of the product (reflected in this model as an increase in the initiation threshold), the primary goal of its inclusion in a comprehensive policy cocktail is to create a perturbation of habits in what is currently a steady state system. Widening the tolerance values in the target population opens a window of opportunity to make inroads into otherwise habituated behaviors. This allows a wider range of neighboring nodes, including media campaigns, to influence the target population.

Policy Intervention 2: Counter-marketing and Health Awareness Campaigns

The Centers for Disease Control and Prevention has defined tobacco counter-marketing as "the use of commercial marketing tactics to reduce the prevalence of tobacco use … attempt[ing] to counter protobacco influences and increase prohealth messages and influences throughout a state, region, or community" (CDC 2003). We apply this definition to a campaign to influence individuals encouraging them to adopt healthy, non-obesogenic behaviors.

A second policy component is a counter-marketing and health awareness campaign coinciding with the elimination perturbation. In the absence of the anticipated industry response, the educational campaign would take advantage of the perturbation situation to leverage the increased tolerance values in the target nodes to increase their awareness of the health effects of the eliminated product. In the event of an industry response, the educational campaign is necessary to counteract the effects of dramatically increased advertising. This policy is denoted as *Ed*: Health-related educational campaign.

Policy Intervention 3: Weight Loss Assistance

The third policy component under consideration is an increase in the cessation threshold. Increasing the ability of people to break out of their habits/addictions would raise this threshold. In addition to making deleterious products unavailable, the hysteresis effects of the obesity-related lifestyle choices would be reduced by policies promoting, for example, evidence-based diet and exercise programs. By making healthier lifestyles easier for individuals to adopt, these programs effectively allow individuals to adopt the changes in behavior more easily by allowing a behavioral change despite having a less extremely negative opinion relating to obesogenic behaviors. This third and final policy intervention is denoted as *WLA*: Weight Loss Assistance in our model.

Policy Intervention 4: Intensive Industry Advertising Response

It is anticipated that a broad and potentially effective policy such as product elimination from schools would elicit an industry response. We incorporate this element of systemic adaptation by introducing a new advertising campaign. The intent of the campaign is to counteract the effect of the policy by raising opinions regarding the affected products. This anticipated industry response is denoted as Ad: Industry advertising push.

Our model anticipates an extremely effective industry advertising campaign. In this model, the most effective media campaigns are those that influence individuals having the greatest centrality as measured by PageRank score, and which combine a mild with a strong advertising message (Moore et al., 2011). By building these advantages into the industry advertising response in the context of this model, proposed policy interventions can be measured against the maximum possible countermeasures likely to be fielded by industry entities.

4. Simulation Results

In order to evaluate the likely effects of the proposed policy interventions, we simulated them both singly and in combination.

An illustrative example of simulation results can be seen in Figure 2 below. The x-axis shows the mean % reduction in obesity-correlated behaviors, which means the change in the number of people in the "obesity regime" (overindulgence) compared to the same network with no interventions. In this setting, a "negative reduction" would reflect the community moving towards a greater rate of obesity.

For the following discussion of simulation results, abbreviations for proposed policy interventions and their associated tolerance levels are given in Table 1.

Table 1: Policy Notations

Abbreviation	Meaning
WLA	Weight Loss Assistance (corresponds to increasing cessation threshold from 0.35 to 0.45)
E	Elimination of soft drink machines from schools (corresponds to increasing tolerance of affected individuals from 0.25 to 0.40)
Ad	Industry Advertising (corresponds to 2 advertising nodes with opinions at 0.65 and 0.85 connected to top 20% of highest Page ranked nodes)
Ed	Health-related Educational Campaign (corresponds to educational node with opinion at 0.15 connected to top 20% of highest Page ranked nodes)

As shown in Figure 2, policies E, WLA, and Ed all have a favorable impact on the population's obesity rate. Combinatorial effects can be seen in the larger-than-additive results from policy combinations.

One interesting simulation result is that the industry advertising campaign always results in an unfavorable impact on the population's tendency to engage in obesogenic behaviors when included as a response to any of the possible policy cocktails. Every policy combination, except the one that integrates all policies, results in an increase in obesogenic behaviors. The final case, which implements all three policies, results in a decrease in obesogenic behaviors despite the advertising campaign. In the absence of either an educational campaign, or the weight loss assistance and the elimination of soft drinks, the advertising campaign brings the population obesity rates above their initial value. These results can be interpreted as "backlash" – a hostile response on the part of the public to what can be portrayed as an excessive government intervention. In terms of the model dynamics, the industry advertising campaign takes advantage of the increased tolerance on the part of the affected population, and the enhanced effectiveness of the campaign ensures a very large response. When the three positive policies are introduced in combination, we see a decrease in obesity rates despite the unfavorable effects of the *Ad* perturbation.

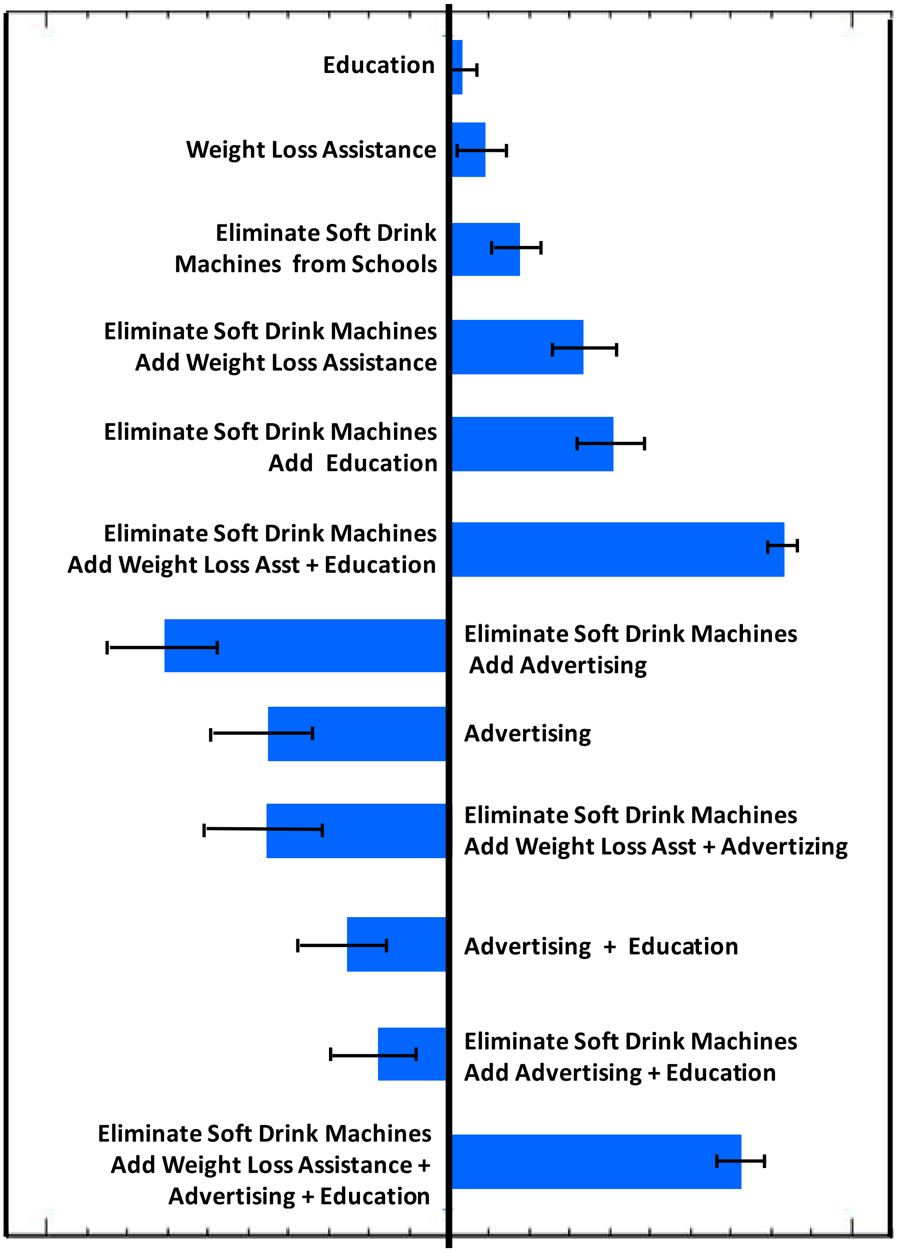

Figure 2: Mean % changes to obesity correlated behaviors in response to a series of proposed policy interventions, acting both singly and in combination

5. Integration with a Population Scale System Dynamics (SD) Model

The IBM opinion dynamics model presented above recognizes the critical importance of the interactions between individuals in a community for collective opinion formation. The analysis therefore primarily involves characterization of the connections between individuals, and testing hypotheses about the relative impact of the social network on the set of N&PA behaviors leading to overweight and obesity. Special emphasis is given to N&PA related behavioral habits that may be maintained, or "carried over," even if the accompanying opinion falls below that which would initially cause its initiation. Health behavior tracking studies point clearly to this type of N&PA habit carryover, or hysteresis effect from the preteen years into the teenage years and then into adulthood on the order of 30% (Kelder *et. al*. 1994, Twisk *et. al*. 1997, and TeVelde *et. al*., 2007).

The IBM we present here has been demonstrated to be an appropriate platform to investigate the effects of policy interventions and to characterize tendencies and trends on a community scale population. It can be implemented for time intervals ranging from months to years. A natural next step is to use output from this analysis to analysis of the longer term dynamics and consequences of these policies on a population scale where the population aging dynamics can be rolled out. The information developed in network analysis is known to be easily integrated into agent-based or system dynamics models. The analysis presented here is well suited for a multi-scale incorporation with the SD methodology.

Being applied to the health care field for forty years since 1970s, health is one of the most central themes of SD. SD methodology has been used to model a wide array of public health problems and related policy issues, such as disease epidemiology with studies on HIV/AIDS, dengue fever, Chlamydia, obesity, polio, and CVD (Homer and Hirsch, 2006; Sterman, 2000).

SD models are known to add value to understanding how, why, and for whom proposed interventions have worked. Overall, SD models tend to focus on a high level characterization of a system and provide insights about the overall system behavior (i.e., generally more of a top-down approach). We think that a multi-scale incorporation of an appropriately scaled SD model to the IBM model we present here might serve as an illustrative example of what a multi-scale modeling process would look like, and serve as a tool to enhance our understanding for the policy intervention analysis.

It should be kept in mind that the IBM model presented here can speak in terms of the relative risk for obesity based on N&PA related health behaviors, e.g. junk food/sugary beverage consumption and inadequate physical activity. As such, we can avoid the burdensome calculation of caloric intakes per se, but go straight from N&PA unhealthy-behavior prevalences to obesity onset rates. We examine existing SD simulation studies on obesity to gain a better understanding of the likely success of attempts at a multi-scale incorporation.

5. 1. Summary and Scope of the Main SD Studies on Obesity

The growing interest in body weight regulation and obesity has culminated in the growth of simulation models that are employed as tools to investigate this complex system and as a means for evaluating hypotheses concerning the induction and maintenance of obesity. Considering the feedback complexity of the underlying structure and the different levels of factors involved (genetic, dietary, life-style, socio-economic), obesity constitutes a suitable area for SD simulation modeling.

Previous SD work in body weight regulation and obesity include those by Abdel-Hamid (2002, 2003, 2009), Oga and Uehara (2003),Flatt (2004), Homer et al. (2004), Homer, Milstein, Dietz et.al, (2006), Karanfil, Osgood and Finegood (2009), Nuhoglu (2009) Nuhoglu and Barlas (2010), Dangerfield and Abidin (2010), Rahmandad and Sabounchi (2010) and Homer et al. (2010).

Abdel-Hamid (2002, 2003) demonstrates the utility of SD modeling to study and gain insight into the physiology related to weight gain and loss. This paper presents an individual based simulation model that integrates nutrition, metabolism, hormonal regulation, body composition, and physical activity. The model was used as an experimental platform for controlled experimentation to investigate the impacts of physical activity and diet on body weight and composition, where the results replicate the mix of results reported in the literature, as well as providing causal explanation for their variability. The simulation results emphasize the significant interaction effects between dietary composition and physical activity, and emphasize the critical role that diet composition can have in exercise-based treatment interventions.

Abdel-Hamid (2009) recently published a book with a special focus on obesity by applying systems thinking concepts to body weight regulation and individual weight management practices. This popular book addresses three categories of readers: (i) individuals (ii) parents and (iii) public policy makers.

Homer (2003) presents a SD model to specifically explore certain eating disorders, including anorexia nervosa. By integrating knowledge on various aspects of normal and abnormal weight control, this model provides new insights into the mechanisms underlying eating disorders.

Oga and Uehara (2003) focus on appropriate health behaviors and how they can be kept under control. They adopt a cognitive intervention approach in fat prevention program. In the first stage, they capture the middle-aged white color workers' pre-existing mental models by focusing on group and in-depth interviews, and in the second stage they demonstrate "the whole map", which consists of the energy metabolism, medical symptom, and the economic factors. By feedback of potential risk of disease and savable expenses, they promote strategic preventing behavior to change program participants' perception.

Flatt (2004) develops an individual based SD model to examine how the interactions between carbohydrate and fat metabolism influence body weight regulation. In contrast to Abdel-Hamid

(2002), he is more concerned with looking at the situation from a dietary intake perspective. This quality model reflects the operation of a two reservoir-system: one representing the body's limited glycogen, and the other, its large fat reserves. Simulation results underscore the significance of metabolic leverages to explain why increased food offerings promote the prevalence of obesity, and demonstrate that equivalent degrees of adiposity can be sustained under a variety of conditions.

Nuhoglu (2009) develops a body weight simulation model for gaming purposes, and to explore the long term dynamics of the body weight, based upon Kevin Hall's body weight simulation model described in Hall (2006). The resulting simulation platform, "Body Weight Websim", provides a useful tool to track body weight changes in the long term, and to design personal dieting and exercising regimes Nuhoglu and Barlas (2010).

Karanfil, Osgood and Finegood (2009) focus on how the important interactions between body composition and food intake influence body weight and obesity at an individual level. They also describe a modeling idea to examine a common feature called "weight cycling" seen in obese people who try to fight against their excessive fatness.

Dangerfield and Abidin (2010) focus on childhood obesity in the context of UK, and describe a model of energy intake and expenditure by a population of children aged 2-15 years. Both energy intake and expenditure is modeled in some detail, and mention is made to the importance of soft variables and the role of social marketing in achieving behavioral change.

Rahmandad and Sabounchi (2010) explore the major drivers of obesity trends in the US by building SD models of these trends and calibrating them to National Health and Nutrition Examination Survey (NHANES) data.

Some of the numerous other examples of body weight regulation-obesity simulation models outside of the SD domain belong to Hall (2006), Chow and Hall (2006), Goldbeter (2006), Christakis and Fowler (2007), Hammond and Epstein (2007), Hall and Jordan (2008), Christiansen and Sorensen (2008), Hammond (2009), Burke and Heiland (2007).

Previous SD models with a focus of obesity at a population level primarily belong to Homer, Milstein, Hirsh and colleagues (2004, 2006, 2009, and 2010). In 2004, Homer et al. modeled the impact of the caloric imbalance on the changes in body weight and BMI of the adult population in the US. Obesity was a small part of the model explorations (Homer et al, 2004a; 2004b) because this study mainly focused on diabetics. Accordingly, the obese have a higher risk of onset of pre-diabetes and diabetes. In particular, the authors estimated these relative risks at 2.6 in both cases (from normoglycemic to pre-diabetic, and from pre-diabetic to diabetic categories).

On the other hand, the Homer, Milstein, Dietz, et.al, (2006) SD simulation model studies the entire US population (including children, teenagers and adults aged 0-99 years) to developing a better understanding of changing obesity trends in the US. The purpose of this study was to understand how the caloric imbalance affects the BMI of various groups in the population. The authors explored the weight transformation from one age group to another using an ageing chain concept. This highly disaggregated model contains sixty stocks for ten age groups and gender and three categories of weight (normal, overweight and obese). Changes of flows were derived from equations through the calculation of height, weight, BMI and the amount of energy balance maintained. In this study, the authors combined data on population body weight from 1971-2002 with information from nutritional science and demography to conduct simulated policy experiments and interventions among school-aged youth and others to explore how effective new interventions would have to be to alter existing obesity trends. One of their findings was that an inflection point in the growth of overweight and obesity prevalence probably occurred during the 1990s. Another finding indicated that new interventions to assure caloric balance among school-age children—even if very effective—would likely have only a relatively small impact on the problem of adult obesity.

In a more recent modeling study developed under the auspices of the Center for Disease Control and Prevention (CDC), the Prevention Impacts Simulation Model (PRISM) explores alternative interventions to prevent and mitigate risk factors that affect cardiovascular disease (CVD) and other health outcomes and costs. A previous version of the model was described in an article with supporting online appendices (Homer et al., 2010). As part of the PRISM modeling of cardiovascular and chronic diseases, the authors developed a section on obesity, nutrition, and physical activity (N&PA). The PRISM model includes representation of habit carryover and the effect of real-world policies on N&PA. Figure 3 below presents a simplified view of the stock-flow structure for obesity as presented in this model. The stocks cover all youth and adults, categorized as either non-obese or obese. The model has now been extended to include of a post-CVD population, certain borderline risk conditions, former smokers, and sodium and trans fat consumption.

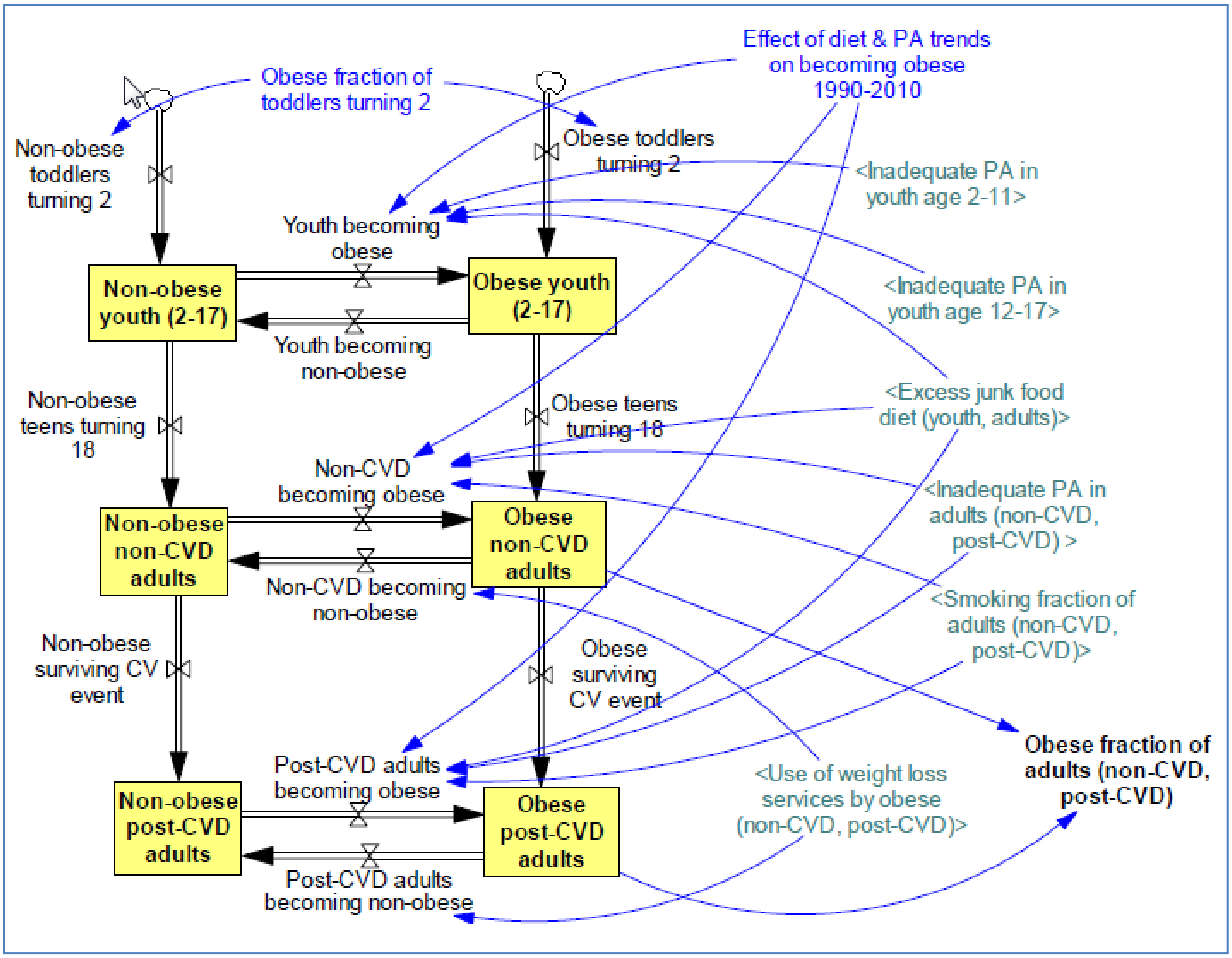

Figure 3: Obese Population Causal Structure (PRISM model Reference Guide for Model Version 09v2q, August 2010, by Jack Homer)

5.2. Rationale for a Multi-scale Incorporation with the SD Methodology

We aim to build on a SD model such as the one presented above to determine the long term effects of policy implementation analyzed using the IBM opinion dynamics network model. The IBM model results, interpreted as changes in obesity rates in model populations, can be applied to alter the input parametric values in an SD model. The SD model can interpret these results on a longer time scale (years to decades), and calculate resulting changes in mortality, morbidity, average lifespan, etc, based on the obesity rates supplied by the IBM.

We believe that the SD model can also be used to identify possible leverage points in the system, which can be fed into the IBM opinion dynamics model for further investigation. For example, the SD model could point the time points where interventions would be most effective. Currently, the opinion dynamics IBM and the suggested obesity SD model do not perform live data exchanges, but we anticipate having an information exchange between the two models in both directions, as potential future areas of investigation.

Why PRISM?

We think that the PRISM model described above would constitute an ideal platform for a multiscale incorporation. In contrast with the other population level SD models on obesity, the PRISM model embraces the important notion of "habit carryover", which is in line with the literature. Tracking studies point clearly to N&PA habit carryover from the preteen years into the teenage years and then into adulthood on the order of 30%. (Kelder et al 1994, Twisk et al 1997, and TeVelde et al 2007.) Accordingly, the IBM puts special emphasis to N&PA related behavioral habits that may be maintained, or carried over, even if the accompanying opinion falls below that which would initially cause its initiation.

Another reason which makes PRISM an good candidate is its comparative advantage to other population level studies in terms of its level of granularity. It is less granular both in terms of age groups and body weight categories, and also does not go down to the level of net caloric intake, i.e. it does not calculate calories per se. Rather, it only speaks in terms of the relative risk for obesity based on junk food consumption or based on inadequate physical activity and goes straight from N&PA unhealthy-behavior prevalences to obesity onset rates –similar with the IBM-- Yet it is sophisticated in terms of real-world policies affecting N&PA related health behaviors.

In the architecture proposed by the PRISM model, the IBM results would be interpreted as affecting the excess junk food in diets among youth as a result of policy interventions. Doing so would have the direct effect of decreasing the rate at which youth become obese and correspondingly increase the number of non-obese youth turning 18 (Please see Figure 2). In addition, to the extent that consumption habits developed during youth and adolescence are carried into adulthood, for which the consequences (in the form of obesity) are delayed due to higher metabolic rates in youth, the interventions would potentially have an effect on the rate of non-CVD adults becoming obese by reducing the excess junk food parameter for adults. Both of these factors would effectively reduce the rates of obesity in society.

In performing the integration of IBM results with the SD model, it is important to consider the variability in the results. For many sets of interventions, the confidence interval is large, which indicates the variability in community structures and distributions of opinions and behaviors will result in variable effectiveness. When integrated into the SD model, this variability will have the effect of introducing uncertainty into the population scale results. Policy cocktails that have the effect of reducing variability are thus additionally desirable because they indicate an increased confidence in parameter values, and so in the results of analysis performed by the SD model.

6. Conclusions and Future Work

Multi-scale analysis of policy cocktails, defined as combinations of policy interventions designed for complementary interactions, provides investigators and policy analysts with a powerful tool for evaluating both the immediate effects of specific combinations of interventions, and the longer term consequences for the public health profile. The two models and more fundamentally the two underlying paradigms of investigation are complementary in their approaches.

By considering large-scale, population level effects, the SD model can identify important leverage points for intervention to bring about the desired changes in population health metrics. By considering the direct effects of interventions on individuals and the second order effects on social networks, the IBM can identify which sets of policies would be most effective in bringing about the required changes.

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List of Abbreviations:

Ad: Industry Advertising

BMI: Body mass index

CDC: Centers for Disease Control

CVD: Cardiovascular disease

E: Elimination of soft drink machines from schools

Ed: Health-related Educational Campaign

IBM: Individual based model. IBM refers to the model with which we consider a hypothetical local community over a limited time interval, e.g. a year.

N&PA: Nutrition and physical activity

NHANES: National Health and Nutrition Examination Survey

PRISM: The Prevention Impacts Simulation Model

SD: System dynamics model. SD model refers to the model with which we consider the effects at a population scale across a time interval measured in years to decades.

WLA: Weight Loss Assistance