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System Dynamics Modeling for Childhood Obesity

by

Behrouz Madahian

A Thesis

Submitted in Partial Fulfillment of the

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Abstract

Behrouz Madahian. M.S. The University of Memphis. December 2011. System Dynamics Modeling for childhood obesity. Major Professor: Ramin Homayouni, Ph.D.

Effective strategies for prevention of obesity, particularly in youths, have been elusive since the recognition of obesity as a major public health issue two decades ago. In general, obesity is a result of chronic, quantitative imbalance between energy intake and energy expenditure, which is influenced by a combination of genetic, environmental, psychological and social factors. Therefore, a systems perspective is needed to examine effective obesity prevention strategies. In this study, a systems dynamics model was developed using the data from the Girls health Enrichment Multi-site Studies (GEMS). GEMS tested the efficacy of a 2-year family-based intervention to reduce excessive increase in body mass index (BMI) in 8-10 year old African American girls. First, an optimum model was built by systematically adding variables to fit the observed data by regression analysis for 50 randomly selected individuals from the cohort. The final model included nutrition, physical activity, and several environmental factors. Next, the model was used to compare two intervention strategies used in the GEMS study. Consistent with previous reports, we found that the two strategies did not affect the BMI increases observed in this cohort. Interestingly however, the model predicted that a 10 min increase in exercise would decrease BMI in the group receiving behavioral counseling. Our work suggests that system dynamics modeling may be useful for testing potential intervention strategies in complex disorders such as obesity.

Table of Contents

List of Tables

List of Figures

Chapter 1

Introduction

System dynamics was created during the mid-1950s by Professor Jay Forrester of the Massachusetts Institute of Technology (Meadows ,1972). His initial goal was to determine how his background in science and engineering could be brought to bear, in some useful way, on the core issues that determine the success or failure of corporations. Forrester's insights into the common foundations that underlie engineering, led to the creation of system dynamics. The creation of System dynamics was triggered, to a large degree, by his involvement with managers at General Electric (GE) during the mid-1950s. At that time, the managers at GE were puzzled because employment at their appliance plants in Kentucky exhibited a significant three-year cycle. The business cycle was judged to be an insufficient explanation for the employment instability. From hand simulations (or calculations) of the stock-flow-feedback structure of the GE plants, which included the existing corporate decision-making structure for hiring and layoffs, Forrester was able to show how the instability in GE employment was due to the internal structure of the firm and not to an external force such as the business cycle. These hand simulations were the beginning of the field of system dynamics (Forrester,1969).

During the late 1950s and early 1960s, Forrester and a team of graduate students moved the emerging field of system dynamics from the hand-simulation stage to the formal computer modeling stage. Richard Bennett created the first system dynamics computer modeling language called SIMPLE (Simulation of

Industrial Management Problems with Lots of Equations) in the spring of 1958. In 1959, Phyllis Fox and Alexander Pugh wrote the first version of DYNAMO (DYNAmic MOdels), an improved version of SIMPLE, and the system dynamics language became the industry standard for over thirty years. Forrester published the first, and still classic, book in the field titled Industrial Dynamics in 1961 (Forrester,1969).

From the late 1950s to the late 1960s, system dynamics was applied almost exclusively to corporate/managerial problems. In 1968, however, an unexpected occurrence caused the field to broaden beyond corporate modeling. John Collins, the former mayor of Boston, was appointed a visiting professor of Urban Affairs at MIT. The result of the Collins-Forrester collaboration was a book titled Urban Dynamics. The Urban Dynamics model presented in the book was the first major non-corporate application of system dynamics (Forrester,1969). The second major non-corporate application of system dynamics came shortly after the first.

In 1970, Jay Forrester was invited by the Club of Rome to a meeting in Bern, Switzerland. The Club of Rome is an organization devoted to solving what its members describe as the global crisis that may appear sometime in the future, due to the demands being placed on the Earth's carrying capacity (its sources of renewable and nonrenewable resources and its sinks for the disposal of pollutants) by the world's exponentially growing population. At the Bern meeting, Forrester was asked if system dynamics could be used to address the predicament of mankind. His answer, of course, was that it could. On the plane back from the Bern meeting, Forrester created the first draft of a system dynamics model of the world's socioeconomic system. He called this model WORLD1. Upon his return to the United States, Forrester refined WORLD1 in preparation for a visit to MIT by members of the Club of Rome. Forrester called the refined version of the model WORLD2. Forrester published WORLD2 in a book titled World Dynamics (Forrester,1969).

An Overview of Modeling and Simulation

A model is a representation of events and/or things that are real (a case study) or artificial. It can be a representation of an actual system, or it can be something used in place of the real thing to better understand a certain aspect of that thing. The model can depict the system at some point of abstraction or at multiple levels of the abstraction, with the goal of representing the system in a mathematically reliable fashion. A simulation is an applied methodology that can describe the behavior of that system using either a mathematical or a symbolic model (Fishwick,1995). Simply, simulation is the imitation of the operation of a real-world process or system over a period of time (Banks, 1998). For example, simulation can be used to represent the effect of changes in governmental policy during a fight with rebels, to analyze the decision-making processes of opposing military leaders, or to assess the social network structure of a political leader and his/her circle of advisers.

Modeling and simulation begins with (1) the development of a computer simulation or design based on a model of an actual or theoretical physical system, (2) execution of that model on a digital computer, and (3) analysis of the output. Modeling and the ability to act-out with those models provide a credible way to understand the complexity and particulars of a real entity (Fishwick,1995). From these three steps one can see that modeling and simulation facilitates the simulation of a system such as a social network structure and then the testing of a hypothesis related to that structure. It is important to note that models are driven by data, so the data collection must be done with great accuracy. Once a model is created, the analyst can design a fairly well thought out and credible hypothesis that digs more deeply into the case study. For example, if one input to the model changed, the following might have been the result. Since there may be some other influential parameters not included into the model due to lack of data or understanding of the model, even that needs to be weighed carefully. Simulation is used when a real system cannot be engaged. This may happen when the real system (1) might not be accessible, (2) it might be dangerous to engage the system, (3) it might be unacceptable to engage the system, or (4) the system might simply not exist. To counter these objections, a computer will imitate operations of the various real-world facilities or processes.

A system is a construct or collection of different elements that together produce results not obtainable using the elements alone (Fishwick,1995). The elements can include people, hardware, software, facilities, policies, and documents: all things required to produce system-level qualities, properties, characteristics, functions, behavior, and performance. Importantly, the value of the system as a whole is the relationship among the parts. It is becoming widely accepted that Modeling and simulation holds a significant place in research and development, due to its inherent properties of modeling, simulating, and analyzing (Banks, 1998).

System

A system is a combination of components acting together to perform a specific objective (Ogata , 2004). A *component* is a single functioning unit of a system. The concept of a system can be extended to abstract dynamic phenomena, such as those encountered in economics, transportation, population growth, and biology.

A system is called dynamic if its present output depends on past input. If its current output depends only on current input, the system is known as *static.* The output of a static system remains constant if the input does not change. The output changes only when the input changes. In a dynamic system, the output changes with time if the system is not in a state of equilibrium (Sterman, 2000).

Why Use Modeling and Simulation

Modeling and simulation is now being used in a variety of domains, including medical modeling, emergency management, crowd modeling, transportation, game-based learning, and engineering design, to name a few. Modeling and simulation applications are used primarily for analysis, experimentation, and training. Analysis refers to an investigation of a model's behavior. Modeling and simulation can be applied in any field where experimentation is conducted using dynamic models. This includes all types of engineering and science studies as well as social science, business, medical, and education domains. Modeling and simulation is often the only tool capable of solving complex problems because it allows for an understanding of system dynamics and includes enabling technology, both of which provide a means to explore credible solutions (Fishwick,1995). There are also many advantages to modeling and simulations (Banks, 1998). Here are some of the processes and results of using modeling and simulation (Fishwick,1995):

1. Compressing and expanding time to allow the user to speed-up or slow-down behavior or phenomena to facilitate in-depth research
2. Understanding why, by reconstructing and examining the scenario closely by controlling the system
3. Exploring possibilities in the context of policies, operating procedures, and methods without disrupting the actual or real system
4. Diagnosing problems by understanding the interactions among variables that comprise complex systems
5. Developing understanding by observing how a system operates rather than predicting how it will operate
6. Preparing for change by answering the “what if” in the design or modification of the system
7. Investing wisely because a simulated study costs much less than the cost of changing or modifying a system

Chapter 2

Methods

System Dynamics

System Dynamics is the application of feedback control systems principles and techniques to model, analyze, and understand the dynamic behavior of complex feedback systems. As stated above, its origins trace back to the pioneering work of Jay W. Forrester, whose book Industrial Dynamics (Huang, Drewnowski, Kumanyika, & Glass, 2009) is still a significant statement of philosophy and methodology in the field. System Dynamics is aimed at the study and analysis of certain kinds of complex systems, known as dynamic feedback systems. These are systems characterized by a large number of interrelated variables that interact dynamically over time through information-feedback structures. Although the words complex, dynamic, and system have been applied to all sorts of situations, feedback is the differentiating descriptor here. Indeed, feedback processes are seen in System Dynamics to hold the key to structuring and clarifying relationships within such systems and in understanding their dynamic behavior.

System dynamics deals with the mathematical modeling of dynamic systems and response analyses of such systems with a view toward understanding the dynamic nature of each system and improving the system's performance. Response analyses are frequently made through computer simulations of dynamic systems. The analysis and design methods of system dynamics can be applied to mechanical, electrical, and hydraulic systems, as well as non-engineering systems, such as economic systems and biological systems System Dynamics models help trace the patterns of behavior of a dynamic system to its feedback structure. In the System Dynamics view, feedback structures are seen as intrinsic in real systems. As such feedback is the structure that makes a system adapt over time (Richardson,1991). Moreover, System Dynamics models are continuous, they do not model discrete events, rather they "view separate events and decisions as riding on the surface of an underlying tide of policy, pressures, and dynamic pattern".

Building a causal model is an iterative process in which the modeler quantitatively formulates feedback relationships between elements of a given system that he is able to identify. A typical feedback-rich model can consist of several dozens to several hundreds of equations. The model goes through various stages of expansion and reduction until a minimal feedback structure is identified which is capable of simulating a predefined reference mode of the systemic problem under study. Testing a model's behavior against historical data and verifying its robustness can be a daunting procedure (Forrester & Senge, 1996). The feedback loop is the basic building block of a complex feedback structure and as such the basic unit of analysis and communication of system behavior (Waldrop,1992). The endogenous perspective of a dynamic system may be the single most characteristic and significant feature of the field. Feedback loops have either positive or negative polarities. This polarity indicates whether a loop has the tendency to reinforce or to counterbalance a change in one or more of its loop elements (Waldrop,1992).

The basic concept of feedback has a wide range of applications in engineering fields such as fluid, temperature, centrifuge, and steam pressure regulations over centuries. But, it needed the utilization of the computer to become accepted and serve as modeling discipline also for other areas than engineering. Most succinctly, feedback is the transmission and return of information. For example, a feedback system exists whenever an action taker will later be influenced by the consequences of his or her actions. More generally, feedback refers to the situation of X affecting Y and Y in turn affecting X, perhaps through a chain of causes and effects. One cannot study the link between X and Y and, independently, the link between Y and X and predict how the system will behave. Only the study of the whole system as a feedback system will lead to correct results.

Ultimate Goal of System Dynamics Modeling

Models are approximations of events, real events as in case studies, or artificial events as in use-case studies. Analysts create models from data; therefore, research for the event or details that go into a case study must be accurate to ensure that the model is sound. With a reliable model, analysts can develop a hypothesis or research question that requires observation of the model. The model is observed via simulation, and the simulation can be modified and repeated. Often, models include systems or collections of different elements that together produce results not obtainable by the elements alone. The analyst then conducts an analysis of the simulations to draw a conclusion or to verify and validate the research. The ability to apply visualization facilitates the communication or presentation of the model, the simulation, and the conclusions drawn. All of this is learning by doing.

Ultimately, the purpose in applying System Dynamics is to facilitate understanding of the relationship between the behavior of a complex system over time and its underlying feedback structure. For this, system dynamicists rely on computer simulation. Even though the dynamic implications of isolated loops such as those discussed above may be reasonably obvious, the interconnected feedback structures of real problems are often so complex that the behavior they generate over time can usually be traced only by simulation. Computer simulation is particularly suited to the study of continuous systems, in which system variables change not in discrete jumps but continuously over time. This is a characteristic of all living systems, which by definition are in constant flux. Yet, because of the complexity and expense of continuous measurements, most experimental studies such as human energy expenditure studies have relied on discrete, rather than continuous, measurement protocols.

This can be a serious limitation, because a negative finding (e.g., finding no association between low energy expenditure and subsequent weight gain) may simply mean that the timing of the measurements did not coincide with the period of reduced/ increased energy expenditure (Saltzman & Roberts,1995).

In addition to handling dynamic complexity and permitting continuous measurements, simulation-type models make “perfectly” controlled experimentation possible. In the model system, unlike real systems, the effect of changing one factor can be observed while all other factors are held unchanged. Internally, the model provides complete control of the system (Sterman, 2000).

Mathematical Modeling of Dynamic Systems

System dynamics deals with the mathematical modeling of dynamic systems and response analyses of such systems with a view toward understanding the dynamic nature of each system and improving the system's performance. Mathematical modeling involves descriptions of important system characteristics by sets of equations. By applying physical laws to a specific system, it may be possible to develop a mathematical model that describes the dynamics of the system. Such a model may include unknown parameters, which must then be evaluated through actual tests. Sometimes, however, the physical laws governing the behavior of a system are not completely defined, and formulating a mathematical model may be impossible. If so, an experimental modeling process can be used. In this process, the system is subjected to a set of known inputs, and its outputs are measured. Then a mathematical model is derived from the input-output relationships obtained (Ogata , 2004).

Simplicity of Mathematical Model Versus Accuracy of Results of Analysis

In attempting to build a mathematical model, a compromise must be made between the simplicity of the model and the accuracy of the results of the analysis. It is important to note that the results obtained from the analysis are valid only to the extent that the model approximates a given physical system. In determining a reasonably simplified model, we must decide which physical variables and relationships are negligible and which are crucial to the accuracy of the model. To obtain a model in the form of linear differential equations, any distributed parameters and nonlinearities that may be present in the physical system must be ignored. If the effects that these ignored properties have on the response are small, then the results of the analysis of a mathematical model and the results of the experimental study of the physical system will be in good agreement. Whether any particular features are important may be obvious in some cases, but may, in other instances, require physical insight and intuition. Experience is an important factor in this connection. Usually, in solving a new problem, it is desirable first to build a simplified model to obtain a general idea about the solution. Afterward, a more detailed mathematical model can be built and used for a more complete analysis (Ogata, 2004).

Basic Approach to System Design

System design refers to the process of finding a system that accomplishes a given task (Ogata, 2004). In general, the design procedure is not straightforward and will require trial and error. The basic approach to the design of any dynamic system necessarily involves trial-and-error procedures. Moreover, the features of the components may not be precisely known. Thus, trial-and-error techniques are almost always needed. Design procedures. Frequently, the design of a system proceeds as follows: One begins the design procedure knowing the specifications to be met and the dynamics of the components, the latter of which involve design parameters. The specification may be given in terms of both precise numerical values and vague qualitative descriptions. (Engineering specifications normally include statements on such factors as cost, reliability, space, weight, and ease of maintenance). It is important to note that the specifications may be changed as the design progresses, for detailed analysis may reveal that certain requirements are impossible to meet. Next, the engineer will apply any applicable synthesis techniques, as well as other methods, to build a mathematical model of the system. Once the design problem is formulated in terms of a model, then the designer carries out a mathematical design that yields a solution to the mathematical version of the design problem. With the mathematical design completed, the engineer simulates the model on a computer to test the effects of various inputs and disturbances on the behavior of the resulting system. If the initial system configuration is not satisfactory, the system must be redesigned and the corresponding analysis completed. This process of design and analysis is repeated until a satisfactory system is found. Then a prototype physical system can be constructed.

It should be noted that the process of constructing a prototype is the reverse of mathematical modeling. The prototype is a physical system that represents the mathematical model with reasonable accuracy. Once the prototype has been built, the designer tests it to see whether it is satisfactory. If it is, the design of the prototype is complete. If not, the prototype must be modified and retested. The process continues until a satisfactory prototype is obtained. One must always keep in mind that the model he or she is analyzing is an approximate mathematical description of the physical system and it is not the physical system itself. In reality, no mathematical model can represent any physical component or system precisely. Approximations and assumptions are always involved. Such approximations and assumptions restrict the range of validity of the mathematical model. The degree of approximation can be determined only by experiments. So, in making a prediction about a system's performance, any approximations and assumptions involved in the model must be kept in mind. The basic approach to the design of any dynamic system necessarily involves trial-and-error procedures. Also, the features of the components may not be precisely known. Thus, trial-and-error techniques are almost always needed (Ogata ,2004).

Mathematical Modeling Procedure

The procedure for obtaining a mathematical model for a system can be summarized as follows (Ogata, 2004):

1. Draw a schematic diagram of the system, and define variables.
2. Using physical laws, write equations for each component, combine them according to the system diagram, and obtain a mathematical model.
3. To verify the validity of the model, its predicted performance, obtained by solving the equations of the model, is compared with experimental results.

If the experimental results deviate from the prediction to a great extent, the model must be modified. A new model is then derived and a new prediction compared with experimental results. The process is repeated until satisfactory agreement is obtained between the predictions and the experimental results.

System Analysis

System analysis means the investigation, under specified conditions, of the performance of a system whose mathematical model is known (Cannon, 1967). The first step in analyzing a dynamic system is to derive its mathematical model. Since any system is made up of components, analysis must start by developing a mathematical model for each component and combining all the models in order to build a model of the complete system. Once the latter model is obtained, the analysis may be formulated in such a way that system parameters in the model are varied to produce a number of solutions. The analyst then compares these solutions and interprets and applies the results of his or her analysis to the basic task. It should always be remembered that deriving a reasonable model for the complete system is the most important part of the entire analysis. Once such a model is available, various analytical and computer techniques can be used to analyze it. The manner in which analysis is carried out is independent of the type of physical system involved-mechanical, electrical, hydraulic, and so on. In the next section we take a look at some major modeling techniques and briefly explain their properties.

Agent-based Modeling

The aim of agent-based (or individual-based) modeling is to look at global consequences of individual or local interactions in a given space. Agents are seen as the generators of emergent behavior (Holland,1999) in that space. Interacting agents, though driven by only a small set of rules which govern their individual behavior, account for complex system behavior whose emergent dynamic properties cannot be explained by analyzing its component parts. In Holland's words, "The interactions between the parts are nonlinear; so the overall behavior cannot be obtained by summing the behaviors of the isolated components. Said another way, there are regularities in system behavior that are not revealed by direct inspection of the laws satisfied by the components (Holland,1999). Emergence, thus, is understood as the property of complex systems where "much (is) coming from little" (Holland & Miller,1991). Emergence is the focal point of what now is called the theory of Complexity. Agent-based models consist of a space, framework, or environment in which interactions take place and a number of agents whose behavior in this space is defined by a basic set of rules and by characteristic parameters. Models can be spatially explicit, i.e., agents are associated with a specific location from which they may or may not be able to move.

Not all models need to be spatially explicit (i.e., the location does not play a role such as in simulations of networks). Individual-based models are a subset of multi-agent systems which includes any computational system whose design is fundamentally composed of a collection of interacting parts. For example an "expert system" might be composed of many distinct bits of advice which interact to produce a solution. Individual-based models are distinguished by the fact that each "agent" corresponds to autonomous individuals in the simulated domain. Certainly, cellular automata (CA) are similar to spatially explicit, grid-based, immobile individual based systems. However, CAs are always homogenous and dense (all cells are identical) whereas a grid-based individual-based model might occupy only a few grid cells, and more than one distinct individual might live on the same grid. The philosophical issue is whether the simulation is based on a dense and uniform dissection of the space (as in a CA), or based on specific individuals distributed within the space. Agent-based models' resulting emergent dynamic behaviors can be linked with those of other models forming an even higher level of complexity and emerging behaviors. In summary, Complexity Theory is the "science of emergence" (Waldrop,1992), and agent-based models are a key element for modeling emergent phenomena.

An agent-based model (ABM) (also sometimes related to the term multi-agent system or multi-agent simulation) is a class of computational models for simulating the actions and interactions of autonomous agents (both individual or collective entities such as organizations or groups) with a view to assessing their effects on the system as a whole. ABMs are also called individual-based models (Tarik, Dietrich, & Christian, 2009). The models simulate the simultaneous operations and interactions of multiple agents, in an attempt to re-create and predict the appearance of complex phenomena. The process is one of emergence from the lower (micro) level of systems to a higher (macro) level. As such, a key notion is that simple behavioral rules generate complex behavior. This principle, known as K.I.S.S. ("Keep it simple stupid") is extensively adopted in the modeling community. Another central principle is that the whole is greater than the sum of the parts. Individual agents are typically characterized as boundedly rational, assumed to be acting in what they perceive as their own interests, such as reproduction, economic benefit, or social status, using heuristics or simple decision-making rules.

Agent-based modeling and simulation (ABMS) is a new approach to modeling systems comprised of autonomous, interacting agents. ABMS promises to have far-reaching effects on the way that businesses use computers to support decision-making and researchers use electronic laboratories to support their research. Some have gone so far as to contend that ABMS is a third way of doing science besides deductive and inductive reasoning. Computational advances have made possible a growing number of agent based applications in a variety of fields. Applications range from modeling agent behavior in the stock market and supply chains, to predicting the spread of epidemics and the threat of bio-warfare, from modeling consumer behavior to understanding the fall of ancient civilizations, to name a few (Richardson,1991).

As long as rules are known or can be discovered by some sort of observation, the modeling and testing of such emergent structures is a relatively straightforward process. However, once the reverse direction of study is employed, that is, a complex aggregate behavior of a system has been observed, and now its agents and the rules by which they interact shall be identified, the process can be anything but straightforward. "Discovering" agents and rules and then building a model which in turn is capable of mimicking the previously observed dynamic behavior can be a very tedious avenue of research. ABMS has its direct historical roots in the notion that “systems are built from the ground-up,” in contrast to the top-down systems view taken by Systems

Dynamics. In System Dynamics modeling the feedback loop is the unit of analysis as seen earlier. Dynamic systems are deductive, in that they are described by their feedback structure at an aggregate level. That is, individual agents or events do not matter much in System Dynamics models, since the dynamics of the underlying structures are seen as dominant. Feedback structures, for example in social-science fields of study, can become subject to controversy since perspectives on a problem and perceptions thereof may differ widely.

System Dynamics Modeling

As opposed to the concept of emergence and agent based modeling whose roots can be traced back to the 1970s, the scientific concept of feedback which is at the core of System Dynamics modeling is significantly older as Richardson demonstrates in his book on Feedback Thought (Richardson,1991). The underlying concept of feedback is its loop structure, or the notion of circular causality. Thinking in circles, and particularly, circular reasoning has been considered flawed by mainstream Western science throughout the last couple of centuries. It is worthwhile to recall, how traditional science establishes causality: "(1) the cause precedes the effect in time, (2) there is an empirical correlation between them, and (3) the relationship is not found to be the result of some third variable" (Babbie, 1998). Only relationships satisfying all three criteria are recognized as causal by traditional research. This strict distinction and isolation of cause and effect has served science well as long as relatively simple (and linear) systems of relationships were studied.

Vensim Software

Vensim is simulation software made by Ventana Systems, Inc (Eberlein & Peterson, 1992). Its purpose is to help companies to find an optimal solution for various situations that need analysis and where it's necessary to find out all possible results of future implementation or decision. The Vensim is a visual modeling tool that allows you to conceptualize, document, simulate, analyze, and optimize models of dynamic systems (Eberlein & Peterson, 1992). Vensim provides a simple and flexible way of building simulation models from causal loop or stock and flow diagrams.

By connecting words with arrows, relationships among system variables are entered and recorded as causal connections. And thus, defining the relationships and the models and running the simulation has been made so easy using Vensim. Vensim is able to simulate dynamic behavior of systems, that are impossible to analyze without appropriate simulation software, because they are unpredictable due to many influences, feedback etc. It helps with causality loops identification and finding leverage points. Simulated situations may come from different sectors such as economics, business, science, social sector, environment etc. We used Vensim PLE version 5.9e for windows. The software can be downloaded from http://www.vensim.com/freedownload.html.

Causal Tracing

Causal Tracing enables fast and accurate analysis of model dynamics. During construction of a model and while analyzing an existing model, it is useful to discover what things are causing other things to change. Looking in one direction, you can discover which variables cause a particular variable to change. Looking in the other direction, you can discover which variables are changed (or used) by a particular variable. The variable under study is called the "workbench variable. Causal Tracing is a powerful method of following the causes or uses of a variable (or its behavior) throughout a model. Model structure is traced with tree diagrams. Model behavior is traced with Strip Graphs. Causal Tracing makes it far easier to thoroughly explore and debug a complex model. Vensim's unique approach to model analysis greatly speeds understanding of model behavior. A dataset stores the dynamic behavior of all variables in the model for later viewing and analysis. Multiple simulations (experiments) can be performed and stored to allow comparison of behavior resulting from different conditions.

Tree Diagram

The Tree Diagram analysis tool creates output windows showing a tree of causes branching off the workbench variable. The Causes Tree Diagram shows the causes of a variable; the Uses Tree Diagram shows the uses of a variable. Tree Diagrams show causes and uses up to two variables distant (the default setting). You can continue to trace the causes (or uses) of a variable throughout a model by selecting a new workbench variable to trace and again clicking on the Causes Tree analysis tool.

Tracing Behavior

Model behavior can be difficult to analyze quickly, especially when trying to discover exactly which variables and feedback loops are contributing certain components of behavior to a particular variable. By creating Causes Strip graph understanding the behavior of variables and causal relationships between them has become easier.

Optimization

Vensim's optimizer provides fast calibration of models and discovery of optimal solutions Validation of the integrity of a model rests in part on comparing model behavior to time series data collected in the "real world." When a model is structurally complete and simulates properly, calibration of the model can proceed to fit the model to this observed data. Dynamic models are often very sensitive to the values of constant parameters. If you want to calibrate your parameters so the model behavior matches observed data, you may need to experiment with thousands of combinations of different parameter values. Vensim calibration makes this procedure automatic. You specify which data series you want to fit and which parameters you want to adjust. Then Vensim automatically adjust parameters to get the best match between model behavior and the data. There are no limits on the numbers of parameters to adjust or data series to fit. This feature exists in Vensim Professional.

Subscripting (Arrays)

Vensim features a powerful subscripting language for constructing very advanced arrayed models. A simple model structure can be disaggregated to show detail complexity. Each subscripted structure can be individually customized with different constants, multiple equations, subscript functions (such as summing over elements of a subscript), and up to eight dimensions of subscripts. Multiple sub ranges make it easy to construct and analyze subsets of an array.

The Power of Vensim

Nothing is easier than Vensim for creating customized causal loop or stock and flow diagrams. Vensim is very efficient for building accurate simulation models of dynamic feedback systems.

Building Models

With Vensim, you can customize diagrams with different colors, fonts, symbols, arrows, and pipes. Variable names can appear alone, or inside or outside of boxes, circles, hexagons, and other shapes. You can create multiple views in one model with each view containing a portion of the total model structure. An Equation Editor helps you build the equations for a simulation model. Vensim can create and simulate models with hundreds of thousands of variables. Vensim has many built-in functions including user defined Lookups, logical operators, random number generators, continuous and discrete delays, forecasts, scientific functions, and customizable Vensim macros and external functions (Eberlein & Peterson, 1992).

Simulation

Vensim contains a highly efficient simulation engine providing fast simulation times and allowing storage of huge datasets. Vensim can also be run over a network allowing multiple users to interact with a single model. Vensim can use external data series as exogenous inputs to drive a model or to compare against data from simulation runs. You can create external data in text editors, or import from (or export to) database and spreadsheet applications.

The Vensim family of software runs on Windows (95/98/ Millennium /NT /2000 /XP/ Vista) and the Power Macintosh running System 7 or higher (in Classic mode under OSX). Vensim requires 8 MB of memory and 8 MB of disk space for a full installation. A demonstration version of Vensim is available free for either Windows or Macintosh (Eberlein & Peterson, 1992). Vensim is available in several configurations to fit different modeling needs.

Vensim PLE (Personal Learning Edition)

Helps you get started with building system dynamics and systems thinking models. Vensim PLE is free for educational or personal use and can be downloaded from their website.

Vensim Professional

Allows you to use subscripting for easy handling of detail complexity, contains a text editor, and has optimization capabilities including model calibration and policy optimization.

Vensim DSS

Vensim DSS enables you to create management flight simulators for models, to customize Vensim by defining macros or external functions, and to link to other programming software through the Vensim DLLs.

Obesity

Obesity is a term used to describe body weight that is much greater than what is healthy. If you are obese, you also have a much higher amount of body fat than is healthy or desirable. Adults with a body mass index (BMI, calculated as weight in kilograms divided by height in meters squared) between 25 kg/m2 and 30 kg/m2 are considered overweight. Adults with a BMI greater than or equal to 30 kg/m2 are considered obese. Anyone who is more than 100 pounds overweight or who has a BMI greater than or equal to 40 kg/m2 is considered morbidly obese. Over nutrition in the form of unusual fatness has been recognized over the ages and in all societies. In the past, fatness was usually seen as a sign of health, wealth, and/or fertility. Today we know that obesity tends to be accompanied by a number of adverse health risks, and obese individuals are too often viewed as figures either of fun or of dislike. Yet, for all the health disadvantages and social criticism, obesity and overweight are developing in epidemic proportions in the westernized developed world. We recognize this epidemic in the need to enlarge and reinforce seats in theatres and airplanes and in the need for change in clothing styles and sizes.

The extent to which the high prevalence of adult obesity has its origins in childhood obesity is widely debated. The question remains unanswered but it is clear that, along with increasing obesity in adults, there is increasing obesity in children at all ages. We are not short of theories for the development of obesity in children but we seem powerless to control the increase – leading to great concerns for future adult health (Flegal et al., 2006). Childhood obesity has now become the most prevalent nutritional disease in developed countries. For example, the prevalence of obesity, defined as a body mass index (BMI) equal to or above the 95th centile for children of the same age and sex, now affects 10–15% of children and adolescents in the United States (Flegal et al., 2006). In assessing fatness an important distinction needs to be made between childhood and adulthood – children grow in size, so that body measurement cut-offs for fatness have to be adjusted for age and in adolescence for maturation as well. For this reason, the assessment of adiposity in childhood and adolescence differs from its assessment in adults (Parsons, Power, Logan, & Summerbell,1999).

When the prevalence of obesity in the United States is compared across nationally representative surveys conducted over the last 30 years, the most rapid increases in prevalence occurred between 1980 and 1994. The greatest increases in body weight have occurred in children and adolescents in the upper half of the BMI distribution (Troiano & Flegal, 1998). Stated another way, the mean BMI for children of the same age and sex has increased more than the median. These observations suggest at least two possibilities. They may suggest that the genes that predispose to obesity occur in approximately 50% of the population. Alternatively, these observations suggest that the factors that influence the development of obesity are discrete, and act only on half of the population (Troiano & Flegal, 1998).

Elsewhere in the world, obesity is also increasing rapidly. Nevertheless, the world-wide prevalence of obesity is generally lower than the prevalence observed among children and adolescents in the United States. The factors that account for the rapid changes in prevalence remain unclear. The rapidity of the changes in prevalence clearly excludes a genetic basis for the changes, because the gene pool remained unchanged between 1980 and 1994. Because obesity can only result from an imbalance of energy intake and expenditure, it may be useful to review the changes in diet and activity that occurred synchronously with the changes in prevalence (Troiano & Flegal, 1998). It should be noted that no data yet exists that link obesity to any of the following behaviors. Nevertheless, these behavioral shifts offer reasonable and testable hypotheses.

For example, in the 1970s, the advent of the microwave oven made it possible for children to select and prepare their own meals without parental oversight. Likewise, substantial increases have occurred in food consumption outside the home. Currently, 35% of a family's food expenditure in the United States is spent on food consumed outside the home. Approximately, 7% to 12% of children and adolescents skip breakfast. Few children consume a dietary pattern consistent with the food guide pyramid. The consumption of soft drinks has almost doubled in the last 15 years. Over 12000 new food products are introduced annually in the United States (Clarke & Lauer,1993) . All of these dietary factors may increase the difficulty associated with the establishment and maintenance of a healthy body weight. Activity deserves equal attention. Marked declines in vigorous physical activity occur in adolescent girls, at a time when susceptibility to obesity is heightened (Heath, Pratt, & Warren, 1994). In the United States, the number of schools that offer daily physical education has declined by almost 30% over the past decade. In addition, the percentage of children who watch five or more hours of television daily has increased to 30%. Increased numbers of working mothers and a perceived lack of neighborhood safety may contribute further to increased levels of inactivity (Clarke & Lauer,1993).

Until quite recently, obesity in children was viewed as a cosmetic problem. The major risks associated with obesity in children and adolescents were those consequences that resulted when obesity persisted into adulthood. However, more recent experience indicates that significant health risks are associated with obesity in childhood. For example, it is recently shown that 65% of overweight 5- to 10-year-olds have at least one cardiovascular disease risk factor, such as elevated blood pressure or lipid levels, and 25% have two or more risk factors (Freedman, Dietz, Srinivasan, & Berenson, 1999). Furthermore, type II diabetes mellitus now accounts for up to 30% of new diabetes cases in some paediatric clinics, and up to 3% of some paediatric populations, such as Native Americans, now suffer from this problem (Freedman et al., 1999).The overwhelming majority of type II paediatric diabetic cases occur in obese patients. To summarize, obesity is prevalent, it appears to be increasing and significant effects are demonstrable in childhood. Effective treatment of affected children and prevention of obesity in children who are susceptible must become a priority. The challenge is how to accomplish both goals. Care for mildly to moderately overweight patients will require the service of primary care practitioners, and guidelines now exist to enhance these (Barlow & Dietz, 1998). Effective treatment for severely obese children is essential and will probably require care in specialty clinics. However, effective prevention of obesity in non-overweight children may also help reduce body weight in children who are already overweight. As with nutritional deficiency diseases, where the addition of iodine to salt reduces goiter, or the addition of fluoride to water reduces dental decay, environmental modification may represent the most durable, effective and cheapest intervention. Nevertheless, until the causes of obesity are better understood, the target of the environmental dietary intervention must be based on logic rather than science (Barlow & Dietz, 1998). In contrast to dietary interventions, efforts that increase physical activity or reduce inactivity appear warranted. Although we lack data to demonstrate that such measures effectively reduce the incidence of obesity in the population, increased physical activity has demonstrated benefit for the comorbidities of obesity, such as hypertension, diabetes and hyperlipidemia (Heath, Pratt , & Warren, 1994). Prevention presents additional challenges. The epidemic of obesity is not yet viewed with the urgency that it demands. Paediatricians are poorly equipped to treat obesity, and methods that help primary-care providers target specific behaviors, like computer-based interactive questionnaires, are still in a developmental phase. Effective means to maintain weight in those who are gaining weight too rapidly or to reduce weight in those who are overweight must be established. Finally, the environmental infrastructure necessary to promote physical activity in the many settings that affect children must be developed and evaluated.

Natural History of Adiposity

Body fat is made up of fat cells or adipocytes. The changes in fat mass that occur in the growing child arise in two separate ways, through changes in the number and in the mean size of adipocytes. In infancy, adipocyte enlargement contributes most to the increasing fat mass, while after infancy fat mass gain arises mainly through cell proliferation (Knittle, Timmers, Ginsberg-fellner, Brown, & Katz, 1979). As a result, fat mass rises steeply during the first year and then falls again, with a second rise in later childhood. Figure 1 illustrates the pattern and also shows how anthropometric indices, like the body mass index, and adipose tissue cellularity follow the same age-related trends.

Measurement of Body Fat

An ideal measure of body fat should be accurate, precise, accessible, acceptable and well documented. Accuracy and precision mean that the measure should be unbiased and repeatable. Accessibility relates to the simplicity, cost and ease of use of the method. Acceptability refers in the broadest sense to the invasiveness of the measurement and documentation concerns the existence of age-related reference values of the measurement for clinical assessment. No existing measure satisfies all these criteria. Highly accurate reference methods like deuterium dilution or underwater weighing are expensive, and more accessible, cheaper methods based on anthropometry are not very accurate (Davies & Cole, 1995).

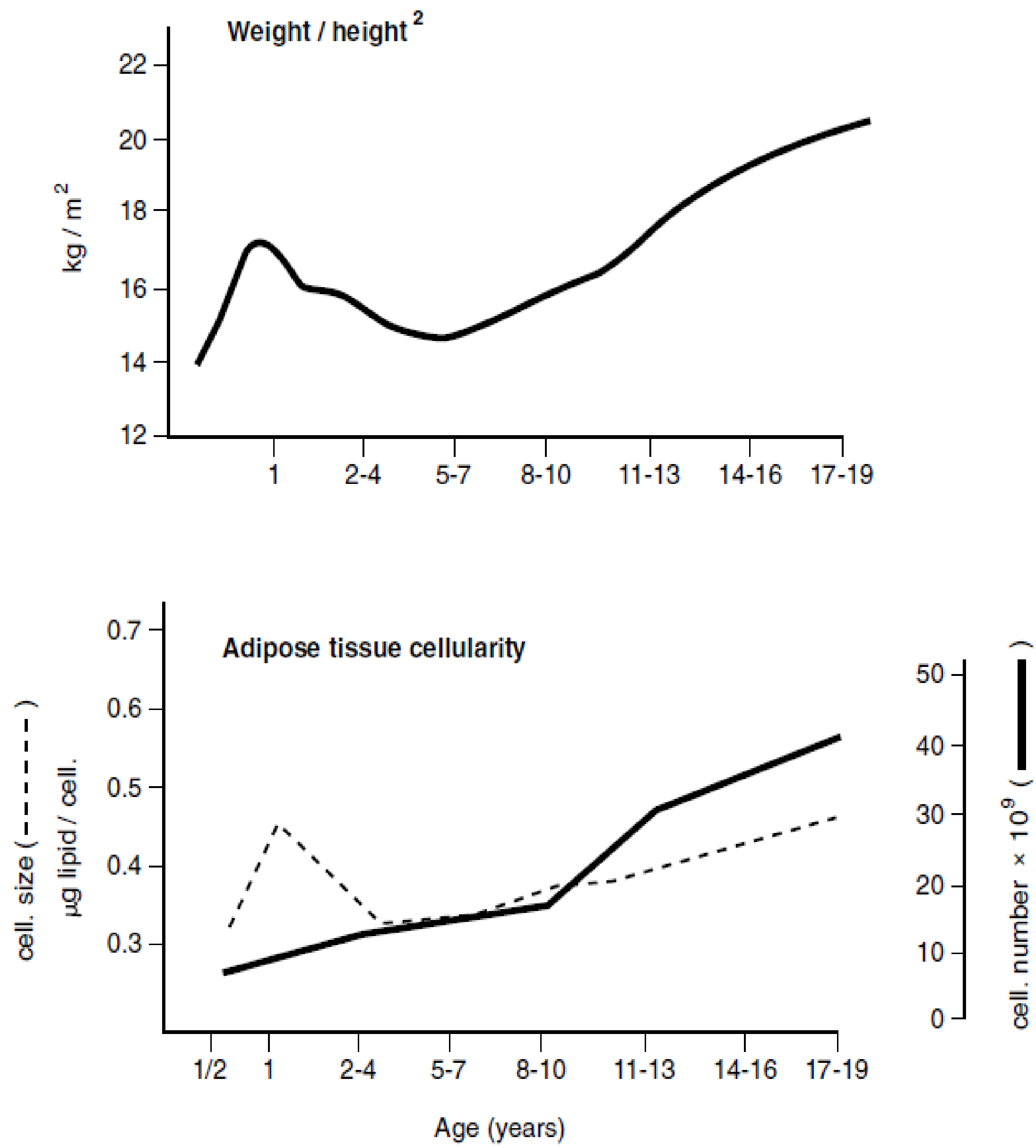

Figure 1. Trends in body mass index through childhood and the corresponding trends in adipose tissue cellularity (Knittle, Timmers, Ginsberg-fellner, Brown, & Katz, 1979).

Anthropometry

Anthropometry is the single universally applicable, inexpensive and noninvasive method available to assess the size, shape and composition of the human body. It reflects both health and nutrition and predicts performance, risk factors and survival (DeOnis & Habicht,1996). The most widely used measurements to predict fatness are weight and height, and circumferences.

Percent of Median, Centiles and Z-scores

Anthropometry changes with age during childhood. To assess individual children, measurements need to be adjusted to compare them with those of other children of the same age. In addition, weight may need to be adjusted for height. The adjustment is made by comparing the child's measurement with a suitable reference value, obtained either from a chart or table, though computers are now simplifying the process. There are three different ways of expressing the adjusted anthropometry value: as a percentage of the median, as a centile and as a Z-score. The percent of median is 100 times the measurement divided by the median or mean reference value for the child's age (or in the case of weight-for-height, weight divided by the median for the child's height). For centiles, the measurement is plotted on a growth centile chart and the child's centile interpolated from the growth curves. Z-scores are closely related to centiles and indicate the number of standard deviations the child's measurement lie above or below the mean or median reference value (Gomez et al.,1956). As an example, three proposed cut-offs to define overweight based on age adjusted weight are

120% of the median, the 97th centile and + 2 Z-scores respectively. These cut-offs are all similar to each other, identifying 2–3% of the reference population as being overweight. Percent of the median is the simplest of the three forms to calculate, and has been in use the longest (Gomez et al., 1956). Centiles are easy to read off the chart and are well understood by parents. If the measurement is normally distributed, centiles and Z-scores are interchangeable. However, often there is no known distribution by which to convert the centiles on the chart to Z-scores. This applies particularly to skew data like weight (Gomez et al.,1956).

Body Mass Index

The interdependence between weight, height, body mass index and body fat is often insufficiently well understood. The body mass index is sometimes criticized because of its association with height (O'Dea & Abraham, 1995), yet this is only a flaw if the index is required to be uncorrelated with height. From a broader perspective the association is actually an advantage, as it flags the greater fatness of tall children during adolescence. Recent studies have shown high correlations between BMI and percent body fat measured (Daniels, Khoury & Morrison,1997). Equally it is important to realize that the body mass index cannot be used to demonstrate an association between adiposity and height in adolescence – body mass index does not measure adiposity directly. To investigate the correlation between adiposity and height a direct measure of body fat should be used. The natural history of body mass index is similar to that for body fat, a steep rise during infancy with a peak at 9 months of age, followed by a fall until age 6 years and then a second rise, which lasts until adulthood. Body mass index for age percentiles for girls aged 2-20 years is shown in figure 2.

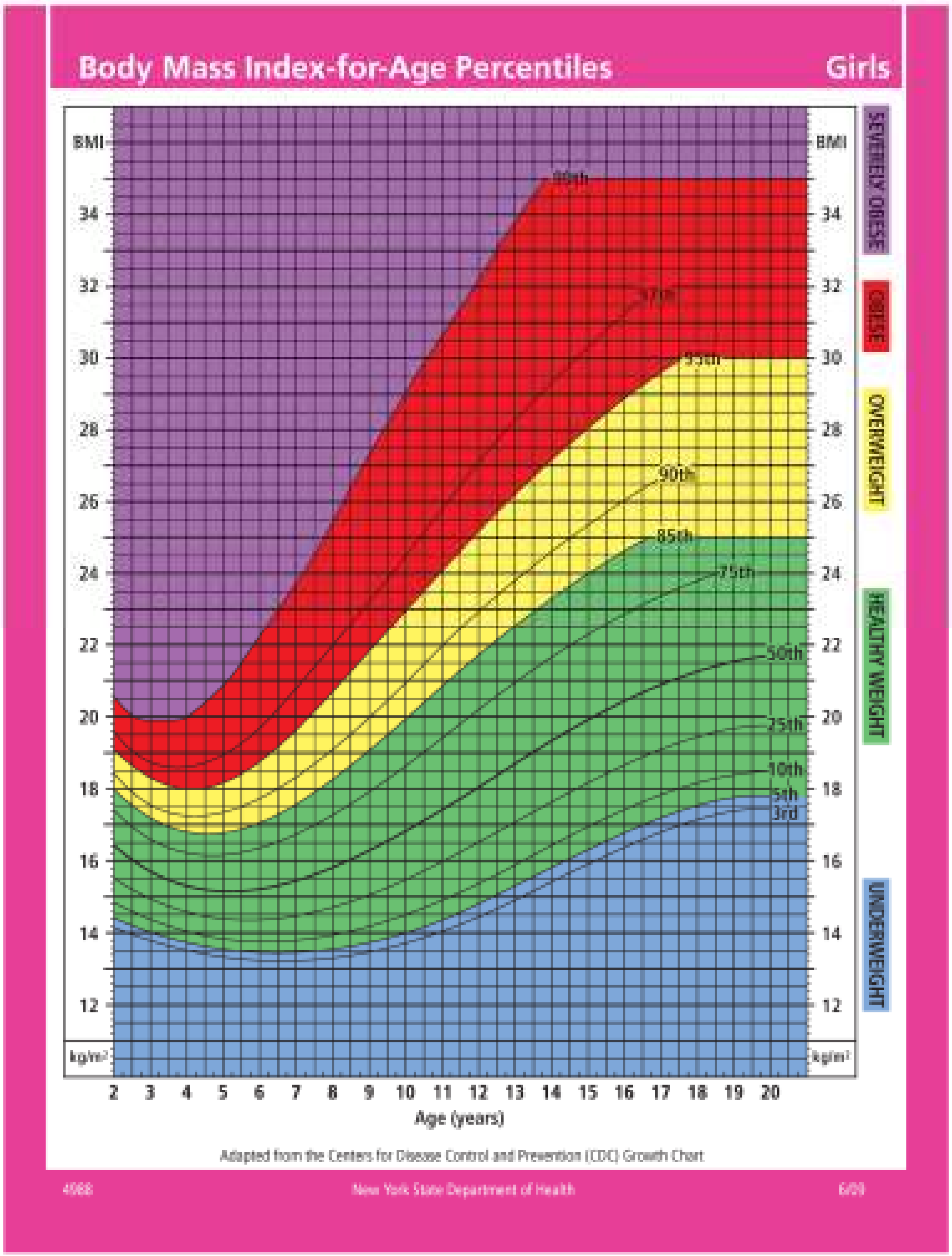

Figure 2. Girls Body Mass Index for age percentiles.

Adiposity as Proxy for Later Adiposity, Morbidity and Mortality

Tracking

Many studies have examined the persistence (tracking) of adiposity from childhood to adulthood, and the literature has recently been reviewed. The magnitude of tracking is important when considering treatment or prevention strategies. The chance of childhood obesity persisting into adulthood depends on the measure of adiposity used, the cut-off used to define obesity and the age of initial assessment. However, it is a consistent finding that fatter children are more likely than thin children to be obese later in life (Power, Lake, &, Cole,1997). There is relatively low tracking from early childhood to adulthood, while fat adolescents have a high risk of obesity as adults (Power, Lake &, Cole,1997). The point of minimal BMI on the centile chart at about age 6 years (see Figure. 2) is known as the adiposity rebound. As a rule, age at adiposity rebound (when the BMI begins to rise again from the minimal level) predicts adult BMI but it is probably not as good a predictor as the child's BMI at that age (Whitaker, Pepe, Wright, Seidel, & Dietz, 1998). Overall, prediction of adult obesity from child adiposity is only moderate.

Morbidity and Mortality

It is important to know if adiposity is associated with current and future morbidity and mortality. There have been several studies relating weight–height indices to subsequent mortality in children. The $\mathrm{weight}/\mathrm{height}^{\mathrm{p}}$ index was used to assess the risk of death in a group of malnourished children. The Measurement and definition optimal height power 'p' was found to be close to 2.

That is, the BMI was a better predictor of early death than the weight-for-height Z-score (Prudhon, Briend, Laurier, & Golden, 1995). Relatively few data are available relating BMI to morbidity and mortality in children and adolescents, but associations have been found between BMI or change in BMI, and increased blood pressure, adverse lipoprotein profile, noninsulin- dependent diabetes mellitus and early atherosclerosis lesions (Prudhon, Briend, Laurier, & Golden, 1995). Two follow-up studies have examined the association between child BMI and adult outcome. In the Harvard Growth Study, overweight girls and boys had an increased risk of later obesity-associated morbidity as compared to their lean adolescent peers (Must, Dallal, & Dietz,1991). The study also found that those who were underweight in childhood had a higher all-cause mortality rate than those of average weight. This is consistent with the increased mortality in adults associated with both low and high BMI. BMI is the optimal single measure for assessing overweight, and the International Obesity Task Force (IOTF) cut-off for BMI offers an internationally acceptable definition of overweight and obesity. As such it should make inter-study comparisons more valid, and may help identify factors responsible for the recent steep rise in child obesity. However, BMI does not distinguish between body fat and lean body mass.

GEMS

Memphis Girls health Enrichment Multi-site Studies (GEMS) was a controlled trial in which girls were randomly assigned to an obesity prevention or alternative intervention. The setting for this intervention was Local community centers and YMCAs in Memphis, Tennessee. The participants were chosen from Girls ages

8-to-10 years (n=303) who were identified by a parent as African American and had body mass index (BMI) ≥25th percentile for age or one parent with BMI ≥25 kg/m2. This study was aimed at testing the results of two interventions on body mass index (BMI) after two years. Intervention groups were 'Group behavioral counseling' to promote healthy eating and increased physical activity (obesity prevention intervention) or self-esteem and social efficacy (alternative intervention). The major results observed in this study is that BMI increased in all girls with no treatment effect (obesity prevention minus alternative) at 2 years and there were no effects on physical activity. And the study concludes that the lack of significant BMI change at 2 years indicates that this intervention alone is insufficient for obesity prevention. Effectiveness may require more explicit behavioral change goals and a stronger physical activity component as well as supportive changes in environmental contexts (Klesges et al., 2007).

Chapter 3

A System Dynamics model for Memphis Girls Health Enrichment Multi-site Studies (GEMS)

Effective strategies for prevention of obesity, particularly in youths, have been elusive since the recognition of obesity as a major public health issue two decades ago. In general, obesity is a result of chronic, quantitative imbalance between energy intake and energy expenditure, which is influenced by a combination of genetic, environmental, psychological and social factors. Therefore, a systems perspective is needed to examine effective obesity prevention strategies. In this study, a systems dynamics model was developed using the data from the Girls health Enrichment Multi-site Studies (GEMS). GEMS tested the efficacy of a 2-year family-based intervention to reduce excessive increase in body mass index (BMI) in 8-10 year old African American girls. First, an optimum model was built by systematically adding variables to fit the observed data by regression analysis for 50 randomly selected individuals from the cohort. The final model included nutrition, physical activity, and several environmental factors. Next, the model was used to compare two intervention strategies used in the GEMS study. Consistent with previous reports, we found that the two strategies did not affect the BMI increases observed in this cohort. Interestingly however, the model predicted that a 10 min increase in exercise plus 100 Cal in energy intake would decrease BMI in both groups. Our work suggests that system dynamics modeling may be useful for testing potential intervention strategies in complex disorders such as obesity.

Introduction

System Dynamics is the application of feedback control systems principles and techniques to model, analyze, and understand the dynamic behavior of complex feedback systems. The ultimate purpose in applying System Dynamics is to facilitate understanding of the relationship between the behaviors of a complex system over time. For this, system dynamics models rely on computer simulation. Even though the dynamic implications of simple loops may be reasonably obvious, the interconnected feedback structures of real problems are often so complex that the behavior they generate over time can usually be traced only by simulation. Computer simulation is particularly suited to the study of continuous systems, in which system variables change continuously over time. Yet, because of the complexity and expense of continuous measurements, most experimental studies of human energy expenditure have relied on discrete, rather than continuous, measurement protocols. This can be a serious limitation, because a negative finding (e.g., finding no association between low energy expenditure and subsequent weight gain) may simply mean that the timing of the measurements did not coincide with the period of reduced/ increased energy expenditure. In addition, system dynamics models make “perfectly” controlled experimentation possible. In the model system, unlike real systems, the effect of changing one factor can be observed while all other factors are held unchanged.

In (Abdel-hamid, 2002), authors developed a system dynamics model to investigate the effect of physical activity and diet on weight gain or loss. Thus, they approach the modeling of dynamics of obesity from diet and exercise perspective. The importance of residual environments and neighborhoods on health and the effectiveness of system dynamics modeling to understand these effects on health are addressed in (Amy & Ana, 2005). In authors mention the need for using multilevel framework in which obesity should be framed as a complex system in which behavior is affected by individual-level factors as well as socio-environmental factors.

The obesity epidemic has grown rapidly into a major public health challenge, in the United States and worldwide. The scope and scale of the obesity epidemic motivate an urgent need for well-crafted policy interventions to prevent further spread and (potentially) to reverse the epidemic. Yet, several attributes of the epidemic make it an especially challenging problem both to study and to combat. Worldwide, nearly half a billion were overweight or obese in 2002 (Hammond, 2009). The growth of the obesity epidemic has significant implications for public health and health care costs. Obesity in children is also growing rapidly, presenting immediate health risks and suggesting the potential for even larger future increases in adult obesity unless the epidemic is contained. Both the scope and the scale of the obesity epidemic motivate an urgent need for well-crafted interventions to prevent further spread and to (potentially) lower current rates of overweight and obesity.

Although many advances have been made with regard to the basic biology of adiposity and behavioral modifications at the individual level, little success has been achieved in either preventing further weight gain or maintaining weight loss on a population level. To a great extent, this is the result of the complex task of trying to change the way people eat, move, and live, and sustaining those changes over time. Historically, obesity research has been conducted within individual disciplines. Now, for both scientific inquiry and for public policies, obesity should be framed as a complex system in which behavior is affected by multiple individual-level factors and socio-environmental factors (i.e. factors related to the food, physical, cultural, or economic environment that enable or constrain human behavior, or both). These factors are heterogeneous and interdependent, and they interact dynamically.

This study attempts to demonstrate the utility of System Dynamics modeling as a vehicle for controlled experimentation to study and gain insight into the complex system of obesity and show the effectiveness of using System Dynamics modeling for simulating complex systems such as obesity. In this study a System Dynamics model for the GEMS intervention data by using Vensim software which includes energy intake, energy expenditure, body weight and BMI, and socio environmental subsystems is developed. The system is aim at capturing most of the variables and effects involved in the model so that reliable simulation results on BMI which are comparable to measurements be obtained.

Vensim

The Vensim (Eberlein & Peterson, 1992) is a visual modeling tool that allows you to conceptualize, document, simulate, analyze, and optimize models of dynamic systems. Vensim provides a simple and flexible way of building simulation models from causal loop or stock and flow diagrams. By connecting words with arrows, relationships among system variables are entered and recorded as causal connections. And thus, defining the relationships and the models and running the simulation has been made so easy using Vensim. We used Vensim PLE version 5.9e for windows. The software can be downloaded from http://www.vensim.com/freedownload.html.

System Dynamics Model Structure- Core Model

Energy intake subsystem.This subsystem includes data on the following macro nutrients: carbohydrate, fat, protein, fiber, fatty acids, sugar, and starch intake. The data points available for this cohort are the baseline and it is expected that each person participating in the study stick to the nutrition data available at the baseline.

Energy expenditure subsystem. This subsystem consists of three variables. Thermic effect of food (TEF) which is the amount of energy used to process the food in the body which is 10% of the energy intake (Abdel-hamid, 2002). The second variable is the thermic effect of activity (TEA) which is the energy used for carrying out the exercise. The final variable is the resting energy expenditure (REE) which is the energy which body requires for maintenance of its biological functions and balance.

Energy surplus deficit and body weight. The difference between energy intake and energy expenditure causes the energy imbalance (energy surplus/deficit) in the system. The energy surplus is stored in the body stores. Thus, the core model incorporates three subsystems of energy intake, energy expenditure, and energy surplus deficit and body weight. Figure 3 demonstrates the core model.

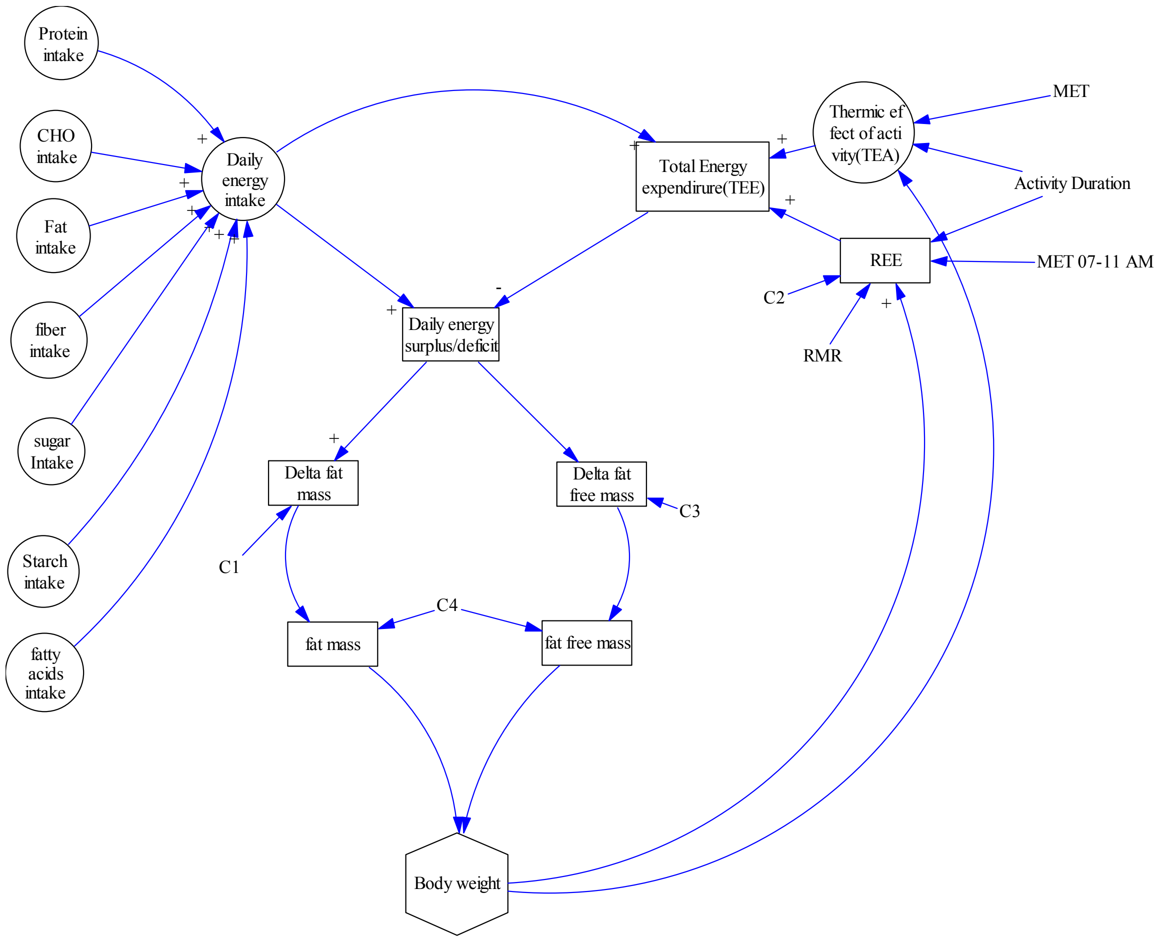

Figure 3. Core model.

Population Average Simulation

Using the model developed, we simulate population average and compare the final BMI simulated for the average BMI measured in the population of 303 individuals. The BMI average is 25.27 and the BMI simulated is 26.8 which shows the result obtained is in agreement with the documented data. For doing this simulation we take the mean of each input variable and insert it into the model.

We used this model for simulation at individual level. The results are not that accurate and the model does not fit reasonably to the data. We selected 50 individuals at random. We ran regression analysis of measured BMI at the end of study on simulated BMI. The regression correlation coefficient was 0.57. This result is in agreement with the statement we made before that the model does not fit the data at individual level. There are many possible explanations to this issue. Individuals are very different each coming from different family socio-environments and may have different genetic and pathological issues and different eating and expenditure habits to mention a few.

In order to deal with this problem we need to capture as much of this variability as possible into the system. To do so, we chose seven environmental variables and incorporated them into the model. These variables and their design and modification are explained in next section.

Core Model Plus Environmental Subsystem

The environmental subsystem consists of seven variables- fast food density, restaurant density, mean fruit vegetable availability, mean fruit vegetable accessibility, baseline family support for healthy eating, family income, and carryout food eating. All these variables will result in “over eating inclination coefficient” which is designed to be between -1 and 1 and directly increase or decrease the energy intake input. Demonstrating these variables by x_i, the overeating inclination coefficient is build based on formula (1).The negative sign is applied when the sum of the seven variables is smaller than zero.

$$\text{overeating inclination coeficient} = \pm\frac{1}{7} * \left|\log(\sqrt{\sum x_i^2} + 0.5)\right| \qquad (1)$$

In order to incorporate the environmental variables into the system all variables are normalized using mean and standard deviation for each variables obtained from the whole population of 303 based on formula (2). In this formula, μ_i and σ_i are mean and standard deviation for the population of each specific variable respectively. In this way, the weight for each variable in the system is calculated by taking into account the population it is coming from and thus it depends on the deviation from the mean of population and standard deviation of the population for the desired variable and thus is independent of the units of measurement. If we demonstrate overeating inclination coefficient by X and baseline energy intake by Y, we obtain the formula (3) for the energy intake used in the system.

$$Z_i = \frac{x_i - \mu_i}{\sigma_i} \qquad (2)$$

$$\text{energy intake} = Y * (1 + X) \qquad (3)$$

Figure 4 shows the environment subsystem incorporated into the model. As it can been seen from the figure, some of the variables have positive correlation with “Overeating inclination coefficient” and some others have negative correlation. This fact is shown by positive and negative signs at arrow heads. For instance, fast food density in the neighborhood has positive correlation with "overeating inclination coefficient". That is, if fast food density increases in an area it increases the value of "overeating inclination coefficient". In other words, the bigger the normalized value of this variable for an individual the bigger the positive effect this variable has on "overeating inclination coefficient".

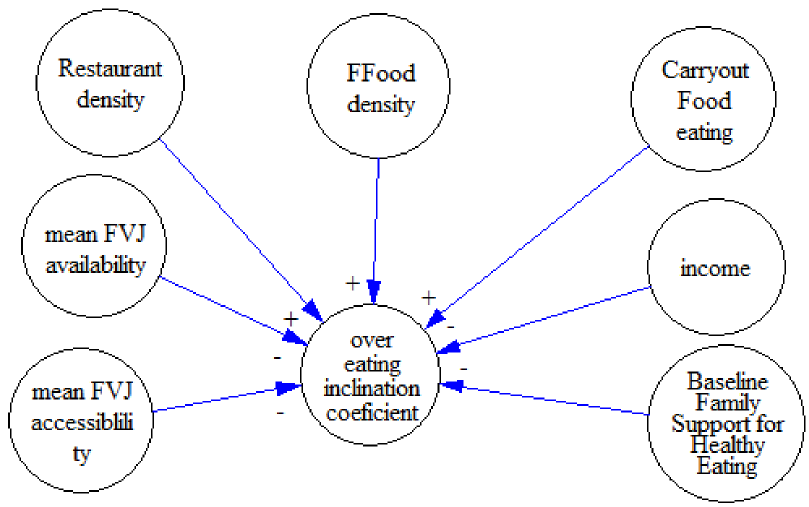

Figure 4. Environment subsystem.

Core Model Plus Behavioral Variables Fat and Sweet Beverage Preference

Even though the values for sugar intake and fat intake are measured in the GEMS study, as it is expected, there will be deviation in these values based on personal lifestyle and eating habits for each person. Thus, we develop two behavioral variables based on data available in GEMS study to target these individual differences and varying eating habits for each individual. These two variables, "food's fat content coefficient" and "sweet beverage preference" are basically built the same way as the seven environmental variables explained in previous section. Food's fat content coefficient is between -1 and 1 and directly increase or decrease the food fat intake incorporated into the system for each individual. This variable comprised of two variables: 1-low fat food preparation and 2- high fat food preparation in the family. In order to incorporate them into the system, these variables are normalized based on formula (2). After this process, the food's fat content coefficient is obtained using formula (4). In this formula, food fat content coefficient, low fat food preparation and high fat food preparation are demonstrated in abbreviation forms FFCC, LFFP, and HFFP respectively.

$$\mathrm{FFCC} = 0.18 * (\mathrm{LFFP} + \mathrm{HFFP}) \qquad (4)$$

Sweet beverage preference is a normalized variable based on formula (2). This variable is between -1 and 1 and directly increases or decreases the sugar intake based on its deviation from the mean of population. That is, a positive deviation (observation bigger than population average for this variable) increases the sugar intake and by the same token a negative deviation decreases the sugar intake. Thus, final sugar intake, final fat intake and fatty acids intake are obtained using formula (5), (6). In these formulas, fat intake, fatty acid intake, and sugar intake are nutrient values measured for each individual at baseline. Final fat intake, final fatty acid intake, fat intake, fatty acid intake, food fat content coefficient, final sugar intake, sugar intake, and sweet beverage preferences are abbreviated to FFI, FFAI, FI, FAI, FFCC,FSI, SI, and SBP respectively.

$$(\text{FFI or FFAI}) = (\text{FI or FAI}) * (1 + \text{FFCC}) \qquad (5)$$
$$\text{FSI} = \text{SI} * (1 + \text{SBP}) \qquad (6)$$

Individual Variability- the Black Box Variable

In addition to variables incorporated into the system, there exists a black box variable named “individual variability”. This variable, which can take a value between -1 and 1, shows the uncertainty in the model and is defined as a fraction of energy intake needed to be added to the measured energy intake in order to get final BMI simulated equal to the value of final BMI measured after 2 years of intervention. The formula representing relationship between energy intake and individual variability is as represented in formula (7). In this formula, final energy intake, energy intake, and individual variability are represented by FEI, EI, and IV respectively. In this formula, energy intake is obtained from nutrients intake documented for each individual in GEMS study. The value obtained from the formula above for individual variability in order to fit the model, is used later in analysis of the model. Based on argument above, the closest the individual variability to zero the more precise is the model. For example the individual variability of 0.1 shows that we need to increase energy intake 10% to adjust simulation to match measured results. And thus, 10% of the system has not been captured by the model that might be due to other subsystems like genetics that are not incorporated into the model. Initially, individual variability is set to zero and the final simulated results are documented for further statistical analysis.

$$\text{FEI(kcal)} = \text{EI} * (1 + \text{overeating inclination coefficient} + \text{I.V}) \qquad (7)$$

Complete Model

The complete model is obtained by putting all the components explained in previous sections together. The result of simulations based on this model for each individual is obtained for statistical analysis of the model. This model is shown in figure 5. In this figure the environment subsystem is just shown by "over eating inclination coefficient) due to lack of space.

Model fitting

The metabolic equivalent of task (MET) for four hours is available for each individual in the GEMS study. Having this information and setting the resting metabolic rate to 1 kcal per each kilogram of body weight in each hour (1 $kcal.kg^{-1}.hr^{-1}$) (Ainsworth et al., 2011) for the remaining 20 hours minus activity duration, the REE is calculated for each individual based on body weight. We set MET for physical activity to be on average 7 for TEA. Since each gram of fat has 9 kcal of energy, the amount of energy required to store one gram of fat in the body is approximately 9 kcal. The energy equivalent of protein is 4 kcal per gram. In average, this energy surplus/deficit during 730 days is accumulated in the body weight variable.

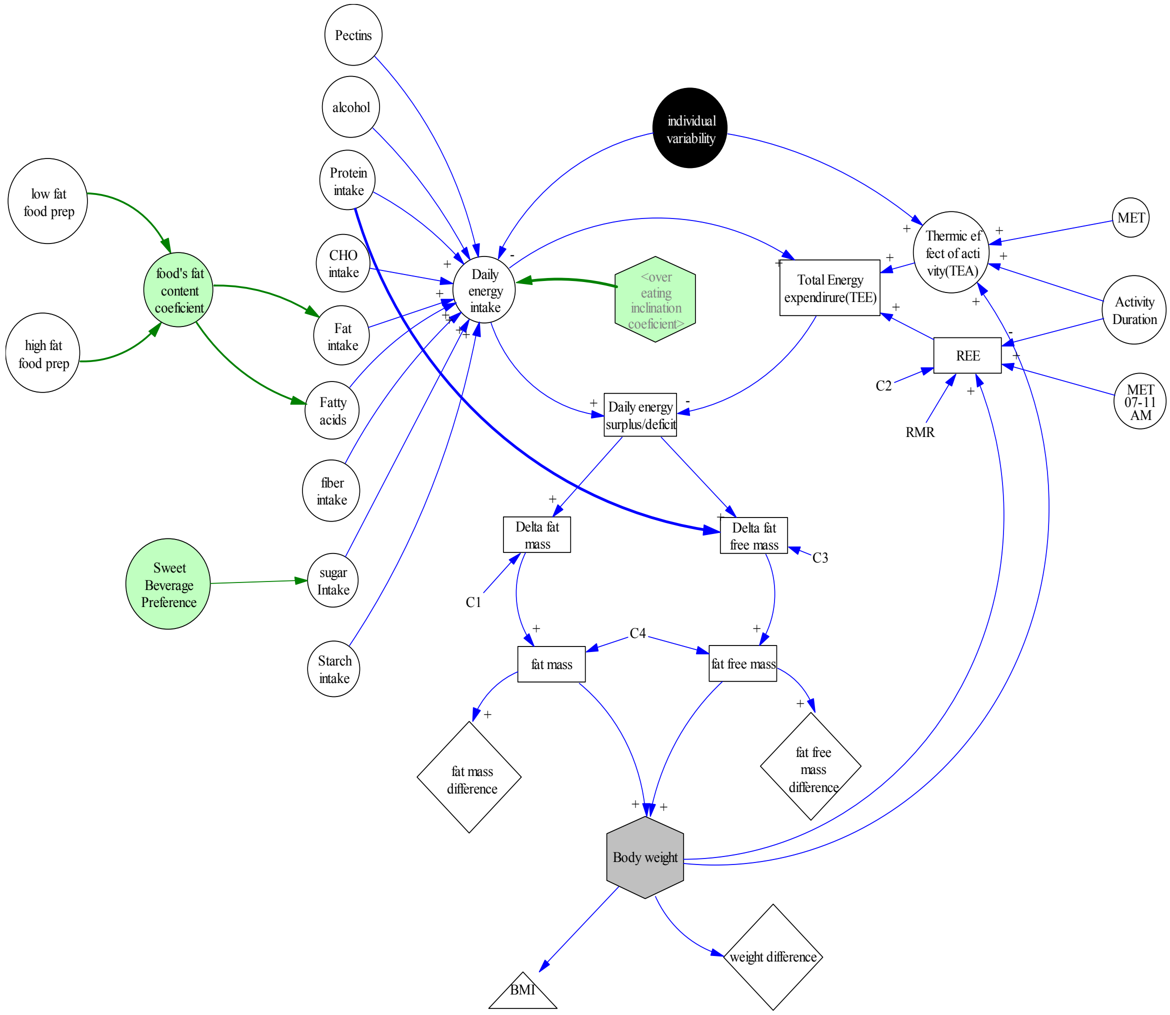

Figure 5. Complete Model.

BMI variable calculates BMI at the end of intervention using individual height after two years and final body weight simulated. Based on the population under study and fitting the model to the real measured data, the fat mass accumulation is designed to be based on 55% of daily energy surplus/deficit. Since protein is involved in fat free mass gain the amount of fat free mass gain is dependent on the amount of daily protein intake. Thus, by taking into account the population under study and fitting of the system for data points, the fat free mass is based on 0.2 of daily energy surplus. Formulas (8) through (11) show the relationship between these variables.

$$\text{delta FatMass(gram)} = (0.55 * \text{daily energy surplus/deficit})/9(\text{kcal}) \qquad (8)$$

$$\text{FatMass(kg)} = \text{initial fat mass} + (\text{delta fat mass})/1000 \qquad (9)$$

$$\text{delta fat free mass(gram)} = (0.2 * \text{daily energy surplus/deficit})/4(\text{kcal}) \qquad (10)$$

$$\text{Fat free mass(kg)} = \text{initial fat free mass} + (\text{delta fat free mass})/1000 \qquad (11)$$

As it is apparent from the formulas above, the delta fat free mass and delta fat mass can be positive or negative depending on whether there exists an energy surplus or deficit which can result in fat mass and fat free mass gain or loss. In order to demonstrate the output of simulation using Vensim software, an individual is chosen and the dynamics of change in final weight is shown in figure 6.

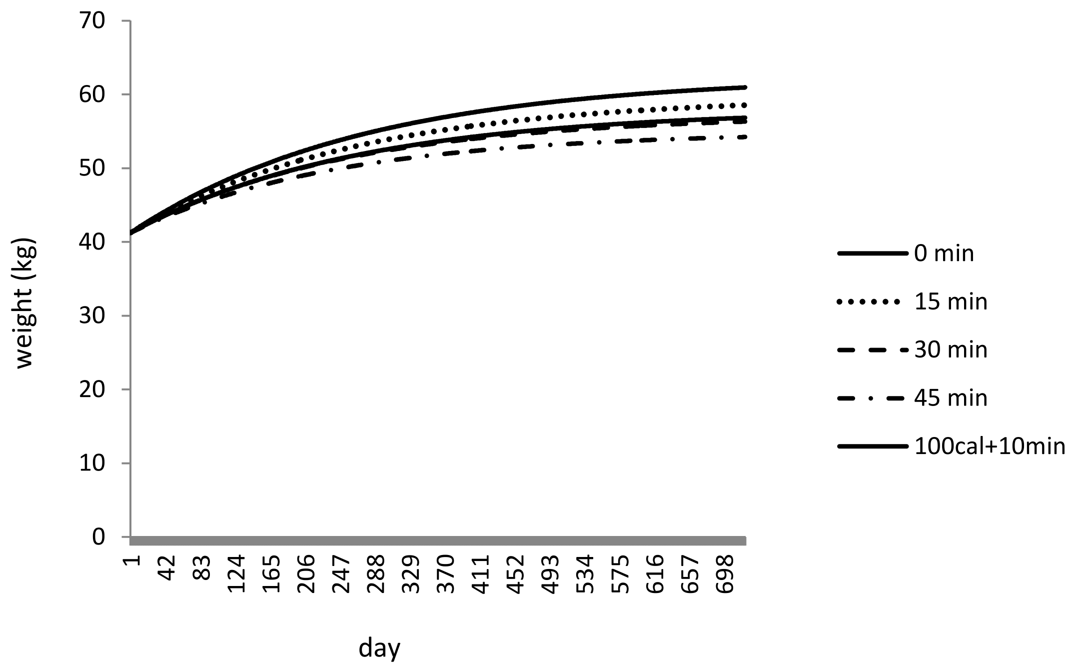

Figure 6. Dynamics of weight change simulation using vensim software.

Results

Much of the research in obesity prevention studies has emphasized one aspect of the problem in isolation. For instance, the effect of one type of diet or special type of workout on body weight gain/loss is investigated. Even though such specific studies are necessary in understanding of any complex systems, breaking the system to its micro components and investigating each part is often insufficient in understanding the whole picture. Thus, in order to have a complete understanding of a complex system it is necessary to be able to put the knowledge of individual components into a whole complex system.

The model described here incorporates body weight and BMI, energy intake, energy expenditure, and environmental factors subsystems to a model to simulate change in the body weight and composition in the two year period of GEMS study. In order to develop the model, we start with three main subsystems which are energy intake, energy expenditure, and body weight/ BMI subsystem. After inserting the values of all variables into the model for each individual, the model is simulated. The values of each non-input variables are updated for the length of the intervention (on average 730 days) times and the final value of the BMI is obtained. We simulated the model at each level of development. Table 1 gives the result of regression analysis between final BMI measured and simulated for the four levels of design. In this table, correlation coefficient and the p value for testing H_0: there's no correlation at each level are presented.

Table1

Regression Analysis of Final BMI at Different Levels of Development

Model	Correlation coefficient	P-value
Core model	0.57	1E-5
Core model+ fat + sugar	0.70	2E-8
Core model + Env comp	0.72	5.08E-9
Complete model	0.83	5.98E-14

In this table, model levels are ordered from the core model to complete model. As was can see, by adding new components to the model correlation coefficient between final BMI measured and simulated increases and the line of regression becomes closer to Y=X and the standard errors of slope and intercept decreases. This demonstrates that by adding new components to the model, the uncertainty in the model decreases and model captures more of the dynamics involved in this system.

Figure 7 shows the histogram of individual variability for the complete model. The individual variability values plotted here are the fraction of this variable required for each individual so that the results of simulation and measured BMI are exactly the same. As we can see for 84% of the individuals (42 out of 50) the value of individual variability is between -0.1 and 0.1. This result demonstrates that uncertainty in the model is very low for 84% of individuals and it demonstrates that the system can capture most of the important variables into the model and just a small fraction (less than 0.1) cannot be explained by the model. Based on Q1-1.5IQR=-0.16 and Q3+1.5IQR=0.16 we have 8 outliers in the system that the final BMIs measured and simulated are different. Based on $\mu+3*\sigma=0.54$ and $\mu-3*\sigma=0.5$ we'll obtain 2 outliers.

The reason for having outlier in the system can range from error in reporting the data like under reporting to pathological issues and genetics which are not addressed in the model. In addition to analysis above, we run two tests for the slope and intercept in complete model as follows. First, we tested the hypothesis of slope=0. By this test we are testing the hypothesis of no association between final weight simulated and final weight measured. The p-value obtained for this test is 5.98E-14. As we can see, the test result is significant which shows that the slope statistically different from zero and there exists a strong association between final BMI measured and simulated. Also the test of intercept=0 is not significant in the sense that intercept is not significantly different from zero. The 95% confidence intervals for slope and intercept are [0.71 1.05] and [-0.88 8.09] respectively. The confidence interval for slope contains 1 and the confidence interval for intercept includes 0 which support the test results on slope and intercept.

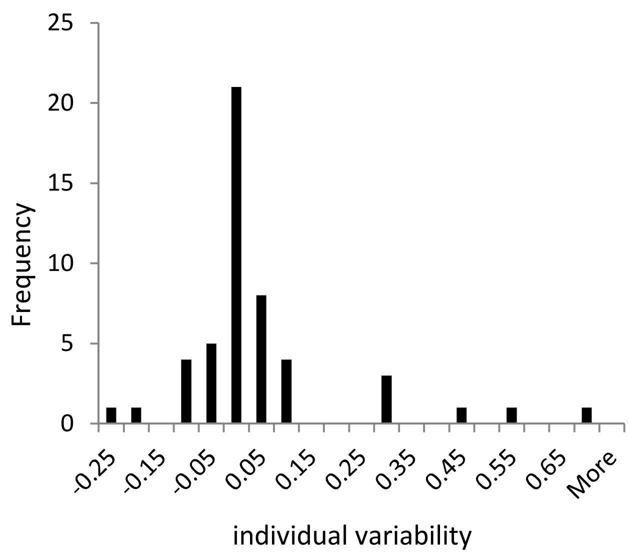

Figure 7. Individual variability frequency

Intervention Study

The major result observed in GEMS study is that BMI increased in all girls with no treatment effect at 2 years and there were no effects on physical activity (Klesges et al., 2007). And the study concludes that the lack of significant BMI change at 2 years indicates that this intervention alone is insufficient for obesity prevention and suggests that Effectiveness may require more explicit behavioral change goals and a stronger physical activity component as well as supportive changes in environmental contexts (Klesges et al., 2007). By comparing the BMI simulated and initial BMI, we obtained the same results as in GEMS study and our conclusion of no effect is in concordance with no effect due to intervention in GEMS study.

As stated in introduction, systems dynamics models make “perfectly” controlled experimentation possible. That is, we utilize this model to examine the effect of changing one factor in the model while all others are held unchanged. In this section, we examine the effect of increasing physical activity by steps of 15, 30, and 45 minutes on BMI in the period of 2 years. In addition, we perform a mixed intervention by accompanying 10 min increase in exercise intervention with constant reduction of 100 kcal in energy intake and simulate the BMI change in period of two years. The results are shown in table below. In addition, 95% confidence intervals for means are shown in table 2.

Table 2

Simulated Exercise Intervention and BMI Change

Study (N=50)	Mean delta BMI after 2 years	95% Confidence interval for delta BMI
GEMS (no increase in exercise)	3.04±0.54	[1.94 4.13]
+15 min exercise simulation	1.77±0.56	[0.63 2.91]
+30 min exercise simulation	0.55±0.52	[-0.34 1.85]
+45 min exercise simulation	-0.16±0.52	[-1.21 0.88]
-100 kcal and +10 min exercise simulation	0.84±0.49	[-0.16 1.83]

As we can see from table above, increasing physical activity by 15 minutes reduces the increase in BMI in half and increasing physical activity by 45 minutes even causes reduction in BMI after the period of two years. Based on the simulation results, we can deduce that for the intervention to be successful, increasing the physical activity should be considered as one of the main effective approaches in reducing the increase in BMI. By looking into the mixed intervention study, we can see that the effect of the mixed intervention is almost equivalent to the 30 min increase in exercise from table 2. By far, the 30 min exercise which may seem a daunting task to lots of individual can be substituted by the mixed intervention to obtain the same effect on the BMI. In order to determine interventions which are significantly different from the original simulation we perform a t-test between the two populations of BMIs: one being the original BMI simulated without any intervention and the other being the population of BMIs simulated after introducing the intervention. The result of this study is represented in table 3.

Table 3

Comparing the Simulation Results of Intervention Studies to no Intervention. Two-tailed t-test

Original VS 15 min intervention	Original VS 30 min intervention	Original VS 45 min intervention	Original VS mixed Intervention
0.11	0.004	5.96E-6	0.0039

As we can see the Interventions 30 and 45 minutes exercise and mixed intervention have significant effect on final BMI. We compared the simulation results for 30 min exercise to 15 min, 45 min, and mixed intervention to see if these interventions are statistically significant. The results shown in table 4 indicate that 30 min exercise intervention is not significantly different from mixed intervention. This result verifies our finding in table 2.

Table 4

Comparison of 30 Min Intervention to 15 Min, 45 Min, and Mixed Intervention. Two tailed t-test

15 VS mixed	15 VS 30	15 VS 45	30 VS mixed	30 VS 45	45 VS mixed
0.22	0.2	0.01	0.9	0.23	0.17

We divide the 50 individuals into intervention and alternative group to see if there exists a difference in BMI change between these two groups. In this table mean BMI change and standard deviation of this mean BMI change is shown for each step of simulation. We perform a t-test to obtain the p-value of comparing the means for the results of simulations at each step of intervention. The results are shown in table 5.

Table 5

Exercise Simulation and BMI Change for Two Intervention Groups

Exercise simulation	0 min	15 min	30 min	45 min	100 kcal + 10min
Int group BMI change (N=25)	3.24±0.58	1.9±0.8	0.84±0.77	0.16±0.75	1.11±0.71
Alter group BMI change	2.4±0.65	0.88±0.88	-0.06±0.85	-0.87±0.81	0.57±0.71
p-value	0.31	0.287	0.326	0.4	0.18

As explained in GEMS study description, the intervention group was the group in which Group behavioral counseling was performed to promote healthy eating and increased physical activity (obesity prevention intervention) and alternative intervention was aimed at increasing self-esteem and social efficacy (alternative intervention). Based on table 3, a constant increase in physical activity has an equal impact on BMI change in the alternative group and obesity prevention group. By looking into the mixed intervention results, we observe that the average BMI gain in the alternative group after period of two years is almost half of this gain in intervention group. That's due to the fact that average energy intake in intervention group is around 100 Cal/day more than that of alternative group.

Discussion

Ideally, all studies on food intake and energy expenditure would be carried out under natural free-living conditions in which eating and exercise behaviors could occur without hindrance and could be measured precisely and accurately. In practice, this is not possible because methods for measuring total energy intake and expenditure under natural circumstances are often unreliable. On the other hand, laboratory-based studies allow the accurate assessment of food intake and energy expenditure but under highly artificial circumstances (Abdel-hamid, 2002). Accordingly, it is useful to seek other methods for testing and experimentation. Simulation-based experimentation provides a viable laboratory tool for such a task. In addition to permitting less costly and less time-consuming experimentation, simulation-type models make "perfectly" controlled experimentation possible. In the model system, unlike the real systems, the effect of changing one factor can be observed while all other factors are held unchanged. Internally, the model provides complete control of the system.

The attribute of the obesity epidemic that makes it an especially challenging problem — both to study and to combat— is the huge range in the levels of scale involved. Empirical evidence suggests important (and potentially interconnected) effects at levels including genes, neurobiology psychology, family structure and influences, social context and social norms, environment, markets and public policy. Not only do these levels entail very different pathways of effect and diverse methodologies for measurement, they are also usually the province of very different fields of science (from genetics to neuroscience to economics and political science).

We developed the core mode and test it on population average. The results obtained are in agreement with documented data in GEMS. At individual level we do not have the same accuracy obtained in modeling of population average and individuals do not fit well into the model. Testing this model on individuals demonstrates lack of important players missing in the system which motivated us to build environment component and other variables and incorporate them into the system. In order to do so, we needed to find a way of incorporating this range of diverse variables with different units of measurement into the system. We normalized these variables using population mean and standard deviation for each variable. By doing so, we incorporate the effect of each variable as it's deviation from the population mean. By adding these variables into the model and simulating the model for a sample of 50 random individuals, we performed regression analysis between final BMI measured and simulated as an indication of fitness of the model. We observe that as new variables are added to the model, the model fit more closely to the data and we can capture more variations that exist at individual level. The complete model developed here fits to the measured data well by correlation coefficient of 0.83 (p-value: 5.98E-14).

The model we developed here fits to the measured data well by correlation coefficient of 0.83 (p-value: 5.98E-14). By adding new environmental components, the uncertainty in the model decreases and we can capture more of the complex obesity system into the model. Based on the individual variability plot, there exist some outliers that do not fit into the model. The reason for having outlier in the system can range from error in reporting the data like under reporting to pathological issues and genetics which is not addressed in the model. In GEMS data, although dietary intake is not a primary outcome variable, this variable is often under reported, particularly in this population. This may account for the data points with finals weights simulated much less than the amount measured. Still about 17% variation that is not be captured into the model. This is due to other important variables not incorporated into the model due to lack of data in that area. These variables include and are not limited to genetics, pathological issues, and other socio-environmental and psychological variables.

References

Abdel-hamid, T. (2002). Modeling the dynamics of human energy regulation and its implications for obesity treatment. *System Dynamics Review,* 18, 431–471.

Ainsworth, B. E., Haskell W. L., Herrmann S. D., Meckes. N., Bassett, J.R., Tudor-locke, C.L., … Leon, A.S. (2011). Compendium of physical activities: a second update of codes and MET values. *Medicine and Science in Sports and Exercise*, Retrieved from https://sites.google.com/site/compendiumofphysicalactivities/

Auchincloss, A. H., & Diez roux, A. V. (2005). A new tool for epidemiology: The usefulness of dynamic-agent models in understanding place effects on health. *American Journal of Epidemiology*, 168,1-8.

Babbie, E. R. (1998).*The practice of social research* (8th ed.). Belmont, CA: Wadsworth Pub. Co.

Banks, J. (1998). *Handbook of simulation: Principles, methodology, advances, applications, and practice*. New York, NY: Wiley.

Barlow, S. E., & Dietz, W. H. (1998). Obesity evaluation and treatment: Expert committee recommendations, *Pediatrics*, 102(*29)*.

Cannon, R. (1967*). Dynamics of physical systems*. New York, NY: McGraw-Hill Book Company.

Clarke, W. R., & Lauer, R. M. (1993). Does childhood obesity track into adulthood?, *Critical Reviews in Food Science and Nutrition*, 33, 423–30.

Daniels, S. R., Khoury, P. R., & Morrison, J. A. (1997). The utility of body mass index as a measure of body fatness in children and adolescents: Differences by age, gender. *Pediatrics*, 99, 804(7).

Davies, P. S. W., & Cole, T. J. (1995). Body composition techniques in health and disease. *Society for the Study of Human Biology Symposium 36*. Cambridge: Cambridge University Press.

De onis, M., & Habicht, J. P. (1996). Anthropometric reference data for international use: Recommendations from a world health organization expert committee. *American Journal of Clinical Nutrition*, 64, 650–658.

Eberlein, R. L. & Peterson, D. W., (1992). Understanding models with Vensim (TM), *European Journal of Operational Research*, *Elsevier*, 59, 216-219.

Fishwick, P. A. (1995). *Simulation model design and execution: Building digital worlds*. Upper Saddle River, NJ: Prentice Hall.

Flegal, M .K., Tabak. J. C., & Ogden, L. C. (2006). Overweight in children: Definitions and interpretation, *health education research*, 21, 755-760.

Forrester, J. W. (1969). Urban dynamics. *Pegasus Communications*. ISBN 1883823390.

Freedman, D. S., Dietz, W. H., Srinivasan, S. R. & Berenson, G. S. (1999). The relation of overweight to cardiovascular risk factors among children and adolescents: The Bogalusa heart study. *Pediatrics*, 103, 1175–82.

Gomez, F., Ramos-galvan, R., Frenk, S., Cravioto, J. M., Chavez, R., & Vasquez, J. (1956). Mortality in second and third degree malnutrition. *Tropical Paediatrics*, 2, 77–83.

Heath, G. W., Pratt, M., Warren, C. W., & Kann, L. (1994). Physical activity patterns in American high school students: Results from the 1990 youth risk behavior survey. *Archives of Pediatric and Adolescent Medicine*, 148, 1131–1136.

Hammond, R. A. (2009). Complex systems modeling for obesity research. *Preventing Chronic Disease*, 6(3): A97.

Huang, T. T, Drewnowski, A., Kumanyika, S. K., Glass, T. A. (2009). A system-oriented multi level framework for addressing obesity in the 21st century. *Preventing Chronic Disease,* 6(3): A82.

Forrester, J. W., & Senge, P. M. (1996). Tests for building confidence in system dynamics models, In modeling *for management, Simulation in Support of Systems Thinking,* 2, 414-434.

Holland, J. H. (1999). Emergence *: From chaos to order*, Mass: Addison-Wesley.

Holland, J. H., & Miller, J. H. (1991). Artificial adaptive agents and economic theory, *American Economic Review*, 81, 365-370.

Klesges, R. C., Barzanek, E., Klesges L. M., Stockton, M. B, Beech, B. M, Murrary, D. M, . . . Mittleman, D.A. (2007). Memphis Girls health Enrichment Multi-site Studies (GEMS), *Pubmed*, 22, 42-55.

Knittle, J. L., Timmers, K., Ginsberg-fellner, F., Brown, R. E., & Katz, D. P. (1979). The growth of adipose tissue in children and adolescents. Cross sectional and longitudinal studies of adipose cell number and size. *Journal of Clinical Investigation*, 63, 239–246.

Meadows, D. H. (1972). *Limits to growth*. New York, NY: University Books.

ISBN 0-87663-165-0.

Must, A., Dallal, G. E., & Dietz, W.H. (1991). Reference data for obesity: 85th and 95th percentiles of body mass index (wt/ht2) and triceps skinfold thickness. *American Journal of Clinical Nutrition*, 53, 839–846.

O'Dea, J. & Abraham, S. (1995). Should body-mass index be used in young adolescents? *Lancet*, 345, 657.

Ogata, K. (2004). *System dynamics* (4th ed.). London: Pearson Education Ltd.

Parsons, T. J., Power, C., Logan, S. & Summerbell, C. D. (1999). Childhood predictors of adult obesity. *International Journal of Obesity*, 23, 1–107.

Power, C., Lake, J. K. & Cole, T. J. (1997). Measurement and long-term health risks of child and adolescent fatness. *International Journal of Obesity*, 21, 507–526.

Prudhon, C., Briend, A., Laurier, D., Golden, M. H. N., & Mary J.Y. (1995). Comparison of weight- and height-based indices for assessing the risk of death in severely malnourished children. *American Journal of Epidemiology*, 116, 116–123.

Richardson, G. P. (1991). *Feedback thought in social science and systems theory*. Philadelphia, PA: University of Pennsylvania Press.

Saltzman, E., & Roberts, S. B. (1995). The role of energy expenditure in energy regulation: Findings from a decade of research. *Nutrition Reviews.* 53, 209–220.

Sterman, J. D. (2000). *Business dynamics: Systems thinking and modeling for a* *complex world*. Boston: Irwin McGraw-Hill.

Tarik, H., & Dietrich, S. C. (2009). Agent-based computer simulations of language choice dynamics. *Annuals of the New York Academy of Sciences*, 1167, 221-229.

Troiano, R. P., & Flegal, K. M. (1998). Overweight children and adolescents: Description, epidemiology, and demographics. *Pediatrics,* 101, 497–504.

Waldrop, M. M. (1992). *Complexity: The emerging science at the edge of order and chaos*. New York: Simon & Schuster.

Whitaker, R. C., Pepe, M. S., Wright, J. A., Seidel, K. D., & Dietz, W. H. (1998). Early adiposity rebound and the risk of adult obesity. *Pediatrics*,101(3).