

Simulating health behavior

A guide to solving complex health system problems with agent-based simulation modeling

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It is clear from everyday observation that the behavior of sellers of medical care is different from that of businessmen in general.

Kenneth Arrow, 1963¹

In some one of its numerous forms, the problem of the unanticipated consequences of purposive action has been treated by virtually every substantial contributor to the long history of social thought. The diversity of context and variety of terms by which this problem has been known, however, have tended to obscure the definite continuity in its consideration. In fact, this diversity of context—ranging from theology to technology—has been so pronounced that not only has the substantial identity of the problem been overlooked, but no systematic, scientific analysis of it has as yet been effected. The failure to subject this problem to such thorough-going investigation has perhaps been due in part to its having been linked historically with transcendental and ethical considerations. Obviously, the ready solution provided by ascribing un contemplated consequences of action to the inscrutable will of God or Providence or Fate precludes, in the mind of the believer, any need for scientific analysis. Whatever the actual reasons, the fact remains that though the process has been widely recognized and its importance equally appreciated, it still awaits a systematic treatment.

Robert Merton, 1936²

Overall, it seems that agents in the health-care market adopt different decision-making procedures and modes of behavior, depending on the circumstances. I think that health economists have done far too little in trying to understand how exactly the agents' decision-making procedure is determined in the different situations and how it can be affected. This is precisely where ideas from behavioral economics might be most helpful.

Jacob Glazer, 2007³

¹ From Arrow (1963), page 949. Kenneth Arrow is the youngest person to receive the Nobel Prize in Economics. This quote is from the paper that gave rise to the field of health economics.

² From Merton (1936), page 894. Robert Merton was a distinguished sociologist who developed the concept “unanticipated consequences” (as well as the terms “role model” and “self-fulfilling prophecy”). Health systems are replete with unanticipated consequences that await a systematic treatment.

³ From Jacob Glazer’s comments about Richard Frank’s chapter titled “Behavioral economics and health economics” in P. A. Diamond & Vartiainen (2007), page 222. Jacob Glazer is a prominent health economist with joint appointments at Boston University and Tel Aviv University. In this work, we will explore how results from behavioral economics can help us better understand the behavior of health system agents.

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 - **John Stark**
 - **Steel Stewart**
 - **Steve Siegel**, SOA Research Actuary
 - **Barbara Scott**, SOA Research Administrator

It is hard to imagine a more helpful oversight group. During each stage of the project, each member actively participated, probing successive report drafts, offering insightful critiques, sharing rich experiences to help clarify my thinking, introducing me to helpful colleagues, and encouraging me to innovate. Members reviewed more than eight hundred pages of project material and examined simulation models with tens of thousands of lines of computer code. Not only did members participate in the project's conference calls, they communicated with me separately—often at length—by phone and email. Such stimulating company was glorious fun.

Steve Siegel expertly navigated the project and the oversight group past each potential obstacle, and was always ready with enthusiasm and gentle suggestions that inspired group members to shine. And **Barbara Scott** cheerfully handled a thousand details in ways that seemed effortless.

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- **David Gochman** graciously shared his extensive knowledge and experience about health behavior research. It was during a conversation in his beautiful home that it dawned on me how urgent and important it is to fill the gaps in health behavior research.
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- **Qiang Hou** carefully reviewed the project’s sample models (described in Chapter sixteen) to make sure they work properly and are useful examples for students of agent-based modeling. He also suggested many innovations to improve the models.
- **Lisa Canar**, my wife, read every word of the project’s reports—many times—and each time offered helpful suggestions. During the long periods of my absence while I worked on the project, she and our children, **Calun** and **Ariana**, stayed consistently and patiently supportive. But when Ariana, my six year old daughter, saw the finished product, she pinned me with a quizzical look, shook her head, and said, “Why didn’t you draw more pictures? It would have taken a lot less time.”

To you all, my heartfelt thanks.

PREFACE

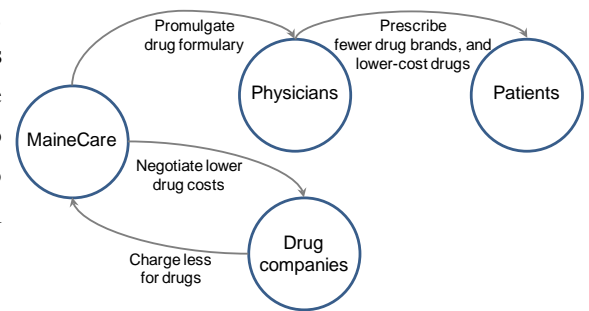
There are few institutional arrangements, i.e., departments or programs, that attract numbers of health behavior researchers. Most health behavior researchers work in relative isolation from one another and do not have the opportunity for the face-to-face interaction that generates conceptual breadth and enhances methodological strengths. Health behavior often “falls between the cracks”, institutionally and organizationally.

David Gochman, 1997¹

A. MAINECARE’S STORY


In 2001, the advisory committee members of MaineCare, Maine’s Medicaid program, came up with a plan to solve a great problem.

The problem was that MaineCare was spending too much on drugs, and was bleeding the state’s budget. The committee’s plan was simple. They would implement a “formulary”, a list of cost-effective prescription drugs from which the state’s physicians would have to choose. In special circumstances, the state would allow a physician to prescribe a drug “off formulary”, but this would require a special request and the state’s explicit approval, or “pre-authorization”.



The conceptual model underlying the plan was also simple.² It went something like this (see the figure at right): MaineCare’s drug costs are too high because (a) physicians prescribe too many high-cost drugs, and (b) physicians prescribe too many drug brands, making it impossible for the program to negotiate volume-based discounts. The formulary would fix these problems, because the physicians would prescribe lower-cost drugs (such as generic drugs) and fewer drug brands (those on the formulary), thus allowing the state to negotiate discounts for the resulting higher volume of allowed drugs.

But their plan didn’t work. In 2005, MaineCare reviewed the plan’s results, and found that, apparently, it had dramatically *increased* total program costs. Rather than its authors’ intended outcome, it appeared that the formulary plan had produced the opposite. For certain, the plan did not produce what MaineCare intended.³



Pause to reflect

Take a moment to return to 2001. If you were on MaineCare’s advisory committee, would you vote for the formulary plan?

Does the conceptual model underlying the plan make sense to you? Why?

¹ Gochman (1997), Volume IV page 410. For more about Dr. Gochman, see page 4.

² I developed this conceptual model based on MaineCare reports about its formulary plan. It appears that explicit computer models were not developed to help solve the problem.

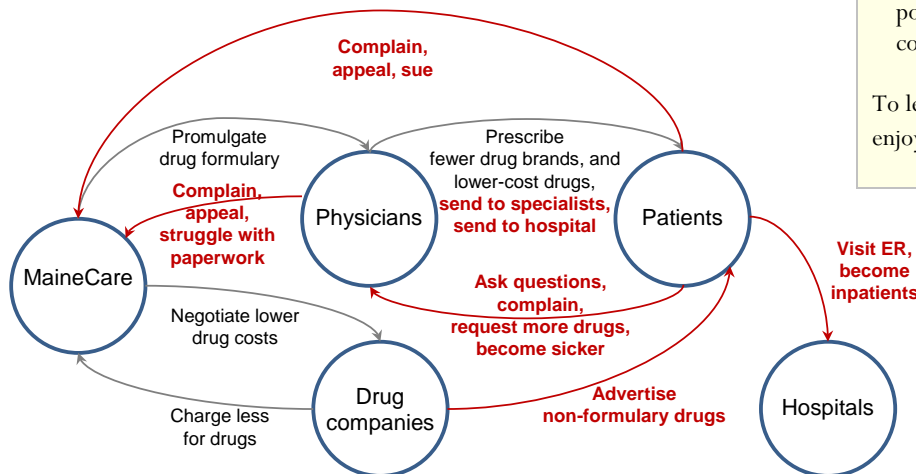
³ MaineCare (2005)

A. MAINECARE’S STORY continued

MaineCare is not alone. Researchers have shown that many formulary strategies, both those of other states and of health insurance companies, can produce unintended outcomes.²

Why? Where is the flaw in MaineCare’s conceptual model? The conceptual model underlying their plan was overly simple. It was like the conceptual model of a mechanic fixing a car: find the defective part (physicians out of control) and fix it (restrain them with a formulary). It failed to recognize that Maine’s health system is not a car; rather, its parts are alive with interrelated complex behavior. It is a complex system (see the sidebar).

In a more realistic model, such as the one shown below, agent behaviors are more complex.³ Drug companies advertise non-formulary drugs and increase patient demand. Patients complain, appeal authorization decisions, and sue, thus increasing administrative expenses. Physicians send patients to specialists and hospitals (where the formulary doesn’t apply) thereby increasing medical expenditures. As they wait for authorization decisions, patients forgo needed drugs and become sicker, thus increasing medical expenditures. In the end, these extra expenditures overwhelm the savings.



Complex systems

Complex systems are the subject of the new field called “complexity science”. Although complex systems can look very different—as different as ant colonies, forest ecologies, health systems, and the global economic system—they have many characteristics in common. For example:

- Their agents (their parts) are adaptive and self-organizing. The agents strive to maintain homeostasis, and resist change. Their behavior is far more nuanced and sophisticated than the behavior of car parts. Just think how challenging it would be to drive a car made of adaptive agents, like a gas pedal that proactively tries to thwart your efforts to push it down.
- Because of the intricate nature of a complex system—with many heterogeneous agents and their interrelated adaptive behaviors—its aggregate behavior is often unexpected and counter-intuitive. Just think of the unexpected turns our global economic system has taken.
- Trying to identify a single cause of a complex system problem is usually futile. The “cause” is often the system itself. Thus, targeted one-time solutions are usually ineffective. This point is one of the central themes of complexity science.

To learn more about complex systems, you might enjoy my introduction to complexity science.¹

¹ “Complexity science—an introduction (and invitation) for actuaries”, found at: “www.soa.org/research/research-projects/health/research-complexity-science.aspx”.

² For examples, see Horn (1996), Horn et al. (1996), Levy & Cocks (1999), Moore & Newman (1993), and L. Schofield (2004).

³ In this report the word “agent” refers to entities within a health system that make decisions and act, such as patients, physicians, hospitals, and health insurance companies. The word does not specifically refer to “health insurance agents”, those people, also called “brokers”, who market and sell health insurance policies.

B. UNINTENDED CONSEQUENCES

It is not only formulary strategies that produce unintended consequences.^A (End notes are referenced with a capitalized alphabetical superscript.) In all areas of health care worldwide, such perverse effects abound, as do other healthcare problems and puzzles that dumbfound us:

- Blood donors stop giving blood when they are offered a reward.
- Millions of uninsured people decline free health insurance.
- People have easy access to information about the quality of healthcare providers, but ignore it.
- Although patients know that physicians often make mistakes, they rely on the advice of only one doctor.
- Physicians across the street from one another commonly have wildly different practice patterns.
- Physicians commonly fail to prescribe treatments that are widely known to improve health outcomes.
- Major shifts in medical inflation and healthcare utilization come as complete surprises.

The fascination of complex health systems

As a family practice physician and health actuary, I am fascinated by the world’s health systems, those kaleidoscopic arrays of people and organizations that try to keep us healthy, but that often thwart our best efforts to improve their effectiveness.

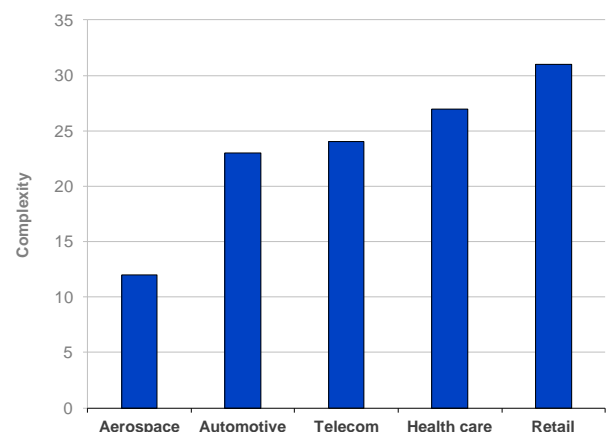
Equally fascinating, at least to me, is a new way of looking at such complex systems, called “complexity science”. In these pages I invite you to join me in using complexity science and its main tool, agent-based simulation modeling, to explore health systems and their problems from a fresh perspective.

C. ONE REASON

Health system problems we cannot solve often boil down to health behaviors we do not understand (see the sidebar). For example, the MaineCare committee launched an ill-fated formulary plan because it did not understand how people and organizations would react to it.

That we do not understand health behavior is hardly surprising. With its millions of doctors, nurses, and other health specialists; thousands of hospitals and other medical care establishments; and hundreds of health insurance companies, each with its peculiar behavior interweaving among the others, our worldwide health system is daunting in complexity.¹

The chart compares the complexity of five US service-oriented complex social systems.² Only the highly fragmented US retail system—moving millions of products through an intricate global supply network to land seductively on shelves—outtranks the US health system in complexity. Walmart beats hospitals, just barely.



¹ World Health Organization (2006) page 4; “hospitals.webometrics.info”; and CEA (2008) page 32.

² See Basole & Rouse (2008) page 64, and Rouse (2008) page 21.

D. THE EASY WAY OUT

In the face of such immense behavioral complexity, no wonder we feel inadequate to model health care at the individual behavioral level. What surprises me, though, is that (with a notable exception—see the sidebar) researchers have not even tried to make sense of it.

Rather than work hard to understand and model how individual health behaviors produce systemic outcomes, researchers have taken the easy way out. They borrowed the top-down statistical mechanics approach that physicists developed to model the random behavior of millions of atoms, and, in econometric, micro-simulation, and epidemiological models, have applied it to the behavior of people. But, where human behavior is involved, such models don't work. Policymakers don't understand them—largely because they don't ring true—and they are usually wrong. This top-down pseudo-physics approach fails because people do not behave like car parts or atoms.

After decades mimicking physicists, we have made little progress in health behavior modeling. Far from understanding health behavior deeply; we do not yet even understand it superficially: We have not yet cataloged the types of health behavior, or even developed a health behavior classification system. We have not organized the research about health behavior facts. We have not sifted through health behavior hypotheses to find those most appropriate for computer modeling. And we have not started developing robust health behavior models of individual people and organizations that are necessary to model health systems from the bottom up.

To be fair, I should point out that it is only recently, with the flowering of complexity science, that we have fully grasped the need for a bottom-up approach. And it is only recently that computer hardware, software, and software development processes have enabled us to pursue such an approach. But the stars are now aligned.

It is time to change our approach from top-down physics to bottom-up complexity science. As healthcare costs escalate beyond control, and as we become the first generation in history that may live longer than our children, it is time to develop realistic models of health behavior that help us solve our health system problems. And it is time to muster the resolve to use them.

David Gochman

Even from outside his Louisville home there are hints that David Gochman is unique. The subtle artistic details set it apart. For example, the hand railings leading to the front door are intricate braids of burnished gold metal, specially wrought by a local sculptor.

The effect is stunning, as is the four-volume work he compiled in 1997, titled "Handbook of health behavior research".¹

The Handbook is unique. In it, Dr. Gochman, a professor of social work at the University of Louisville, presents a broad selection of health behavior findings and theories. To organize the research, he also sketches a taxonomy of health behavior.

He makes it clear that health behavior research is a new field: "Health behavior is not a long-established, traditional area of inquiry, comparable to chemistry or psychology, but a newly emerging interdisciplinary and multidisciplinary one. Health behavior is still establishing its identity as a domain of scientific research. ... There are still relatively few institutional or organizational structures, i.e., departments and programs, that reflect the field, and few books and no journals are directed at it."

Gochman hoped that his remarkable work would provide a spark to coalesce researchers around a new science of health behavior.

I asked Dr. Gochman why researchers have not yet taken up his call to establish a science of health behavior. Now 75 years old with smiling eyes, he replied quietly, "It's not too late to start."

¹ Volumes of Gochman (1997) can be found in most university libraries.

E. THIS REPORT

In this report, we will explore how to develop agent-based simulation models of the many dimensions of health behavior, in order to help solve health system problems.

In particular, by studying this report you can learn how to:

- Think clearly about behavior in general, and health behavior in particular.
- Organize and classify healthcare agents and their behaviors.
- Make sense of the facts that we know about the health behaviors of individuals and organizations.
- Apply results from behavioral economics to better understand health behavior.
- Organize the wide variety of behavioral hypotheses, and apply them to health behavior modeling. In particular, you will learn the strengths and weaknesses of that foundation of traditional health economics, rational choice theory.
- Develop agent-based simulation models of health behavior that can help solve real-world health system problems.
- Fill gaps in our understanding of health behavior facts, theories, and tools.
- Better understand the paradigm of complexity science.
- Convince your boss or a funding source that agent-based simulation of health behavior is a valuable approach to solving health system problems.

Along the way we will encounter interesting supporting topics such as information theory, software engineering, and genetic algorithms. And you will get to know many of the people and organizations prominent in fields related to health behavior research.

F. THEMES

Interwoven throughout the report you will find five main themes:

1. **The need to better understand health behavior.** To solve the great health system problems around the world, our researchers and policymakers must better understand and explicitly model the behaviors of healthcare agents, from the bottom up.
2. **The need to close significant gaps in our health behavior knowledge.** Although the amount of health research is vast, researchers have barely scratched the surface of what we need to know about health behavior. There is no consensus about how we should describe any behavior, much less health behavior. Moreover, we do not have a classification system for health behavior, our stock of useful health behavior facts is meager, there is no easy way to find what is known about a particular health behavior, and there are no satisfactory health behavior theories. (See the sidebar.)
3. **Complexity science as an appropriate paradigm.** Complexity science is a good paradigm to guide the work of health behavior practitioners. Complexity science helps us think clearly about important aspects of complex health systems, such as agent heterogeneity, causality, hierarchy, robustness, management of complexity, and the importance of modeling from the bottom up.
4. **Computer modeling as an essential, but ill-supported, skill.** To develop agent-based simulation models, one must know how to program a computer. Effective computer modeling, following best-practice guidelines, is an essential skill for health behavior practitioners. However, complete best-practice guidelines for simulating health behavior do not yet exist. Neither does a complete method for developing agent-based models for simulating health behavior. Further, even though we now have the computer hardware and software to perform sophisticated agent-based health system simulations, we do not yet have adequate health behavior facts and theories such simulations will require.
5. **The need to establish a new group devoted to health behavior.** Currently there is no organized academic field, scientific discipline or profession that focuses either on researching health behavior or on solving health system problems by modeling the many dimensions of health behavior from the bottom up. Because the current fields related to health behavior—such as health economics, health psychology, and public health—are fragmented and entrenched in traditional approaches, there is a need to establish a new group devoted to health behavior.

Seven gaps

The report identifies seven important gaps. In Chapter seventeen (Seven health behavior gaps) is a summary of the gaps, and in Chapter eighteen (Eight health behavior challenges) I propose a way to fill the gaps. The gaps are:

1. **No accepted description of health behavior.** We will explore this gap in Chapter one (Dimensions of behavior).
2. **No classification of health behavior.** We will explore this gap throughout Part II (Classification of agents and behavior).
3. **No catalog of health behavior facts.** Chapter seven (Overview of health behavior facts) addresses this gap.
4. **Inadequate health behavior facts.** We will explore this gap in Part III (Health behavior facts).
5. **No health behavior theory.** Chapter ten (Overview of health behavior theories) addresses this gap.
6. **No complete modeling method or standards for simulating health behavior.** We will explore these gaps in Chapters thirteen (Agent-based modeling method) and fourteen (Simulation modeling guidelines).
7. **Inadequate use of agent-based simulation modeling for informing health system decisions.** Chapters two (Health behavior fields) and seven (Overview of health behavior facts) address this gap.

G. ORGANIZATION

This work is organized in six parts:

- **Part I – Health behavior:** Describes what health behavior is, and gives an overview of the major fields related to health behavior.
- **Part II – Classification of agents and behaviors:** Proposes a classification system for healthcare agents and their behaviors. A detailed catalog of health behavior, based on the proposed classification system, is found in the accompanying *International compendium of health behavior*.
- **Part III – Health behavior facts:** Provides an overview of the facts we know about health behavior, based on the *International compendium of healthcare behavior* and its main results. A separate chapter discusses results from behavioral economics, and provides a mapping of these results to health behaviors.
- **Part IV – Health behavior theory:** Provides an overview of health behavior theories, and a detailed discussion of five health behavior hypotheses that are particularly important.
- **Part V – Methods and tools:** Gives an overview of the hardware, software, and processes available for modeling health behavior. In this part, I provide an overview of three sample agent-based simulation models that accompany this work. I also propose seven good practice guidelines for developing simulation models.
- **Part VI – Filling the gaps:** Identifies gaps in the facts, theories, and tools that we need to fill in order to successfully model health behavior, and proposes a way to fill them.

Each chapter ends with exercises and solutions to help you better understand its material.

I have tried to make the text easy for you to read. I put important citations and explanatory material in footnotes, but more detailed supplemental material in the end notes. Footnotes are referenced with a numerical superscript (¹) and end notes with a capitalized alphabetical superscript (^A).

Reference citations are found at the end of the report. There you will also find a glossary of technical terms. When a technical term is first introduced, it is bold and in quotation marks, like “**new term**”.



Pause to reflect

To further help you learn the material, throughout the text are short notes like this.

They provide questions to help you absorb the material. When you find these, be sure to pause and ponder the questions.

H. TO LEARN MORE

To learn more about complex systems and complexity science, read my report titled “Complexity science—an introduction (and invitation) for actuaries”.¹ Although the report was written with actuaries in mind, it is useful for anyone who wants to learn more about the subject. In particular, it refers you to essential references about complexity science.

I. REVIEW AND A LOOK AHEAD

In this Preface, I introduced the idea that if we are going to develop better solutions to our healthcare problems, we need to understand health behavior more fully, and to model it from the bottom up.

In the next chapter we will explore in more detail what “health behavior” means. We will then take a look at the current fields related to health behavior, and see what they are missing.

I hope you enjoy working with this material, and find it interesting. But more, I hope you will use it to develop new models of health behavior that will help solve our health system problems. I hope you will also have fun.

Alan Mills
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May 27, 2013

¹ Found at: “www.soa.org/research/research-projects/health/research-complexity-science.aspx”

EXERCISES

At the end of each chapter of the report, you will find exercises such as these to help you better absorb the chapter's material.

1. In his work on the kinetic theory of gases, James Clerk Maxwell introduced statistical analysis into physics. He showed that for models of large numbers of virtually identical objects, it is simpler and most effective to deal with their average characteristics (such as average motion) and extent of deviation, rather than with their individual details. This top-down approach also works well in modeling some areas of social science, such as demography and life insurance. Why might it not be an appropriate approach for modeling health behavior?
2. Think of an important health system problem that we have been unable to solve. Show how the source of our inability to find a solution is our lack of understanding of health behavior. Can you think of a counter-example (that is, an unsolved problem for which we understand the relevant behaviors)?
3. The chart in Section C (One reason) compares the complexity of the retail sector to the complexity of the healthcare sector. What is not shown in the chart (but is in the referenced paper) is that the consumer complexity for retail is *less* than the consumer complexity for health care. In other words, even though retail is more complex than health care, to consumers it seems simpler. Given this, what do you think the healthcare sector might learn from retail?

SOLUTIONS

Following are potential solutions to the exercises. You may find better ones.

1. In contrast to demography and life insurance where largely uniform physical factors such as aging are most important, in health behavior individual cognitive factors are central. Physical factors lend themselves to traditional statistical analysis, but cognitive factors—with their highly individual and adaptive characteristics—do not. Even for certain aspects of demography, such as birth rates, cognitive behavior is important. For example, traditional demographers were unable to predict or explain the downturn in Japan's birth rates.
2. I cannot think of a counter-example.

SOLUTIONS continued

3. The retail sector employs new technology and automated processes to simplify the consumer experience (think of bar codes, retail websites, and Amazon.com), while the healthcare consumer experience is still mired in old administrative technology and processes (think of the paperwork involved). If one considers the health sector's emphasis on new treatment technology, this is ironic. How would you describe the goals that drive health system agents to invest in treatment technology, but not in administrative technology?

PART I: HEALTH BEHAVIOR

Psychology, although describing itself as “the science of behavior”, has not to date arrived at any consensus in the matter of what the concept of “behavior” means.

Raymond Bergner, 2011¹

Sometimes it is better just to make a fresh start.

Peter Ossorio, 1978²

¹ Bergner (2011), page 147. Dr. Bergner is a professor of psychology at Illinois State University.

² Ossorio (1971), page 1. This sentence begins Peter Ossorio’s groundbreaking work about the dimension of behavior. To learn more about Peter Ossorio, see page 15.

INTRODUCTION

This part orients you to the concept of behavior, and provides background material about the current fields related to healthcare behavior. It consists of two chapters:

- **Dimensions of behavior:** Presents an effective way to describe the dimensions of health behavior.
- **Health behavior fields:** Provides an overview of the fields that have contributed to our understanding of health behavior.

In this part, I present two big ideas, both of which are about making a fresh start. The first idea is that, because the behavioral sciences have not yet developed a satisfactory definition of behavior, we need to take another approach, one that is at once more scientific and more conducive to agent-based simulation modeling. This idea is developed in the first chapter.

The second idea is developed in the second chapter. It is that, because the existing health behavior fields do not adequately address all the dimensions of health behavior, we should start afresh and develop a new field focused on health behavior, with a new guiding paradigm (complexity science) and new tools (including agent-based simulation modeling).



Pause to reflect

Before turning to the first chapter, develop your own definition of behavior. Do not consult Google or a dictionary. Just come up with your definition.

Soon, you will be able to compare your definition to definitions from experts.

CHAPTER ONE: DIMENSIONS OF BEHAVIOR

In science, precise definitions are important. As a new discipline develops, it is healthy for relevant definitions to evolve as understanding progresses. But available definitions of behaviour are generally both contradictory and imprecise.

Daniel Levitis et al, 2009¹

A. DEFINITIONS

Because I will often use the terms “health system”, “health system problem”, “agent”, “health” and “health behavior”, let’s start by being clear about their meaning.

- A “**health system**” is the set of agents that affect the health of a specific group of people, together with their relevant behaviors.^B The group of people might be the population of a country, a state, a city, a kindergarten, or the world.
- An “**agent**” is a self-directed and adaptive entity. It is able to make decisions and take actions on its own to attain a goal, and can change its behavior to fit in with a new environment. Agents are a system’s actors. A nurse is a health system agent, as is a hospital. An agent can include other agents, just as a hospital includes physicians and nurses. The sidebar lists common health system agents.^C
- “**Health**” is a person’s robustness, the ability of the person’s body and mind to operate effectively within a usually wide (but always limited) range of conditions, but to fail outside that range.^D The range of conditions varies from person to person, and depends on factors such as the person’s age and disease state.
- A “**health system problem**” arises when a health system agent, or a group of agents, cannot achieve one of their goals. As examples, a health system problem arises when a group of people cannot achieve its preferred state of health, a group of physicians cannot attain its desired level of income, a state government cannot obtain adequate health insurance coverage for its people, or maintain sustainable levels of healthcare expenditures. Because some goals may always be at odds with others, health system problems may never end.

I will devote the rest of the chapter to describe “**health behavior**”.

Health system agents

Commonly, a health system includes the following agents:

- **Consumers:** Individuals and families
- **Medical professionals:** Physicians and other medical professionals
- **Provider organizations:** Hospital systems, medical groups, provider associations, etc.
- **Supply organizations:** Medical supply companies, pharmaceutical companies, etc.
- **Educational and research organizations:** Medical schools, research institutes, foundations, etc.
- **Private financing organizations:** Health insurance companies, brokers, employers, employer associations, unions, etc.
- **Governmental organizations:** Federal Health and Human Services, state insurance departments, state health agencies, courts, legislatures, etc.

A health system can also include agents not commonly associated with health, such as genetic engineers and McDonald’s marketers.

In Part II, we will explore health system agents in more detail.



Pause to reflect

The definition of “health system” is broad. Can you think of any agent that is not part of one of the world’s health systems?

¹ See Levitis, Lidicker, & Freund (2009), page 103.

B. EXPERT DEFINITIONS OF BEHAVIOR

“What is behavior, exactly?”

While a teaching assistant for an animal behavior course at Berkeley, Daniel Levitis asked his professor this question. The professor referred him to a textbook, which he consulted. But what he found there did not satisfy him. So, with the help of colleagues, he looked further. In dozens of behavioral textbooks and dictionaries, and hundreds of articles, they searched for one good definition of behavior. They found 25 distinct definitions, but none that is satisfactory (see the sidebar).

Unsatisfied, they surveyed 174 members of behavior-focused scientific societies about their understanding of the term.² Their survey had two parts:

- The first presented 13 statements about potentially essential features of behavior, such as “Behaviors are always the actions of individuals, not groups.”
- The second provided 20 examples of natural phenomena, such as “Flocks of geese fly in V formations”. The purpose of the second part was to check the internal consistency of each scientist’s thinking about behavior. For example, a person who thinks that both the sample statements above are characteristic of behavior would exhibit internally inconsistent thinking.

The researchers found an astounding lack of agreement among the scientists, and much internal inconsistency. There was no consensus about any of 33 items on the survey, including “A spider builds a web” (which the researchers thought was an obvious example of behavior). And more than half of the scientists contradicted themselves, some multiple times.

Most agreed that a spider spinning a web, a person making plans, algae swimming toward food, and geese flying in V formations are behavior, but that a rabbit growing fur and a mouse floating in space are not.

But for our purpose of modeling health behavior, such vague descriptions are useless.

Behavior defined

Here is a sample of the definitions that Daniel Levitis and his colleagues found:

- The total movements made by the intact animal.
- Externally visible activity of an animal, in which a coordinated pattern of sensory, motor and associated neural activity responds to changing external or internal conditions.
- A response to external and internal stimuli, following integration of sensory, neural, endocrine, and effector components. Behavior has a genetic basis, hence is subject to natural selection, and it commonly can be modified through experience.
- Observable activity of an organism; anything an organism does that involves action and/or response to stimulation.
- Behavior can be defined as the way an organism responds to stimulation.
- What an animal or plant does.
- All observable or otherwise measurable muscular and secretory responses (or lack thereof in some cases) and related phenomena such as changes in blood flow and surface pigments in response to changes in an animal’s internal and external environment.

In 1953, the famous logician and thinker Ludwig Wittgenstein (who did much of his thinking while in World War I trenches) asked, “What is left over if I subtract the fact that my arm goes up from the fact that I raise my arm?” His answer was, “Almost everything!”¹ That is, the majority of behavior happens before we can witness the output.

But according to many of the definitions above, the answer to Wittgenstein’s question would be “Almost nothing!”

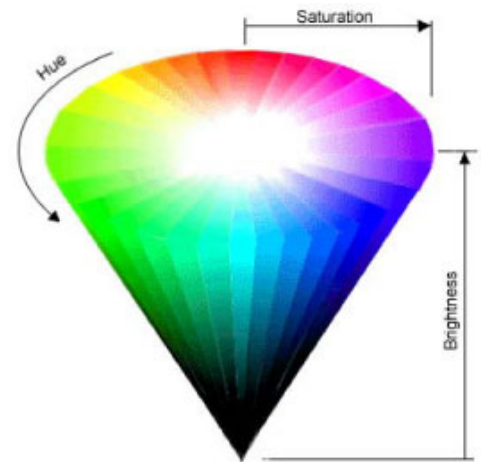
¹ Wittgenstein (1953), number 621.

² Levitis, et al. (2009)

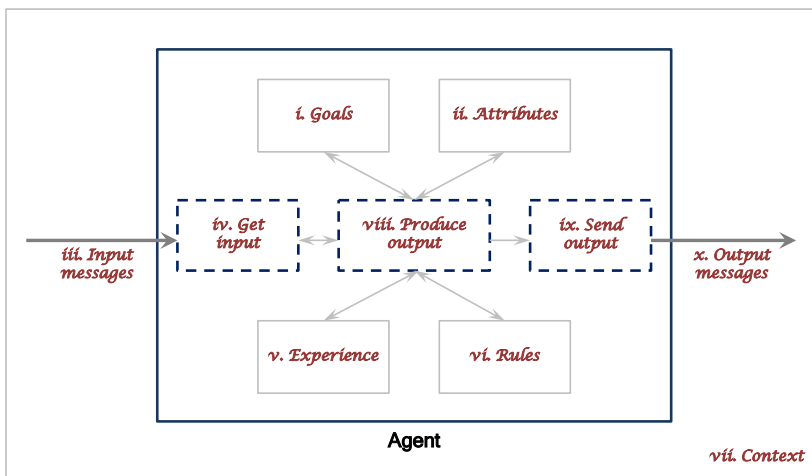
C. THE SPACE OF BEHAVIOR

We will take a different, more practical, approach to describe behavior.

Our approach is like the approach scientists take to describe color. Rather than rely on a formal definition of color, scientists describe it as the set of all combinations (also called vectors) of three parameters: hue, saturation, and brightness. Using this parametric method, one can precisely specify each color as a point in a three-dimensional space, and precisely describe how one color differs from another. We can even talk about (and measure) the “distance” between two colors.



Similarly, based on the work of Peter Ossorio (see the sidebar), we will describe behavior as a vector of the ten components shown in the following diagram:



Peter Ossorio

Recognizing the limitations of traditional approaches to behavior, Peter Ossorio started afresh. While a professor at the University of Colorado, he devoted more than twenty years to developing a new approach to understand behavior, and called it Descriptive Psychology.

In Descriptive Psychology, behavior is described as a vector of eight parameters, similar to the ten parameters we will use.^E (Remember: alphabetic superscripts refer to endnotes.)

Dr. Ossorio died in 2007, at the age of 80. The field of Descriptive Psychology has not yet been widely adopted.

- i. **Goals:** States of the world the agent wants to achieve. For example, goals for an individual person in a health system might be: “elimination of my hip pain”, “decrease the amount I pay for health insurance”, or “increase the number of miles I can run”. For an organization, goals might be “increase annual profit”, “perform administrative processes more effectively”, or “increase the number of insured people”. This component includes the concept of “intention”, which is commonly considered the highest-priority goal.
- ii. **Attributes:** Data uniquely identifying the agent producing the behavior. For example, attributes for an individual person might be some combination of the person’s name, address, age, gender, health status, relationships, etc.

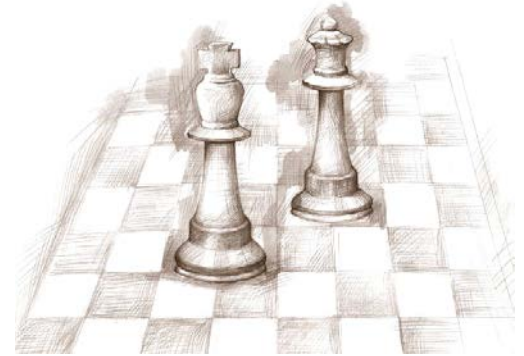
C. THE SPACE OF BEHAVIOR *continued*

- iii. ***Input messages***: Messages the agent receives that enable or induce the agent to produce the behavior. The agent may actively seek these messages, or may receive them passively. For example, in selecting a primary care physician (a health behavior) an individual may receive recommendations from friends and family. Similarly, in offering consumers a health insurance plan, a health insurance company may receive messages from a governmental agency that restrict the plan's provisions.
- iv. ***Get input***: The agent's process for receiving and interpreting input messages. For example, it is a well-known result from behavioral economics (called "reference dependence" or "framing") that people interpret input messages based on references and cues in the messages. You will learn more about this in Chapter eight (Behavioral economics).
- v. ***Experience***: The agent's memory and evaluation of its past experiences. This component also includes the agent's processes for storing and retrieving experiences from memory. For example, a person's recollection of a prior medical experience may color how the person interacts with healthcare providers. Included in this component are a person's emotions.
- vi. ***Rules***: The agent's store of rules that are used to produce output. One can think of these as the sub-processes of the "Produce output" behavior component. They include psychological concepts such as "attitudes", "habits", and "values", as well as heuristics ("rules of thumb") and formal algorithmic decision processes.
- vii. ***Context***: The environment in which the behavior is rooted, such as the place and time and culture.^F For example, an American deciding whether to purchase health insurance makes the decision in the context of the U.S. culture and economy, as well as the context of the person's workplace, friends, and family.
- viii. ***Produce output***: The agent's process to develop its "output messages". This process may draw on the agent's goals, attributes, get input processes, experience, and rules.
- ix. ***Send output***: The agent's process to send its output message.
- x. ***Output messages***: The messages associated with the behavior that the agent sends.

C. THE SPACE OF BEHAVIOR *continued*

For example, suppose Stella is playing chess in a tournament, and she moves her queen. This behavior might be described as:

- | | |
|------------------------------|---|
| <i>i. Goals:</i> | Stella wants to win the game |
| <i>ii. Attributes:</i> | Stella |
| <i>iii. Input messages:</i> | Stella's opponent moved |
| <i>iv. Get input:</i> | Stella realizes it is her move |
| <i>v. Experience:</i> | Stella remembers past chess games |
| <i>vi. Rules:</i> | Stella knows strategies for winning |
| <i>vii. Context:</i> | Move number x in the tournament |
| <i>viii. Produce output:</i> | Stella decides on a move |
| <i>ix. Send output:</i> | Stella moves the queen |
| <i>x. Output messages:</i> | The queen is on a new space |



This approach meets several basic criteria for a good description of behavior:

- It includes the behaviors covered by the definitions that Daniel Levitis found.
- It is meaningful (rather than self-referential or vacuous)
- It is unambiguous.
- It applies to all types of agents, including people, families, organizations, geese, and robots. (In our example, Stella could also be Deep Blue, IBM's chess-playing program.)
- It applies to all kinds of behavior, from simple to complex.

And it has additional virtues:

- Just as we can organize and classify color based on the hue, saturation, and brightness parameters, the parameters of behavior will help us organize and classify behaviors, behavior theories, behavior models, and even the fields of health behavior.
- It helps us to envision a 10-dimensional space, or landscape, of behavior and thus to think about useful concepts such as the distance between two behaviors, behavior clusters, behavior robustness, behavioral risk, efficient behaviors, and so on.
- Its output messages help us to think of the behavior results as "information", and thereby to consider information theory concepts such as "noisy" behavior, probability distributions of behavior, "entropy", the "value" of behavior, the speed of behavior generation, behavior "carrying capacity", and so on.



Pause to reflect

Does this method of describing behavior make sense to you?

Try a thought experiment: Using the chess example, assume that one of the parameters does not apply, and see if the description then makes sense. For example, suppose the "Get input" parameter doesn't apply. Then Stella would be moving her queen in a game of chess without knowing that it is her move. Because this doesn't make sense, the "Get input" parameter is necessary.

Do this for each parameter. To completely describe the behavior, is any one of them unnecessary?

D. DESCRIBING BEHAVIOR

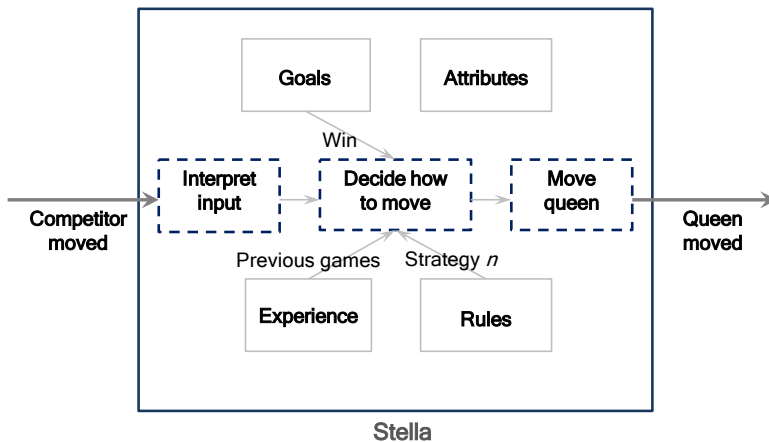
In this report, there are three ways I will describe behavior:

- **Vector description:** Our description of Stella’s chess behavior on the previous page uses a vector description, in which we specify each of the ten behavior components (which I will sometimes also call behavior parameters).
- **Freeform language:** For example, “Playing in a chess tournament and wanting to win, on the x th move Stella moved her queen.”
- **UML diagrams:** To design and document health behavior models, we will use diagrams based on the Unified Modeling Language (UML) (see the sidebar). Following is a simplified example of such a diagram for Stella’s chess behavior. In later chapters we will explore such diagrams in detail.

UML

The Unified Modeling Language (UML) is the world standard for specifying, visualizing, and documenting object-oriented computer software.

The standard is maintained by the Object Management Group (OMG) consortium, headquartered in Massachusetts. Its website is www.omg.org.



E. HEALTH BEHAVIOR

In this report we are concerned with health behavior. By “**health behavior**”, I mean any behavior of any health system agent. We will be most interested in health behaviors that are related to health system problems we want to explore.

For example, consider our MaineCare example from the Preface. The problem was how Maine could reduce its drug expenditures for the MaineCare program. For this problem, health behavior would include the relevant behaviors of primary care physicians, specialist physicians, hospitals, MaineCare participants, MaineCare management, state politicians, pharmaceutical companies, health insurance companies, and perhaps even the media and other agents.

E. HEALTH BEHAVIOR *continued*

To determine the relevant health behaviors for the MaineCare problem, one would sift through the universe of agents and their behaviors, and select those that could have a direct or indirect impact on the MaineCare program. In Part II, we will discuss a process to facilitate such sifting.

Dr. Gochman’s definition of health behavior is similarly broad (see the sidebar). The main difference between our definition and his is that we extend health behavior to the behavior of all agents within a health system, including organizations.

F. ISSUES AND FUTURE DIRECTIONS

As we have seen, among behavioral scientists there is no consensus about how we should describe behavior, much less about how we should model it. I also searched the artificial intelligence, simulation modeling, and other computer literature, to see if perhaps these experts have reached some agreement about how we should describe or model behavior, but found nothing useful. To make progress in modeling health behavior, it would be helpful for us to agree—at least provisionally—on a basic approach for describing behavior, perhaps like the parameterized approach that I propose. Such agreement could also help unite the fragmented fields related to health behavior (a topic we’ll cover in the next chapter).

G. TO LEARN MORE

To learn more about the behavior of agents in complex systems, take a look at my report titled “Complexity science—an introduction (and invitation) for actuaries”.²

To learn more about UML, visit the UML website, “www.omg.org”.

Another view of health behavior

Dr. Gochman defines health behavior as: “Those personal attributes such as beliefs, expectations, motives, values, perceptions, and other cognitive elements; personality characteristics, including affective and emotional states and traits; and overt behavior patterns, actions and habits that relate to health maintenance, to health restoration and to health improvement.”¹

He further notes, “ ‘Behavior’, moreover, denotes something that people do or refrain from doing, although not always consciously or voluntarily. It is not something done to them. A treatment is not a behavior. Furthermore, mending of broken bones, healing of wounds, immunity against disease, resistance to infections, and the like, are not behaviors. They are, rather, physiological functions. ... A person’s health status or health condition is not a behavior, but a person’s perceptions of health status or of its deterioration or improvement, or of recovery or nonrecovery from an illness or accident, or other changes in health status are health behaviors. Finally, the definition’s broad construction of behavior explicitly includes not only directly observable, overt actions, but also those mental events and feeling states that are ‘observed’ or measured indirectly. ... Health behavior is conceptually distinct from treatment and from physiological/biological/pharmacological responses to treatment. It is also conceptually distinct from health care and from the organization or structure of the health care delivery system.”

¹ Gochman (1997), Volume I page 3.

² Found at: “www.soa.org/research/research-projects/health/research-complexity-science.aspx”.

H. REVIEW AND A LOOK AHEAD

In this chapter, after reviewing the confusion among behavioral scientists about the concept of behavior, I presented a parameterized method to describe behavior. I then discussed the advantages of the method, and showed how to use it to specify any behavior, including health behavior. In the next chapter we will explore the various fields that have contributed to our understanding of health behavior.

(Don't forget to take a look at the exercises for this chapter. They start on the next page.)

EXERCISES

1. Which of the following is a “health system”, as we have defined the term: a doctor’s office, a hospital, or the healthcare provider network of a large health insurance company?
2. Which of the following is an “agent”, as we have defined it: an MRI machine, an insurance broker, or an H1N1 virus?
3. Is “health”, as we have defined it, the statistical average state of being of people in a specific population?
4. Is the profit of a health insurance company a “health system problem”, as we have defined the term?
5. What happens when you zero out one or more of the parameters in our approach to describing behavior? Is the result still a behavior?
6. In the following scenario, describe the doctor’s behavior with a vector: Susan, age 20 and a patient of Dr. Jameson, implores the doctor to send her to a heart specialist. Dr. Jameson, although he knows that it is unlikely that Susan has a heart problem, thinks of his cardiologist friend and of lawsuits, and writes a specialist referral for Susan.

SOLUTIONS

1. None is a health system. A larger set of agents affects the health of a specific group of people, including the people themselves, their family members, employers, etc. In addition, as we have defined it, a health system includes not only agents, but also their relevant behaviors.
2. Only the insurance broker is an agent. The MRI machine and the virus are not autonomous (although one might persuasively argue that the virus is).
3. No. Health is a person’s robustness. For more about this, see the endnotes.
4. Profit is a goal that the health insurance company wants to achieve. Excess profitability might be a problem.
5. For example, you might zero out everything except iii. Input messages, iv. Get input, vi. Rules, viii. Produce output, ix. Send output, and x. Output messages. This would then be classic stimulus/response behavior. However, zeroing out other combinations may not produce a realistic behavior.

SOLUTIONS continued

6.
 - i. Goals: Help friend, avoid lawsuit
 - ii. Attributes: Dr. Jameson
 - iii. Input messages: Susan's plea
 - iv. Get input: Interpret the plea as a potential threat
 - v. Experience: Past experiences of referral
 - vi. Rules: The process to write a referral
 - vii. Context: The culture that encourages making unnecessary referrals
 - viii. Produce output: Drawing from past behavior, and the memory of the behavior of his colleagues, decide to write a referral
 - ix. Send output: Write a referral
 - x. Output messages: A referral

CHAPTER TWO: HEALTH BEHAVIOR FIELDS

It is a peculiar feature of current health care research that far less money is invested in understanding health-related behavior than is aimed at, say, understanding the genetic basis of disease.

Daniel Callahan, 1999¹

A. MANY FIELDS, MANY GAPS

In trying to solve health system problems, no single academic field, scientific discipline, or profession takes into account all the dimensions of health behavior, or even a majority of them. Nor is there an organized group of academics, scientists, or professionals trying to solve such problems with agent-based simulation models of health behavior.

Even if we sew together all the fields, disciplines, and professions (all of which I'll simply call "fields") that consider some of the dimensions of health behavior, our quilt would not keep us warm on cold nights.

The major fields that focus on health system problems and health behavior are:²

- Epidemiology
- Health economics
- Health psychology
- Medical anthropology
- Medical geography
- Medical sociology

Most of our facts and hypotheses about health behavior come from practitioners in these fields. Therefore, if you know something about these fields, you will be able to better understand and assess health behavior facts and theories.

In particular, as you develop agent-based simulation models, you may need health behavior facts that are not yet included in the *International compendium of health behavior*. To find these facts it will help to know where to look. Section D (To learn more) of this chapter introduces you to reference materials about each of these fields.

¹ Callahan (1999)

² You may notice that the field of public health is absent from the list. It is absent because it is too general a category; most of the fields listed are part of public health.

B. OVERVIEW OF MAJOR FIELDS

In this section, I will sketch the main health system problems that each major field addresses, the agents its practitioners consider in their work, and the dimensions of health behavior they address. In providing these sketches, my purpose is to show you the origins of our facts and hypotheses about health behavior, and the perspectives from which they arise. From them, and the summary chart below, I hope you will see that none of these fields—or even all of them put together—provides full coverage of problem areas, agents, and dimensions of health behavior.

The chart lists the major fields, and shows the problem areas, agents, and health behavior dimensions that they address. The chart also notes whether they employ agent-based simulation modeling. As you see, there are marked differences among the fields, and no field covers everything. For example, the field that covers financial problems—health economics—has relatively light coverage of behavior dimensions, while fields that have greater coverage of behavior do not cover financial problems.

Health behavior fields	Problem areas			Agents							Health behavior dimensions										Agent-based simulation modeling				
	Disease status	Healthcare consumption	Financial status	General population/patients	Health practitioners	Hospitals	Physician groups	Health insurance companies	Drug companies	Employers	Governmental agencies	<i>i. Goals</i>	<i>ii. Attributes</i>	<i>iii. Input messages</i>	<i>iv. Get input</i>	<i>v. Experience</i>	<i>vi. Rules</i>	<i>vii. Context</i>	<i>viii. Produce output</i>	<i>ix. Send output</i>		<i>x. Output messages</i>			
1. Epidemiology																									
2. Health economics																									
3. Health psychology																									
4. Medical anthropology																									
5. Medical geography																									
6. Medical sociology																									

Though experts might quibble over the chart’s details, I hope it helps convince you that, even considered as a whole, the fields do not provide all the resources we need to address our many health system problems.

The following pages provide an overview of these fields.

B. OVERVIEW OF MAJOR FIELDS continued

1. Epidemiology

History

Although excellent epidemiological studies were conducted before the 20th century (such as John Snow's famous study of the London cholera outbreak of 1854), epidemiology as a field with a systemized body of principles arose during the 1940s. In 1949, the major epidemiological Framingham Heart Study commenced. Even more than 60 years after it was begun, this remarkable study continues to provide valuable findings about heart health. In 1954, the Salk vaccine study commenced; it was the largest formal human experiment ever conducted. In the ensuing years, there were landmark studies about the effects of smoking, the relationship between hormone replacement therapy and heart disease, and many others. Especially in the last 20 years there has been a surge of epidemiological studies helping to form public health policy.

Problem areas

Epidemiologists mainly study the distribution and determinants of disease. Thus, their primary focus is on the treatment of disease.

Agents

Epidemiologists focus on individuals within a population who fall ill. To a lesser extent, they study the roles of healthcare providers in the prevention and treatment of disease.

Behavior dimensions

Epidemiologists are primarily concerned with the "Attributes" (personal variables), "Input messages" (determinants of disease), and "Output messages" (disease) of health behavior.

Agent-based simulation modeling

Epidemiology is the only one of these six health-related fields that has begun to use agent-based models. Joshua Epstein of Johns Hopkins University has led the way (see the sidebar). In the wake of the September 11 attacks, he developed an agent-based model to help create the US smallpox outbreak strategy. He is now working on an agent-based model with 6.5 billion agents (the world's population) to study pandemics.³

Joshua Epstein

In 1996 while at the Brookings Institution, Joshua Epstein and Robert Axtell wrote one of the classics of agent-based simulation modeling, a little book titled "Growing artificial societies: social science from the bottom up".¹ In it they demonstrated that economic markets and disease transmission could be studied from the bottom up, using agents in what they called an "artificial society". They wrote, "We interpret the question, 'can you explain it?' as asking 'can you grow it?' In effect, we are proposing a generative program for the social sciences and see the artificial society as its principal scientific instrument."

It was this little book that convinced me that we could address the most intractable health system problems with agent-based simulation modeling.

In 2006, Dr. Epstein wrote another book, summarizing his agent-based modeling work, titled "Generative social science: studies in agent-based computational modeling".² In it he presents many models, including ones that address infectious pandemics, chronic pandemics (such as obesity, and teen smoking), adaptive organizations, and thoughtless conformance with social norms, all of which relate to health system problems.

Dr. Epstein is now at Johns Hopkins University, in charge of its Center for Advanced Modeling in the Social, Behavioral, and Health Sciences. He is working on large-scale agent-based models of pandemics and urban disaster (with millions and billions of agents).

In the last paragraph of "Growing artificial societies", he writes, "Just as the community of biologists had to learn to fully exploit the microscope when it was first invented, so we have only begun to explore the uses and limits of the artificial society as a scientific tool."

¹ Joshua M. Epstein & Axtell (1996)

² Joshua M. Epstein (2006)

³ J. M. Epstein (2009)

B. OVERVIEW OF MAJOR FIELDS continued

2. Health economics

History

In 1963 the Nobel Laureate Kenneth Arrow wrote an article that included a section summarizing the special characteristics of medical care. He introduced the section by writing, “This section will list selectively some characteristics of medical care which distinguish it from the usual commodity of economic textbooks. The list is not exhaustive, and it is not claimed that the characteristics listed are individually unique to this market. But, taken together, they do establish a special place for medical care in economic analysis.”¹ The list led to the establishment of health economics.

Problem areas

Health economists address health system problems related to financial matters, such as consumption, investing, and profit making. Even health is typically measured in currency such as dollars, euros, or yen.

Agents

Following the tradition in economics, health economists view a health system as a collection of markets of buyers and sellers in competitive equilibrium of supply and demand. The main markets they consider are **institutional services** (how consumers and healthcare provider organizations such as hospitals interact), **production factors** (how healthcare organizations and their suppliers and employees interact), **healthcare financing** (how private and public health insurance is provided to consumers), and **healthcare services** (how healthcare practitioners and patients interact). Thus, health economists consider nearly every major health system agent.

Behavior dimensions

Health economists are mainly interested in the financial inputs and outputs of agents, and they assume that an agent’s behavior rules are rational. However, as we know from behavioral economics (see Chapter eight) agent behavior is generally not rational. But this perspective has not yet found its way into health economics.

Agent-based simulation modeling

In their work, healthcare economists have not yet applied agent-based simulation models. They mainly use econometric (mathematical) or micro-simulation models.

¹ Arrow (1963), page 143.

B. OVERVIEW OF MAJOR FIELDS continued**3. Health psychology***History*

Health psychology was established as a separate field in 1979. As with health economics, its birth was spurred by an article. Written by the psychologist William Schofield, the article describes how psychological insights could be used to improve the delivery of health care.¹ “Behavioral medicine” and “medical psychology” are terms often used synonymously with health psychology.

Problem areas

Health psychologists are primarily interested in changing risky health behaviors (such as smoking, unprotected sexual activity, overeating, and under-exercising) and improving management of chronic diseases such as diabetes and hypertension.

Agents

Health psychologists deal with individuals, mainly those who have impaired health and are already patients within the health system. However some health psychologists also work with healthcare practitioners to help them communicate more effectively with patients.

Behavior dimensions

Health psychologists are concerned with more dimensions of behavior than are health economists. Besides the attributes, inputs, and outputs of health behavior, health psychologists are also interested in how people cognitively represent illness (the “Get input” dimension), how we process input to produce output (“Produce output”), how our experiences and memories affect our output (“Experience”), the variety of cognitive rules we use to develop output (“Rules”), and the impact of economic, cultural, and social environmental factors (“Context”).

Agent-based simulation modeling

Health psychologists do not use agent-based simulation modeling.

¹ W. Schofield (1969)

B. OVERVIEW OF MAJOR FIELDS continued**4. Medical anthropology***History*

An outgrowth of anthropology, the field of medical anthropology arose in the late 1950s, about the same time as health economics. William Caudill was the first to recognize the field, in a paper he wrote in 1953, titled “Applied anthropology in medicine”.¹ A closely related field is “ethnomedicine”.

Problem areas

Medical anthropologists study relationships between culture and disease. They study how physician practices change in different cultural settings, how cultural beliefs affect risky behavior and the use of medication, how culture affects patient care seeking, and the training of healers in different cultural settings. For example, a medical anthropologist might explore the cultural factors that contribute to a population’s risky sexual behavior leading to AIDS, and whether the ways that healthcare practitioners interact with people push them away from medical treatment or draw them closer.

Agents

Medical anthropologists are concerned mainly with the general population and healthcare practitioners.

Behavior dimensions

The field is mainly interested in how culture (“Context”) affects health behavior, how people absorb input messages (“Get input”), and how our beliefs (“Experience” + “Rules” + “Produce output”) affect our behavior.

Agent-based simulation modeling

Medical anthropologists do not use agent-based simulation modeling.

¹ Caudill (1953)

B. OVERVIEW OF MAJOR FIELDS continued**5. Medical geography***History*

Medical geography is the oldest of the health behavior fields. It has a venerable heritage, dating back at least 2,000 years. Up until the discovery of microbes, and the resulting germ theory of disease in the late 19th century, disease and health were thought to depend most strongly on place: the variations of air, water, rain, sun, soil, altitude, and vegetation where one lived and worked. The discovery of germs, the resulting hunt for the germs that cause disease, and the discovery of medicines that kill them diverted attention from medical geography for decades. Then, with most germ-derived illnesses conquered, the impact of geography on degenerative disease such as heart disease, stroke, and cancer once again came to prominence. The emergence of a systemic interest in medical geography can be dated from the first “Report of the Commission on Medical Geography of Health and Disease to the International Geographic Union” in 1952.

As the earth warms and climate patterns change, as we deplete the earth’s vegetation, as people crowd into cities, and as our ability to map and monitor each small patch of the earth’s surface increases, the importance of medical geography continues to grow.

Problem areas

Medical geographers study relationships between geography and population health. For example, they study the spatial distribution of healthcare services, the accessibility of health care, and the impact of geography on health and disease.

Agents

Medical geographers are concerned mainly with individual patients and healthcare practitioners.

Behavior dimensions

The field is mainly interested in how the geographic environment (“context”) affects health behavior.

Agent-based simulation modeling

Strange to say, even with the availability of petabytes of satellite geographic data and advanced geographic information systems (GIS), it appears that medical geographers do not yet employ agent-based simulation modeling.

B. OVERVIEW OF MAJOR FIELDS continued**6. Medical Sociology***History*

A branch of sociology, medical sociology began in the late 1950s. The field arose mainly as a result of government funding: After World War II, the US government provided extensive funding through the National Institutes of Health for joint sociological and medical research projects that had a practical orientation. Postwar government had come to understand that social factors, such as race, education, living conditions, and income level, are important for understanding and improving population health. Medical sociologists have been particularly critical of the medical establishment for not adequately appreciating the health impact of social differences.

Problem areas

Medical sociologists study the social relationships among population members, between patients and healthcare practitioners, and between patients and organizations, as well as the impact of the social factors on these relationships. They also study the training of healthcare practitioners, and the social organization of healthcare institutions.

Agents

Medical sociologists are concerned with individual patients and healthcare practitioners, as well as healthcare provider organizations such as hospitals and clinics.

Behavior dimensions

The field is mainly interested in relationships among agent characteristics (“Attributes”), environment, and culture (“Context”).

Agent-based simulation modeling

To study social networks, medical sociologists employ network analysis, an important complexity science method. But they do not use agent-based simulation modeling.

C. ISSUES AND FUTURE DIRECTIONS

Even if we were to assemble a team with prominent experts from each of the health behavior fields, it is unlikely that it would be able to address health system problems from the bottom up, using realistic agent behaviors in agent-based simulation models.

For example, suppose the team tried to tackle a financial problem like determining the potential financial impact of adverse selection on health insurance companies under US health reform. The health economists would not know how to model the behavior of individuals selecting health insurance under the new environment of health reform. And experts from the other fields would not have much to add; their areas of study don't include such financial behavior.

Equally important, team members would find it difficult to communicate, because they lack a common language, common theories, and common methods.

Agent-based modeling and the dimensions of health behavior described in Chapter one (Dimensions of behavior) would provide such a common language and method. But given the entrenched nature of academic disciplines, it is unlikely that many experts could be enticed to join such a team.

Perhaps, as Peter Ossorio suggested, it would be better to start afresh, and establish a new field of health behavior and agent-based simulation. Read more about this in Part VI (Filling the gaps).

D. TO LEARN MORE

To learn more about the health behavior fields, you might enjoy the following resources:

Epidemiology

- A good epidemiology textbook is Rothman (2012).
- Major epidemiology journals are the *American Journal of Epidemiology*, *Epidemiologic Reviews*, *Epidemiology*, the *International Journal of Epidemiology*, and the *Journal of Epidemiology and Community Health*.

D. TO LEARN MORE continued

Health economics

- A good health economics textbook is Feldstein (2012).
- For a refreshing perspective on the limitations of health economics, read Rice & Unruh (2009).
- The main health economics journals are *Health Economics*, and the *Journal of Health Economics*.
- Two additional excellent resources, both “handbooks”, are Culyer & Newhouse (2000), and Sherry Glied & Smith (2011).
- For an interesting “bibliometric” perspective on health economics and its history, see the paper Wagstaff & Culyer (2012).
- For an introduction to behavioral economics, see Altman (2012).

Health psychology

A good health psychology textbook is Marks (2010).

- The main health psychology journals are *Health Psychology*, the *Journal of Health Psychology*, the *British Journal of Health Psychology*, and *Applied Psychology: Health and Well-Being*.

Medical anthropology

- The standard textbook is McElroy & Townsend (2009).
- The main medical anthropology journals are *Medical Anthropology Quarterly*, and *Anthropology and Medicine*.

Medical geography

- A good textbook is Meade & Emch (2010). The book provides an especially interesting history of medical geography.

Medical sociology

- The standard textbook is Cockerham (2012). The book provides a thorough history of medical sociology.
- The main medical sociology journals are *Sociology of Health and Illness*, and the *Journal of Health and Social Behavior*.

Although now somewhat dated, there are excellent discussions of health psychology, medical anthropology, medical geography, and medical sociology in Gochman (1997), Volume IV pages 396-410.

E. REVIEW AND A LOOK AHEAD

In this chapter, I have argued that there is no academic field, scientific discipline, or profession that takes into account all the dimensions of health behavior, or even a majority of them. Further, I have suggested that we need to establish a new field of health behavior that uses agent-based simulation models to solve health system problems from the bottom up.

In Part II, we will look more closely at the variety of agents and behaviors in a health system, and develop a way to classify them.

(Don't forget to take a look at the exercises for this chapter. They start on the next page.)

EXERCISES

1. Choose one of the health behavior fields, and research it. Read about it on Wikipedia and take a look at its references given in Section D (To learn more). Then see if you agree with its description in this chapter, and its entries in the summary chart. If you come up with differences, do they change the chapter's major argument?
2. Suppose you were asked to establish a new health behavior field. How would you approach the task? Who would you ask to be part of the new field? How would you train them?

SOLUTIONS

1. The solution depends on your choice.
2. See Part VI (Filling the gaps).

PART II: CLASSIFICATION OF AGENTS AND BEHAVIOR

The art of ranking things in genera and species is of no small importance and very much assists our judgment as well as our memory. You know how much it matters in botany, not to mention animals and other substances, or again moral and notional entities as some call them. Order largely depends on it, and many good authors write in such a way that their whole account could be divided and subdivided according to a procedure related to genera and species. This helps one not merely to retain things, but also to find them. And those who have laid out all sorts of notions under certain headings or categories have done something very useful.

Gottfried Wilhelm von Leibniz, 1704¹

A fundamental element in the development of a scientific body of knowledge is the availability of a widely accepted and usable classification scheme.

Bill McKelvey, 1975²

A half century of health behavior research has generated a number of productive theoretical models, vast amounts of data unevenly and inequitably distributed across and among numerous populations, at least hundreds of supported and unsupported predictions, and a host of interventions and programs (too often unimpressive, unsuccessful, or both) directed at changing behavior. However, the findings of the past 50 years are inchoate and thus minimally useful to health professionals. ... Critical to any organizing framework is an encompassing taxonomic model.

David Gochman, 1997³

¹ Leibniz, a prominent mathematician, philosopher, and inventor—who, among many other accomplishments, developed the mathematical subject of infinitesimal calculus independently of Issac Newton—wrote this in “New essays on human understanding”, Leibniz, Remnant, & Bennett (1996).

² McKelvey (1975). Bill McKelvey is a professor of Strategic Organizing and Complexity Science at UCLA.

³ Gochman (1997), Volume IV, page 416.

INTRODUCTION

The lack of a classification scheme for health system agents and health behavior is a significant obstacle for effective health systems research and policymaking.

This part describes a new classification scheme—called a health systems ontology—for health system agents and behavior. It consists of four chapters:

- **Classification schemes:** This chapter introduces the concept of a classification scheme and its importance. It then explores four types of classification schemes and sketches an ontology scheme that I propose for health system agent roles and health behavior.
- **Classification of agents:** This chapter describes the agent role taxonomy and gives the rationale behind its structure and numbering system.
- **Classification of behavior:** This chapter describes how I developed a taxonomy for health system agent goals, and how it can be used to classify agent behavior.
- **Using the health system ontology:** This chapter describes the benefits of a health system ontology, and how it might be used.



Pause to reflect

Before you start to read the chapters of this part, pause a moment to consider how you would organize and classify the many health system agents and their behaviors.

Have you come across a classification scheme for health system agents or behaviors? What did it look like?

What other classification system do you know that might be a useful model for creating a classification system for health system agents and their behaviors?

CHAPTER THREE: CLASSIFICATION SCHEMES

... the organization of medical care cannot be understood with reference solely to medicine, the relationships between doctors and patients, or even all the various forces internal to the health care sector. The development of medical care, like other institutions, takes place within larger fields of power and social structure.

Paul Starr, 1982¹

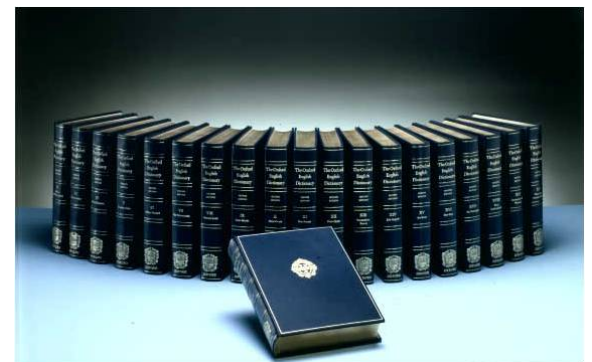
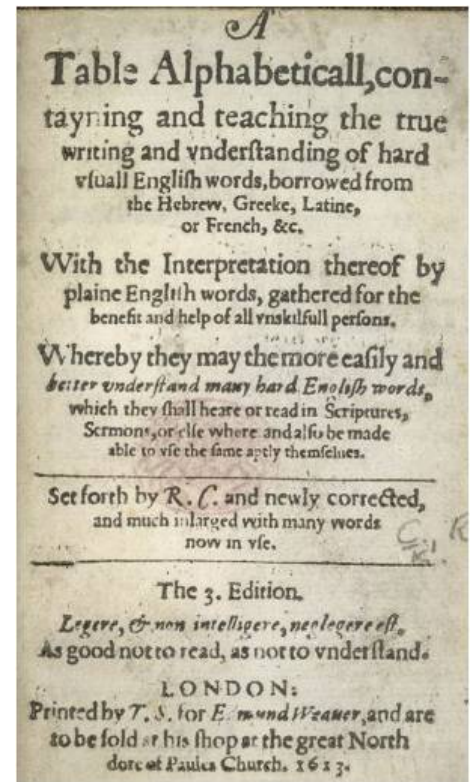
A. A TABLE ALPHABETICAL

Four hundred years ago, Robert Cawdrey, a village school teacher, prepared a visionary book with an imposing title that began, “A table alphabeticall contayning and teaching the true writing and understanding of hard usuall English words”. In its 120 pages, Cawdrey organized and standardized the spelling for about 2,500 words, and thus began the never-ending process to standardize our understanding, usage, and spelling of English words. He based his classification system on the alphabet.

When Cawdrey introduced this groundbreaking work, the understanding, usage, and spelling of words varied widely. For example, the word *cony* (rabbit) appeared as *conny*, *conye*, *conie*, *connie*, *coni*, *cuny*, *cunny*, and *cunnie* in a single 1591 pamphlet. Such fuzziness in words leads to fuzzy thinking, for we think with words.²

The premier English dictionary, the *Oxford English Dictionary* (OED), now has more than 22,000 pages, defines about 1 million words, and helps clarify the thinking of over 1 billion English-speaking people.

Just as standardized weights and measures have helped us make remarkable scientific progress, the flowering of Cawdrey’s classification system has helped us think and communicate more clearly about ever-more complex concepts and inter-relationships. We have progressed beyond our struggles with spelling “rabbit”.



¹ See “The social transformation of American medicine”, Starr (1982), page 8. This is an important book about the evolution of American health care. With it, Paul Starr won the Pulitzer Prize for general non-fiction literature in 1984.

² For a fascinating account of Cawdrey’s work and its meaning, see Gleick (2011), Chapter 3.

B. LACK OF A CLASSIFICATION SCHEME

But health systems researchers and policymakers still wrestle with the equivalent of spelling “rabbit”. Although there have been numerous attempts to organize and classify subsets of health system agents (such as healthcare practitioners), it appears that no one has yet classified all such agents using one classification scheme. It is as if we had separate classifications of the words from G to L, and the words from T to X, but no consistent classification of all the words from A to Z.

Nor, it appears, has anyone consistently classified the behaviors of health system agents. The number of attempts to classify even subsets of health behavior appears to be small, and the efforts sporadic.⁶ Such neglect is hardly surprising. As we saw in Part I, behavior is hard to define, much less classify.

The current immature state of the field of health behavior research and health system policymaking appears to stem, at least in part, from this underlying lack of a consistent classification scheme. Until we have a consistent way to name, understand, model, and discuss the agents and behaviors of health systems, researchers and policymakers will continue to be at the mercy of the unintended consequences that abound in health systems planning and policymaking.

C. PURPOSE

Just as Cawdrey took the tentative first step toward the OED, in this part, I propose a first step toward a classification scheme for health system agents and agent behavior. The classification scheme that I propose—a “health systems ontology”—has each of the desired attributes of an ideal classification system (see the sidebar). But, by way of full disclosure, these attributes are largely my invention.

I intend for the classification scheme to be used by:

- health system researchers who want to develop agent-based simulation models of complex health systems,
- health system policymakers who must clearly communicate with health system researchers in order to develop effective policies,
- other health system stakeholders who must clearly communicate with one another.

Desired classification scheme attributes

An ideal classification scheme for health systems agents and agent behavior would have the following attributes:

- **Complete:** The scheme would include all relevant health system agents and agent behaviors to model a complex health system such as the US health system.
- **Consistent:** It would classify agents and behaviors in one consistent way.
- **Intuitive:** Its organization would make sense to health system experts.
- **Useful:** It would help health systems researchers and policymakers to name, understand, model, and discuss the agents and behaviors of health systems. In particular, the scheme would enable them to develop agent-based simulation models of health systems.
- **International:** It would apply to agents and agent behaviors in health systems around the world.
- **Compliant:** It would conform to classification standards, such as those established by the International Standards Organization (ISO), the American National Standards Institute (ANSI), and the British Standards Institution.
- **Maintainable:** It would be easy to update and maintain.
- **Scalable:** It would apply to both small and large health systems.
- **Independent:** To avoid licensing issues, it would be independent of other classification schemes.



Pause to reflect

Remember the MaineCare example introduced in the Preface? As the MaineCare advisory committee thought about the potential impact of a formulary, how would a health systems classification scheme with the desired attributes listed above have been useful to them?

D. CLASSIFICATION SCHEMES

As the following table shows, an ontology is one of the four main types of classification schemes.

Controlled vocabulary	Taxonomy	Thesaurus	Ontology
Brain surgeon Dentist Generalist Healthcare practitioner Internist Neurologist Physician Specialist	Healthcare practitioner Dentist Physician Generalist Specialist Brain surgeon Internist Neurologist	Neurosurgeon Brain surgeon BT Specialist NT Pediatric neurosurgeon Pediatric brain surgeon RT Neurologist BT = Broader Term NT = Narrower Term RT = Related Term	Patient seeks Physician Generalist refers Patient to Neurosurgeon Neurosurgeon operates on Patient Neurosurgeon reports results to Generalist

- **Controlled vocabulary.** A “**controlled vocabulary**” is a listing of terms (usually called “entry terms”), sometimes in a certain order. It is called “controlled” because for the domain covered, only the entry terms may be used. This is Cawdrey’s classification scheme.
- **Taxonomy.** A “**taxonomy**” is a hierarchy of entry terms, an upside-down tree, and is the most common organization system. Two common taxonomies are the Dewey Decimal Classification system for cataloging books, and the North American Industrial Classification Systems (NAICS) codes for classifying businesses.
- **Thesaurus.** A “**thesaurus**” shows simple relationships among terms, such as whether they are synonymous. The terms may also be shown hierarchically, as in the example above.¹ The International Organization for Standardization (called ISO, from the Greek “isos”, meaning “equal”), the American National Standards Institute (ANSI), and the British Standards Institution (BSI) all promulgate thesauri standards.
- **Ontology.** An “**ontology**” is the type of classification scheme with the most complex relationships among entry terms. Its purpose is to fully describe a domain of knowledge, including both the domain’s agents as well as relevant agent relationships and behaviors.² The World Wide Web Consortium (WC3) and the ISO have promulgated ontology standards.



Pause to reflect

How are the four types of classification schemes used in your company or school? Give an example of a controlled vocabulary, a taxonomy, and a thesaurus.

Has your company or school created an ontology? (Most haven’t.) If not, how do the relational databases in your organization compare to an ontology?

¹ For an interesting example of a thesaurus, see the Getty Art & Architecture Thesaurus at “www.getty.edu/research/tools/vocabularies/aat/index.html”. To see how the entry terms are arranged, click on “Browse the AAT hierarchies” in the search box.

² In Hedden (2010), Chapter 1, Heather Hedden discusses the types of classification schemes, and shows how to develop a classification scheme.

E. A HEALTH SYSTEMS ONTOLOGY

There are several ontologies in the biological and health sciences. In fact, although the concept of ontological classification schemes arose in the artificial intelligence and computer science fields, it is flourishing mainly in the biological and health sciences. As examples, there is a “gene ontology”, a “protein ontology”, and a “systems biology ontology”. There is also a “disease ontology”, the HL7 Reference Information Model (RIM) ontology for exchange of medical record information, and the Systematized Nomenclature of Medicine (SNOMED) ontology for medical terminology.¹

But it appears that there is no health systems ontology. There is no ontology that organizes the concepts of agents and agent behaviors for the domain of health systems. (And, it appears, neither is there a complete health systems taxonomy or thesaurus.)

Because health systems stakeholders need a complete classification scheme for their domain, and because the ontology is the most precise type of classification scheme, in the next two chapters I propose a design for a health systems ontology. It consists of three components:

- **Agent role taxonomy.** A hierarchical taxonomy of agent roles. For example, in a health system a person might play the role of a patient or a pediatrician, or both. This taxonomy is discussed in Chapter four (Classification of agents).
- **Goal taxonomy.** A hierarchical taxonomy of agent goals, discussed in Chapter five (Classification of behavior). For example, common goals in a health system are to “enhance health” and “treat disease”.
- **Behavior.** The third component consists of agent behaviors. Each behavior is composed of a source agent role, a target agent role, a goal, and other behavior components from our behavior dimensions in Chapter one. Thus, in the proposed ontology, behaviors are built from the agent role taxonomy, the goals taxonomy, and other behavior components, as described in Chapter five (Classification of behavior).



Pause to reflect

Do you agree that health systems stakeholders (such as researchers and policymakers) would benefit from having a complete classification system for the health systems domain?

How might they benefit? What kind of classification system would be most beneficial?

¹ Gene Ontology: “www.geneontology.org”; Protein Ontology: “pir.georgetown.edu/pro/pro.shtml”; Systems Biology Ontology: “www.ebi.ac.uk/sbo/main”; Disease Ontology: “do-wiki.nubic.northwestern.edu/do-wiki/index.php/Main_Page”; HL7 RIM ontology: “www.hl7.org/implement/standards/rim.cfm”; SNOMED ontology: “www.ihtsdo.org/snomed-ct”.

E. A HEALTH SYSTEMS ONTOLOGY continued

An important feature of the ontology is a “cross-impact” attribute for each behavior. This attribute indicates if the behavior might affect other behaviors in the ontology. For example, the cross-impact attribute for a health insurance company’s behavior to issue a drug formulary indicates that it might affect the referral behavior of physicians. In Chapter six (Using the health systems ontology) I discuss this attribute in more detail. There, I also review the potential benefits of the health systems ontology, and how you can use it.

You will find details about the design of the health systems ontology, and a description of the Protégé software that I used to implement it, in the *International compendium of health behavior* that accompanies this work.

F. ISSUES AND FUTURE DIRECTIONS

Developing even the first draft of a complete ontology takes time. For example, developing the first draft of the HL7 RIM ontology for exchange of medical record information took a team of experts ten years. Similarly, it will take time and a team to complete the first draft of a health systems ontology. Most importantly, though, it will take knowledge and resolve, knowledge that such a classification scheme is a vital missing link in our efforts to improve health systems, and firm resolve to complete this difficult task.

G. TO LEARN MORE

To learn more about classification schemes and classifying information, you might enjoy reading Hedden (2010). The book is easy to read, entertaining, and filled with detailed suggestions about developing classification schemes. Its Chapter 5 (Software for taxonomy creation and management) reviews the many software tools for developing taxonomies, thesauri, and ontologies.

To learn more about ontologies, you might start with Hedden (2010). Then, take a look at the Wikipedia entry for “ontology-information science” (“[wikipedia.org/wiki/Ontology_\(information_science\)](http://wikipedia.org/wiki/Ontology_(information_science))”) and its references. It is also fun to look at the ontology websites listed in the footnotes of this chapter.

H. REVIEW AND A LOOK AHEAD

In this chapter, I introduced the concept of a classification scheme and its importance. We then explored the four types of classification schemes: controlled vocabularies, taxonomies, thesauri, and ontologies.

Next, I listed existing ontologies in the biological and health sciences, and noted that for the health systems domain an ontology does not yet exist (and neither does a complete classification scheme of any type).

Then, I sketched the three main components of the health systems ontology that I will propose in the next two chapters: an agent role taxonomy, an agent goal taxonomy, and health behaviors (formed in part using the two taxonomies). I also emphasized the importance of the ontology's "cross-impact" attribute.

In the next chapter, we will look more closely at how agents are represented in the proposed health systems ontology.

(Don't forget to take a look at the exercises for this chapter. They start on the next page.)

EXERCISES

1. Name five classification schemes that have helped mold your thinking. For each scheme, identify its type, and discuss how it has affected your thinking. Be specific.
2. For each of the following health-related classifications, identify its type, and discuss how it benefits health systems stakeholders:
 - International Statistical Classification of Diseases and Related Health Problems (ICD10) codes
 - Current Procedural Terminology (CPT) codes
 - US National Health Expenditures (NHE)
 - Medical subject headings (MeSH) of PubMed
 - Read codes (codes used by physicians in the UK)
3. Show how each of the four types of classification schemes might be applied to the game of tennis.
4. An ontology is a “linguistic semantics”, the language and meanings used in a particular domain, such as health care. Think about an instance when two teams or departments in your company or school used the same term (language) to mean different things. What problems arose? How might a consistent ontology have been helpful?
5. Is it possible to have two different health system ontologies? If so how would you judge whether one is better than the other?

SOLUTIONS

1. Among our common classification schemes are:
 - The *Oxford English Dictionary*: Controlled vocabulary, with some features of a thesaurus
 - Telephone yellow pages: Taxonomy
 - Linnaean taxonomy of biological organisms: Taxonomy
 - Dewey Decimal Classification system: Taxonomy
 - *Roget's Thesaurus*: Thesaurus
2.
 - ICD10 codes: Taxonomy
 - CPT codes: Taxonomy
 - NHE: Taxonomy
 - MeSH terms: Taxonomy
 - Read codes: Taxonomy

3.

Controlled vocabulary	Taxonomy	Thesaurus	Ontology
Athletic game Court game Double fault Equipment Game Love Players Racket Rules Steffi Graf Tennis	Game Athletic game Court game Tennis Rules Double fault Love Equipment Racket Players Steffi Graf	Racket Raquet BT Equipment NT Handle Grip RT "Real" tennis racket BT = Broader Term NT = Narrower Term RT = Related Term	Player holds Racket Player hits Ball to Opponent Score is Love

4. For example, some people use the term "healthcare provider" to refer to physicians and other individual healthcare practitioners. Others use the term to refer to institutions, such as hospitals. The different language often causes confusion among people trying to communicate clearly.
5. It is possible to have more than one health system ontology. In fact, there are many possible health system ontologies, corresponding to the many different ways that politicians, scientists, physicians, and other stakeholders think about a health system. As an ontology includes more of the desired attributes of an ideal classification scheme (see Section C), it becomes better able to help stakeholders solve a variety of health system problems, and thus more "robust".

CHAPTER FOUR: CLASSIFICATION OF AGENTS

When we speak of the “health care system” today, we usually have in mind a great array of organizations: hospitals and medical centers, public health and planning agencies, professional associations, health insurance and pharmaceutical companies, and so on. Although some of these organizations have distant historical antecedents, they did not really constitute an interdependent system, even in a loose sense, before the late nineteenth century.

Paul Starr, 1982¹

A. HEALTH SYSTEM AGENTS

As we saw in Part I, an agent is a self-directed and adaptive entity. It is able to take actions on its own to attain a goal, and can change its behavior to fit in with a new environment. Health system agents are the agents within a health system, the system’s actors.

In today’s complex health systems, agents include medical professionals such as physicians and chiropractors; provider organizations such as hospitals, medical centers, and imaging centers; medical supply organizations such as pharmaceutical companies; physician networks; educational and research organizations; financing organizations such as health insurance companies; governmental organizations of all sorts; and, of course, millions of people who are concerned about their health.

And one person or organization might act in many agent roles. For example, a mother of two might be a pediatric physician, a hospital board member, head of a professional organization, and a sick patient, all at the same time. How do we make sense of this splendid array of people and organizations?

B. CLASSIFICATION OF AGENT ROLES

To account for the many roles that a health system agent might play, I propose using a taxonomy of agent roles. By “role” I mean a set of functions within a health system. For example, “physician” is a health system role, with a culturally defined set of functions (e.g., diagnose disease, offer treatments, confer with other physicians, etc.).



Pause to reflect

How many health system roles do you play?

Would you expect to see your roles in a taxonomy of health system roles? Where in such a taxonomy would you expect to find them?

¹ See Starr (1982), page 24.

B. CLASSIFICATION OF AGENT ROLES continued

The table at right shows the top two levels of the taxonomy of health system agent roles. The roles are first divided into individual roles (such as the role of an individual physician) and group roles (such as the role of a hospital).

The next division is based on six function classes:

- **Care recipient class.** The roles associated with receiving health care. Two roles associated with this class are the “Patient role” (a patient of a healthcare practitioner) and “Individual person role” (others in the recipient role).
- **Healthcare class.** The roles associated with providing health care. An example of a role in this class is the “Primary care practitioner”.
- **Financial class.** The roles associated with the financial processes of healthcare systems. A prominent example of this role is a “Health insurer organization role”. Another is the “Head of household role”.
- **Social policy class.** The roles associated with social policies for a health care system, such as policies about healthcare equity. Group roles within this class are “Healthcare legislation role”, and “Healthcare social policy consumer advocacy”.
- **Scientific class.** The roles associated with scientific research to support health systems. An example of this role is “Research laboratory role”.
- **Administrative class.** The roles associated with the functioning of health system processes. An example of a role in this class is “Healthcare information systems supplier role”.

The second table (at bottom right) shows five levels of the hierarchy for individual healthcare practitioners. It illustrates the numbering system I propose to identify each entry term in the taxonomy. The identifier for each role starts with “A” (for “agent”). Then, the entry terms within a level are numbered sequentially starting at 1. For levels that could have more than 9 entry terms, the number is two digits, such as “01”. For levels that do not explicitly list all possible roles, I provide the numbers “9” or “99” for an “other” category. This numbering scheme enables additional roles to be added in the future.

The complete agent role taxonomy is provided in the *International compendium of health behavior*.

<p>A1. Individual role A1.1. Individual care recipient role A1.2. Individual healthcare role A1.3. Individual financial role A1.4. Individual social policy role A1.5. Individual scientific role A1.6. Individual administrative role</p> <p>A2. Group role A2.1. Group care recipient role A2.2. Group healthcare role A2.3. Group financial role A2.4. Group social policy role A2.5. Group scientific role A2.6. Group administrative role</p>
--

A1.2.	Individual healthcare role
A1.2.1.	Healthcare practitioner role
A1.2.1.1.	Primary care practitioner
A1.2.1.2.	Specialist practitioner
A1.2.1.2.01.	Anatomical specialist
A1.2.1.2.01.01.	Ear nose throat specialist
A1.2.1.2.01.02.	Eye specialist
A1.2.1.2.01.03.	Dental specialist
A1.2.1.2.01.04.	Respiratory system specialist
A1.2.1.2.01.05.	Digestive system specialist
A1.2.1.2.01.06.	Genito-urinary system specialist
A1.2.1.2.01.07.	Reproductive system specialist
A1.2.1.2.01.08.	Podiatry specialist
A1.2.1.2.01.09.	Dermatological specialist
A1.2.1.2.01.10.	Cardiovascular system specialist
A1.2.1.2.01.11.	Hemic and lymphatic specialist
A1.2.1.2.01.12.	Endocrine system specialist
A1.2.1.2.01.13.	Genetic specialist
A1.2.1.2.01.14.	Immune system specialist
A1.2.1.2.01.15.	Musculo-skeletal specialist
A1.2.1.2.01.16.	Nervous system specialist
A1.2.1.2.01.17.	Multiple systems specialist
A1.2.1.2.01.99.	Other anatomical specialist

C. DEVELOPMENT PROCESS

Following is the process I followed to develop the agent role taxonomy. I hope that describing the process I followed will prove helpful to a team that will develop a complete taxonomy.

- **Collect agent types.** To find common types of health system agents, I searched books (such as health economics and health policy books), taxonomies, reports, and websites (see the sidebar for sources). In the course of this search, I also collected synonyms for common agent types.
- **Organize the types.** To organize the many agent types, I first determined the ones that are most likely to significantly affect international health systems and that users would expect to see. I then sorted them into hierarchical levels.
- **Develop preferred term names.** I then decided on names for the entry terms. Even though the taxonomy is intended to be international in scope, in general I chose names in American English.
- **Check for compliance.** I then checked to ensure that the taxonomy structure and terminology conform to guidelines and standards, in particular the ANSI standard NISO Z39.19-2005 (Guidelines for the construction, format, and management of monolingual controlled vocabularies).
- **Check for consistency.** Lastly, I checked the taxonomy for logical coherence and consistency of style.

After a complete taxonomy is developed, the next step will be for experts to use it and uncover its defects, so that needed changes can be made. This process will continue iteratively for the life of the taxonomy.

D. ISSUES AND FUTURE DIRECTIONS

The agent role taxonomy is incomplete and untested. To determine if it is useful, it needs to be completed and then tested. In particular the functions associated with each agent role need to be carefully defined.

E. TO LEARN MORE

To learn more about developing a taxonomy, see Hedden (2010).

Sources for agent types

Following are some of the sources I consulted to collect the most common types of health system agents.

- **Health care provider taxonomy:** A detailed taxonomy of individual and organizational healthcare providers, prepared by the American Medical Association. I consulted version 8.0.
- **ISCO-08:** International Standard Classification of Occupations, version 08, prepared by the International Labour Organization. Health occupations in the ISCO-08 were developed in cooperation with the World Health Organization (WHO) and the Organization for Economic Co-operation and Development (OECD).
- **NAICS:** North American Industry Classification System, developed under the auspices of the US Office of Management and Budget.
- **Classification of economic and social affairs:** An international classification of expenditures according to purpose, prepared by the United Nations Statistics Division.
- **MeSH:** PubMed medical subject heading terms.
- **Library of Congress subject headings.** Subject headings related to health care.

F. REVIEW AND A LOOK AHEAD

In this chapter, I proposed a taxonomy for health system agent roles. I also described how I developed the taxonomy, and the rationale behind its structure and numbering.

(Don't forget to take a look at the exercises for this chapter. They start on the next page.)

EXERCISES

1. Where in the taxonomy would you expect to find the following?
 - The chief medical officer of the Mayo Clinic.
 - A janitor who works for the Georges Pompidou European Hospital in Paris.
 - The cardiac surgeon role.
 - The public health agency role.
2. Where in the agent role taxonomy would you expect to find the health system roles that you play?

SOLUTIONS

1. The chief medical officer of the Mayo Clinic and the French janitor would not be found in the taxonomy, because they are real agents and not roles. However, the administrative component of the chief medical officer's job would be found in the taxonomy under A1.6 (Individual administrative role). The janitor role would be found under A1.2.9 (Other individual healthcare role). The cardiac surgeon role is found in the role A1.2.1.2.01.10 (Cardiovascular system specialist) and the regulation component of the public health agency role is found under A2.2.04 (Public health regulatory agency role). To find this, you would need to consult the complete taxonomy in the *International compendium of health behavior*.
2. Everyone plays the individual care recipient role (A1.1).

CHAPTER FIVE: CLASSIFICATION OF BEHAVIOR

At the present time, there is no accepted taxonomy of health behaviors.

Klaus Warner Schaie, 2002¹

A. THE IMPORTANCE OF BEHAVIOR

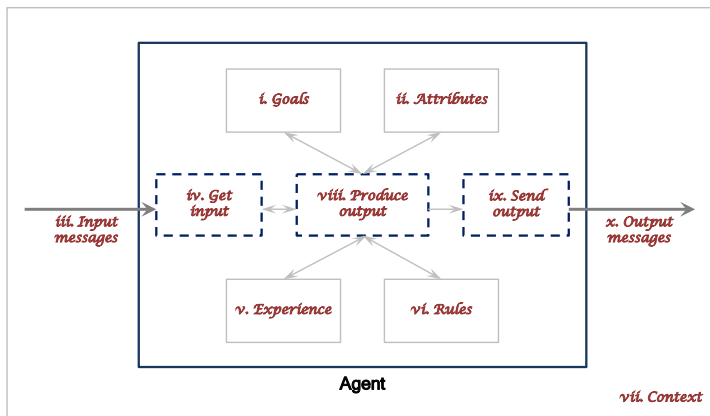
It is curious that when we think of health systems, our minds naturally turn toward objects, things like hospitals, insurance companies, and our favorite (or least favorite) physicians and nurses, things that we are calling “agents”.

Yet, in general, it is not agents that are most important in a health system. Rather, it is the behavior, the functions, the actions. Certainly, there is one agent that is of utmost importance, and that is the person the system should be keeping healthy. But otherwise, what does it matter how the functions of a health system are accomplished? It is conceivable that someday many of the functions of health systems will be performed by intelligent computers and robots, rather than physicians and other people.

It is even more curious that there is no complete taxonomy or ontology of health behavior. Our current health taxonomies—such as the AMA’s “Healthcare provider taxonomy” (see the sidebar in Section C of Chapter four)—are mainly of agents. My hope is that this report will be a first step toward changing this state of affairs.

B. BEHAVIOR DEFINED

As a reminder, in Chapter one (Dimensions of behavior) I proposed a new definition of health behavior, where behavior is represented by the ten components in the following diagram:



Pause to reflect

Can you imagine the functions of a great health system being carried out by agents completely different than we now know?

Why do you think that we fixate on the agents of health care, rather than on health behavior?

¹ Schaie, Leventhal, & Willis (2002)

C. CLASSIFICATION OF HEALTH BEHAVIOR

In this chapter, I propose a method to classify health behavior. The method is part of a proposed general health systems ontology.

To fully classify health behavior, ideally we would create a taxonomy with ten dimensions, one for each of the behavior components. But, because we do not yet know how to sub-divide most of the behavior components (such as “Experience”), we cannot take such an ideal approach.

Instead, I propose a practical approach that classifies behavior based on one of the ten components, namely “Goals”. Accordingly, I have developed a hierarchical taxonomy of goals. The first two levels are shown in the table at right. (You will find the complete taxonomy in the accompanying *International compendium of health behavior*.) As you see, there are six goal classes:

- **Healthcare goal.** The goals in this class are related to health care.
- **Financial goal.** The goals in this class focus on financial processes of a health system.
- **Social policy goal.** The goals in this class are related to a health system’s social policies.
- **Scientific goal.** The goals in this class focus on scientific research to support a health system.
- **Administrative goal.** The goals in this class are related to a health system’s administrative processes.
- **Non-healthcare goal.** The goals in this class are not related to a health system per se. Rather they are focused on non-healthcare needs of health system agents.

In the next level of the taxonomy, below each of these goal classes, are several sub-goals, as shown in the table at right.

In the ontology, an instance of health behavior is described as:

- The agent role performing the behavior (from the Agent role taxonomy), plus
- The primary goal driving the behavior (from the Goal taxonomy), plus
- The agent role receiving output from the behavior (from the Agent role taxonomy), plus
- A description of the ten behavior components associated with the behavior.

G1.	Healthcare goal
G1.1.	Enhance health
G1.2.	Decrease health risk
G1.3.	Eliminate unwanted sign or symptom
G1.9.	Other healthcare goal
G2.	Financial goal
G2.1.	Decrease expenditures
G2.2.	Decrease financial risk
G2.9.	Other financial goal
G3.	Social policy goal
G3.1.	Increase healthcare equity
G3.2.	Increase healthcare choice
G3.9.	Other social goal
G4.	Scientific goal
G4.1.	Expand healthcare knowledge
G4.2.	Improve existing healthcare procedures
G4.9.	Other scientific goal
G5.	Administrative goal
G5.1.	Perform administrative process effectively
G5.2.	Increase administrative process effectiveness
G5.9.	Other administrative goal
G6.	Non-healthcare goal
G6.01.	Increase agent income
G6.02.	Increase agent power
G6.03.	Increase agent enjoyment
G6.04.	Decrease agent effort
G6.99.	Other non-healthcare goal

C. CLASSIFICATION OF HEALTH BEHAVIOR continued

For example, if Dr. Smith, a primary care practitioner, prepares a specialist referral for the patient Mary Jones because Dr. Smith thinks the specialist will help Mary to treat her disease, the behavior “Refer a patient” would be classified as:

Source: A1.2.1.1.Primary care practitioner (“Dr. Smith”)

Goal: G1.3.Eliminate unwanted sign or symptom

Target: A1.1.02.02.Sick patient (“Mary Jones”)

In addition, a full description of the behavior would require descriptions of the ten behavior components.

D. DEVELOPMENT PROCESS

The process to develop the goal taxonomy was far less structured than the process to develop the agent role taxonomy. The process was unstructured, highly iterative, and involved organizing many health behaviors into goal-oriented classes.

E. ISSUES AND FUTURE DIRECTIONS

As with the agent role taxonomy, the goal taxonomy and the method for classifying behavior are incomplete and untested. To determine if they are useful, they need to be completed and tested.

F. TO LEARN MORE

To learn more about the tentative and sporadic efforts to classify individual health behavior, see Gochman (1997), Volume IV pages 416 to 422, and Volume I pages 4-6.

G. REVIEW AND A LOOK AHEAD

In this chapter, I proposed a goal taxonomy for health behavior, and how it could be used to classify health behavior.

(Don’t forget to take a look at the exercises for this chapter. They start on the next page.)



Pause to reflect

Think of another health behavior, perhaps one performed by an organization such as a health insurance company. Using the method described here, how would the behavior be classified?

EXERCISES

1. Using the behavior classification scheme presented in this chapter, how would you classify the following behavior: Because Joe Jones wants to reduce his risk of disease, he stops smoking.
2. Imagine a clean slate, a small country without any health system infrastructure. There are no doctors, no hospitals, no insurance companies, no public health agencies, no health system providers or other similar agents at all. There are only people who need health care. You have a list of all the behaviors and agent roles required to operate another country's health system, a system that reflects the healthcare goals that you value. What would you do with the list?

SOLUTIONS

1. The behavior could be classified as:
Source: A1.2.Individual healthcare role ("Joe Jones")
Goal: G1.2.Decrease health risk
Target: A1.1.Individual care recipient role ("Joe Jones")

In addition, to fully describe the behavior, there would be descriptions of the ten behavior components.

2. With a clean slate and a complete list of required behaviors and agent roles, you would not be constrained by existing organizations and relationships, and could design a health system from scratch that is aligned with desired goals.

CHAPTER SIX: USING THE HEALTH SYSTEMS ONTOLOGY

A classification scheme provides insight regarding the resources that will be needed to achieve the desired level of behavior change.

Klaus Warner Schaie, 2002¹

A. POTENTIAL BENEFITS OF THE HEALTH SYSTEMS ONTOLOGY

Once it is fleshed out, the health systems ontology described in this part offers stakeholders several potential benefits:

- **Better communication.** It could provide stakeholders a common vocabulary, and a common understanding of the structure of health systems, thus increasing their ability to communicate. For example, stakeholders could talk explicitly about particular classes of agent roles and their behavior classes, goals, rules, and other behavior components, rather than vaguely about objects and superficial behaviors.
- **Greater efficiency.** It would not have to be reinvented. Just as we do not need to reinvent the alphabet, for each policy decision health system stakeholders would not have to reinvent a way to talk about health system entities.
- **Better understanding.** The ontology makes domain assumptions explicit and thereby would help us separate domain knowledge (the behaviors and agent roles necessary to run a health system) from operational knowledge (how things are done now). Moreover, just as the first dictionaries helped us clarify our thinking and form broader concepts, clarifying health system fundamentals would help us form broader concepts and conceive grander patterns.
- **Better research.** Establishing a complete classification system would help us to better understand the gaps in our knowledge, and to focus on the most important areas for research. For examples, see Chapter seven (Overview of health behavior facts).
- **Better analysis and problem solving.** Perhaps most importantly, the ontology's bottom-up nature would enable the application of agent-based modeling—as well as other complexity science tools—to solve health system problems.



Pause to reflect

Can you think of any other potential benefits of a health systems ontology?

Would such an ontology help you in your work?

Can you think of a health system stakeholder that might be opposed to the use of the ontology?
Why might entrenched stakeholders oppose it?

¹ Schaie, et al. (2002)

B. USING THE ONTOLOGY

To demonstrate how to use the ontology, let's consider again the MaineCare problem introduced in the Preface. Let's explore how MaineCare's stakeholders might have analyzed the potential impact of introducing a formulary had they had access to the health systems ontology.

Step 1: Pose the problem. The first step would be to pose the problem using the ontology's vocabulary. Accordingly, one formulation of MaineCare's problem might be: What is the potential impact on MaineCare's budget if MaineCare in the role of "Medicaid administrator" were to "promulgate a formulary" (a behavior) to all Maine agents in the role of **Generalist physician**?

Step 2: Determine the relevant agent roles and behaviors. The next step is to determine the relevant agent roles and behaviors. Clearly, the roles of "Medicaid administrator", "Primary care physician", and "Pharmaceutical company" are relevant, as are the "Medicaid administrator" behaviors of "promulgate formulary" and "negotiate drug cost", the "Primary care physician" behaviors of "prescribe drug" and "submit claim"¹, and the "Pharmaceutical company" behavior of "negotiate drug cost".

But what other roles and behaviors are needed to fully understand and model the problem? Here we reach an impasse. Without an ontology, it is extremely difficult to tease out which agent roles and behaviors in the Maine health system might be important to consider for the problem. To see this, consider the "influence matrix" at right. It shows the top-level goal classes in our goal taxonomy. The cell where a row goal intersects a column goal indicates whether a behavior related to a row goal can impact a behavior related to the column goal. A colored cell indicates that there is an impact; green indicates a positive impact, red indicates a negative impact, and blue indicates an indeterminate impact. As you see, all cells at this level are blue. Within each class, there is a related behavior that can affect a behavior related to a goal in each of the other classes, and the aggregate direction of impact is indeterminate.

G1. Healthcare goal						
G2. Financial goal						
G3. Social policy goal						
G4. Scientific goal						
G5. Administrative goal						
G6. Non-healthcare goal						

Now consider the analysis if MaineCare had the ontology.

¹ For simplicity, let's assume that the primary care physician submits claims for drugs that patients purchase.

B. USING THE ONTOLOGY *continued*

Step 2: Determine the relevant agent roles and behaviors *continued*.

Because each behavior in the ontology includes its potential impact on each other behavior (in the “cross-impact” attribute), with the ontology one can obtain a more granular influence matrix, such as the following one.

Role/behavior	Behavior impacted					
	State Medicaid program	Physician	Specialist	Patient	Hospital	Pharmaceutical company
State Medicaid program						
balance budget						
promulgate drug formulary		1		1		
negotiate drug costs	5			1		
pay claims	3			1		
administer appeals	3			1		
handle complaints	3			1		
litigate	3			1		
Physician						
prescribe drug		2				
prescribe alternative treatment		2				
set fees		2				
refer to specialist						
send to hospital						
respond to patient request						
submit claim		2				
complain						
appeal						
complete paperwork						
Specialist						
submit claim						
Patient						
complain						
sue						
appeal program decision						
visit ER						
request drug						
Hospital						
submit claim						
Pharmaceutical company						
negotiate drug costs						
advertise drug						

This matrix shows the potential feedback and follow-on effects of relevant agent roles and behaviors in the Maine health system. For example, take a look at the behavior “promulgate drug formulary” under “State Medicaid program” in the left column. It first impacts the behavior “prescribe drug” under “Physician” in the top row, and the impact has a positive financial impact on the MaineCare program (doctors will prescribe more of the less-costly formulary drugs). This positive financial impact is indicated by the green color. This is a first-order impact, indicated by the number “1”.

B. USING THE ONTOLOGY continued

Step 2: Determine the relevant agent roles and behaviors continued.

For the second-order impact, denoted by “2”, “prescribe drug” under Physician (in the left column) affects “negotiate drug costs”, again in a positive financial direction. For the third-order impact, “negotiate drug costs” under “State Medicaid program” (in the left column) will affect “negotiate drug costs” under “Pharmaceutical company”. And so on.

The matrix shows that the potential positive financial effects of promulgating the drug formulary (shown in green) may be swamped by the unintended side effects. It also shows that the timing of favorable drug negotiations may come too late (at the time of the fifth-order impact denoted by “5”) to offset earlier side effects.

But, more importantly, it indicates the agent roles and behaviors that MaineCare should include in its agent-based model of the problem.

Step 3: Develop an agent-based model. The next step is to model the problem, based on the agent roles and behaviors determined in the previous step, with an agent-based simulation model. One could imagine that a fully developed ontology could automatically generate much of this model.

After running such a model under various scenarios, MaineCare would better understand the potential impact of promulgating a formulary.

C. ISSUES AND FUTURE DIRECTIONS

It will take additional effort to develop an ontology that generates influence diagrams, and even more effort to develop an ontology that generates the first draft of an agent-based model. But both projects could be well worth the effort.

D. REVIEW AND A LOOK AHEAD

In this chapter, we explored the potential benefits of the health systems ontology, and how to use it.

In Part III (Health behavior facts) we will explore what we know about health behavior.

(Don't forget to take a look at the exercises for this chapter. They start on the next page.)

EXERCISES

1. If conditional probabilities of cross-behavior impacts were included as an attribute of each behavior in the ontology, then the ontology could generate cross-impact matrices. How might such conditional probabilities be useful for a significance matrix like that introduced in Section B?

SOLUTIONS

1. Conditional probabilities would enable a user of the health systems ontology to determine the potential significance of behavior impacts. The user might then establish thresholds to determine the agent roles and behaviors to include in an agent-based model. For example, the user might include only agents and behaviors that could cause a deviation in certain behaviors of more than, say, 10 percent.

PART III: HEALTH BEHAVIOR FACTS

If one examines the salient economic institutions of the health sector, one might expect that sector to be a breeding ground for applied behavioral economics. Consider a set of economic activities where addictions figure prominently; where consumers have limited information that they must use to make choices in the context of fear, urgency, and trust in an expert; and where the services used are often credence goods whose applications are frequently governed by professional norms and habit. In such an economic environment, the methods of behavioral economics might be expected to be prevalent in modifying traditional models to take account of those features that appear to conflict with simple notions of rationality in economic behavior. Yet the application of behavioral economics to issues in health economics has been largely confined to understanding addictive behavior around cigarettes, drugs, and alcohol.

Richard Frank¹

There are few, if any, sectors in the economy where the growing paradigm generally termed “behavioral economics” seems to be as relevant and important as the market for health services. Starting with Arrow (1963), many economists have recognized the fact that, in the health services and health insurance market, consumers and providers cannot (on the basis of their behavior) reasonably be described as rational agents acting to maximize their expected utility or profit. Furthermore, motives and considerations such as altruism, trust, and norms, often outside the economists’ usual playground, appear to play an important role in the agent’s decision-making process. Most of these researchers, however, have implemented their own, often ad hoc, assumptions about how agents behave in these markets and very few have actually relied on models developed and results obtained in related behavioral fields such as psychology, sociology, and, especially, the more recently emerging field of behavioral economics.

Jacob Glazer²

¹ Richard Frank is the author of “Behavioral economics and health economics” in P. A. Diamond & Vartiainen (2007).

² From Jacob Glazer’s comments about Richard Frank’s chapter titled “Behavioral economics and health economics” in P. A. Diamond & Vartiainen (2007). Jacob Glazer is a prominent health economist with joint appointments at Boston University and Tel Aviv University.

INTRODUCTION

In Part I (Health behavior) we explored what health behavior is and I proposed a way to describe its components. In Part II (Classification of agents and behavior) I proposed a way to classify health behavior. In this part, Part III (Health behavior facts), we will take a look at what we know about the real health behaviors of health system agents, the facts, and we will use our classification scheme to organize these facts.

In the first chapter, I first describe the first version of the *International compendium of health behavior* (“Compendium”), a catalog of what we know about health behavior.

Then, based on work I did to prepare the Compendium, I show that our stock of useful health behavior facts is meager, that in spite of much effort researchers have not produced the rigorous knowledge about health behavior that we need in order to make good decisions about health systems.

In the second chapter, I review key contributions of the new field called “behavioral economics” and show how they might apply to health behavior. I also argue that although these contributions are important, they fall short of helping us accurately model the behavior of health system agents. They are disorganized, incomplete, and have not yet been adequately applied to health behavior.

For all the effort, all the trillions we have spent on health research, all the spinning at the health research loom, we simply do not know enough about health behavior to make decent health system policy decisions. Health behavior research is threadbare.

CHAPTER SEVEN: OVERVIEW OF HEALTH BEHAVIOR FACTS

So the honest minister went to the room where the two swindlers sat working away at their empty looms. “Heaven help me,” he thought as his eyes flew wide open, “I can’t see anything at all”. But he did not say so.

Hans Christian Andersen²

A. DISENCHANTMENT

A little knowledge can be a disenchanting—if not downright embarrassing—thing. After the U.S. Congress passed the “ACA”, the law that is supposed to weed, fence in, and pave new paths through the U.S. healthcare system, I watched with hope and enchantment as new flora sprang up. “Accountable Care Organizations”, “Exchanges”, “Medical Homes”. I liked the cozy sound of medical homes, and I hoped that whoever wrote the ACA and whoever coded genomes for the new flora knew how they might fare—how families, physicians, hospitals, health insurance companies, and others in the healthcare system might behave in their presence. But now I have a little more knowledge. Based on research I did for this report, I am embarrassed to say that our ignorance about health behavior is vast. I am not convinced that medical homes will be cozy, or that the new flora will survive the winter. In this chapter, we will explore how meager our stock of behavioral facts really is.

B. INTERNATIONAL COMPENDIUM OF HEALTH BEHAVIOR

My conclusions about the paucity of our health behavior knowledge are drawn mainly from work I did to prepare the first version of the *International compendium of health behavior* (“Compendium”), a work that accompanies this report (see the sidebar). This first version includes thirty behaviors of individuals, primary care physicians, specialist physicians, provider networks, health insurance companies, Exchanges, state insurance commissioners, and others.

The titles of these thirty behaviors are listed in the summary chart on the following page. For each behavior, greyed squares indicate the behavior components for which research is available, with a tally at the bottom.³ As you will see, the chart is sparse.

International compendium of health behavior

The purpose of the *International compendium of health behavior* is to catalog and describe what we know about each of the significant health behaviors that health system agents perform.

For each such behavior, the *Compendium* presents the following information:

1. **Classification reference.** A reference code to uniquely identify the behavior.
2. **Behavior title.** The health behavior’s title.
3. **Behavior description.** A brief description of the behavior.
4. **Terminology.** Key terms that are used to describe the behavior.
5. **Research results.** A detailed review of research available about each component of the behavior. Behavior components are described in Chapter one (Dimensions of behavior) of this report.
6. **Reference citations.** In the footnotes are citations for research about the behavior.

The *Compendium* also discusses limitations and gaps in research about the behavior and identifies simulation models that use the behavior.

The *Compendium*’s main intended use is to help researchers easily locate what is known about a particular health behavior, and to incorporate such knowledge in agent-based simulation models of health systems.

Of course, because the *Compendium* is a comprehensive reservoir of facts about health behavior, it can also help health system stakeholders of all kinds better understand and think about the behavior of health system agents.¹

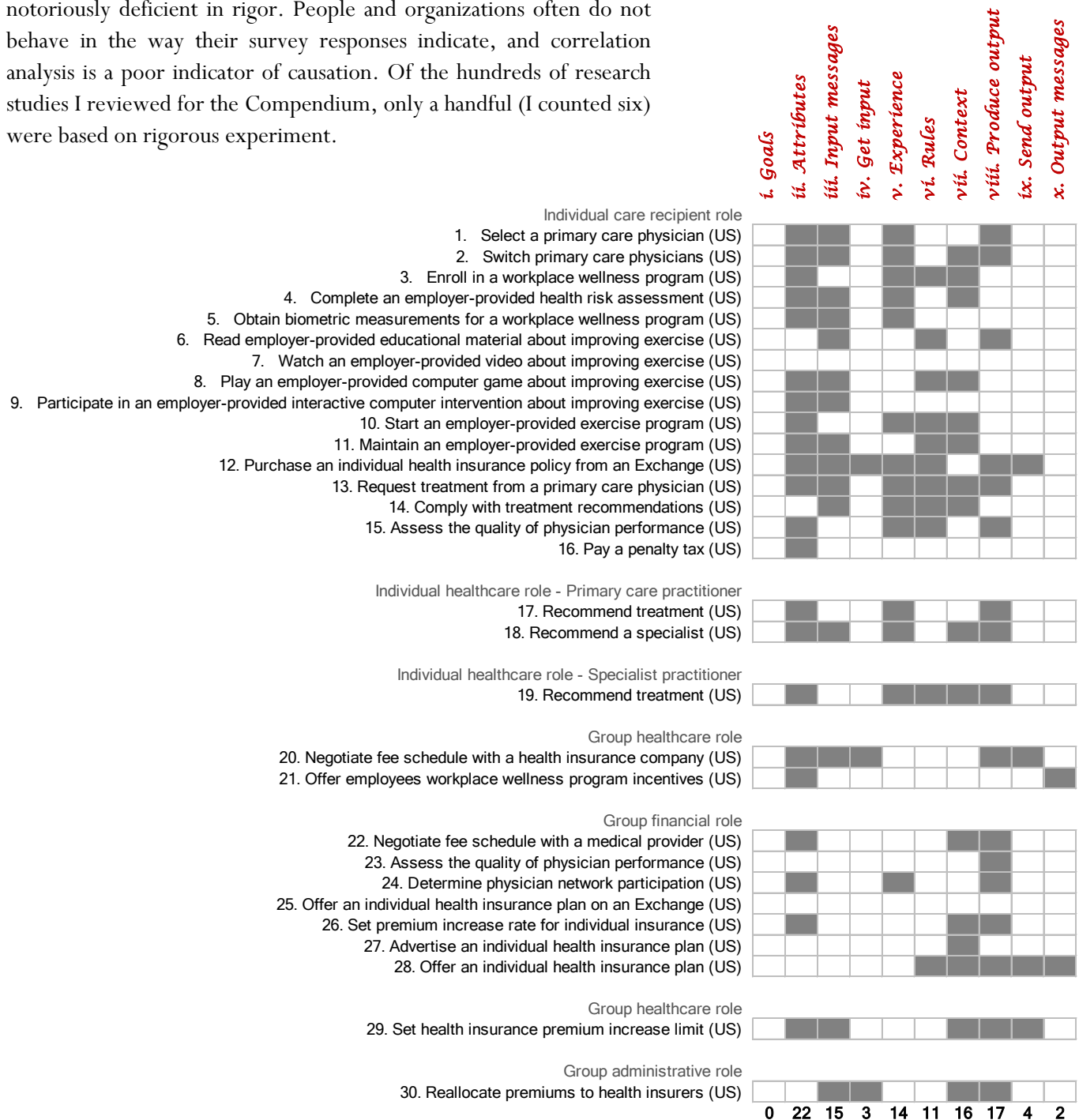
¹ To find the *Compendium*, go to the web page for this report, found on the Society of Actuaries website “www.soa.org” under Research > Completed research projects > Health.

² From the tale titled “The emperor’s new clothes”, about two weavers who promise to make the Emperor a new suit of clothes that will be invisible to those who are incompetent or stupid.

³ Keep in mind that underlying one greyed square may be copious research, whereas for another there may be only one or two studies.

B. INTERNATIONAL COMPENDIUM OF HEALTH BEHAVIOR continued

Although the summary chart is sparse—showing that little research has been performed for most of the behavior components—the situation is worse than it appears. Where work has been performed, researchers generally took easy over-trodden paths; they mainly based their research on correlation analyses and survey; approaches notoriously deficient in rigor. People and organizations often do not behave in the way their survey responses indicate, and correlation analysis is a poor indicator of causation. Of the hundreds of research studies I reviewed for the Compendium, only a handful (I counted six) were based on rigorous experiment.



B. INTERNATIONAL COMPENDIUM OF HEALTH BEHAVIOR *continued*

As the summary chart shows, researchers were especially attracted to the study of health behavior attributes. One explanation of this result is that the study of attributes is easily amenable to correlation analysis.

The summary chart also shows that research about individual behaviors is less sparse than research about the behavior of organizations. This is perhaps because organizations are harder to pin down with correlation studies and surveys. And it is particularly striking that research about the “Produce output” behavior component exists for only about half of the behaviors. This behavior component is particularly important, because it ties together all the other parameters. It is curious that it has been so widely ignored.

Not surprisingly, for nearly every behavior, there is no known simulation model incorporating it.

C. WHY IS IT SO HARD?

It was only two weeks into Ted Kaptchuk’s randomized experiment, but already nearly a third of his 270 subjects were complaining about awful side effects—sluggishness, redness and swelling, extreme pain. All the subjects had joined the study to relieve pain, but for many the study was making the pain worse. The study had two interventions: pills for half the subjects, and acupuncture for the other half. But the pills were filled with cornstarch, and the “acupuncture needles” were retractable shams that never punctured the skin. Nevertheless, subjects from both groups were complaining bitterly. The study’s purpose was not to compare two treatments. Rather, it was another of Ted Kaptchuk’s experiments to unravel another strand of the mechanism behind the mysterious response called the “placebo effect”. Using clever experiments, he and his colleagues are being spectacularly successful at understanding this psychological mystery.¹

And, as we will see in the next chapter, using clever experiments, Daniel Kahneman and his colleagues have been successful in understanding facts about people’s economic behavior.

Why is it so hard to do the same with health behavior?

¹ Feinberg (2013)

D. ISSUES AND FUTURE DIRECTIONS

The primary issue that this chapter brings to light is that health behavior researchers appear to be in a rut of correlation analyses and surveys applied to too few behavior components. Researchers have not produced the rigorous knowledge we need in order to make good decisions about our health systems. We need more health behavior experiments about all the health behavior components.

Another, related, issue is that it is difficult to determine what we know about a particular behavior. Research about a behavior may be scattered across decades and dozens of scientific journals, without any central resource pointing to the relevant work. The Compendium will become this central resource; it will bring together in one place all the research about particular health behaviors.

E. TO LEARN MORE

To more fully appreciate the poverty of our health behavior knowledge, thumb through the *International compendium of health Behavior*.

F. REVIEW AND A LOOK AHEAD

In this chapter, we explored the paucity of health behavior knowledge. In the next chapter, we will look at a field that is expanding our knowledge about behavior generally: behavioral economics.

(Don't forget to take a look at the exercises for this chapter. They start on the next page.)

EXERCISES

1. Choose one of the thirty health behaviors included in the first version of the Compendium. Then, without first looking at the Compendium, try to find all the research that has been done about the behavior. Lastly, compare what you find to what is in the Compendium. Was it challenging to find the existing research? Did you find something important that is missing from the Compendium?

SOLUTIONS

1. If you find something important that is missing from the Compendium, please let me know.

CHAPTER EIGHT: BEHAVIORAL ECONOMICS

I hope to enrich the vocabulary that people use when they talk about the judgments and choices of others.

Daniel Kahneman³

A. BEHAVIORAL ECONOMICS

In 1969, Daniel Kahneman taught psychology at the Hebrew University of Jerusalem. For a guest lecturer, he invited a rising star in decision research from the University of Michigan, Amos Tversky. During that visit, while dining at Café Ramon—according to Kahneman, a favorite haunt for bohemians and professors—they decided to work together to explore human intuition about statistics. What they discovered was surprising and fateful. Expert statisticians have intuitions about statistics that are like most people—extremely inaccurate. More important, Kahneman and Tversky discovered that they loved working together (see the sidebar).

One result of this fertile collaboration was behavioral economics, the study of how normal people—driven by normal social and emotional forces, and constrained by limited resources and cognitive abilities—make judgments and decisions. Behavioral finance and behavioral game theory are closely related fields. Behavioral finance studies why people in financial markets make systematic errors. Behavioral game theory studies how real people make strategic decisions. From here on when I refer to “behavioral economics”, I mean to also include behavioral finance and behavioral game theory.

In this chapter, I will review key contributions of behavioral economics and show how they might apply to the behavior of health system agents. I will argue that although these contributions are important—surely worthy of a Nobel Prize or two—they fall short of helping us accurately model the behavior of health system agents. Thanks to Daniel Kahneman, Amos Tversky, and their colleagues, we now have a rich new vocabulary to talk about judgments and choices, but we need to also develop new syntax—and maybe a dictionary and thesaurus—so that we can make meaningful statements about health behavior.

Kahneman and Tversky

Psychologists Daniel Kahneman and Amos Tversky shared one of the most productive collaborations in the history of social science. Starting in 1969, for more than 25 years they conducted groundbreaking experimental research about human judgment and decision making.

About their study of human statistical intuition, Kahneman’s wrote, “While writing the article that reported these findings, Amos and I discovered that we enjoyed working together. Amos was always very funny, and in his presence I became funny as well, so we spent hours of solid work in continuous amusement. The pleasure we found in working together made us exceptionally patient; it is much easier to strive for perfection when you are never bored. ... We were sufficiently similar to understand each other easily, and sufficiently different to surprise each other. We developed a routine in which we spent much of our working days together, often on long walks. For the next fourteen years our collaboration was the focus of our lives, and the work we did together during those years was the best either of us ever did.”¹

Their research had such a profound impact, both theoretically and practically, that in 2002 Kahneman became the first psychologist to win a Nobel Prize in Economics (an honor that, had he lived, Tversky would have shared).

For an excellent introduction to their work, see the YouTube videos of Kahneman presenting *Explorations of the mind*.²

¹ From the introduction to Daniel Kahneman (2011).

² Daniel Kahneman (2008a) and Daniel Kahneman (2008b).

³ From the introduction to Daniel Kahneman (2011).

B. ECONS AND HUMANS

The most important contribution of behavioral economics is to show clearly that one of the key assumptions of the elegant mathematical theory called neoclassical economics—the basis of what we think we know about markets and economies, from the trend of coffee prices to national health policy—is basically wrong.

The key assumption, called “rational choice” (see the sidebar), holds that people and organizations are rational: that we have the facts necessary to make good decisions, that we can correctly line up the options open to us, and that we can figure out which option is the best.² Conventional economics has a name for us: *homo economicus*, economic man.³ Richard Thaler, a prominent American behavioral economist with a lively sense of the absurd, shortened it to “Econ”.

Behavioral economics assures us that we are not Econs. We are humans. Our judgments and decisions are frequently irrational. We err, but our mistakes are neither random nor senseless. They are systematic and predictable.⁴

Behavioral economics takes the argument further: “We are pawns in a game whose forces we fail to comprehend. We think of ourselves sitting in the driver’s seat, with control over the decisions we make and the direction our lives will take. But this view is an illusion, reflecting our desire, how we want to view ourselves, more than reality. Our tendency is to vastly under-estimate the power that several forces (emotions, relativity, social norms, etc.) have over us. They affect experts just as much as non-experts.”⁴

Sixty percent of Americans are obese or overweight, and obesity increases risks of heart disease and diabetes, often leading to premature death. But still we reach for French fries and chocolate ice cream. Control and rationality are indeed illusions.

Shouldn’t our economic models reflect how we actually behave? And shouldn’t we develop ways to help us avoid our systematic and predictable errors?

The formidable shadow of rational choice

In their introduction to their important collection of papers about behavioral economics, Thomas Gilovich and Dale Griffin wrote:

“Any discussion of the modern history of research on everyday judgment must take note of the large shadow cast by the classical model of rational choice. The model has been applied most vigorously in the discipline of economics, but its considerable influence can be felt in all the behavioral and social sciences and in related policy fields such as law and medicine. According to this model, the ‘rational actor’ (i.e., the typical person) chooses what options to pursue by assessing the probability of each possible outcome, discerning the utility to be derived from each, and combining these two assessments. The option pursued is the one that offers the optimal combination of probability and utility.

“Calculations of probability and multiattribute utility can be rather formidable judgments to make, but the theory of rational choice assumes that people make them and make them well. Proponents of the theory do not insist that people never make mistakes in these calculations; but they do insist that the mistakes are unsystematic. The model assumes, for example, that the rational actor will follow the elementary rules of probability when calculating, say, the likelihood of a given candidate winning an election or the odds of surviving a surgical intervention.”¹

¹ Gilovich, Griffin, & Kahneman (2002)

² For a good discussion of this, see chapter two (Getting real about assumptions) of Altman (2012).

³ The term was first used by John Stuart Mill in 1836, in an essay about economics.

⁴ Thaler & Sunstein (2009)

C. HEURISTICS AND BIASES

Not only did behavioral economics humble the Econ. Not only did it show that we err. It also showed *how* we err, how humans make decisions.

Rather than laborious mathematical and logical processing beloved by Econs and economists, humans often use fast seat-of-the-pants “**heuristics**”—shortcuts, rules of thumb we evolved over millennia. The technical definition of heuristic is a simple procedure that helps us make adequate, but often imperfect, responses to hard questions. The word comes from the same root as “eureka”. In the sidebar I describe the three first heuristics Kahneman and Tversky identified. In Section G below (Behavioral economics and health behavior), I describe others and show how they might apply to health behavior.

Especially in our complex world, heuristics often produce biases—systematic departures from rational choice theory, errors that can cause havoc.

To try out your “representativeness” heuristic, answer this: A city cab was involved in a hit-and-run accident at night. In the city two cab companies operate, Green and Blue. 85 percent of the cabs in the city are Green cabs; 15 percent are Blue. A witness identified the cab as Blue. The court tested the reliability of the witness and concluded that the witness correctly identified each of the two colors 80 percent of the time, and failed 20 percent of the time. Knowing the witness identified the cab in the accident as Blue, what is the probability that it was Blue?

Three original heuristics

In their early work, Kahneman and Tversky identified three important heuristics:

Anchoring and adjustment: To make estimates, answer questions, or make choices, people often start with a largely arbitrary reference point (the anchor) and from there make adjustments that are often insufficient.

Availability: To construct a “prior” probability distribution about an issue, rather than objectively cull data from the literature or another objective source, people rely on recent or vivid personal memories.

Representativeness: People guess the probability of an event from the probability of a comparable event.¹



Pause to reflect

Take a moment to answer this question, but not too long. You’ll find the correct answer in the footnotes below.²

¹ To learn more about these early heuristics, see Daniel Kahneman, Slovic, & Tversky (1982) and Gilovich, et al. (2002).

² If you are like most people, you used the representativeness heuristic (based on the 80 percent probability of correctly identifying the cab color) and answered more than 50 percent, perhaps a lot more than 50 percent. However, if like a good Econ we use Bayes’ theorem to compute the answer, we get 41 percent: there is a 12 percent chance (0.15×0.80) that the witness would correctly identify a Blue cab as Blue, and a 17 percent chance (0.85×0.20) that the witness would incorrectly identify a Green cab as blue, giving a result of $0.12 / (0.12 + 0.17) = 0.41$. This example comes from Kahneman’s and Tversky’s work.

C. HEURISTICS AND BIASES continued

Two things about heuristics and biases are worth keeping in mind:

- **Few of them.** We are early in their study. Although hundreds of biases have been conjectured and prematurely named² —and often confused with underlying heuristics—there are not many well-studied heuristics.
- **Incorrigible.** There is not much we can do about biases, even if we are experts. Heuristics are so deeply ingrained that even though we know they exist and are error prone, we are powerless to halt them or improve their operation. Kahneman writes, “We would all like to have a warning bell that rings loudly whenever we are about to make a serious error, but no such bell is available...”³

D. SYSTEMS 1 AND 2

Not only did Kahneman identify several heuristics—many of which belong in the “Rules” behavior component—he also worked on a higher-level behavior hypothesis that we might place in “Produce output”. The hypothesis is that our behavior is based on the interactions of two systems that he called “System 1 and System 2”, or, for short, “Fast and slow”.⁴

System 1 refers to the fast, intuitive, and often emotion-driven way we make choices. It relies on heuristics. System 2 is ponderous, conscious, based on logic and algorithms—more like how an Econ decides. System 2 also monitors the quality of System 1 decisions, and can override System 1. System 1 quickly figures out “2 + 2”, but we call on System 2 to compute “17 x 24”.⁵

We are unaware of System 1. According to Kahneman, “The attentive System 2 is who we think we are. System 2 articulates judgments and makes choices, but it often endorses or rationalizes ideas and feelings that were generated by System 1.”⁶ In spite of its biases, System 1 is the genius of our behavior (see the sidebar).

The marvel of System 1

Kahneman does not want us to get the wrong impression about System 1.

In his book “Thinking fast and slow”, he writes, “I have spent more time describing System 1, and have devoted many pages to errors of intuitive judgment and choice that I attribute to it. However, the relative number of pages is a poor indicator of the balance between the marvels and the flaws of intuitive thinking. System 1 is indeed the origin of much that we do wrong, but it is also the origin of most of what we do right -- which is most of what we do.”¹

¹ Daniel Kahneman (2011)

² Just take a look at “en.wikipedia.org/wiki/List_of_cognitive_biases”.

³ Daniel Kahneman (2011)

⁴ Kahneman did not develop this hypothesis. It dates back at least 100 years, to the time of William James.

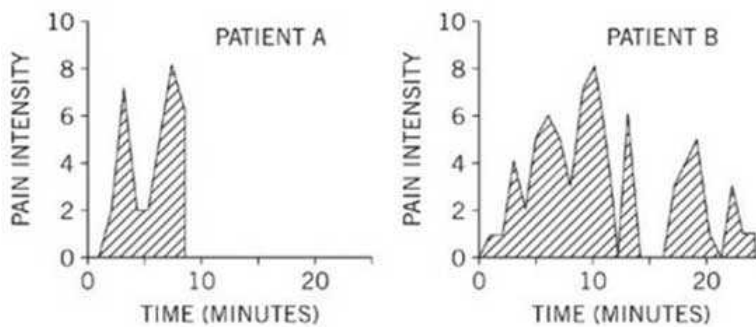
⁵ Indeed, it is System 2 that behavioral economics researchers use to probe and analyze System 1.

⁶ Daniel Kahneman (2011)

E. EXPERIMENTS


As we saw in Chapter seven (Overview of health behavior facts), it is rare for health behavior researchers to use experiments to shed light on how health behavior works. But in behavioral economics researchers routinely conduct experiments—another important contribution. These are not the randomized placebo-controlled experiments common in medical research, but careful observations of how people behave in controlled situations, more like experiments common in physics and experimental economics (see the sidebar).

For example, in the 1990s, Daniel Kahneman and colleagues asked 154 patients having colonoscopies to report the intensity of their pain, on a scale from 0 to 10, every 60 seconds. The charts below show what two patients reported.



As you see, patient B had a colonoscopy that lasted more than twice as long as patient A's, experienced pain intensity at least as great as patient A's, and accumulated much more pain than patient A (the shaded area).

After the procedure, patients were asked to rate the total amount of pain they experienced during the procedure. Who do you think reported more pain? Patient A or patient B?


Pause to reflect

Imagine yourself in their place. What would you have reported? To find out what the patients reported, read the footnote.²

Experimental economics

Behavioral economics researchers use many of the methods of the older field “experimental economics”, but add new twists.

For example, in their research, experimental economics researchers make experimental data and software publicly available, so that experiments can be replicated. They also avoid deceiving experiment participants. These are methods that behavioral economics researchers emulate.

But in their experiments, behavioral economics researchers also collect data that experimental economics researchers eschew, such as demographic data, self-reports, response times, and other cognitive measures. Behavioral economics researchers also often carefully craft the context of experiments, a detail that many experimental economics researchers consider unnecessary.¹

¹ For more information about the methods of experimental economics, see the first chapter of Camerer, Loewenstein, & Rabin (2004).

² Patient A reported twice as much pain as patient B, and this was a typical result. This study led to the discovery of the “peak-end rule” heuristic: The total amount of pain a person remembers is predicted by the average of the levels of pain reported at the worst moment of the experience and at its end. The duration of pain doesn't matter.

F. CHOICE ARCHITECTURE

In their book *Nudge*¹, Richard Thaler and Cass Sunstein introduce the concept of “choice architecture”: using behavioral economics results to organize and present choices to people in ways that will influence (or nudge) their behavior in beneficial directions. For example, a physician is a choice architect if the physician presents treatment options in a way that will “nudge” the patient toward choosing a beneficial treatment. A “nudge” prompts a person’s behavior in a certain way, without forbidding any options or significantly changing economic incentives. To count as a nudge, a person should also be able to easily and cheaply avoid it.

Thaler and Sunstein point out that there are many parallels between choice architecture and traditional architecture. One important parallel is that there is no “neutral” design. Everything in a building’s design—even apparently insignificant details, such as the direction that doors swing open or the location of bathrooms—can have major impacts on behavior.

In the language of behavioral components, a choice architect manages the “Input messages” and “Context” components of behavior, to influence how a person will behave.

Following are principles of good choice architecture that Thaler and Sunstein proposed:

- **Provide a default option.** Use a beneficial default option.
- **Expect error.** Expect humans to make mistakes, and help them minimize adverse effects from errors.
- **Give feedback.** To help people improve their performance, provide feedback. Let them know when they are making beneficial decision, and when they are not.
- **Clarify alternatives.** Help the person making a decision to understand the alternatives that may make them better off.
- **Structure complex choices.** Keep the number of alternatives low, but show relevant alternatives in a clear way.
- **Provide incentives.** Point out the salient incentives for each choice.

Many organizations are implementing choice architectures, and at least one is researching them for health systems (see the sidebar).

CHIBE

One organization, the Center for Health Incentives and Behavioral Economics (CHIBE), is starting to explore how to apply behavioral economics results to improve health systems.

Founded in 2008 by the University of Pennsylvania and the Center for Behavioral Decision Research at Carnegie Mellon University, and funded by the National Institutes of Health, CHIBE is one of the first organizations dedicated to applying behavioral economics research results to improve health systems.

Following are examples of CHIBE projects:

Medication adherence: This project explores behavioral economics interventions to overcome cognitive and motivational barriers to medication adherence.

Cardiovascular risk: This project tests whether behavioral economics choice architecture can improve the uptake of comparative effectiveness research about cardiovascular disease risk.

Healthier diet: This project explores ways to use behavioral economics results to encourage consumption of healthier foods.²

¹ Thaler & Sunstein (2009). Kahneman calls this book the “bible of behavioral economics”.

² For more information about CHIBE, go to “chibe.upenn.edu”.

G. BEHAVIORAL ECONOMICS AND HEALTH BEHAVIOR

Showing the gulf between Econs and humans, shedding light on behavioral heuristics and biases, exploring Systems 1 and 2, employing behavioral experiments, and inventing choice architecture—these are major contributions to our understanding about how people behave and how to influence their behavior. But, aside from CHIBE’s incipient efforts, researchers have done little to apply the insights and methods of behavioral economics to health behavior.

As the sidebar illustrates, applying the insights and methods of behavioral economics could improve—perhaps revolutionize—how we view and understand health behavior and health systems.

This section focuses on key behavioral heuristics that behavioral economics researchers have discovered, and shows how we might apply these to health behavior. The section presents a description of each heuristic and how it might apply to health behavior, accompanied by a discussion of the results.

Perhaps because of the almost random manner they were discovered, no one has yet arranged the heuristics of behavioral economics in a useful order. They are usually presented scattershot, often as independent curiosities.² This section places each heuristic in the behavioral component to which it most commonly applies. Most of the heuristics end up in the “Rules” component. But some do not.

The chart on the next page shows how the heuristics might apply to the 30 behaviors in the initial version of the *International compendium of health behavior* that we explored in Chapter seven (Overview of health behavior facts). If a heuristic applies to a behavior, the intersection is colored grey.³

The chart shows that few heuristics apply to organizational or group health behavior, that no behavior is fully explained by heuristics (probably a gap in research), and that no heuristic is in the “Attributes” behavior component, the focus of most current health behavior research.

Health insurance coverage: bringing human behavior front stage

When policymakers and analysts think about health insurance coverage—such as coverage under U.S. health reform—they usually focus on the role of market forces. The role of individual health behavior, how real people choose health insurance, remains backstage.

They assume that people are Econs; that they know what they need, that they know their wealth and income constraints, that they will accurately evaluate the costs and benefits of insurance options, that they will respond to economic incentives, and that they will have perfect willpower to carry out their perfect decisions.

But behavioral economics provides abundant evidence that such assumptions may be wrong. No matter how well U.S. health system policies are written to work with Econs as the actors, the performance of real people may provide a dramatically different spectacle. Instead of Econs happily smiling and singing paeans to policy architects, we may see utterly confused humans falling off the stage.

Before implementing such policies, perhaps we should take time for a dress rehearsal, time to bring human health behavior front stage and see how it performs, before the curtain goes up.¹

¹ The idea for this sidebar came from Baicker, Congdon, & Mullainathan (2012).

² In the tables on the following pages, you may also notice that there is considerable overlap among several heuristics.

³ Strictly speaking, in addition to heuristics, the chart also shows how two behavioral economics hypotheses, “System 1 and System 2” and “Prospect theory” apply to health behaviors. These hypotheses are in the “Produce output” behavior component.

G. BEHAVIORAL ECONOMICS AND HEALTH BEHAVIOR *continued*

For each behavior component, in the following tables I describe its key behavioral economics heuristics. For each heuristic, I then discuss relevant health behavior applications.

i. Goals

Behavioral economics results	Health behavior applications
<p>Loss aversion. People would rather avoid a loss than secure a gain. A potential loss can be twice as psychologically powerful as a potential gain.¹ One of the key features of Kahneman’s Prospect theory (described in Chapter eleven) is that people do not view gains and losses symmetrically.²</p> <p>Kahneman wrote, “The concept of loss aversion is certainly the most significant contribution of psychology to behavioral economics.”³</p>	<p>When patients were given a choice between surgery and radiation therapy, describing surgery outcome statistics as a 90 percent survival rate yielded a significantly higher preference for surgery than when described as a 10 percent mortality rate.⁴</p> <p>This result underlies the potential power of the ACA penalty tax. Under health reform, if people do not purchase health insurance, many will have to pay a penalty tax, an income loss many would rather avoid.</p> <p>This result could be useful in designing wellness program participation incentives. For example, a wellness program might include a feature that if an employee did not participate, something—perhaps something as nominal as a coffee mug used to advertise the program—would be taken away.</p>
<p>Endowment effect: People often demand more to give up an object than they would be willing to pay to acquire it. They like to keep their rewards. This result is similar to “loss aversion” (under i. Goals) and “status quo” (under vi. Rules).⁵</p>	<p>This result could be useful in designing physician performance incentives. Give physicians a reward for participating in the incentive program, but take it away if they don’t meet program performance requirements.</p>
<p>Regret avoidance: People want to avoid regretting their decisions.⁶</p>	<p>This result could be helpful to understand physician-induced demand (intensity of physician prescriptions and frequency of referrals and patient visits).</p>

¹ Thaler & Sunstein (2009)

² Altman (2012), Daniel Kahneman (2011)

³ Daniel Kahneman (2011)

⁴ McNeil, Pauker, Sox, & Tversky (1982)

⁵ Thaler & Sunstein (2009). For an interesting comparison of endowment effect, loss aversion, and status quo, see “Anomalies: the endowment effect, loss aversion, and status quo bias” in Daniel Kahneman & Tversky (2000).

⁶ Thaler & Sunstein (2009)

G. BEHAVIORAL ECONOMICS AND HEALTH BEHAVIOR continued

ii. Attributes

Behavioral economics results	Health behavior applications
None.	

As we saw in Chapter seven (Overview of health behavior facts) most health behavior researchers focus their efforts on discovering how health behavior varies by agent attributes. Behavioral economics researchers, however, have little to say about the variation of behavior heuristics by agent attributes.

G. BEHAVIORAL ECONOMICS AND HEALTH BEHAVIOR *continued*

iii. Input messages

Behavioral economics results	Health behavior applications
<p>Default choice: In a choice set, people have an exaggerated preference for the default option.¹</p>	<p>If the default option for organ donation at death is to not donate, most people won't. But if the default option is to donate, most will.²</p> <p>In presenting health insurance plan options for consumers to purchase, this result could indicate that the default option should be to purchase a plan that would be beneficial for most people.</p>
<p>Choice overload: As the number of options in a choice set increases, people often become overwhelmed and choose nothing.³</p>	<p>In communicating alternative treatments to patients, this result could indicate that the physician should keep the number of choices manageable.</p> <p>In presenting health insurance plan options for consumers to purchase, this result could indicate that the number of choices should be kept low.</p>
<p>Crowding out: If people are intrinsically motivated to perform a behavior, a small monetary incentive can decrease the behavior because it can "crowd out" intrinsic motivations.⁴</p>	<p>This result could help employers design wellness program participation incentives: For health promotion behaviors that most people intrinsically want to perform (such as eating healthier food) the employer might use cooperation or competition to encourage the behavior, rather than small monetary incentives.</p>
<p>Extremeness aversion: In a choice set, people tend to choose the option that is a compromise. For example, people won't buy the cheapest or the most expensive item on a wedding registry.⁵</p>	<p>This result could help employers design wellness program participation incentives: If the employer wants employees to choose a particular behavior, it might flank the choice by one that is harder to implement and one that is easier.</p>

¹ Camerer, et al. (2004), Altman (2012)

² Altman (2012), Thaler & Sunstein (2009)

³ Baicker, et al. (2012)

⁴ Mellstrom & Johannesson (2008)

⁵ Thaler & Sunstein (2009)

G. BEHAVIORAL ECONOMICS AND HEALTH BEHAVIOR *continued*

iv. Get input

Behavioral economics results	Health behavior applications
<p>Reference dependence: People interpret information based on references and cues in the information.¹ This result is also called “framing”.</p>	<p>In learning about the results of a specific operation, if physicians hear “ninety out of one hundred patients are alive”, they are far more likely to recommend the operation than if they hear “ten out of one hundred patients are dead”.²</p> <p>People are more likely to engage in self-examination for skin and breast cancer if they are told not about the reduced risk if they do so, but about the increased risk if they fail to do so.³</p> <p>To encourage people to purchase health insurance, based on this result a marketer might communicate information about people who had high medical expenses that were covered by insurance.</p>
<p>Confirmation: People focus on evidence that supports their views, and ignore contrary evidence.⁴</p>	<p>People who believe that their physicians practice with high quality will focus on evidence that supports such belief, and ignore contrary evidence.⁵</p> <p>This result helps us understand the reluctance among many patients to switch their physicians.</p>
<p>Substitution: To answer a hard question, people often substitute a related, but easier, one.⁶</p>	<p>This result might help us understand how patients and physicians quickly respond to hard questions, and alert us to the likely error of such responses.</p>
<p>Misperception of complexity: People often misunderstand complex information.⁷</p>	<p>To accurately estimate costs of health insurance, people may have difficulty figuring out premiums, cost-sharing provisions, and other factors.⁸</p>

¹ Daniel Kahneman & Tversky (2000), especially the chapter titled “Rational choice and the framing of decisions”.

² Thaler & Sunstein (2009)

³ Thaler & Sunstein (2009)

⁴ Altman (2012)

⁵ P. A. Diamond & Vartiainen (2007)

⁶ Daniel Kahneman (2011)

⁷ Baicker, et al. (2012)

⁸ Baicker, et al. (2012)

G. BEHAVIORAL ECONOMICS AND HEALTH BEHAVIOR *continued*

v. Experience

Behavioral economics results	Health behavior applications
<p>Availability: To construct a “prior” probability distribution about an issue, rather than objectively cull data from the literature or another objective source, people rely on recent or vivid personal memories.¹</p> <p>This is one of the original three heuristics identified by Kahneman and Tversky.</p>	<p>This result helps us understand how people choose their physicians. Rather than rely on an examination of systematic information collected about physician qualifications or performance, a person often selects a physician based on reports from family and friends. These reports are often distorted, because they present only what is most vivid or memorable in the minds of family and friends.</p> <p>It also helps explain how physicians choose treatments to recommend. When deciding treatment options, physicians often rely on local and low-cost sources of information, rather than perform research for evidence-based alternatives. This also helps to explain the phenomenon of “small area variation”.²</p> <p>Given this result, it could be helpful to remind health system decision makers about true probability distributions and systematic information.</p>
<p>Over-confidence: People tend to be too confident in their judgments.³</p>	<p>Asked to envision their future, people typically say that they are far less likely than their friends and colleagues to have a heart attack or get cancer. Gay men systematically underestimate the chance they will contract AIDS, most smokers believe they are less likely than non-smokers to be diagnosed with lung cancer or heart disease, and older people underestimate the likelihood they will suffer major diseases.⁴</p> <p>This result might help explain why it is difficult for many people to engage in health promotion activities, why physicians can be over-confident in their diagnostic and prescribing abilities, and why some people avoid purchasing health insurance.</p>

¹ Thaler & Sunstein (2009), Daniel Kahneman (2011)

² Daniel Kahneman, et al. (1982)

³ Thaler & Sunstein (2009), Daniel Kahneman (2011)

⁴ Thaler & Sunstein (2009)

G. BEHAVIORAL ECONOMICS AND HEALTH BEHAVIOR *continued*

v. Experience continued

Behavioral economics results	Health behavior applications
<p>Priming: People tend to behave in conformance with what is most prominent in their minds. ¹ A closely related result is the “mere measurement effect”: merely asking what a person intends to do increases the likelihood that the person will act in conformance with the person’s answer.</p>	<p>If people are asked how often they expect to floss their teeth in the next week, they floss more. If they are asked whether they intend to consume fatty foods in the next week, they consume fewer fatty foods. In general, if people are asked whether they intend to eat certain foods, to diet, or to exercise, their answers affect their behavior. ²</p>
<p>Affect: Emotions can have a dramatic impact on decision making. Decisions under emotionally aroused or “hot” states tend to be significantly different from “cold” calculated decisions. Our assessment of risk is often colored by our emotional attitude. ³</p>	<p>Knowing that emotions can affect our decisions helps us understand most health behaviors.</p>
<p>Misperception of past experiences: People often incorrectly remember and evaluate past experiences. ⁴</p>	<p>Patients remember the painfulness of a medical procedure by averaging the level of pain at the worst moment and at the end of the procedure. Other attributes, such as how long the pain continued, do not seem to matter. ⁵</p> <p>A physician could ensure that patients retain a more favorable memory of a painful procedure by adding to it a medically superfluous period of diminished pain, or even of pleasure. But such pleasure, or even diminished pain, might lead to greater utilization.</p>

¹ Thaler & Sunstein (2009), Daniel Kahneman (2011)

² Thaler & Sunstein (2009)

³ Ariely (2008b), Altman (2012), Daniel Kahneman (2011)

⁴ “New challenges to the rationality assumption” in Daniel Kahneman & Tversky (2000).

⁵ “New challenges to the rationality assumption” in Daniel Kahneman & Tversky (2000) and Daniel Kahneman, Diener, & Schwarz (1999).

G. BEHAVIORAL ECONOMICS AND HEALTH BEHAVIOR *continued*

vi. Rules

Behavioral economics results	Health behavior applications
<p>Anchoring and adjustment: To make estimates, answer questions, or make choices, people often start with a largely arbitrary reference point (the anchor) and from there make adjustments that are often insufficient.¹</p> <p>This is one of the original three heuristics identified by Kahneman and Tversky.</p>	<p>Based on this result, in negotiating a fee schedule, negotiators might start with an anchor that is at the extreme end of where they would like to settle. For example, a provider network might start with a high number, and a health insurer might start low.</p>
<p>Representativeness: People guess the probability of an event from the probability of a comparable event. This heuristic leads to making decisions based on stereotypes, and can cause people to confuse random fluctuations with causal patterns.²</p> <p>This is one of the original three heuristics identified by Kahneman and Tversky.</p>	<p>American public health officials receive more than one thousand reports a year about suspected cancer “clusters”, places where there are unusually high rates of cancer. Most of the cases turn out to be random fluctuations.³</p> <p>This heuristic may help explain how people select physicians and how physicians select the specialists to whom they refer patients. Both may be based on stereotypes.</p>
<p>Social conformity: People have a strong tendency to conform to social norms, to do things because others do.⁴</p>	<p>Researchers have found that many undesirable health behaviors—such as smoking and excessive eating—are “contagious”. If many in your social group have such behaviors, chances are you will too.</p> <p>To encourage Montana teens not to smoke, an advertising campaign merely stated, “Most (70 percent) of Montana teens are tobacco free”. The ad decreased teen smoking.⁵</p> <p>Using this result, marketing material designed to encourage healthful behavior in a certain social group could highlight that many people in the group are performing the desired behavior.</p>

¹ Thaler & Sunstein (2009), Daniel Kahneman (2011)

² Thaler & Sunstein (2009), Daniel Kahneman (2011)

³ Thaler & Sunstein (2009)

⁴ Thaler & Sunstein (2009), Altman (2012)

⁵ Thaler & Sunstein (2009)

G. BEHAVIORAL ECONOMICS AND HEALTH BEHAVIOR *continued*

vi. Rules continued

Behavioral economics results	Health behavior applications
<p>Status quo: People have a strong tendency to continue with the status quo.¹ Inertia is powerful. This result is one reason that the “default choice” (a result under iii. Input messages) influences behavior.</p>	<p>When Harvard University added new healthcare plan options, faculty members hired before the new options were available were allowed to switch to the new options. Researchers found that, compared with newer faculty members, older faculty members tended to stick to their previous options.²</p> <p>This result could help us understand why many people do not change their physicians even when they have ample evidence that other physicians would serve them better. More generally, it helps us see why many people are loathe to change health behaviors such as smoking, over-eating, and unprotected sex, even when they understand that such behaviors could kill them.</p> <p>It also helps us understand why physicians are slow to change prescribing habits, even after learning about superior practices.</p>
<p>Small sample generalization: People often generalize about facts obtained from a small sample to an entire universe. They also treat facts from a small sample with the same level of trust as they do facts from a larger sample.³</p>	<p>This result helps us understand why physicians continue to use treatments they have seen work for a few patients, instead of treatments that studies have shown work better for large samples of patients.</p>
<p>Recognition: People choose what they recognize.⁴</p>	<p>This result helps us understand how people choose physicians, health insurance plans, and treatments. For example, many people may choose “Blues” plans, because they are well-known. Branding matters.</p>
<p>Risk seeking for losses: People often gamble to try to prevent any loss rather than take a small loss with certainty.⁵</p>	<p>In offering health insurance to consumers, this result indicates that it could be more successful to frame health insurance as a way to avoid loss.</p>

¹ Thaler & Sunstein (2009)

² Camerer, et al. (2004)

³ Altman (2012)

⁴ Altman (2012)

⁵ Daniel Kahneman, et al. (1982)

G. BEHAVIORAL ECONOMICS AND HEALTH BEHAVIOR *continued*

vi. Rules continued

Behavioral economics results	Health behavior applications
<p>Mis-prediction of future feelings: People often have difficulty predicting future states or feelings.¹</p>	<p>This result helps us understand why people do not strive to achieve better health states in the future. They have trouble predicting how such states would feel.</p>
<p>Preference projection: People expect their future preferences to be close to their present ones. This result causes people to underestimate the extent to which they will adapt to future circumstances.²</p>	<p>People were asked to choose either a healthy snack or a rich unhealthy snack to be delivered a week later. Some were asked when they were hungry (in the late afternoon), and some were asked when they were satiated (after lunch). The number who chose the rich unhealthy snack in the first group was 78 percent, but in the second group was 42 percent.³</p> <p>This result can help us understand why people sometimes seek excessive care for their medical conditions.</p>
<p>Hyperbolic discounting: People tend to discount the value of an event in the future by a factor that increases—sometimes dramatically—with the length of delay. This type of discounting is markedly different from typical economic discounting, which employs a constant discount factor.⁴</p>	<p>This result helps us understand why people are reluctant to delay immediate gratification (such as in diet and relaxation) for future health benefits.</p>
<p>Procrastination: People put off doing what they know they should do.⁵</p>	<p>Researchers found that imposed deadlines reduced procrastination.⁶</p> <p>Based on this result, employers could impose deadlines (perhaps tied to incentives) for people to obtain health screening examinations, a frequent object of procrastination.</p>

¹ Daniel Kahneman, et al. (1999). See also “A bias in the prediction of tastes” in Daniel Kahneman & Tversky (2000).

² DellaVigna (2009)

³ DellaVigna (2009)

⁴ P. A. Diamond & Vartiainen (2007), Chapter two.

⁵ Ariely (2008b)

⁶ Ariely (2008b)

G. BEHAVIORAL ECONOMICS AND HEALTH BEHAVIOR *continued*

vi. Rules continued

Behavioral economics results	Health behavior applications
<p>Outcome sequence preferences: People prefer sequences of outcomes that increase in value.¹</p>	<p>To increase treatment compliance, a series of treatment steps could be presented as increasing in value, with the last step more important than the first.</p>
<p>Intensity matching: To supply an answer to a hard question that involves an intensity scale, people will often provide the intensity of an answer to a related but simpler question, even if the scale is different.²</p>	<p>This result helps us understand how patients and physicians often answer hard questions quickly, but incorrectly.</p>
<p>Planning optimism: People tend to be unrealistically optimistic about the time it takes to complete projects.³</p>	<p>This result may help us understand why people find it difficult to maintain an exercise program. They do not experience desired results as quickly as they had planned.</p>

vii. Context

Behavioral economics results	Potential health system applications
<p>Relative positioning: People care about levels of performance, possessions, and well-being relative to others, rather than in absolute terms.⁴ This result is closely related to “social conformity” in <i>vi. Rules</i>.</p>	<p>This result helps us understand why people with low levels of well-being may not want to change, if their neighbors also have low levels of well-being.</p>

¹ See the chapter “Preferences for sequences of outcomes” in Daniel Kahneman & Tversky (2000).

² Daniel Kahneman (2011)

³ Thaler & Sunstein (2009)

⁴ Altman (2012), Ariely (2008b)

G. BEHAVIORAL ECONOMICS AND HEALTH BEHAVIOR *continued*

viii. Produce output

Behavioral economics results	Health behavior applications
<p>System 1 and System 2 (hypothesis): People have two kinds of thinking, System 1 (also called Fast, Automatic, or Intuitive thinking) and System 2 (also called Slow or Reflective thinking). System 1 is unconscious, effortless, associative, and fast. It employs many of the heuristics listed above. System 2 is conscious, effortful, deductive, and slow. The systems—especially in our complex world—are often at odds with one another.</p>	<p>This hypothesis might help us understand most individual health behaviors.</p>
<p>Prospect theory (hypothesis): An alternative to expected utility theory of neoclassical economics, prospect theory describes how people make risky decisions. Under prospect theory, value is assigned to gains and losses rather than to final assets, and probabilities are replaced by decision weights. The value function is normally concave for gains, convex for losses, and generally steeper for losses than for gains. Decision weights are generally lower than corresponding probabilities, except that people generally over-weight low probabilities. Chapter eleven (Five useful health behavior hypotheses) describes prospect theory in detail.¹</p>	<p>Prospect theory helps us understand all health behavior that involves risky decisions,² such as how people decide which treatment regimen to follow.</p>

Although these hypotheses are important contributions to our understanding of human behavior, neither is a fully-developed “Produce output” behavior component. Neither describes how or when a person calls upon the many behavioral economics heuristics, or how the results of these heuristics are combined and packaged for a behavior output. These hypotheses fall short of providing the syntax we need to combine the rich new vocabulary of behavioral economics into useful sentences.

¹ See “Part one: Prospect theory and extensions” in Daniel Kahneman & Tversky (2000).

² A risky decision is one for which we do not know the outcome beforehand.

G. BEHAVIORAL ECONOMICS AND HEALTH BEHAVIOR continued

ix. Send output

Behavioral economics results	Health behavior applications
None	

x. Output messages

Behavioral economics results	Health behavior applications
None	

H. ISSUES AND FUTURE DIRECTIONS

Many have tried to disprove the validity of behavioral economics results, but they have failed (see the sidebar). Nevertheless, there are significant issues to address

- **Unclear terminology.** Even though Daniel Kahneman and his colleagues have provided us a rich new vocabulary to describe human behavior, the vocabulary can be unclear and misused. For example, many speak of biases when they mean heuristics, and vice versa.
- **Disorganized.** There are many heuristics, and hundreds of biases, but they have not yet been organized in a coherent structure. Our arrangement of heuristics according to behavior components is a first organizing step.
- **Incomplete.** The heuristics and hypotheses are far from complete. They do not address groups or organizations, nor do they address all behavior components.
- **Not health behavior specific.** Most importantly, researchers have not yet adequately employed the insights and methods of behavioral economics to shed light specifically on health behavior.

Critiques

Following are common criticisms of behavioral economics results:

- **We can't be that dumb.** Humans have travelled to the moon and discovered the Higgs boson. We must be more rational than behavioral economics suggests.
- **It's only parlor games.** Behavioral economics results are merely lab curiosities that arose because study participants were tricked.
- **The bar is too high.** Behavioral economics researchers hold study participants to rationality standards that are unreasonably high.
- **Lab experiments are misleading.** Lab experiments do not reflect behavior in real life. Only "revealed preferences" of neoclassical economics are valid indicators of how people behave in real situations.

But, in the face of evidence, all such critiques have crumbled.¹

¹ For a more complete discussion of the critiques, see Gilovich, et al. (2002).

I. TO LEARN MORE

To learn more about behavioral economics, you may enjoy exploring the following key resources. In the description of each resource I include:

- **Reference:** A reference to the resource, giving the primary author, the year published, and the title. The full citation for the resource is in the “Resources” section at the end of this report.
- **Format:** Its format (book, book section, journal article, presentation, report, or video).
- **Annotation:** A brief comment introducing the resource.
- **Level:** One asterisk (*) indicates a general introductory resource, two (**) indicate a more specific or more advanced resource, and three (***) indicate a resource specifically about applications of behavioral economics in health care.

The resources are arranged according to the primary author’s name. A nice place to start is the article by Craig Lambert.

Altman (2012): *Behavioral economics for dummies*. Book*

An introduction to the fields of behavioral economics and behavioral finance. Self-contained chapters help you easily find and focus on a topic of interest. A concise overview that is crisp and clear.

Ariely (2008a): *Authors @ Google: Dan Ariely*. Video*

Dan Ariely discussing his book “Predictably irrational”. Lecture format. Entertaining and informative. About 56 minutes.

Ariely (2008b): *Predictably irrational: the hidden forces that shape our decisions*. Book*

An exploration of major forces—like emotions, social norms, context, and sexual arousal—behind our illogical decisions. With experiments that are imaginative and often humorous, Ariely shows why irrational thought often trumps level-headed thinking, and offers insight into why people make the same mistakes repeatedly. Entertaining and insightful.

Ariely (2008, 2009): *Predictably irrational*. Series of seven videos*

Dan Ariely discussing his book “Predictably irrational” and behavioral economics in general. Lecture format. A pithy introduction to behavioral economics. About 26 minutes for all seven videos.

I. TO LEARN MORE continued

Ariely (2010): *The upside of irrationality: the unexpected benefits of defying logic at work and at home*. Book*

Based on behavioral economics research results, Ariely recommends ways to change behavior to improve how we work, live, and love. Entertaining and insightful.

Ariely (2012): *The honest truth about dishonesty: how we lie to everyone--especially ourselves*. Book*

An exploration of the behavioral economics of dishonesty. Provocative and entertaining.

Bickel & Vuchinich (2000): *Reframing health behavior change with behavioral economics*. Book***

A collection of contributions from different authors, showing how behavioral economics results can be applied to a broad array of health behaviors, including smoking, drug and alcohol abuse, and overeating. The second chapter presents behavioral economic methods that are suitable for studying health behavior.

Camerer (2003): *Behavioral game theory: experiments in strategic interaction*. Book**

A presentation of the most important research results in behavioral game theory. The first chapter provides an excellent introduction to the field, and its second appendix (Experimental design) provides guidelines for performing behavioral economics experiments. Well-written. Textbook.

Camerer, et al. (2004): *Advances in behavioral economics*. Book**

A collection of 25 of the most important articles about behavioral economics published since 1990, emphasizing applied articles.

Cartwright (2011): *Behavioral economics*. Book*

An overview of behavioral economics from the perspective of game theory. Textbook. Easy to read.

I. TO LEARN MORE continued

DellaVigna (2009): *Psychology and economics: evidence from the field*. Journal article**

Presentation of empirical evidence supporting the research results of behavioral economics. Particularly interesting is the discussion of empirical evidence about how firms and politicians respond to non-rational behavior.

P. A. Diamond & Vartiainen (2007): *Behavioral economics and its applications*. Book**

A collection of articles showing how behavioral economics research results can be applied in fields beyond economics and finance, such as public policy, health care, and organizational behavior. The article about health care is especially valuable. Each article is followed by excellent expert commentary.

Gilovich, et al. (2002): *Heuristics and biases: the psychology of intuitive judgment*. Book**

A collection of important behavioral economics articles. One article discusses research that compares expert clinical prediction with algorithmic methods (called "actuarial methods" in the article).

D. Kahneman (2002): *Prize lecture by Daniel Kahneman*. Video*

Nobel Prize presentation about the basics of behavioral economics. Lecture format.

Daniel Kahneman (2008a): *Explorations of the mind—Intuition: the marvels and the flaws*. Video*

Daniel Kahneman talking about his work in behavioral economics. Lecture format.

Daniel Kahneman (2008b): *Explorations of the mind—Well-being, Hitchcock Lectures*. Video***

Daniel Kahneman talking about his work in behavioral economics. Lecture format

I. TO LEARN MORE continued

Daniel Kahneman (2011): *Thinking, fast and slow*. Book*

A summary of Kahneman's work in behavioral economics. A wonderfully humble account of wisdom accumulated over five decades. An entertaining theme of the book is how we might use the vocabulary of behavioral economics to talk with colleagues around the water cooler about human behavior. Each chapter ends with what we might say. For example: "He likes the project, so he thinks its costs are low and its benefits are high. Nice example of the affect heuristic." This is my favorite book about behavioral economics, because reading it is like having a friendly conversation with the genial Daniel Kahneman.

Daniel Kahneman, et al. (1999): *Well-being: the foundations of hedonic psychology*. Book***

A collection of articles about behavioral experiments related to happiness, health, and hedonism. Kahneman et al. begin by announcing, "Our aim in editing this book was not at all modest: we hoped to announce the existence of a new field of psychology. Hedonic psychology—that could be its name—is the study of what makes experiences and life pleasant or unpleasant."

Daniel Kahneman, et al. (1982): *Judgment under uncertainty: heuristics and biases*. Book**

A classic of behavioral economics, presenting a colorful array of human judgmental heuristics and biases found in social, medical, and political situations. Well-written and interesting.

Daniel Kahneman & Tversky (2000): *Choices, values, and frames*. Book**

A classic of behavioral economics, presenting prospect theory as an alternative to traditional utility theory. A collection of papers published in various journals, introduced and summarized in the preface. It contains the seminal 1979 paper by Kahneman and Tversky about prospect theory.

Lambert (2012): *The marketplace of perceptions*. Article*

A short excellent introduction to behavioral economics. The author writes, "Today, behavioral economics is a young, robust, burgeoning sector in mainstream economics, and can claim a Nobel Prize, a critical mass of empirical research, and a history of upending the neoclassical theories that dominated the discipline for so long".

I. TO LEARN MORE continued

Pink (2009): *Dan Pink on the surprising science of motivation*. Video*

Daniel Pink arguing that we should reconsider our ideas about motivation. Entertaining.

Pink (2010): *Drive: the surprising truth about what motivates us*. Video*

Daniel Pink discussing his work on incentives and motivation. A fascinating animation style.

Thaler (1992): *The winner's curse: paradoxes and anomalies of economic life*. Book**

A presentation of how behavioral economics research explains several anomalies in traditional economic theory. Advanced but readable.

Thaler (2010): *Conversations with history: Richard H. Thaler*. Video*

Richard Thaler talking with host Harry Kreisler about behavioral economics and its implications for public policymaking. Thaler says, "Economic theory is elegant, simple, and wrong". He then goes on to give examples regarding human lack of self control and the obesity epidemic, the housing crisis, and other public policy issues. Fascinating discussion. Discussion format.

Thaler (2012): *Advances in behavioral finance: Volume II*. Book**

Twenty papers providing an overview of recent developments in behavioral finance.

Thaler & Sunstein (2009): *Nudge: improving decisions about health, wealth, and happiness*. Book*

Daniel Kahneman called this book "the bible of behavioral economics". The authors argue for using behavioral economics results to nudge people toward better decisions, without restricting their freedom of choice. This is where the authors introduced the terms "Econ" and "choice architect". Part III of the book contains three chapters about health-related nudges. Well-written and insightful.

I. TO LEARN MORE continued

Weber et al. (2007): *Asymmetric discounting in intertemporal choice: a query-theory account*. Journal article**

Results of three experiments about the behavioral economics concept of asymmetric discounting, and a discussion about how we might design decision environments that promote less impulsive behavior. Interesting and readable.

J. REVIEW AND A LOOK AHEAD

In this chapter, I introduced the new view of human behavior that behavioral economics provides, and I showed how we might apply this view to health behavior. This concludes Part III (Health behavior facts).

In Part IV (Health behavior theory) we will ask whether there are scientific theories of health behavior.

(Don't forget to take a look at the exercises for this chapter. They start on the next page.)

EXERCISES

1. Shakespeare's Hamlet says "What a piece of work is a man! How noble in reason, how infinite in faculty! In form and moving how express and admirable! In action how like an Angel! in apprehension how like a god!" Do you agree?
2. When a person chooses a health insurance plan from the website of a Health Insurance Exchange under U.S. health reform, name three heuristics the person might employ, and how the heuristics might lead the person to make a disadvantageous choice.
3. Are the heuristics in Exercise 2 part of System 1 or System 2? Are they conscious or unconscious? Can we change them?
4. In a powerful article that Steven Brill wrote for *Time* magazine, titled "Bitter pill: why medical bills are killing us", he describes several problems with the hospital "chargemaster", the database of retail (non-discounted) rates a hospital charges uninsured patients for each service and product. He writes, "Insurers with the most leverage, because they have the most customers to offer a hospital that needs patients, will try to negotiate prices 30% to 50% above Medicare rates rather than discounts off the sky-high chargemaster rates. But insurers are increasingly losing leverage because hospitals are consolidating by buying doctors' practices and even rival hospitals. In that situation—in which the insurer needs the hospital more than the hospital needs the insurer—the pricing negotiation will be over discounts that work down from the chargemaster prices rather than up from what Medicare would pay. Getting a 50% or even 60% discount off the chargemaster price of an item that costs \$13 and lists for \$199.50 is still no bargain. 'We hate to negotiate off of the chargemaster, but we have to do it a lot now,' says Edward Wardell, a lawyer for the giant health-insurance provider Aetna Inc." What behavioral economics heuristic explains why negotiating from a chargemaster is more problematic for health insurers than negotiating from Medicare rates?

SOLUTIONS

1. The results of behavioral economics would make us question at least part of this quote. Of course, Shakespeare may have meant it sardonically.
2. If there are many health insurance plans to choose from, the “Choice overload” heuristic (from the “Input message” behavior component) might lead the person to become overwhelmed and not choose a plan at all. If many of the person’s friends chose Plan A, the “Social conformity” heuristic (from the “Rules” component) might lead the person to also choose Plan A, regardless of its value. If the person recognized the name of the insurance company offering Plan B, but did not recognize the names of any other companies, the “Recognition” heuristic (from the “Rules” component) might mislead the person to simply choose Plan B.
3. The heuristics are part of System 1, are mainly unconscious, and are generally incorrigible.
4. The “Anchoring and adjustment” heuristic explains this phenomenon. The lawyer is right to hate to negotiate starting from the high chargemaster rates. The result is likely to be much higher than it would be if the negotiations were to start with the lower Medicare rates.

PART IV: HEALTH BEHAVIOR THEORY

A great scientific theory, like Newton's, opens up new areas of research. ... Because a theory presents a new way of looking at the world, it can lead us to ask new questions, and so to embark on new and fruitful lines of inquiry.

Philip Kitcher, 1982¹

A theory is a good theory if it satisfies two requirements: It must accurately describe a large class of observations on the basis of a model that contains only a few arbitrary elements, and it must make definite predictions about the results of future observations.

Stephen Hawking, 1988²

One needs a criterion more sophisticated than immediate predictability to assess a scientific theory—since when computational irreducibility is present this will inevitably be limited.

Stephen Wolfram, 2002³

¹ From the book *Abusing science: the case against creationism*, page 45. Philip Kitcher is a professor of the philosophy of science at Columbia University.

² From the book *A brief history of time*, tenth edition, page 10. Stephen Hawking is a highly respected theoretical physicist.

³ From Wolfram (2002), page 1196. Stephen Wolfram is one of the pioneers of complexity science.

INTRODUCTION

A scientific theory bundles vast fields of fact into a small package, while pointing to new vistas worth exploring. In this Part IV we ask if there are any scientific theories that succinctly capture the essence of the health behavior facts that we reviewed in Part III. This part consists of four chapters:

- **Scientific theory:** Reviews what a scientific theory is, and what a scientific health behavior theory should be.
- **Overview of health behavior theories:** Observes that today there are no scientific health behavior theories, and provides an overview of various health behavior hypotheses that may someday lead to scientific health behavior theories.
- **Five useful health behavior hypotheses:** Describes five health behavior hypotheses that are useful for modeling the behavior of agents in health system simulation models. These hypotheses are: rational choice theory, game theory, prospect theory, the belief-desire-intention model of agency, and the theory of planned behavior.
- **One good theory:** Proposes a program for developing scientific health behavior theories.

In this part I present three main ideas. First, although many of the names of hypotheses that researchers have developed to explain health behavior include the word “theory”, in fact none of them is a true scientific theory, and none reflects all—or even most—of the ten components of health behavior. Second, among these hypotheses, there are only a few that are useful for modeling the behavior of agents in agent-based simulations of health systems. And third, in order to develop true scientific theories of health behavior, there is much work to be done.

CHAPTER NINE: SCIENTIFIC THEORY

*Nature and nature's laws lay hid in night,
God said "Let Newton be" and all was light.*

Alexander Pope¹

A. PRINCIPIA

In 1687, Issac Newton, age 44 and childless, published the first great scientific theory, a theory that would become the basis of classical mechanics and guide scientific enterprise for the next three centuries.

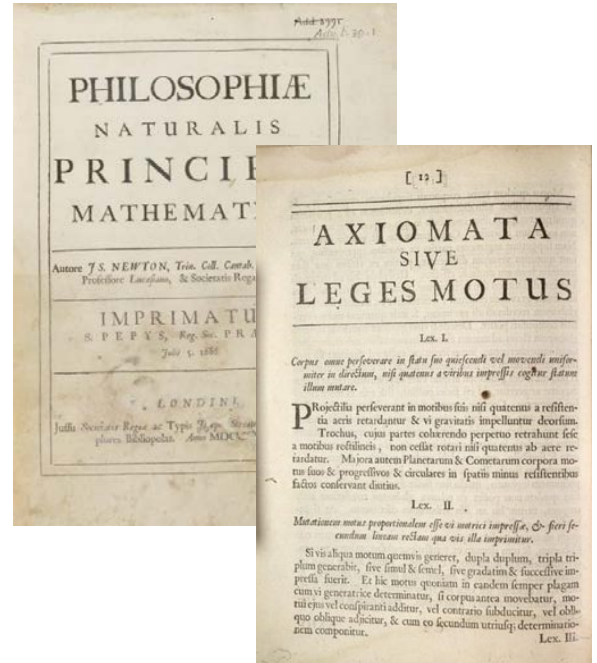
He titled his monograph *Philosophiae naturalis principia mathematica* (mathematical principles of natural philosophy, often simply called the *Principia*). In it Newton presents laws of motion and gravitation, which together explain the trajectory of a rock thrown into the air as well as the path of planets through the solar system, laws that have enabled the development of automobiles and spaceships (see the sidebar). As I write this, the rover *Curiosity* is meandering through the Gale crater on Mars; it is Newton's child.

B. THE ESSENCE OF SCIENTIFIC THEORY

Newton's laws were not born as bona fide scientific theory. Rather, to meet the standards for scientific theory, it took legions of scientists, countless experiments, and decades of maturation.

Scientific theory is a well-substantiated explanation of some aspect of the natural world, based on a body of facts that have been repeatedly confirmed through observation and experiment. Most philosophers of science agree that bona fide scientific theory must be²:

- **Consistent with all experimental results.** One inconsistent experimental result, if verified, nullifies a theory.
- **Supported by many independent strands of evidence.** It must be verified by several researchers and sundry experiments.
- **Able to make falsifiable predictions.** It must make specific predictions that can be tested and potentially disproved (falsified) through experiment.¹ However, as we shall see, some complexity scientists are questioning this criterion.



Newton's laws

In the *Principia* Newton presents the following simple laws:

- **First law of motion:** An object continues in a state of either rest or uniform motion in a straight line unless an external force acts upon it.
- **Second law of motion:** $F = ma$, where F is the net force acting upon the object, m is an object's mass, and a is its acceleration.
- **Third law of motion:** When one object exerts a force upon another, there is an equal but opposite force from the other object upon the first.
- **Law of gravitation:** $F = Gm_1m_2/r^2$, where F is the gravitational force between two objects, m_1 and m_2 are the masses of the objects, G is a gravitational constant, and r is the distance between the centers of the objects.

Together, these laws explain a vast number of natural facts.

¹ Although the famous English poet Alexander Pope wrote this epitaph for Newton, authorities did not allow it to be inscribed on his tomb.

² Poincaré (1982), Popper (1972), Suppe (1977). Poincaré originally published his book in 1913.

B. THE ESSENCE OF SCIENTIFIC THEORY continued

The best scientific theories are also strong (they explain a wide range of phenomena) and parsimonious (they are simple). Newton’s laws meet all these criteria, at least for phenomena within our common experience.¹ K

Other scientific theories that meet these criteria are the wave theory of light and the germ theory of disease.

C. HYPOTHESES, LAWS, MODELS, CONSTRUCTS, AND PARADIGMS

Because people often use terminology related to scientific theory in different ways, for this work let’s give them precise meanings:

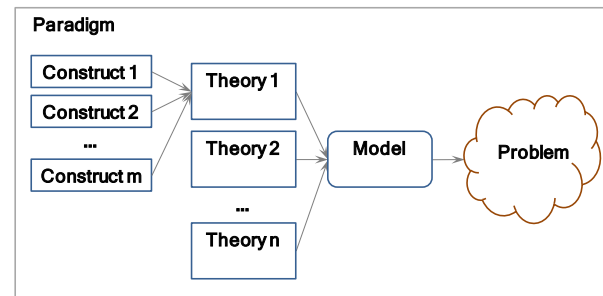
- **Hypothesis:** A scientific theory starts as a hypothesis, a proposed explanation of phenomena that is testable. Newton’s laws started out as hypotheses to be tested. And today “string theory”, an attempt to describe fundamental forces and matter in the universe, is—even though called a theory—merely a hypothesis.
- **Law:** A scientific law is the same as a scientific theory, except that it is typically expressed in more formal, often mathematical, language.
- **Model:** A model is a logical framework, often incorporating several theories, that represents or explains a set of phenomena, or that helps to solve a particular problem (see the figure at right). For example, a model of the solar system might employ Newton’s laws for the motion of most planets, but use Einstein’s theory of general relativity for the motion of the planet Mercury (because it is so close to the sun, where Newton’s laws are inaccurate).
- **Construct:** Constructs are concepts that are the building blocks of a theory, and are sometimes only understandable in relation to the theory. For example, “force” is a construct that Newton used for his laws of motion.
- **Paradigm:** In 1962, Thomas Kuhn gave “scientific paradigm” its contemporary meaning², namely the set of practices that define a scientific discipline during a historical period, including its theory, what is to be observed, how experiments should be conducted, and how results should be interpreted. With *Principia*, Newton laid groundwork for the current scientific paradigm for physics.



Pause to reflect

Think of a few ways that scientific theories—such as Newton’s laws of motion or the germ theory of disease—have been useful. As a result of such theories, what do we humans have that we would not otherwise have?

Analogously, considering the facts that we sketched in Part III (Health behavior facts), how might scientific health behavior theories prove useful?



¹ For the very small and the very fast, the theories of quantum mechanics and relativity are more accurate.

² See Kuhn (1996), pages 10-12.

D. THEORY AND PRACTICE

In most disciplines with successful scientific theories, the relationship between theory and practice is close. For example, an aerospace engineer must master the theory of classical mechanics, just as a theoretical physicist must understand results from field experiments and practical experience.¹

E. THEORY AND COMPUTATION

Every process in the universe may be viewed as a “**computation**”, a transformation of input into output, based on rules underlying the transformation. Thus, the blooming of a rose is a computation, and the universe is an immense computer processing the rules for roses to bloom.

Some computations, such as the movement of Jupiter around the sun, are relatively simple. For many of these, scientists like Newton have found shortcuts—usually mathematical formulae such as Newton’s laws of motion—to determine their results at any point in time without having to wait for the actual computation to complete. For example, merely by plugging numbers into mathematical formulas, it is possible to determine the location of Jupiter ten years from now. We don’t have to wait ten years for the universe to complete its computation. Thus, for such computations, scientific theory can make falsifiable predictions.

But many computations are not simple. In fact, according to Stephen Wolfram, most computations—most of the universe’s processes—are complex and “**computationally irreducible**”. By this, he means that for most processes it is not possible to find a shortcut, mathematical or otherwise. For most processes, the shortest way to determine the outcome is to go through the same steps that the universe would follow.¹ Thus, because it is generally not possible to compute faster than the universe, long-term prediction for such processes is impossible. It follows that, according to the standard criteria, scientific theory for such processes is impossible. Newton may have had the good fortune to find one of the few natural processes that is simple enough to allow a mathematical shortcut (see the sidebar).

The end of scientific theory?

In *A new kind of science* Wolfram says the following about the usefulness of scientific theory:

“In the past it has normally been assumed that there is no ultimate limit on what science can be expected to do. And certainly the progress of science in recent centuries has been so impressive that it has become common to think that eventually it should yield an easy theory—perhaps a mathematical formula—for almost anything.

“But the discovery of computational irreducibility now implies that this can fundamentally never happen, and that in fact there can be no easy theory for almost any behavior that seems to us complex.

“It is not that one cannot find underlying rules for such behavior. Indeed, ... particularly when they are formulated in terms of programs I suspect that such rules are often extremely simple. But the point is that to deduce the consequences of these rules can require irreducible amounts of computational effort. ...

“So given this, can theoretical science still be useful at all?

“The answer is definitely yes. ... to capture the essential features of systems with very complex behavior it can be sufficient to use models that have an extremely simple basic structure. Given these models the only way to find out what they do will usually be just to run them. But the point is that if the structure of the models is simple enough, and fits in well enough with what can be implemented efficiently on a practical computer, then it will often still be perfectly possible to find out many consequences of the model.”

¹ See Wolfram (2002), pages 737 - 750.

F. STANDARDS FOR SCIENTIFIC HEALTH BEHAVIOR THEORIES

The standards to determine if a statement about health behavior is a bona fide scientific theory should be no different from the standards for physics and other “hard” sciences. In particular, a scientific health behavior theory must be consistent with all experimental results, and supported by many independent strands of evidence.^M

If a statement about health behavior has not yet been verified by a variety of independent experimental results, it is merely a working hypothesis. If such a statement is contrary to experimental results, it must be discarded.

Because health systems are complex systems, for health behavior theories it may be appropriate to modify the standard that a scientific theory should make accurate long-term predictions.

G. ISSUES AND FUTURE DIRECTIONS

As we have seen, one of the criteria for a scientific theory is that it can accurately predict. However, we know that it is not possible to predict the behavior of many complex systems. For example, it is impossible to predict the weather for more than ten days, and many think that it is impossible to predict the behavior of a stock exchange for more than a few seconds. One reason we cannot perfectly predict such systems is that we cannot know all their initial conditions.

However, according to Stephen Wolfram’s concept of “computational irreducibility”, even if we knew all initial conditions perfectly, it is often inherently impossible to predict the behavior of a complex system (because the system’s computation cannot be short-cut).

Thus, it may become important to redefine scientific theory to remove the strict prediction criterion, so that the concept is useful for complex systems such as health systems.

H. TO LEARN MORE

To learn more about:

- The concept of computational irreducibility, see Chapters 11 and 12 of Wolfram (2002).
- Scientific theory and the scientific method, see Popper (1972), one of the most important books about the philosophy of science.
- The concept of a scientific paradigm, see Kuhn (1996).

I. REVIEW AND A LOOK AHEAD

In this chapter, we reviewed the concept of “scientific theory”, including its criteria, related terminology, and limitations.

In the next chapter, we will explore scientific theories of health behavior.

(Don't forget to take a look at the exercises for this chapter. They start on the next page.)

EXERCISES

1. Choose a scientific theory, describe it, and show how it satisfies the criteria to be a bona fide theory.
2. How would you replace the predictability criterion for scientific theory, so that the concept is useful for complex systems?

SOLUTIONS

1. For example, the germ theory of disease states that microorganisms cause many diseases. The theory is consistent with all relevant experimental results, can predict the onset of disease for infected hosts, and is supported by decades of widely varied experimental evidence from around the world. Further, the theory explains a wide assortment of diseases, and is simple (parsimonious).¹
2. Even though a scientific theory cannot predict the behavior of a complex system in real time, it should be able to trace realistic paths that the system might take, and identify paths that the system will not take.

¹ For a good summary of the germ theory of disease, see “Germ theory of disease” in Wikipedia.

CHAPTER TEN: OVERVIEW OF HEALTH BEHAVIOR THEORIES

... spending the year in a community composed predominantly of social scientists confronted me with unanticipated problems about the differences between such communities and those of the natural scientists among whom I had been trained. Particularly, I was struck by the number and extent of the overt disagreements between social scientists about the nature of legitimate scientific problems and methods ... somehow, the practice of astronomy, physics, chemistry, or biology normally fails to evoke the controversies over fundamentals that today often seem endemic among, say, psychologists or sociologists.

Thomas Kuhn, 1962¹

A. IN SEARCH OF ONE HEALTH BEHAVIOR THEORY

The most interesting thing about health behavior theories is that they do not exist. There are many hypotheses about health behavior, several of which we will explore in this chapter and the next (many of which are optimistically called “theories”). But no one has yet developed a health behavior hypothesis that satisfies the criteria for a scientific theory. In particular, no hypothesis is consistent with all experimental results. Indeed—as we shall see—in the field of health behavior, experimental results are rare.

Nor is there a scientific paradigm to guide the work of researchers and practitioners who develop and apply health behavior theories.

B. MANY HYPOTHESES

Even though the field of health behavior has no theory or paradigm, there is no lack of hypotheses. Since the mid-1980s, Karen Glanz and her colleagues have tracked the hypotheses (they call them “theories” or “models”) that health behavior researchers and practitioners have used to help people change their health improvement behaviors (such as exercising more, eating better, using seat belts, getting medical screening tests, etc.).

Even though such hypotheses are not yet scientific theory, they have been extremely useful. They have provided systematic ways for researchers to think more deeply about why and how health system agents produce health behaviors.

¹ Kuhn (1996), page x.

B. MANY HYPOTHESES continued

When they started, in the mid 1980s, Glanz et al. found 51 such hypotheses. In the mid-1990s, they found 66, and most recently (for the period 2000 to 2005) they found 139.¹ The number of health behavior hypotheses appears to be increasing. However, of the many hypotheses, researchers commonly employ only about a dozen. In the next section I will summarize several of these “key hypotheses”.

The health behavior hypotheses surveyed by Karen Glanz and colleagues are about behaviors to improve health, so-called health promotion behaviors. Mainly, the hypotheses concern the behaviors of individual people and healthcare practitioners. But in a health system, there are many other agents and behaviors. There are companies providing health insurance, firms making medical equipment, policy-makers developing policies that affect the health of millions, clinics competing with one another, and so on. For such agents and behaviors, there are many other health behavior hypotheses. For example, there are hypotheses about the economic behaviors of healthcare consumers and businesses, as well as hypotheses about the organization and management of healthcare firms. Some of these are also summarized in the next section.

C. KEY HYPOTHESES

In the following tables, I summarize several important health behavior hypotheses. These are hypotheses that health behavior researchers commonly employ, or hypotheses that have had a marked impact on health system policy. They are divided into three groups: hypotheses applicable to individuals, hypotheses applicable to groups (such as healthcare businesses), and hypotheses applicable to either individuals or groups.

For each hypothesis, I give its name, describe its main provisions, and provide resources for learning more about it. As part of each description, I note whether the hypothesis is “verbal-conceptual”, “mathematical”, or “computational”. A verbal-conceptual hypothesis is one that is presented mainly in words and concepts. A mathematical hypothesis is one that is based on mathematical formulas. And a computational hypothesis is presented as a computer program.

¹ Glanz, Rimer, & Viswanath (2008), Chapter 2 (Trends in the use of health behavior theories and models).

C. KEY HYPOTHESES continued

In the next chapter, we will explore five of these hypotheses (each noted by an asterisk after its name) in detail.

1. Key hypotheses applicable to individual health behavior

Name	Description	Resources
Belief-desire-intention model*	Computational. A person's health behavior depends on three mental attitudes: beliefs (the information the person has gathered about the world), desires (the person's goals), and intentions (the goals to which the person is committed). To carry out an intention, the person executes a plan that often includes several sub-plans.	Wooldridge (2000) Rao & Georgeff (1995) Rao & Georgeff (1991)
Common-sense model of illness representations	Verbal-conceptual. A person's reaction to disease depends on the person's beliefs about the disease and about recommended actions. The hypothesis includes constructs about symptoms, time frames, potential consequences, disease causes, and the person's control.	Leventhal et al. (1997) Hagger & Orbell (2003)
Health belief model	Verbal-conceptual. A person's behavior to counteract a personal health threat (such as a potential illness) depends on the person's perception of the threat and the person's belief in the effectiveness of the behavior to counteract the threat.	Conner & Norman (2005) Glanz, et al. (2008)
Health locus of control model	Verbal-conceptual. The likelihood that a person will perform a certain health behavior depends on the person's expectation that the behavior will lead to a particular result and how much the person values the result.	Conner & Norman (1996)
Precaution adoption process model	Verbal-conceptual. In deciding to take a health behavior action, a person passes through certain stages: unaware of the issue, unengaged in the issue, undecided about acting, decided not to act or decided to act, acting, and maintenance.	Glanz, et al. (2008)
Prospect theory*	Mathematical. A person makes health behavior decisions based on the person's evaluation of the value of losses and gains (rather than on an evaluation of final outcomes). The person's evaluation of losses and gains is based on heuristics (rules of thumb) that do not conform to traditional rational choice theory.	Daniel Kahneman & Tversky (2000)
Protection motivation theory	Verbal-conceptual. A person's intention to perform a behavior in response to a personal health threat depends on the person's perception of susceptibility to and severity of the threat, the person's expectation that carrying out the behavior can remove the threat, and the person's belief in his or her ability to execute the behavior.	Conner & Norman (2005)
Social cognitive theory	Verbal-conceptual. A person's motivation to perform a health behavior is based on three expectations: situation outcome expectation (beliefs about consequences that will occur without the person's actions), action outcome expectation (beliefs that certain behaviors will lead to a specific outcome), and perceived self-efficacy (beliefs that the person is capable of performing a particular behavior). The hypothesis includes the construct of reciprocal determinism: a person and the environment influence each other.	Conner & Norman (2005) Glanz, et al. (2008)
Theory of planned behavior*	Mathematical. A person's decision to perform a health behavior is proximally determined by the person's intention to engage in the behavior and the person's perception of control over the behavior.	Conner & Norman (2005) Glanz, et al. (2008)
Transtheoretical change model	Verbal-conceptual. To change health behavior, a person goes through five well-defined stages: pre-contemplation, contemplation, preparation, action, and maintenance.	Conner & Norman (2005)

C. KEY HYPOTHESES continued

2. Key hypotheses applicable to group health behavior

Name	Description	Resources
Diffusion of innovations model	Verbal-conceptual. Diffusion is how a health behavior innovation is communicated among the members of a social system. It is affected by the following factors: relative advantage of the innovation; compatibility with intended users' values, norms, beliefs, and perceived needs; complexity; ability to be tested on a limited basis; and how easily the benefits are identified and visible. There are five categories of innovation adopters: innovators, early adopters, early majority adopters, late majority adopters, and laggards.	Rogers (2003) Oldenburg & Glanz (2008)
Interorganizational relations theory	Verbal-conceptual. Collaboration among organizations leads to more comprehensive coordinated approaches to complex issues than one organization can achieve alone.	Butterfoss, Kegler, & Francisco (2008)
Patient-centered communication model	Verbal-conceptual. There are several pathways linking the quality of clinician-patient communications to health outcomes: a direct impact on health; indirect impacts through intermediate psychological effects such as improved understanding, trust, and satisfaction; and indirect effects mediated by improved adherence, decisionmaking, and other health promotion behaviors.	Street & Epstein (2008)
Social network model	Mathematical (network theory). Social networks influence health via several pathways: Social ties provide companionship that promotes health and well-being; social networks provide resources to help people cope with illness; resource mobilization through social networks provides a buffer to help people cope with stress; and social networks influence health behaviors, such as exercising with friends, which in turn influence health.	Berkman & Kawachi (2000) Valente (2010)
Stage theory of organizational change	Verbal-conceptual. Organizations pass through the following stages as they change: awareness, action initiation, change implementation, and change institutionalization.	Butterfoss, et al. (2008)

3. Key hypotheses applicable to health behavior of individuals or groups

Name	Description	Resources
Game theory*	Mathematical. In strategic interactions, agents choose their actions rationally in order to maximize the value of their expected outcomes.	Rosenthal (2011) Poundstone (1993)
Rational choice theory*	Mathematical. In choosing among alternative options, an agent will choose one that provides the greatest "utility" (where utility is a measure of the agent's preferences) that is possible within the agent's constraints.	Green (2002) Feldstein (2012)

As the tables show, most of the key hypotheses are about individual behavior, and most are verbal-conceptual. Verbal-conceptual hypotheses are—because of the nature of words—inexact. In fact, some are so inexact that they do not even qualify as scientific hypotheses.

D. HOW HEALTH BEHAVIOR HYPOTHESES ARE USED

In their latest review (covering articles published during the years 2000 to 2005) Karen Glanz and her colleagues classified each article that employed a health behavior hypothesis (referred to in their study as a “theory”) into one of four categories:

- **Informed by theory:** The article identified a theoretical framework, but in its analysis did not apply the theory. For example, in one article the researchers stated that they used the Health Belief Model (HBM) to develop intervention materials, but they did not specify any application or measurement of an HBM construct.
- **Applied a theory:** The article specified a theoretical framework, and applied or measured at least one, but less than half, of the theory’s constructs. For example, in one article the researchers stated that they based their intervention on the HBM model and described how they applied two of the HBM’s constructs.
- **Tested a theory:** The article specified a theoretical framework, and either applied more than half of the theory’s constructs, or compared two or more theories to one another.
- **Created a theory:** The article developed a new or expanded theory, using constructs that were specified, measured, and analyzed in the article.

Of the articles in their study that mentioned at least one “theory”, they found that¹:

- 41 articles (59 percent) were informed by theory.
- 15 articles (22 percent) applied a theory.
- 5 articles (7 percent) tested a theory.
- 8 articles (12 percent) created a theory.

Thus, over the study period, few researchers applied, tested, or created a health behavior hypothesis. However, even if a researcher did apply a health behavior hypothesis, it does not follow that the researcher applied it correctly. Researchers often do not understand how to measure or analyze the constructs of health behavior hypotheses. Moreover, they may simultaneously employ variables from several hypotheses in an incoherent way. There is much confusion about the proper use of health behavior hypotheses.²

¹ Painter, Borba, Hynes, Mays, & Glanz (2008)

² Glanz, et al. (2008), Chapter 2 (Trends in the use of health behavior theories and models)

E. TRANSFORMING HEALTH BEHAVIOR HYPOTHESES INTO THEORY

As we have seen, there are many health behavior hypotheses, and many researchers actively employing them to address health system problems. Given such activity, one would naturally assume that researchers are also actively engaged in testing the hypotheses to reject ones that do not conform to fact, and to promote others to the status of scientific theory. But this is not the case.

Twenty years ago Neil Weinstein observed, “ ... despite a large empirical literature, there is still no consensus that certain models of health behavior are more accurate than others, that certain variables are more influential than others, or that certain behaviors or situations are understood better than others. In general, researchers have failed to carry out the winnowing process that is necessary for scientific progress.”¹

The same is true today: Health behavior researchers are still not scientifically testing health behavior hypotheses and transforming the best of them into validated scientific theory. Rather than winnow the hypotheses, researchers are rapidly introducing new hypotheses that do not significantly improve or replace older hypotheses. And researchers rarely discard older hypotheses.²

In fact, rather than objectively searching for hypotheses that are true, health behavior researchers often advocate the hypotheses they like the most. In 2003, Jane Ogden examined 47 health behavior theory studies and found that when data did not support the theories, the authors offered various explanations, none of which was that the theory may be incorrect.³ As Barbara Rimer reminds us, “Theory is not theology. Theory needs questioners more than loyal followers.”⁴

Thus, in health behavior, there is much research activity and a lot of literature, but little cumulative knowledge or progress in the formation of scientific theories. A great danger is that healthcare policy makers and other stakeholders will blindly accept these inadequately tested hypotheses called “theory” as true scientific theory, and use them to develop health system policy.

¹ N. D. Weinstein (1993)

² Noar & Zimmerman (2005)

³ Ogden (2003)

⁴ Rimer (1997)

E. TRANSFORMING HEALTH BEHAVIOR HYPOTHESES INTO THEORY continued

What gives rise to this curious state of affairs for health behavior theories? Here are a few reasons:

- **Inconsistent terminology.** Many health behavior hypotheses employ constructs that are essentially identical, but that use different terminology.¹ Similarly, many researchers use one term to represent significantly different ideas. For example, researchers use the term “belief” with a wide variety of meanings. Such inconsistent terminology leads to confusion, ineffective communication, and lack of consensus.
- **Unscientific hypotheses.** Many health behavior hypotheses—such as the “Health belief model”—are not true scientific hypotheses, because they are not falsifiable.²
- **Lack of experimental studies.** There are few tests of hypotheses, and most of these are only correlation studies. There are essentially no experimental tests.³
- **Lack of comparative studies.** There are few studies that compare one hypothesis to another. In 2007, Neil Weinstein wrote, “Literally thousands of studies of health behaviors describe themselves as either testing or being guided by specific theories. ... Given this enormous effort, one might expect that the determinants of health behaviors would be well understood, but this is not the case. Most of these studies tell us little about the causal factors underlying health behaviors, the completeness of existing theories, or the superiority of one theory over another.”⁴
- **Lack of a scientific paradigm.** Because of fragmentation among the disciplines related to health behavior (for a discussion of this, see Part I), and the complexity of health systems, health behavior researchers do not have a commonly agreed-upon paradigm to follow. There is much random exertion, with little forward progress.

¹ Noar & Zimmerman (2005)

² Ogden (2003)

³ Noar & Zimmerman (2005)

⁴ N. D. Weinstein (2007)

F. ISSUES AND FUTURE DIRECTIONS

The primary issue related to health behavior theories is that there is no widely-accepted theory or paradigm. Subsidiary issues are the overabundance of uncoordinated and untested health behavior hypotheses, the fragmentation of health behavior fields, and the lack of a scientific paradigm to guide health behavior researchers.

Chapter twelve (One good theory) proposes an approach to address these issues.

G. TO LEARN MORE

To learn more about health behavior hypotheses that relate to health promotion, read Glanz, et al. (2008) and Conner & Norman (2005). To learn more about the five key health behavior hypotheses that I identified as particularly useful for modeling agents in health system simulations, see the next chapter.

H. REVIEW AND A LOOK AHEAD

In this chapter, I observed that currently there is no widely accepted scientific health behavior theory, and gave several reasons for this state of affairs. I also briefly described several common health behavior hypotheses, and critiqued how such hypotheses are being used.

In the next chapter, we will look in detail at five of these common health behavior hypotheses.

(Don't forget to take a look at the exercises for this chapter. They start on the next page.)

EXERCISES

1. Select one of the key hypotheses summarized in this chapter, and find a journal article applying the hypothesis (you can do this by searching for the hypothesis name using Google Scholar). Classify the article as “informed by theory”, “applied a theory”, “tested a theory”, or “created a theory” according to the classification scheme used by Karen Glanz and her colleagues (described in Section D). Does it appear that the researcher applied the hypothesis correctly?

SOLUTIONS

1. For this exercise, the “Transtheoretical change model” would be a good choice. For a description of this model, see Section C (Key hypotheses).

CHAPTER ELEVEN: FIVE USEFUL HEALTH BEHAVIOR HYPOTHESES

You guys really believe that?

Philip Anderson¹

A. OVERVIEW OF THE USEFUL HYPOTHESES

This chapter describes five hypotheses that are useful for modeling the health behavior of agents in agent-based simulation models of health systems:

- **Rational choice theory:** This hypothesis is the basis of neoclassical microeconomics, the most widely used and influential model of the economic behavior of health system individuals and firms.
- **Game theory.** A way to model the strategic behavior of health system individuals and firms.
- **Prospect theory.** A recently developed and psychologically based hypothesis about how individuals make decisions under conditions of uncertainty.
- **Belief-desire-intention model of agency.** A widely employed “cognitive architecture” that provides the structure underlying how individuals decide to act.
- **Theory of planned behavior.** A commonly used hypothesis that was developed to explain the process by which individuals plan and carry out behaviors.

I selected these particular hypotheses for detailed review because they are commonly used, they provide a cross-section of the different types of health behavior hypotheses, they are conducive to modeling agents in agent-based simulation models, and, I hope you will agree, they are interesting.

For each hypothesis, I present its history, describe it in detail, discuss how it has been used to model health behavior, and discuss its strengths and weaknesses.

¹ Philip Anderson is an American physicist and Nobel Laureate. He said this to prominent economists during a meeting at the Santa Fe Institute (the meeting is described in this chapter) in reference to neoclassical economic theory.

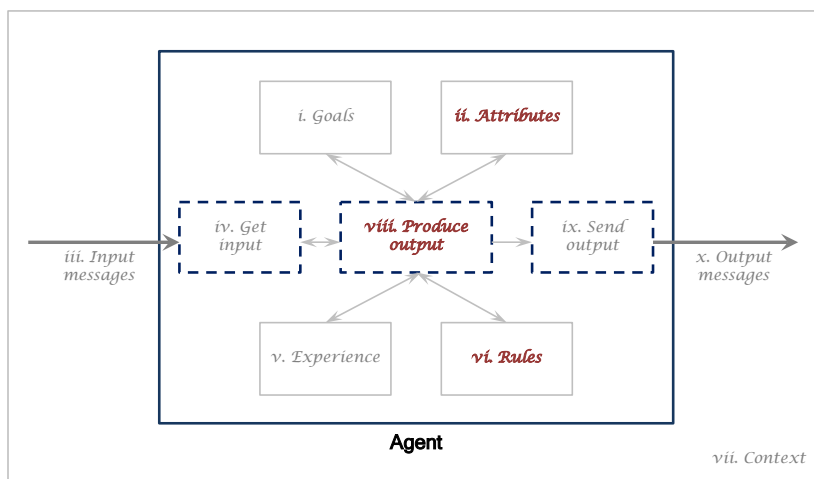
B. RATIONAL CHOICE THEORY

1. Introduction

The most widely used and influential idea about the economic behavior of individual consumers and firms—including health system individuals and firms—is modern (so-called “neoclassical”) microeconomics. The basis of neoclassical microeconomics is rational choice theory, a theory about how consumers decide which goods and services to purchase, and how firms decide which inputs to use in producing goods and services.

In this section, we will explore what rational choice theory says about how consumers determine the health goods and services they purchase, in situations of certainty and uncertainty. And we will discuss the strengths and weaknesses of this approach. One prominent—and potentially fatal—weakness is that, as numerous experiments have shown, people do not act rationally.

As we will see in Section 3 (Description), rational choice theory includes three of the ten health behavior parameters (highlighted in the figure below).



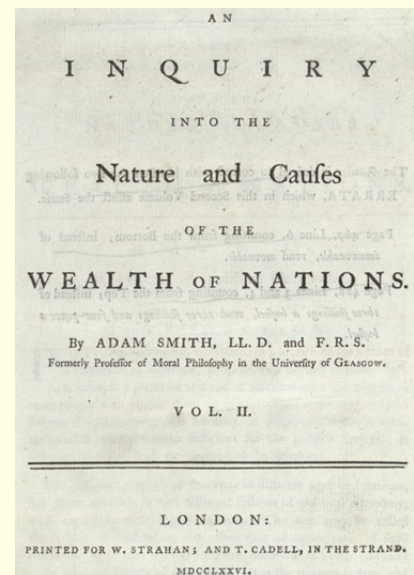
2. History

The birth of economics as a separate discipline began in 1776 when the Scottish philosopher Adam Smith published his book *The wealth of nations*. In it, he identified an “invisible hand” that leads an individual merely pursuing his own narrow interests to, without knowing it, also promote the greater good (see the sidebar).

The invisible hand

In *An inquiry into the nature and causes of the wealth of nations*, Adam Smith identified an “invisible hand” that guides economic affairs of a society:

“He [every individual] generally, indeed, neither intends to promote the public interest, nor knows how much he is promoting it. By preferring the support of domestic to that of foreign industry, he intends only his own security, and by directing that industry in such a manner as its produce may be of the greatest value, he intends only his own gain, and he is in this, as in many other cases, led by an invisible hand to promote an end which was not part of his intention. ... By pursuing his own interest he frequently promotes that of the society more effectually than when he really intends to promote it.”



Thus, at an early stage in the development of economics, it was recognized that the economic results of a society arise from the self-interested behavior of individual agents within the society, from the bottom up.

B. RATIONAL CHOICE THEORY continued

2. History continued

Jeremy Bentham, an English philosopher, is considered the founder of modern “utilitarianism”, the philosophy on which rational choice theory is based. In 1780, he wrote, “Nature has placed mankind under the governance of two sovereign masters, pain and pleasure. It is for them alone to point out what we ought to do, as well as to determine what we shall do.”¹

From 1870 to 1910, economists such as Alfred Marshall sought to introduce more theory and mathematical rigor into economics, just as Newton had done for physics. To model consumer behavior they introduced the marginal utility theory of preferences, and to model supplier behavior, they introduced production theory. They called their approach “neoclassical economics”, and this approach is now employed by most economists, including health economists, today.

In the 1930s and 1940s, Paul Samuelson pioneered “revealed preferences theory”, a method to define consumer utility functions by observing their purchasing behavior. Before Samuelson developed this theory, economists had been unable to define realistic² consumer utility functions.

In 1944, John von Neumann and the economist Oskar Morgenstern wrote the book that gave rise to game theory, titled *Theory of games and economic behavior*³. In it, they presented a theory of behavior for people making decisions about situations with uncertain outcomes. They called it the “expected utility theorem”.

3. Description

Rational choice theory asserts that the choices that a consumer makes about purchasing goods and services are those choices that maximize the consumer’s ‘utility’ within the constraints of the consumer’s budget. Here “utility” has a precise meaning. It is a continuous function $U(X, Y, Z, \dots)$ that ranks a consumer’s preferences for bundles (sets) of goods and services, where X, Y, Z, \dots are units of various goods and services.

¹ Bentham, Burns, & Hart (1982)

² For an excellent history of economics, see Heilbroner (1999).

³ Von Neumann & Morgenstern (1944). For more about game theory, see Section C (Game theory).

B. RATIONAL CHOICE THEORY continued

3. Description continued

The utility function must satisfy two criteria:

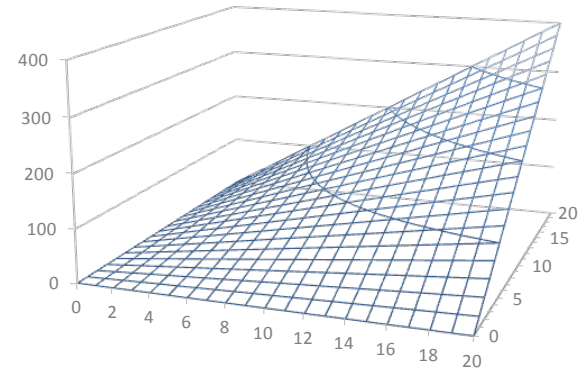
- **Complete.** So that a consumer can compare all possible goods and services, it must be defined over all bundles.
- **Transitive.** If

$$U(A) > U(B) \text{ and } U(B) > U(C) \text{ then } U(A) > U(C)$$

In words: if a consumer prefers the bundle A to bundle B, and prefers the bundle B to bundle C, then the consumer must prefer bundle A to bundle C.

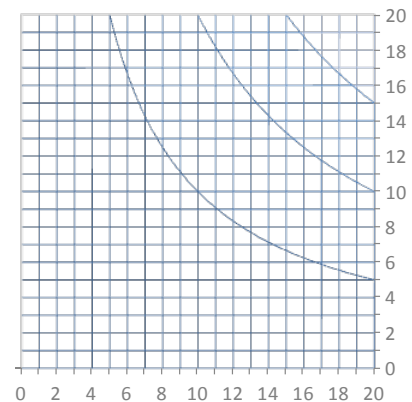
In rational choice theory, if a consumer's preferences satisfy these criteria, the consumer is said to be "rational".

For example, $U(X, Y) = XY$ might be a utility function providing a consumer's preferences for medical doctor visits (X) and nurse practitioner visits (Y). The function is complete, because it is defined over all real numbers. And, as you can see from the function's graph (top right) it is transitive (because it monotonically slopes upward).



Utility function

The bottom chart shows the utility function's "indifference curves". These are curves giving all the points that generate the same utility for the consumer. The consumer is therefore indifferent about which point is chosen. For example, the lowest indifference curve shows that the consumer would be indifferent between the bundle [5 medical doctor visits, 20 nurse practitioner visits] and the bundle [5 nurse practitioner visits, 20 medical doctor visits]. The consumer would be just as happy with either bundle, because the utility for each is 100.



Indifference curves

If the consumer is indifferent about infinitely many bundles, how, according to rational choice theory, will the consumer choose one? The consumer's choice is constrained by the consumer's budget; only so much money can be spent on visits to medical doctors and nurse practitioners.

Suppose the consumer's budget for such visits is 140 (using the same units as for the utility function), and the price for a medical doctor (MD) visit is 10 whereas the price for a nurse practitioner (NP) visit is 5.



Pause to reflect

You now have all the data you need to determine the number of visits of each kind that the consumer will rationally purchase. How would you arrive at an answer?

B. RATIONAL CHOICE THEORY continued

3. Description continued

There are three common ways to determine the consumer’s choice. The first is to use the concept of “marginal utility”. Marginal utility is the additional satisfaction that the consumer obtains from purchasing an additional amount of a good or service. For our example, if the consumer already has the bundle (X_0, Y_0) , then one more MD visit (an increase in X) increases the consumer’s utility by Y_0 , and one more NP visit increases the consumer’s utility by X_0 .¹

According to rational choice theory, the consumer maximizes utility when the budget is allocated so that the marginal utility per dollar of expenditure (that is, the marginal utility divided by the price) is the same for each good or service.

The table below shows several consumer choices, together with their costs, utilities, marginal utilities, and marginal utilities per dollar of the price. For example, one choice is to spend all the budget on NP visits, in which case the consumer could visit an NP 28 times (because the cost of each visit is 5).

Medical doctor					Nurse practitioner				
Visits	Cost	Utility	Marginal utility	Marginal utility/Price	Visits	Cost	Utility	Marginal utility	Marginal utility/Price
0	\$ -	-	28	2.8	28	\$ 140	-	0	0.0
1	\$ 10	26	26	2.6	26	\$ 130	26	1	0.2
2	\$ 20	48	24	2.4	24	\$ 120	48	2	0.4
3	\$ 30	66	22	2.2	22	\$ 110	66	3	0.6
4	\$ 40	80	20	2.0	20	\$ 100	80	4	0.8
5	\$ 50	90	18	1.8	18	\$ 90	90	5	1.0
6	\$ 60	96	16	1.6	16	\$ 80	96	6	1.2
7	\$ 70	98	14	1.4	14	\$ 70	98	7	1.4
8	\$ 80	96	12	1.2	12	\$ 60	96	8	1.6
9	\$ 90	90	10	1.0	10	\$ 50	90	9	1.8
10	\$ 100	80	8	0.8	8	\$ 40	80	10	2.0
11	\$ 110	66	6	0.6	6	\$ 30	66	11	2.2
12	\$ 120	48	4	0.4	4	\$ 20	48	12	2.4
13	\$ 130	26	2	0.2	2	\$ 10	26	13	2.6
14	\$ 140	-	-	0.0	-	\$ -	-	14	2.8

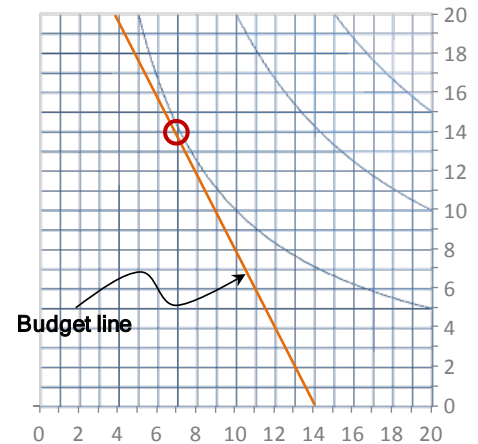
¹ You can also see this by taking the partial derivatives of $U(X, Y) = XY$ with respect to X and Y at (X_0, Y_0) . For example, the partial derivative of XY with respect to X is Y, which is Y_0 when evaluated at (X_0, Y_0) .

B. RATIONAL CHOICE THEORY continued

3. Description continued

As the table shows, the marginal utility per dollar is the same for each of the two services when it equals 1.4, corresponding to 7 MD visits and 14 NP visits. According to rational choice theory, this is where the consumer’s utility is maximized. In fact, you can verify this by comparing the consumer’s utilities for the various choices. For 7 MD visits and 14 NP visits, the utility is 98, which is the highest among the consumer’s available choices.

The second way to determine the consumer’s choice that maximizes utility is to employ graphical analysis. The chart to the right shows the indifference curves again, but this time a “budget line” is added. This line includes all the variations of MD and NP visits that the consumer can afford. The consumer’s utility is maximized where the budget line intersects the appropriate indifference curve (the curve with utility equal to 98), or again at 7 MD visits and 14 NP visits.



The third way to determine the consumer’s choice involves more mathematics, but has wider applicability. It is to use the “Lagrangian multiplier” to solve the “constrained optimization” problem. To do this, first write the “Lagrangian”:

$$\Phi = U(X, Y) - \lambda(P_X X + P_Y Y - B)$$

where P_X is the price of X , B is the budget amount, and λ is the “Lagrangian multiplier”. For values of X and Y that satisfy the budget constraint, the second term of the Lagrangian is zero and so for these values maximizing Φ is equivalent to maximizing $U(X, Y)$.

To find the solution of the constrained optimization problem, differentiate Φ with respect to X , Y , and λ , set the derivatives equal to 0, and then solve the resulting three equations for X and Y :

$$\begin{aligned} \frac{\partial \Phi}{\partial X} &= Y - 10\lambda = 0 \\ \frac{\partial \Phi}{\partial Y} &= X - 5\lambda = 0 \\ \frac{\partial \Phi}{\partial \lambda} &= -10X - 5Y + 140 = 0 \end{aligned}$$

The solution is $\lambda = 1.4$, $X = 7$, $Y = 14$.



Pause to reflect

Solve the three differential equations to find X , Y , and λ . Why do you think the Lagrangian is equal to 1.4? If you find these concepts particularly interesting (or challenging) see the references for further study in Section H (To learn more).

B. RATIONAL CHOICE THEORY continued

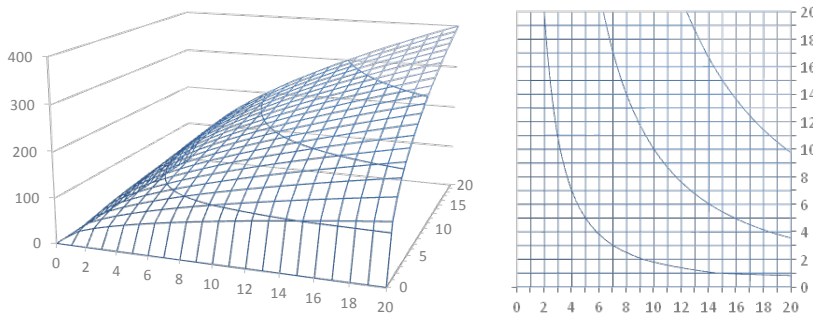
3. Description continued

There are many—infinately many—utility functions. One that economists commonly use is called the Cobb-Douglas utility function. For two goods or services, it has the following form:

$$U(X,Y) = kX^\alpha Y^{(1-\alpha)}$$

For their Sugarscape simulation, Josh Epstein and Rob Axtell used a Cobb-Douglas utility function (see the sidebar).

For our MD/NP example, with $k = 20.0$ and $\alpha = 0.6$, the following charts show the Cobb-Douglas utility function and its indifference curves. As you can see, they look different from the other utility function we used for our example. And the answer is different: for a budget of 140 with this Cobb-Douglas utility function, the consumer would choose 9 MD visits and 10 NP visits.



How do we know which utility function is right? One way is to interview consumers about the products and services they would purchase at a given price. But this approach has significant drawbacks: consumers often lack interest and information, and provide responses that are biased.

The best way is to see how consumers actually behave—how they reveal their preferences—and then fit their actual behavior with utility functions. This can be done through marketing experiments or statistical analysis of consumer data. Unfortunately, as we saw in Part III, for health systems such data is rare.

Sugarscape

In the early 1990's, Joshua Epstein (whom we met in Chapter two) attended a conference at the Santa Fe Institute that changed his worldview. Always enamored with models, at the conference he discovered models unlike any he had seen: models that grew lifelike artificial trees, flocks of birds, and schools of fish, from simple rules, from the bottom up.

Inspired to try such models with human societies, Epstein returned home to the Brookings Institution, and, in the cafeteria, told his colleague Robert Axtell about his idea. Together, on a napkin, they sketched such a rudimentary society, with agents moving around an artificial world, gathering its only resource—sugar. They called their artificial society Sugarscape, and spent the next few years working on it. In 1996, they published their paradigm-shattering book about Sugarscape, titled *Growing artificial societies*.¹

In the world of Sugarscape, agents trade sugar and spice to maximize their utility, which is expressed as a Cobb-Douglas utility function. With this simple model, simulating a simple economy from the bottom up with a common utility function, Epstein and Axtell demonstrated that, contrary to traditional economic theory, prices and quantities traded in Sugarscape do not correspond to the intersection of supply and demand curves.

Thus, a simple simulation model inspired deeper understanding about how real economies work.²

¹ Joshua M. Epstein & Axtell (1996)

² To learn more about Sugarscape, see Chapter six of my report *Complexity science: an introduction (and invitation) for actuaries*, found at: "www.soa.org/research/research-projects/health/research-complexity-science.aspx". Or, better, read Epstein and Axtell's book.

B. RATIONAL CHOICE THEORY continued

3. Description continued

Until now, we have explored consumer choices in situations of certainty. But what if the consumer is thinking about purchasing health insurance? The price is high, and the consumer might never need it. On the other hand, the consumer might become very sick and could become bankrupt in the absence of insurance. This is a situation of uncertainty, for which another component of rational choice theory—called “expected utility theory”—applies.

Expected utility theory was pioneered by the mathematician Daniel Bernoulli (see the sidebar). It is employed to model a consumer’s behavior when the consumer must choose between two sets of risks, what in rational choice theory is called a “gamble”, a “lottery” or a “prospect”.

The form of a gamble is:

$$G = (X_A, P_A; X_B, P_B; \dots)$$

where A, B, \dots are states, X_A, X_B, \dots are outcomes associated with the states, and P_A, P_B, \dots are the probabilities of the states occurring.

For example, two gambles associated with purchasing health insurance might be:

Gamble G1: Purchase insurance: $(-\$10,000, 1.0; \$0, 0.25)$

Gamble G2: Do not purchase: $(\$0, 1.0; -\$100,000, 0.25)$

where the cost of insurance is \$10,000, the probability of becoming sick is 0.25, and the cost of medical care is \$100,000.

The consumer’s utility for the gamble $G = (X_A, P_A; X_B, P_B; \dots)$ is:

$$U(G) = P_A u(X_A) + P_B u(X_B) + \dots$$

where $u(X)$ is a utility function over outcomes. Thus, the consumer’s utility over gambles is defined in terms of utility over outcomes.

Saint Petersburg paradox

Nicolas Bernoulli, a cousin of the famed mathematician and physicist Daniel Bernoulli, posed an intriguing problem that Daniel Bernoulli published in the *Commentaries of the Imperial Academy of Science of Saint Petersburg* (thus the problem’s name):

Suppose a gambling casino offers the following single-player game: The casino starts with an amount of \$2 and then flips a fair coin. Every time a head appears, the amount doubles. The game ends when the first tail appears and the casino then pays the player the resulting amount. For example, if the coin results were HHT, the casino would pay the player \$8.

The problem is to determine the minimum bet the casino should allow for a player to play the game. What would you bet?

The mathematically correct answer is:

$$\$2 \times \frac{1}{2} + \$4 \times \frac{1}{4} + \dots + \$2^n \times \frac{1}{2^n} + \dots = \$\infty$$

The minimum bet is infinite. Thus, the player should be willing to play the game at any price the casino offers, even if it is a million dollars.

But most people would not pay more than \$25 to play the game. Thus the paradox.

In 1738, Daniel Bernoulli resolved the paradox by introducing what we now call “expected utility theory”. He suggested that as the game progresses (the more heads in a row) the player’s payoff utility diminishes. After 30 heads in a row, the player will have accumulated more than \$2 billion. The payoff from the 31st head will not make the player as happy as the previous payoffs, because the player now needs it less.

Thus, the player’s expected utility for the game is

$$u(\$2) \times \frac{1}{2} + \dots + u(\$2^n) \times \frac{1}{2^n} + \dots$$

For example, for the utility function $u(X) = \ln(X)$, the player’s expected utility is: \$1.39.

B. RATIONAL CHOICE THEORY continued

3. Description continued

For example, if we employ a utility function $u(X)$ similar to Bernoulli's, we can determine whether our consumer will purchase health insurance:

$$u(X) = -\ln(-X) \text{ if } X < 0$$

$$0 \text{ if } X = 0$$

Then:

$$U(G1) = -\ln(10,000) \times 1.0 + 0 \times 0.25 = -9.2$$

$$U(G2) = 0 \times 1.0 - \ln(100,000) \times 0.25 = -2.9$$

Because $-2.9 > -9.2$, the consumer will forgo purchasing health insurance.

Once we have the utility function $U(G)$, it can be incorporated into constrained optimization methodologies, similar to what we did for utilities under conditions of certainty.

Now that we have explored what rational choice theory says about the behavior of consumers under conditions of certainty and uncertainty, you might wonder what it says about the other side of the market relationship, the behavior of firms.

According to the theory, firms make decisions to maximize profit, similar to the way consumers make decisions to maximize utility. Firms purchase inputs (such as labor and raw materials) and transform them into outputs. This process is represented by a "production function" $P(a, b, \dots)$ where a, b, \dots are the inputs. The constrained optimization problem for firms is to determine the set of inputs that produces the greatest profit given the constraints of the firm's budget and input prices.

As you now see, rational choice theory provides significant detail for the behavior parameters "Produce output" and "Rules". It also relies on agent "Attributes" such as income.



Pause to reflect

Note that the utility function in expected utility theory is *not*:

$$U(G) = u(P_A X_A + P_B X_B + \dots)$$

In other words, consumer preferences are not defined over the expected value of outcomes.

Why do you suppose Daniel Bernoulli and von Neumann did not define utility in terms of expected values?¹

¹ Hint: When you make decisions under conditions of uncertainty, do you think about your preferences for alternative expected values? Or, rather, do you think about your preferences for alternative states?

B. RATIONAL CHOICE THEORY continued

4. Health system applications

Because health economics is a mature field with many practitioners, there are many applications of rational choice theory to health system problems. Indeed, practically all major health system policy decisions involve some aspect of rational choice theory and neoclassical microeconomics. Refer to any health economics textbook for plenty of examples.²

Nevertheless, I am not aware of any agent-based simulation model of a health system that employs rational choice theory to model behavior.

5. Strengths and weaknesses

The great strength of rational choice theory is its wide applicability, mathematical rigor, and legions of practitioners.

Even so, rational choice theory is not a scientific theory. As we will see in Section D (Prospect theory), researchers have assembled abundant evidence that rational choice theory often does not conform to actual behavior.

For health care in particular, rational choice theory may not be an accurate model of behavior. In his book *The economics of health reconsidered*, Thomas Rice shows that several key assumptions underlying rational choice theory do not hold in health care:

- Individuals are rational and the best judge of their own welfare.
- Consumers have sufficient information to make good choices.
- Consumers know, with certainty, the results of their consumption decisions.
- Individuals reveal their preferences through their actions.
- Social welfare is based solely on individual utilities, which in turn are based solely on the goods and services consumed.³

The mathematics of rational choice theory is elegant, but the foundations are weak (see the sidebar).

At the Santa Fe Institute

In 1987, there was a landmark meeting at the Santa Fe Institute for prominent physicists (such as Philip Anderson) and prominent economists (such as Kenneth Arrow) to share ideas. Here is how Michael Waldrop described the meeting:

“For the first two or three days ... Arrow and Anderson had asked several of the economists to give survey talks on the standard neoclassical theory. ‘We were fascinated by this structure,’ says Anderson, for whom economic theory has long been an intellectual hobby. ‘We wanted to learn about it.’ And indeed, as the axioms and theorems and proofs marched across the overhead projection screen, the physicists could only be awestruck at their counterparts’ mathematical prowess—awestruck and appalled.

“‘They were almost too good,’ remembers one young physicist, who remembers shaking his head in disbelief. ‘It seemed as though they were dazzling themselves with fancy mathematics, until they really couldn’t see the forest for the trees. So much time was being spent on trying to absorb the mathematics that I thought they often weren’t looking at what the models were for, and what they did, and whether the underlying assumptions were any good. ...

“And then there was the business of rational expectations. ... Unfortunately, the economists’ standard solution to the problem of expectations—perfect rationality—drove the physicists nuts. ... The only problem, of course, is that real human beings are neither perfectly rational nor perfectly predictable—as the physicists pointed out at great length. ... The physicists were shocked at the assumptions the economists were making—that the test was not a match against reality, but whether the assumptions were the common currency of the field. I can just see Phil Anderson, laid back with a smile on his face, saying, ‘You guys really *believe* that?’”¹

¹ Waldrop (1992), pages 136-143.

² For example, Feldstein (2012) is an excellent resource.

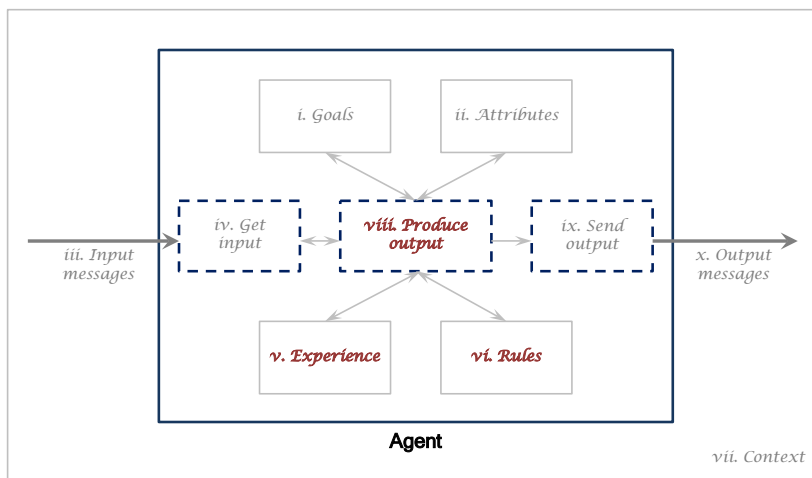
³ Rice & Unruh (2009)

C. GAME THEORY

1. Introduction

Game theory is a relatively new way to study strategic behavior. In a health system, agents must often act strategically, that is, in anticipation of how other agents will act. For example, in setting premium levels, a health insurance company must anticipate how its policyholders will react, as well as how other firms will price their insurance products. Similarly, in prescribing treatments, a physician must anticipate how patients will react. Using game theory, we can exactly (mathematically) simulate such behaviors if we make one crucial (and often incorrect) assumption, namely that the behaviors are—in a special sense that we will discuss below—“rational”.

As we will see in Section 3 (Description), game theory includes three of the ten health behavior parameters (highlighted in the figure below).



2. History

Game theory is relatively new. In the 1930s and 1940s, the renowned mathematician and physicist John von Neumann (see the sidebar) puzzled over the phenomenon of bluffing in poker and wondered if it could be expressed mathematically. As his thoughts took shape, and as he realized their great import, he teamed with the economist Oskar Morgenstern to write one of the world’s most influential—but least-read—books, titled “Theory of games and economic behavior”².

Von Neumann

From early childhood, John (“Johnny”) von Neumann displayed a remarkable mind. At his home in Budapest, Hungary, he would entertain his parents’ guests by memorizing random pages from a telephone book. A guest would select a random page; Johnny would look at it, hand the book back to the guest, recite the names, addresses, and telephone numbers in any order, and answer any question about the information. As an adult, he could recite long passages from books he had read years before.

After becoming the youngest professor at the University of Berlin, and publishing thirty-two papers in mathematics (at a rate of about one paper a month), in 1930 at the age of 27, he was invited to be one of the first four members of the faculty of the prestigious Princeton Institute for Advanced Study.

While in America, he made major contributions to many fields, including mathematics, physics, economics, and computer science. He was a principal member of the Manhattan Project, and worked out key steps of thermonuclear reactions. He also pioneered the digital computer. Edward Teller once said, “probably the IBM company owes half its money to Johnny von Neumann”.¹

He also developed the concept of cellular automata, a study that has greatly influenced the development of complexity science (the four-cell neighborhood of a cellular automata central cell is called a “von Neumann neighborhood”). In the preface to his posthumously published book, “The computer and the brain”, his wife Klara wrote “until his last conscious hours, he remained interested in and intrigued by the still unexplored aspects and possibilities of the fast-growing use of automata”.

All his life, he was fascinated by play. He kept a collection of children’s toys and played childish pranks on his colleagues. He played poker (badly) and this interest led to game theory.

¹ Blumberg & Owens (1976)

² Von Neumann & Morgenstern (1944)

C. GAME THEORY continued

2. History continued

The book is hard to digest. It is over 600 pages, delightfully pretentious, disorganized, and chock full with formulas written in new mathematical notation—a mathematician’s dream; a layperson’s nightmare.

Although scholars immediately hailed the book as a great achievement and welcomed game theory as an important new field, it was not until more than a decade later, in 1957, when Duncan Luce and Howard Raiffa wrote a more accessible introduction¹, that game theory took root.

In 1994, Nobel prizes in economics were awarded to three game theorists², and today game theory is widely used in economics, politics, foreign policy, and even biology ... but, as we shall see, not in the study of health systems.

3. Description

Two children, Calun and Ariana (brother and sister) like rhubarb pie. Their mom brings one large piece of pie for them both, and tells Calun he can divide it as he wishes, but that Ariana gets to choose the piece she will eat. How will Calun cut the pie? What strategy will he choose? What will Ariana do?

According to game theory, before cutting the pie, Calun will ponder the following table.

Calun's strategies	Ariana's strategies	
	Choose the larger piece	Choose the smaller piece
Divide the pie evenly	Calun = 2, Ariana = 2	2, 2
Make one piece larger	1, 3	3, 1

The table is called a “payoff matrix”. For each combination of strategies, the table shows the relative “payoff” (benefit or utility) that each child will receive. Calun’s payoff is listed first, then Ariana’s.

¹ Luce & Raiffa (1957)

² They were John Harsanyi, John Nash, and Reinhard Selten, “for their pioneering analysis of equilibria in the theory of non-cooperative games”.

C. GAME THEORY continued

3. Description continued

For example, if Calun chooses the strategy “make one piece larger” and Ariana chooses the strategy “choose the larger piece”, then Calun’s payoff (“1”) will be less than Ariana’s (“3”), because Calun will receive a smaller piece.

According to game theory, in order to select a strategy, Calun should consider Ariana’s strategy first. He should see from the table that her most rational strategy would be “choose the larger piece”, the first column, because this column gives her the largest payoffs. Calun will therefore choose the strategy “divide the pie evenly” in order to avoid the worst consequence of Ariana’s presumed strategy. Thus, game theory shows how Calun and Ariana will act.

This simple example highlights important ideas about game theory:

- **Theory basics.** Game theory applies to situations in which there are two or more players, a goal (in this case the assumed goal of each child is to obtain the largest piece of pie), rules for playing the game, multiple strategies for each player to choose (in this case, two), and payoffs for each combination of strategies.
- **Optimal strategies.** There is an optimal set of strategies for the players to choose. In their book, von Neumann and Morgenstern proved that for games of two players there is always an optimal set of strategies, provided the players’ interests are completely opposed. This optimal solution is called the “minimax” solution (avoiding the worst consequences of another’s presumed strategy, or maximizing the minimums that the other player would leave).
- **Constant-sum game.** This game is called a “constant-sum game”, because the size of the pie does not change. As we shall see, in game theory there can be many types of games.
- **Rationality.** Players are assumed to act rationally. As we shall see, this is a weakness of the theory. In this example, Calun and Ariana are my children. It is highly probable that Ariana—who is younger and smaller, and who adores her brother—would gladly give Calun the bigger piece should he choose the strategy “make one piece bigger”. So, in acting rationally, Calun may not be choosing the optimal solution.

C. GAME THEORY continued


3. Description continued

Now let’s consider a game for two prisoners. Freddy and Fredericka are arrested for a crime (that they did commit). Because the police do not have enough evidence to convict either, they tell each suspect:

- if one rats against the other, he or she will receive a reward and will be released, provided the other suspect does not also rat
- if both rat against each other, each will go to jail but with a reduced sentence
- if one keeps quiet but the other rats, he or she will go to jail for a long time
- if both keep quiet, both will go free

What will Freddy and Fredericka do?

This is the most famous game in game theory, the so-called “prisoner’s dilemma”. But it was not discovered by von Neumann or Morgenstern. Rather, in 1950 two scientists at the RAND Corporation, Merrill Flood and Melvin Drescher, developed it in order to test how real people choose strategies for an unusual game. It turns out, though, that in real life the prisoner’s dilemma is far from unusual.



Pause to reflect

If you were Freddy or Fredericka, what would you do? Why?

Following is its payoff table:

Freddy's strategies	Fredericka's strategies	
	Keep quiet	Betray Freddy
Keep quiet	2, 2	0, 3
Betray Fredericka	3, 0	1, 1

Clearly, the best overall outcome would be for both to keep quiet (in game theory parlance, to “cooperate”). But, according to an extension of the minimax principle developed by John Nash¹, called the Nash equilibrium, the rational strategy for both is to betray the other (to “defect”).

¹ John Nash developed the Nash equilibrium as a 21-year-old student at Princeton. He soon followed this with several brilliant papers about game theory and other areas of mathematics. Then, at a young age, he began to suffer from schizophrenia. Sylvia Nasar tells his story in the book “A beautiful mind”, which became an Oscar-winning movie with the same title.

C. GAME THEORY continued

3. Description continued

The prisoner’s dilemma arises whenever a person is tempted to better his or her own interests at the expense of others. It lurks in situations as diverse as marriage, business strategy, war, nuclear arms control, and even medical consultations (see the sidebar). Although our lives depend on cooperation, people usually choose their narrow self-interest over the common good and end up with sub-optimal total payoffs.^N Indeed, some see the prisoner’s dilemma as society’s fundamental problem, the subversion of common good by narrow rationality.^O

The prisoner’s dilemma we have explored is a single-round game; players play it only once. However, life’s dilemmas are usually not so simple. Marriage, business, war, and medical consultations usually have many rounds. A patient may visit the same general practitioner many times. For a prisoner’s dilemma game with many rounds, the so-called iterated prisoner’s dilemma, what are the best strategies?

In 1980, Robert Axelrod studied this question in a novel way. He invited several well-known game theorists, psychologists, sociologists, political scientists, and economists to submit strategies for an iterated prisoner’s dilemma tournament that would be played by agents on a computer. Each strategy specified whether a player should cooperate or defect at a point in the game, given the history of the game up to that point. For example, a simple strategy might be “always defect”. The winning strategy would be the one that obtained the highest cumulative payoff, determined according to the payoff matrix, after thousands of iterations.

The result? A simple strategy submitted by Anatol Rappoport, an American mathematical psychologist, won hands down. It was called “tit for tat”: cooperate the first time, and thereafter do what the other agent did in the game’s previous turn.² If the doctor in the sidebar does not provide full assessments, then take antibiotics the first time, but thereafter seek a second opinion.

The prisoner’s dilemma in a medical consultation

On a Friday afternoon at a busy general practitioner’s office, an adult patient visits the doctor for help with a sore throat the patient has had for several days. The patient has a red throat, a slight fever, and slightly swollen lymph nodes.

The doctor considers what strategy to pursue: whether to quickly deal with the patient by prescribing a course of antibiotics (which is probably not called for), or to take more time to assess the patient’s lifestyle and other contributing factors, and then to provide the patient more tailored advice.

The patient is also considering strategies: whether to follow the doctor’s recommendation, or to forgo the recommendation and consult another doctor.

The following payoff matrix captures one way of viewing the relative utilities of these strategies.

Doctor’s strategies	Patient’s strategies	
	Follow advice	Consult another doctor
Assessment	2, 2	0, 3
Antibiotics	3, 0	1, 1

For this payoff matrix, clearly the best overall outcome would be for the doctor to fully assess the patient, and for the patient to follow the doctor’s resulting recommendations. But, as you can see, the game is in the form of a prisoner’s dilemma, and rational players would choose strategies that lead to the sub-optimal outcomes in the lower right corner of the matrix.¹

¹ This example is from a journal article by researchers in the UK, Tarrant, Stokes, & Colman (2004).

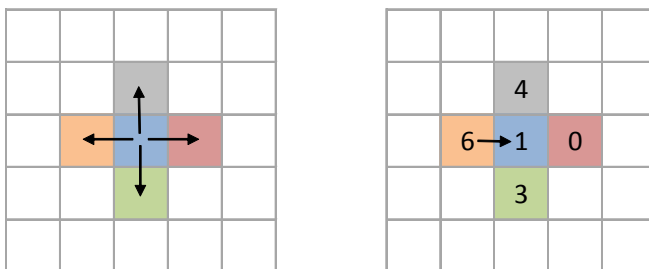
² Axelrod (1997)

C. GAME THEORY continued

3. Description continued

For the iterated prisoner’s dilemma, is “tit for tat” really the best long-term strategy? Kristian Lindgren, a physicist at Göteborg University in Sweden, studied the question further and found an answer no one dreamed.

Rather than have pairs of agents play the prisoner’s dilemma against one another (as in Axelrod’s tournament) Lindgren set up a simulation on a 128 x 128 checkerboard grid where each cell is an agent playing the prisoner’s dilemma with its four nearest neighbors (its von Neumann neighbors—see the figure at left below). Thus, in the simulation there are 16,384 (128 x 128) agents simultaneously playing the game. After a round of play, the agent with the highest score among the von Neumann neighbors takes over the center cell (see the figure at right below).



Lindgren started the simulation by randomly distributing four strategies among the agents:

- **Always defect.** Defect no matter what the neighbors do.
- **Always cooperate:** Cooperate no matter what the neighbors do.
- **Tit for tat:** Do what the opponent did in the previous iteration of the game.
- **Anti-tit for tat:** Do the opposite of what the opponent did in the previous iteration.

He assigned each agent a color according to its strategy, with different strategies having different colors. He then allowed the strategies of the agents to evolve, using a variant of the genetic algorithm (see sidebar). To do this, he represented an agent’s strategy by a string of 0’s and 1’s, where ‘0’ represents “defect” and ‘1’ represents ‘cooperate’.

Genetic algorithm

In the 1970s, John Holland—a professor of psychology, electrical engineering, and computer science at the University of Michigan—was inspired by the mechanics of biological evolution to create an innovative method to search for optimal solutions in vast solution spaces. He called the method the “**genetic algorithm**”.

To apply the genetic algorithm:

1. Encode potential solutions as strings, similar to the strings of A, C, G, T nucleotide bases on a chromosome.
2. Assess the current solution to see if it is optimal.
3. If the solution is not optimal, apply mutation (changing or deleting parts of the current string), crossover (exchanging parts of the string either with itself or another string), or copying (copying one part of a string to either itself or another string) in order to find a new solution string.
4. Repeat from step 2.

Through repetition of such a process, the genetic algorithm iteratively evolves an optimal solution.¹

¹ To learn more about the genetic algorithm, see Mitchell (1996).

C. GAME THEORY continued

3. Description continued

The strategy strings are of length 2^m , where m is the number of prior moves the agent remembers. For example, if the agent only remembers one prior move, the string length is 2. In this case, the string '01' means that if the opponent's prior move was '0' (defect) the agent's current move will be '0' (defect), and if the opponent's prior move was '1' (cooperate), the agent's current move will be '1'. This is the 'tit for tat' strategy. It is illustrated by the figure to the right.

Prior moves		Agent's Strategy
Agent	Opponent	
	0	0
	1	1

Similarly, if the agent can remember three moves, it might have a strategy '00011001', illustrated by the second figure to the right.

Prior moves		Agent's Strategy
Agent	Opponent	
	0	
0	0	0
0	1	0
	0	
1	0	0
1	1	1
	1	
0	0	1
	1	
0	1	0
	1	
1	0	0
	1	
1	1	1

During the game iterations, an agent's strategy can evolve in three ways:

- **Point mutation.** A random point on the agent's strategy string (its DNA) can be flipped from '0' to '1', or '1' to '0'.
- **Gene duplication.** A random piece of the agent's DNA can be tacked on to the end of its DNA string. This allows the agent's memory to grow.
- **Split mutation.** From a random point, the end of the DNA can be discarded.

In addition, Lindgren allowed an agent to sometimes apply its strategy incorrectly. The frequency of DNA changes and mistakes were governed by parameters that Lindgren set prior to the start of the simulation.

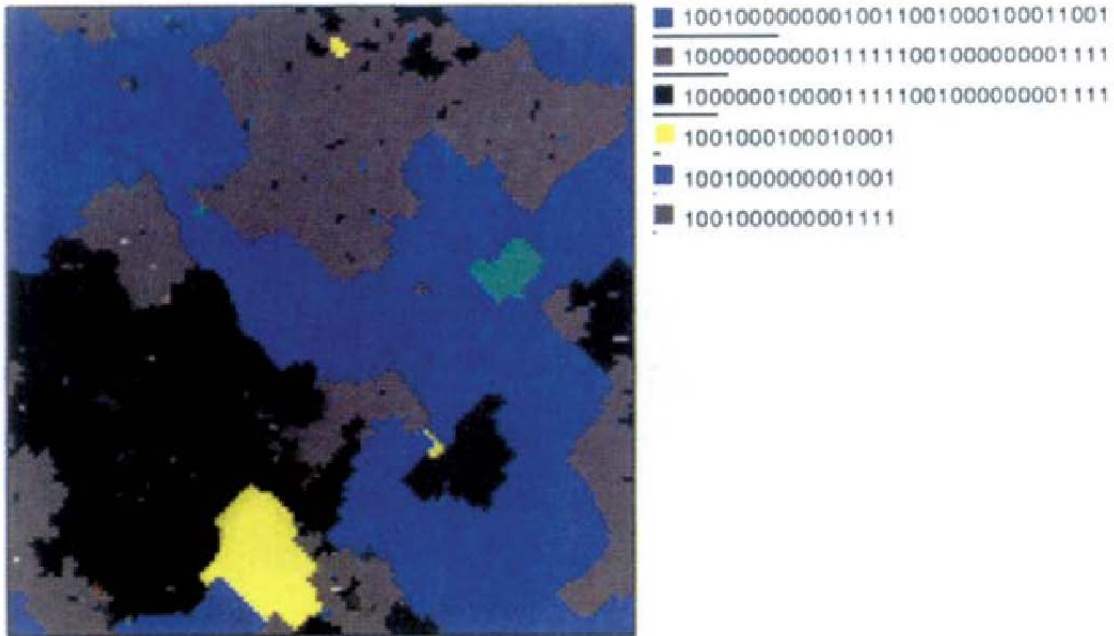
When Lindgren started the simulation, ecologies took shape. First, agents with the original four simple strategies competed for space on the grid. They died out as agents with more evolved strategies took over.

In order to survive, some agents cooperated with others. For example, a group of advanced agents would surround a group of agents with more simple DNA, allowing them to survive longer than they otherwise would have.

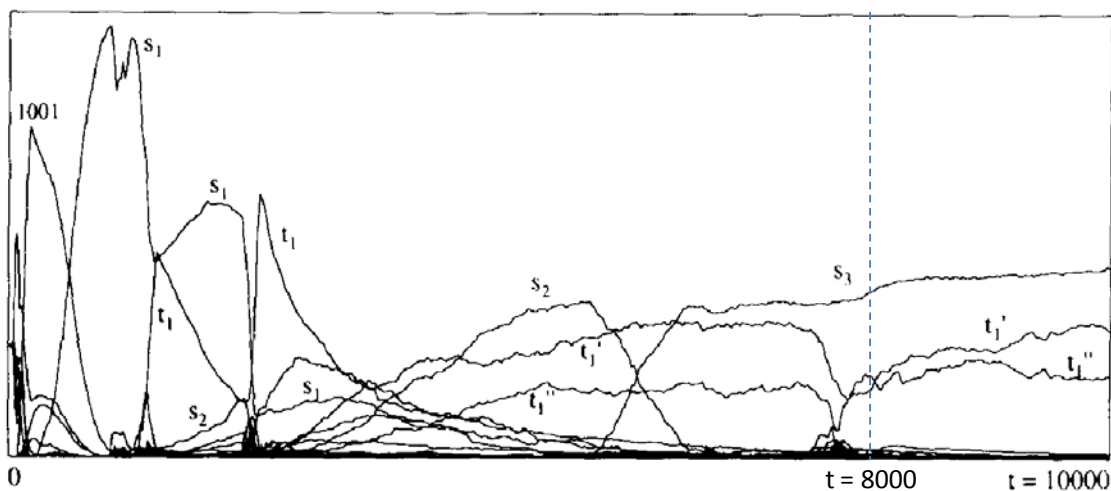
C. GAME THEORY continued

3. Description continued

The diagram below shows the arrangement of agents with different strategies at iteration 8,000 of one simulation. The strategy strings are shown to the right of the diagram. As you can see, they have evolved to strings of length 32, involving a memory of the prior five moves. It appears that more memory is an advantage.



The chart below corresponds to the figure above. It traces the simulation's history. As you see, agent strategies (labeled s_i and t_i) come and go. No one strategy remains forever.



C. GAME THEORY continued

3. Description continued

Lindgren’s work highlights several important points about the behavior of complex systems.

- **Complex systems evolve in cycles.** One group of strategies will dominate and be stable for a period of time, only to be extinguished and followed by another group of strategies.
- **There is no best strategy.** Because the system evolves, there is no “best” strategy or behavior. What is best at one time may be worst at another.
- **Prediction is impossible.** The only way to see how the system will evolve is to run the simulation. Forecasting its evolution is impossible.
- **Understanding is key.** Although it is not possible to forecast how the system will evolve, by exploring simulation parameters and collecting statistics, we can understand the system better. In the long run, this understanding may be as valuable as an ability to accurately predict, for—like a farmer’s understanding of how crops grow—it enables us to focus on significant parameters and to manage system risks.

In addition to the prisoner’s dilemma, there are 77 other types of two-person two-strategy games (see the sidebar). But there are many other types of games explored by game theory. To learn about these, see the references in Section H (To learn more).

4. Health system applications

There are few examples of game theory being used to model health behavior, and none that I could find of it being used in a simulation model of a health system.

As examples, researchers have applied game theory to model the medical consultation², vaccination policy³, medical decision making⁴, and health care utilization⁵.

The variety of games

In 1966, Melvin Guyer and Anatol Rapoport, both then at the University of Michigan, catalogued all the games with two players making a choice between two strategies. They found 78 such games.¹

Of these, the “symmetric games”—those in which the payoffs are the same for each player under comparable circumstances—are most common in real life. For such games, the payoff matrix is:

Player A	Player B	
	Cooperate	Defect
Cooperate	C, C	C, D
Defect	D, C	D, D

Thus, in symmetric games, there are only four payoffs, CC, CD, DC, and DD, and each preference ordering of these (from the perspective of Player A) is a different game.

There are 24 ways to arrange these payoffs, and, of these, three are true dilemmas:

- DC > CC > DD > CD:** Prisoner’s dilemma
- DC > CC > CD > DD:** Chicken
- CC > DC > DD > CD:** Stag hunt

The games of “Chicken” and “Stag hunt” are also widely studied models of conflict for two players.

For each of these games, even though mutual cooperation is valued highly, there is an incentive for Player A to defect. These are social dilemmas, common in real life and in health systems.

¹ Guyer & Rapoport (1966)

² Tarrant, et al. (2004), as described in a sidebar above.

³ Bauch & Earn (2004)

⁴ G. A. Diamond, Rozanski, & Steuer (1986)

⁵ Dowd (2004)

C. GAME THEORY continued

5. Strengths and weaknesses

In his book titled “The bounds of reason: game theory and the unification of the behavioral sciences”, Herbert Gintis writes, “Game theory is an indispensable tool in modeling human behavior. Behavioral disciplines that reject or peripheralize game theory are theoretically handicapped.”¹

Many agree, and consider game theory a sound theoretical basis for modeling social interactions.

However, there are strong reservations about using game theory in the social sciences. In his book, Gintis says that the Nash equilibrium—the fundamental equilibrium concept in traditional game theory—is not an appropriate concept for social theory.

Moreover, many game theory results do not square with reality. In 1952 and 1954, a team of scientists at the RAND Corporation, including John Nash, carried out an experiment to test the applicability of von Neumann’s n-person game theory. The result: subjects of the experiment did not act as von Neumann theory predicted.

In the late 1950s and early 1960s, researchers at Ohio State University carried out a series of psychological experiments about 2 x 2 games. In one, the researchers provided the payoff matrix at right to subjects, and asked them to play the game. Game theory predicts that they would all cooperate and that each would win four cents. In fact, 47 percent of the subjects defected and won nothing.

Player A	Player B	
	Cooperate	Defect
Cooperate	4¢, 4¢	1¢, 3¢
Defect	3¢, 1¢	0¢, 0¢

As more evidence accumulated that game theory was not particularly good at predicting human behavior, the field of behavioral game theory arose. Results from this field are covered in Chapter eight (Behavioral economics).

Game theory is a powerful mathematical theory that can prescribe what rational behavior should be in a wide variety of circumstances, but it is not very good at predicting what people will actually do.^P

¹ Gintis (2009), page 248.

D. PROSPECT THEORY

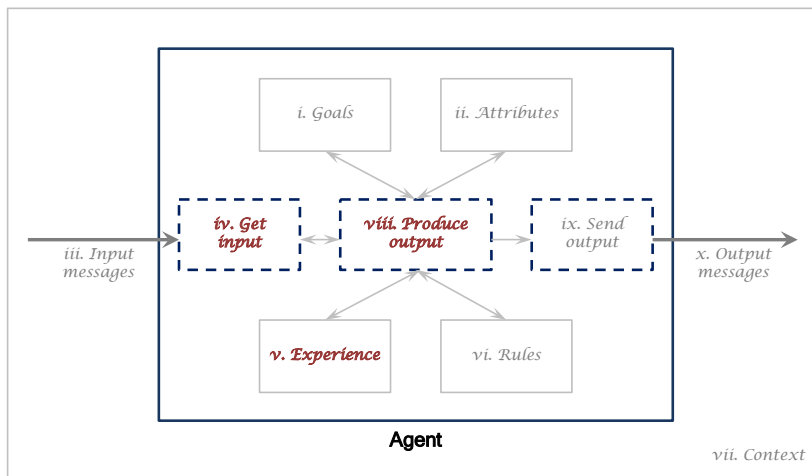
1. Introduction

The most-cited paper in the prestigious economics journal *Econometrica* was written by two psychologists, Daniel Kahneman and Amos Tversky (see the sidebar). It is titled “Prospect theory: an analysis of decision under risk”, and has been cited over 23,000 times.

In this paper, Kahneman and Tversky challenged the dominant theory underlying neoclassical economics: expected value theory. They challenged the theory in the way that scientific theories should be challenged: by finding contrary experimental results.

They proposed an alternative hypothesis that squared better with experimental results, and called it “prospect theory”.² Prospect theory proposes that in deciding among alternatives for which probabilities are known, people choose based on the potential value of losses and gains, rather than on final outcomes. And, people evaluate the potential value of losses and gains using inexact “heuristics” (rules of thumb).

As we will see in Section 3 (Description), prospect theory includes three of the ten health behavior parameters (highlighted in the figure below).



Kahneman and Tversky

Psychologists Daniel Kahneman and Amos Tversky shared one of the most productive collaborations in the history of social science. Starting in 1969, for more than 25 years they conducted groundbreaking experimental research into human judgment and decisionmaking. Their research had such a profound impact that in 2002 Kahneman became the first psychologist to win a Nobel Prize in Economics (an honor that, had he lived, Tversky would have shared).

As an example of one of their experiments, participants were asked to choose A or B from two scenarios:

- Scenario 1: A: \$4,000 with probability 0.80 or B: \$3,000 with probability 1.00
- Scenario 2: A: \$4,000 with probability 0.20 or B: \$3,000 with probability 0.25

80 percent of participants chose B from Scenario 1, and 65 percent chose B from Scenario 2. Thus, most participants violated expected utility theory from neoclassical economics (which would require participants to choose A from Scenario 1, because $0.80 \times \$4,000 = \$3,200 > \$3,000$, and A from Scenario 2, because $0.20 \times \$4,000 = \$800 > 0.25 \times \$3,000 = \750).

This, and a host of similar experiments, led Kahneman and Tversky to conclude that expected utility theory from neoclassical economics does not conform to human behavior. Rather, another theory—what they called “prospect theory”—was closer to reality.

For an excellent introduction to their work, see the YouTube videos of Kahneman presenting *Explorations of the mind*.¹

¹ Daniel Kahneman (2008a) and Daniel Kahneman (2008b).

² The name of the theory is from the following usage of the term “prospect”: if there is a 25 percent probability that I might obtain \$100, and a 30 percent probability that I might obtain \$75, then I have a “prospect” of obtaining either \$100 (with a probability of 25 percent) or \$75 (with a probability of 30 percent). Such a prospect might be represented as (100, 0.25; 75, 0.30).

D. PROSPECT THEORY continued

2. History

In 1957, one of the most influential social scientists of the 20th century, Herbert Simon, wrote: “The capacity of the human mind for forecasting and solving complex problems is very small compared with the size of the problems whose solution is required for objectively rational behavior in the real world—or even for a reasonable approximation to such objective rationality.”

Although Herbert Simon coined the phrase “bounded rationality” (the concept that a person’s rationality is limited by available information, the cognitive limits of the mind, and the time for making decisions) it was not until Kahneman and Tversky’s work, more than 20 years later, that the concept found firm experimental footing.

Prospect theory and the rest of Kahneman and Tversky’s work gave rise to the fields of behavioral economics, behavioral finance, and behavioral game theory, powerful subjects we explored in Part III.

3. Description

Prospect theory proposes that people make decisions in two stages:

- **Editing.** In the editing stage, people transform actual outcomes offered into simpler, but inexact, representations. To do this, they use simplifying operations such as “coding”, “combination”, “segregation”, “cancellation”, “simplification”, and “detection of dominance” (see the sidebar). Many anomalies of preference are a result of such editing. The editing operation corresponds to the behavior parameters “Get input” and “Rules”.
- **Evaluation.** After the outcomes offered are edited, people evaluate the resulting prospect according to the following formula:

$$U = \sum_{i=1}^n w(p_i)v(x_i)$$

where x_i is a potential outcome, p_i is the probability of the outcome, $w(p_i)$ is a probability weighting function such that people overreact to small probabilities ($w(.001) > 0.001$), but underreact to larger probabilities ($w(0.9) < 0.9$), and $v(x_i)$ is an asymmetrical S-shaped value function that passes through an often arbitrary reference point.



Pause to reflect

Suppose you are at a party with 25 people, and someone asks you the probability that two people at the party have the same birth date.

Standing there, holding your glass of wine (or apple juice), what would you say? Most people answer less than 10 percent ($25/365 = 0.07$).

Now take a look at the footnote.¹ Does the correct answer prompt you to reflect about the cognitive limits of the human mind?

Editing operations

Following are some of the editing operations that people use:

Coding: People perceive gains and losses as deviations from a reference point that they can set arbitrarily.

Combination: People can simplify prospects by combining probabilities. For example, (200, .25; 200, .25) might be simplified to (200, .5).

Segregation: People can segregate a riskless component of a prospect from the risky component. For example, the prospect (300, .30; 200, .20) might be decomposed into a riskless gain of 200 plus a risky component involving 100.

Cancellation: People can discard components shared by prospects. For example, the choice between (200, .20; 100, .50; -50, .30) and (200, .20; 150, .50; -100, .30) might be reduced to a choice between (100, .50; -50, .30) and (150, .50; -100, .30), after discarding (200, .20).

Simplification: People often round probabilities or outcomes. For example, (101, .49) is likely to be simplified to (100, .50).

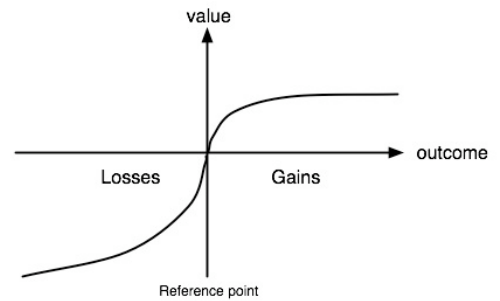
Detection of dominance: People often reject outcomes with small probabilities. For example, (100, .10; 100000, .00015) might be reduced to (100, .10).

¹ The correct answer is 57 percent. With 57 people at the party, the probability is 99 percent.

D. PROSPECT THEORY continued

3. Description continued

The chart at right shows a typical value function according to prospect theory. As you see, a loss of 100 hurts more than a gain of 100 feels good, and a change of -100 to -110 hurts more than a gain from 100 to 110 feels good. Thus, according to prospect theory, losses feel worse than gains in both a marginal and in an absolute sense.



In neoclassical expected utility theory, the value function is symmetrical and the reference point is equal to total assets, rather than some arbitrary point. Also, in neoclassical expected utility theory $w(p_i) = p_i$.

For an example of an application of prospect theory relevant to health systems, consider a person who is considering the purchase of individual health insurance. Assume that for a given year the probability of a significant adverse health event is 1 percent and the person’s potential loss is \$100,000. Further assume that the cost of insurance is \$1,500. Thus, the person’s choices are (100,000, 0.01; 1,500, 1.0).

What, according to prospect theory, will the person choose? First, the person might edit the prospect using detection of dominance, and simply discard the choice with the small probability (0.01). In this case, the person would choose to forgo purchasing the insurance.

If the person does not edit out the choices, there would be two choices, with the following utilities:

$$U_1 = w(1.00)v(-\$1,500)$$

$$U_2 = w(0.01)v(-\$100,000) + w(0.99)v(0)$$

It is likely that $w(0.01)$ will be evaluated as larger than 0.01, perhaps as much as 0.02, and that the potential loss of \$100,000 would be valued as much more than \$100,000, perhaps as much as \$150,000, in which case:

$$U_1 = -\$1,500$$

$$U_2 = 0.02 \times (-\$150,000) = -\$3,000$$

Thus, the person would purchase the insurance.

D. PROSPECT THEORY continued

4. Health system applications

There are not yet many examples of prospect theory used for health behavior, and none that I could find of it being used in a simulation model of a health system.

As an example, in 2008, researchers at the University of Chicago and Northwestern University suggested that shifting the reference point of the prospect theory value function (by judiciously framing medical recommendations) could help to convince people to undergo invasive screening tests or painful treatments, such as prostate cancer treatment.¹ However, the paper is only theoretical; it does not present empirical evidence to support its thesis.

5. Strengths and weaknesses

Prospect theory is mature and well-grounded in experimental research. It is now well-accepted that prospect theory provides a more realistic hypothesis about decision making under risk than neoclassical expected utility theory.

However, more research is needed to determine the proper weighting and value functions to use in health system simulations.

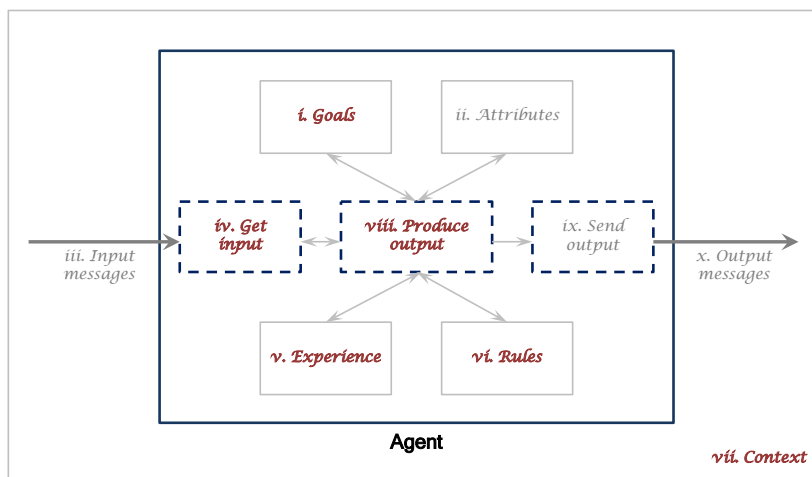
¹ Schwartz, Goldberg, & Hazin (2008)

E. BELIEF-DESIRE-INTENTION MODEL OF AGENCY

1. Introduction

The belief-desire-intention model of agency (BDI) is a widely employed hypothesis about the reasoning process we humans follow in deciding how to act. It has been used to control air traffic, to simulate air combat, to manage call centers, to control robots, and to handle malfunctions on NASA’s space shuttle Discovery. But it has not yet been used to simulate the behavior of health system agents.

BDI is a “cognitive architecture” (see the sidebar), and is designed for use in computational models that simulate human cognition and behavior. As we will see in Section 3 (Description), the BDI model includes six of the ten health behavior parameters (highlighted in the figure below).



2. History

In 1987, Michael Bratman, a philosophy professor at Stanford University, recognized the pivotal role that intention plays in human behavior. He wrote, “My desire to play basketball this afternoon is merely a potential influencer of my conduct this afternoon. It must vie with my other relevant desires ... before it is settled what I will do. In contrast, once I intend to play basketball this afternoon, the matter is settled: I normally need not continue to weigh the pros and cons. When the afternoon arrives, I will normally just proceed to execute my intentions.”³

Cognitive architectures

A “cognitive architecture” is a framework that provides the general structures and processes that are involved in human thinking and, consequently, human behavior. They are generally based on what psychologists, biologists, and other scientists have learned about human thinking.

Researchers use cognitive architectures as a starting point for modeling the cognition and behavior of specific agents in a particular domain. With a cognitive architecture in place, researchers need only worry about adding details of the behaviors they are simulating.

Cognitive architectures are meant to be used in computational simulation models, that is, simulation models that are run on computers.

In his groundbreaking work “Unified theories of cognition”, Allen Newell called on researchers to formulate general theories of cognition and behavior in the form of cognitive architectures.¹ Newell was a researcher in computer science and cognitive psychology at the RAND Corporation and at Carnegie Mellon. He helped develop the first artificial intelligence computer programs.

In addition to BDI, other well-known cognitive architectures are: ACT-R, Soar, and CLARION.²

¹ Newell (1990)

² Sun (2006)

³ Bratman (1987)

E. BELIEF-DESIRE-INTENTION MODEL OF AGENCY continued

2. History continued

Based on the importance of intention, he developed a theory of practical reasoning that was called the “belief-desire-intention model of agency” (BDI). Working with colleagues at the Stanford Research Institute, he then developed the first BDI computer framework; he called it IRMA.

Subsequently, researchers around the world have developed:

- Several computer platforms for implementing BDI, including JACK, JAM, and JADEX, all of which are Java-based (thus the “J”s).¹
- A second-order predicate logic of BDI reasoning, called LORA.²
- A methodology for designing BDI simulation models, called Prometheus.³
- Many BDI-based applications.

As a result of this work, BDI has become one of the most mature and widely used cognitive architectures.

3. Description

In the BDI model “beliefs” are what an agent believes about the environment, based on input the agent has received. It is equivalent to the “Experience” parameter in our definition of behavior. “Desires” are states of the environment that an agent prefers, equivalent to the “Goals” parameter. And an “intention” is a desire (goal) to which an agent commits and attempts to achieve.

“Intention” is the pivotal concept of BDI. An agent’s intention:

- **Drives planning.** Once an agent adopts an intention, it will develop plans to achieve it.
- **Persists.** An agent will not give up on an intention without good reason.
- **Constrains future deliberations.** An agent will entertain only those goals that are consistent with its intention.
- **Influences beliefs.** An agent assumes it will achieve its intention, and thus modifies its beliefs about the future.



Pause to reflect

Now that you know about the three essential concepts of BDI (beliefs, desires, and intentions) think about how you might use these as a template for simulating the behavior of a health system agent.

For example, how might you simulate a student in medical school trying to decide whether to pursue a career as a general practitioner or as a cardiac specialist?

¹ For links to these platforms, see “Belief-desire-intention software model” in Wikipedia.

² Wooldridge (2000)

³ Padgham & Winikoff (2004)

E. BELIEF-DESIRE-INTENTION MODEL OF AGENCY continued

3. Description continued

Let’s consider an example. Suppose a medical school student is deciding whether to pursue a career as a cardiac specialist or as a general practitioner. The sidebar shows a simple BDI algorithm for how the student might proceed.¹

The core of the algorithm is a “while” loop, in which:

- **Lines 1 and 2:** The variables “beliefs” and “intentions” are filled with the student’s initial beliefs and intentions. Perhaps the student’s initial beliefs include a belief that general practitioners are closer to the real practice of medicine, and perhaps her initial intention is to practice medicine to help people stay well.
- **Line 6:** The student obtains information related to her decision. A “percept” is an item of information obtained from the environment (the “context”).
- **Line 7:** Based on the new information, the student revises her beliefs about the world and her decision. Perhaps she learns that cardiac specialists make more money than general practitioners.
- **Line 8:** From her new beliefs and her intentions, the student forms a set of desires. Becoming a cardiac specialist now might be one of these desires.
- **Line 9:** The student forms an intention. Perhaps the intention is to become a cardiac surgeon.
- **Lines 10 and 11:** The student forms plans to realize the intention of becoming a cardiac surgeon, and executes the plans.
- **Line 12:** The student assesses the success of the plan by comparing the resulting environmental context to her intention. If they are the same, then the plans have succeeded. However, if the student finds that success has become impossible (perhaps she is unable to execute a step in the plan, such as performing open heart surgery) then she deems the plans impossible, and the loop starts over.

Although a real BDI model would have a more detailed and nuanced algorithm, I hope this example gives you an idea about how a BDI model works.

Simple BDI model

Following is an algorithm, written in Java syntax, implementing a simple version of the BDI model.

```

1  beliefs = initialBeliefs;
2  intention = initialIntention;
3
4  while ( planStatus != success)
5  {
6      percept = getNewPercept(context);
7      beliefs = reviseBeliefs(beliefs, percept);
8      desires = developDesires(beliefs,
9                              intention);
9      intention = reviseIntentions(beliefs,
10                                 desires, intention);
10     plans = developPlans(beliefs, intention);
11     executePlans(plans);
12     planStatus = getPlanStatus(context,
13                               beliefs, intention);
13 }

```

¹ This algorithm is based on algorithms in Chapter 2 of Wooldridge (2000).

E. BELIEF-DESIRE-INTENTION MODEL OF AGENCY continued

4. Health system applications

I have been unable to find an example of a health system simulation model that uses the BDI cognitive architecture. Indeed, I have not found an example of any cognitive architecture used in a health system simulation model.

5. Strengths and weaknesses

The BDI model provides a framework for agents to perform relatively complex reasoning and arrive at realistic courses of action relatively quickly. Moreover, the model is relatively mature: it has a large community of researchers, a formal underlying logic, many development platforms, a software development method, and many applications (although there are none in health systems simulation).

However, the iterative nature of the BDI model requires significant computer resources, especially when it is used for the reasoning of thousands or millions of agents. Because most BDI platforms are written in Java—a computer language that itself consumes significant computer resources—this problem is compounded.

Moreover, Stephen Stich, a professor of philosophy at Rutgers University, and others claim that the BDI model is based on a “folk psychology” that we use in our everyday lives, a commonsense psychology that includes concepts such as believing, desiring, and intending ... but that is not how the mind works. Thus, they claim that models such as BDI that are based on such folk psychology are ill-suited to simulate human cognition.¹

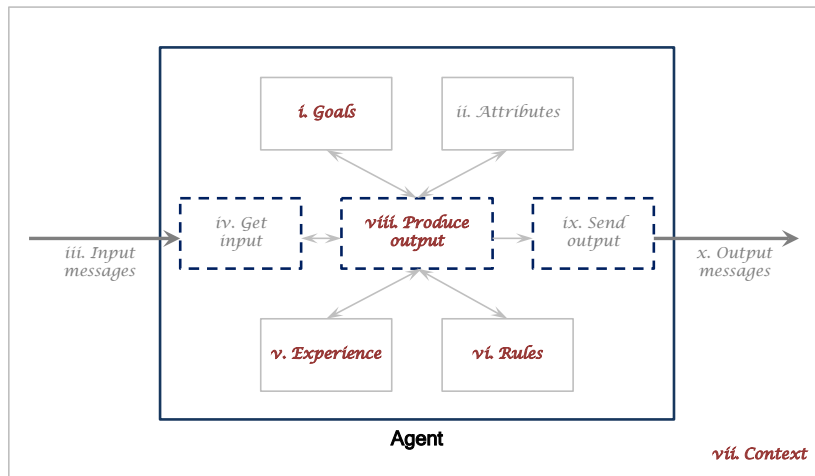
¹ Stich (1983). For more information about “folk psychology” see the article “Folk psychology as a theory” in the Stanford Encyclopedia of Philosophy, at [“plato.stanford.edu/entries/folkpsych-theory/”](http://plato.stanford.edu/entries/folkpsych-theory/)

F. THEORY OF PLANNED BEHAVIOR

1. Introduction

The “theory of planned behavior” (TPB) is a mathematical hypothesis that was developed to explain why people perform certain behaviors. Researchers have successfully employed the TPB in scores of studies to predict health behavior, and have used it to represent agent behavior in a health system simulation model.

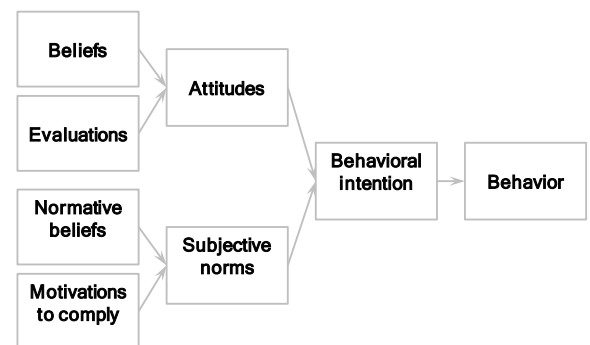
As we will see in Section 3 (Description), the TPB includes five of the ten health behavior parameters (highlighted in the figure below).



2. History

Icek Ajzen, a psychology professor at the University of Massachusetts, developed the TPB in the late 1980s, as an extension of a behavior theory that he and Martin Fishbein, a professor of communications at the University of Pennsylvania, had developed in the mid-1970s called the “theory of reasoned action”.

Ajzen and Fishbein had developed the theory of reasoned action to better explain relationships between attitudes, intentions, and behaviors. Prior researchers had found relatively low correspondence between attitudes and behavior, and some proposed eliminating attitude as a relevant factor altogether. Ajzen and Fishbein disagreed. They held that attitudes about a behavior are a significant factor in determining the intention of a person to perform a behavior, as are subjective norms (social pressures to perform a behavior), and that the resulting intention is the most significant factor determining behavior. The relationships between attitudes, norms, intention, and behavior in this precursor theory are summarized in the figure to the right.



F. THEORY OF PLANNED BEHAVIOR continued

2. History continued

In recent years, Martin Fishbein and his colleagues have expanded the theory of planned behavior (TPB) to incorporate constructs from other behavioral theories, resulting in what they call the “integrated behavioral model”.¹

3. Description

The figure to the right illustrates the TPB, and underneath the figure are the meanings of the TPB’s constructs.

As you can see, with the TPB, Ajzen expanded the theory of rational action by adding the construct “perceived behavioral control” as a factor giving rise to both behavioral intention and behavior, and by adding two secondary factors supporting “perceived behavioral control”. The construct “perceived behavioral control” enables researchers to apply the TPB hypothesis to behaviors that are difficult to perform because they are outside of the agent’s immediate control. An example of such behavior is maintaining a healthy diet.

The TPB’s constructs have the following mathematical relationships:

$$Behavior = w_1BI + w_2PBC \text{ and}$$

$$BI = w_3A + w_4SN + w_5PBC$$

where:

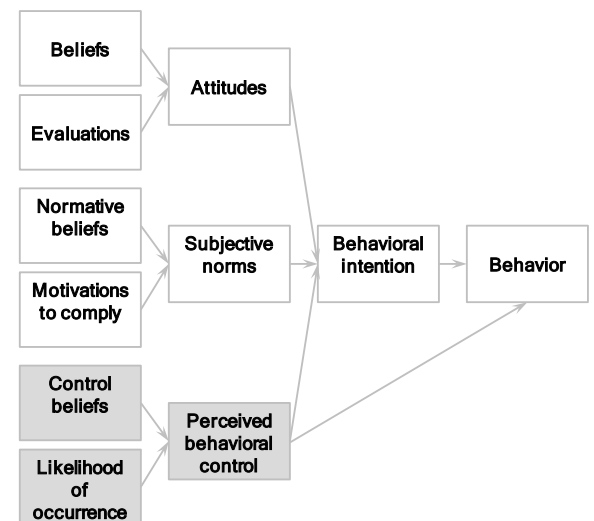
$$A = \sum_{i=1}^p b_i e_i$$

$$SN = \sum_{j=1}^q nb_j mc_j$$

$$PBC = \sum_{k=1}^r cb_k lo_k$$

The values of the constructs *BI*, *A*, *SN*, and *PBC* are obtained by surveying the population of interest about the behavior of interest. The values *w_i* are empirically determined regression weights that vary from individual to individual, and from behavior to behavior.

In the next section, we will explore how to apply the TPB.



Behavioral intention (BI): The agent’s decision to follow a specified plan to perform the behavior.
Attitudes (A): The agent’s favorable or unfavorable disposition about the behavior.
Subjective norms (SN): Social pressures the agent feels to perform or not perform the behavior.
Perceived behavioral control (PBC): The agent’s perception of the behavior’s difficulty.
Beliefs (b_i): The agent’s belief that performing the behavior leads to the outcome i.
Evaluations (e_i): The agent’s evaluation of outcome i.
Normative beliefs (nb_j): The agent’s probability assessment that a significant other agent j thinks that the behavior should be performed.
Motivations to comply (mc_j): The agent’s motivation to comply with agent j.
Control beliefs (cb_k): The agent’s perception of the facilitating or inhibiting power of factor k.
Likelihood of occurrence (lo_k): The agent’s perceived likelihood of occurrence of factor k.

¹ The information in this section is primarily from Glanz, et al. (2008) and Conner & Norman (2005).

F. THEORY OF PLANNED BEHAVIOR continued

3. Description continued

The following table shows the correspondences between primary TPB constructs and the ten behavior components.

TPB construct	Behavior component
Attitudes	Experience, Rules, Goals
Subjective norms	Experience, Rules, Goals, Context
Perceived behavioral control	Experience, Rules

In addition, the entire TPB hypothesis corresponds to the “Produce output” behavior parameter. Thus, the TPB includes five of the ten behavior parameters (Experience, Rules, Goals, Context, and Produce output).

4. Health system applications

Researchers have applied the TPB to predict health behavior in scores of studies. For example, in one meta-analysis from 1996 the reviewers found 76 applications of the TPB to health behaviors.²

Most of the applications of the TPB to health behavior are related to health promotion behavior, such as smoking, alcohol use, illicit drug use, physical activity, dietary behavior, driving behavior, sun protective behavior, preventive health screenings, breast and testicular self-examination, and adherence to medication. Some of the applications involve interventions.

However, I found only one study that applied the TPB in a health system simulation model. It is described in the sidebar.

Simulating breast cancer screening

In 2012, Sally Brailsford—a business management professor at the University of Southampton in the UK—and her colleagues developed a computational model to simulate how women decide to obtain breast cancer screening.¹ They modeled the screening behavior using the theory of planned behavior (TPB). The researchers used the TPB because “The TPB was found to be a popular model, and was also regarded as more formally structured therefore lending itself more easily to being tested, measured, and modeled.”

To obtain estimates of the distributions of and correlations among the three TPB constructs, the researchers used raw data from a study for predicting attendance at breast cancer screening appointments. The study’s dataset contains responses of 2,058 randomly sampled women about 106 demographic and socio-economic variables, including measures for the TPB constructs. The dataset also includes screening attendance information for each woman.

For the simulation, each individual agent was assigned measures for the three constructs corresponding to measures from an actual case in the original dataset selected at random.

Screening attendance was modeled as a Bernoulli trial, where the probability of success is a linear function of the three TPB constructs.

An important finding of the study was that a 4 percent increase in detected breast cancers could be achieved by simply increasing the TPB values of the population (attitudes, subjective norms, and perceived behavioral control) by 10 percent and by not otherwise altering the current screening program. The researchers therefore call for additional research to determine what methods (education, publicity, etc.) would increase the TPB values.

¹ Brailsford, Harper, & Sykes (2012)

² Godin & Kok (1996)

F. THEORY OF PLANNED BEHAVIOR *continued***5. Strengths and weaknesses**

The TPB has mathematical underpinnings, and so is more conducive than verbal-conceptual models for incorporation in computational simulation models. Moreover, there are scores of studies in which researchers have applied the TPB to health behaviors.

However, because all of the TPB studies have been correlation studies, rather than experimental studies, and because the correlation studies have produced varied results, the TPB hypothesis has not yet been rigorously verified. Moreover, because the weight values w_i in TPB's mathematical formulation can vary from individual to individual, it is unclear how the hypothesis would be rigorously applied to large populations to simulate health system behaviors.

G. ISSUES AND FUTURE DIRECTIONS

The major issue of the five health behavior hypotheses is whether they correspond to actual health behavior. As we have seen, there are significant concerns about the validity of rational choice theory and game theory. Moreover, the belief-desire-intention model may be based on “folk psychology” that has little basis in reality.

H. TO LEARN MORE

To learn more about:

- **Rational choice theory.** For an introduction to rational choice theory, see Pindyck & Rubinfeld (2009). For a more advanced treatment, see Mas-Colell, Whinston, & Green (1995) and the article by Miller (2006). For applications of rational choice theory in health care, see Feldstein (2012). For discussions about the limitations of neoclassical microeconomics in health care and generally, see Rice & Unruh (2009) and Beinhocker (2006), respectively. Lastly, for a beautiful and powerful account of the history of economics, read Heilbroner (1999).
- **Game theory.** For an entertaining introduction to game theory and the people who developed it, see Poundstone (1993). For a more advanced treatment, see Fudenberg & Tirole (1991). To learn about behavioral game theory, read Camerer (2003).
- **Prospect theory.** Perhaps the best introduction to prospect theory is the original paper by Kahneman and Tversky, found as Chapter 2 in Daniel Kahneman & Tversky (2000). The paper is well-written and entertaining; it will give you a sense of the humble yet adventurous spirits of Kahneman and Tversky. Another excellent paper about prospect theory is Thaler (1980).
- **The belief-desire-intention model:** Read Wooldridge (2009). This book provides an excellent overview of the BDI model, and describes in detail how the model incorporates plans to achieve intentions.
- **The theory of planned behavior:** Excellent resources to learn more about the TPB are: Glanz, et al. (2008) Chapter 4, Conner & Norman (2005) Chapter 5, and Gochman (1997) Volume I Chapter 7. These books provide references to the original articles and books by Ajzen, Fishbein, and others, as well as to literature about TPB applications.

I. REVIEW AND A LOOK AHEAD

In this chapter, we explored in detail five health behavior hypotheses, including the history of each, its application to health system analysis, and its strengths and weaknesses.

In the next chapter, I will propose an approach to develop a bona fide behavior theory.

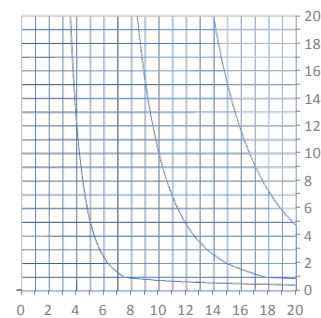
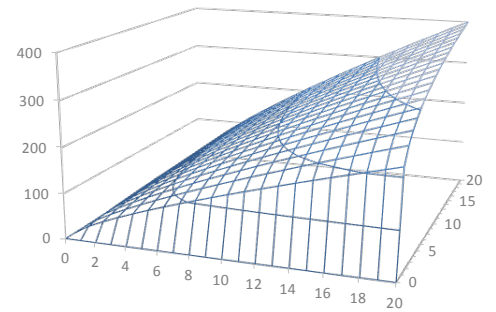
(Don't forget to take a look at the exercises for this chapter. They start on the next page.)

EXERCISES

1. Using Excel, reproduce the graphs of the Cobb-Douglas utility function described in Subsection 3 (Description) of Section B (Rational choice theory). Start with the parameters $k = 20.0$ and $\alpha = 0.6$, then vary α to see how the graphs change.
2. Give examples of the prisoner’s dilemma in real life.
3. Discuss how you might employ a simulation such as Lindgren’s simulation of the prisoner’s dilemma to demonstrate the phenomenon of small area variation in treatments prescribed by physicians.
4. Discuss how a healthcare policymaker might use prospect theory to improve the function of a health system.

SOLUTIONS

1. Use Excel’s “wireframe 3D surface” and “wireframe contour” graphs. To the right are graphs with $\alpha = 0.8$.
2. The “free rider” phenomenon is an example of the prisoner’s dilemma in action: a young man jumping a subway turnstile, parents refusing immunizations for their children, etc.
3. You might set up a simulation that evolves prescribing strategies between patients and physicians, using the genetic algorithm. You could also make the strategy of a physician dependent on the strategies of other physicians in the physician’s neighborhood. The resulting ecology would likely have shifting patterns similar to Lindgren’s simulations. This result might lead to the conclusion that patterns of small area variation can shift over time.
4. In prompting people to change their behavior, the policymaker might employ the asymmetrical nature of prospect theory’s value function. For example, to encourage people to engage in a particular behavior, the policymaker might demonstrate how the behavior would help them avoid significant losses.



CHAPTER TWELVE: ONE GOOD THEORY

There is nothing so practical as a good theory.

Kurt Lewin¹

A. THEORY IN COMPLEX DOMAINS

In this Part IV (Health behavior theory) we started by reviewing the success of Newton's laws of motion, elegant scientific theory that for three centuries continually increased our ability to understand and manage the domain of our physical environment.

We then reached the startling conclusion that, in the domain of health systems, there is not yet any scientific health behavior theory. Although researchers have developed many hypotheses, some of which are useful, there is not yet a counterpart to Newton's laws.

Perhaps this is as it should be, for the domain of our physical environment and the domain of healthcare systems are different. One is simple; the other wildly complex. The laws of one were fixed within nanoseconds after the big bang; the laws of the other (if there are any) have evolved over time and continue to evolve.

Even though it is no wonder that the Newton of health behavior has not yet arrived, how are we to understand and manage our complex health systems? How are we to organize the many health behavior facts? What are we to do with the current health behavior hypotheses?

B. CLEAN HOUSE

First, health behavior researchers should clean house. We should first prepare a complete catalog of all health behavior hypotheses. Then we should discard those that are not falsifiable and that have not withstood the test of scientific tests. We should test the remaining hypotheses with rigorous scientific experiment, and compare them to one another, discarding those that do not measure up or are redundant.

¹ Kurt Lewin was a German-American pioneer of applied psychology, and the founder of social psychology. This quote is found in the book *Field theory in social science; selected theoretical papers*, page 169.

B. CLEAN HOUSE continued

As two prominent health behavior researchers wrote, “What the field needs are researchers who are willing to put these concepts and theories to the strongest possible tests, so we can progress further in understanding health behavior and health behavior change.”²

C. DEVELOP AN ONTOLOGY

After cleaning house, health behavior researchers should develop an ontology for health systems research—such as the one I introduced in Part II (Classification of agents and behavior)—and use its terminology for all health behavior constructs and hypotheses.

D. DEVELOP ONE GOOD THEORY

Then the real work begins, that of developing one good health behavior theory that accords with health behavior facts. Such a theory cannot arise from the current fragmented perspectives of the various health behavior fields. Rather it must integrate what we know about health behavior from all the social sciences, including economics, as well as fields such as psychology and behavioral neuroscience.

To support the development of such a theory, health behavior researchers must begin to conduct scientific health behavior experiments, rather than mere correlation studies. As Weinstein wrote, “Correlational studies have an important, but limited, place in theory development. Forcing authors to acknowledge explicitly the limitations of such studies should encourage more experiments. Even a small shift away from correlational designs would be beneficial, for without such a shift, it is doubtful whether there will be any real progress in understanding health behavior.”³

No one knows what health behavior theory will look like. We do not even know the proper search space in which to look for such a theory.^Q My guess is that the space will have ten dimensions, corresponding to the ten components of behavior. And a true health behavior theory may even end up having a slightly alien flavor, such as the theory of entropy that Jing Chen is developing as a more rigorous basis for behavioral economics and finance (see the sidebar).

Behavior and entropy

Jing Chen is a Chinese-born mathematician and professor in the school of business at the University of Northern British Columbia.

He has developed a unified theory of human psychology based on the thermodynamic law of entropy. Entropy is one of the fundamental laws of the physical universe, and extends to the concept of information. This law provides that the state of a closed system tends toward maximum dispersion of energy and information. In a warm room, an ice cube melts. Similarly, it is far easier for social and information structures to collapse than to remain an integral whole.

Because the universe tends to disperse information, it is costly for the human mind to acquire information and to maintain information structures. Therefore, human psychology has developed heuristics, rules of thumb, to minimize the costs of acquiring and maintaining information structures.

Much of human behavior—including conservatism, framing, herd behavior, overconfidence, and loss aversion—can be understood in terms of the entropy of information and our need to efficiently acquire and maintain information structures.

Professor Chen has written, “It is in a data driven and highly technical subject that revolutionary ideas originate. Modern astronomy was a data driven and highly technical subject aimed to understand the movements of several planets. Newtonian mechanics, which was originally developed to provide a physical foundation of celestial movements, has come to dominate the thinking of social sciences for many years. Life processes, however, are thermodynamic processes instead of mechanical processes. Social processes, as life processes of one species, should be built on the theory of thermodynamics instead of Newtonian mechanics.”¹

¹ Chen (2003) and Chen (2011)

² Noar & Zimmerman (2005)

³ N. D. Weinstein (2007)

E. DEVELOP ONE GOOD PARADIGM

As health behavior researchers start the hard work of developing theories, they must also develop an appropriate paradigm in which to work. Although such a paradigm will evolve naturally, hand-in-hand with the development of theory, I suggest that complexity science is a good place for health behavior researchers to start their search for an appropriate paradigm. Because health systems are complex systems, complexity science is an appropriate framework in which to study them.

F. ISSUES AND FUTURE DIRECTIONS

This chapter addresses several issues about health behavior theories that were raised in the previous chapters of this part, and proposes a future direction for health behavior research. The only remaining issue is how to encourage health behavior researchers to pursue such a program.

G. TO LEARN MORE

To learn more about entropy and information, read James Gleick's entertaining new book *The information: a history, a theory, a flood*.¹

H. REVIEW AND A LOOK AHEAD

In this chapter, I addressed several issues raised in previous chapters by proposing a program for health behavior researchers to develop scientific theories of health behavior.

This concludes Part IV (Health behavior theory). In the next part, we will explore the methods and tools you will need to develop agent-based simulation models of health systems.

(Don't forget to take a look at the exercises for this chapter. They start on the next page.)

¹ Gleick (2011)

EXERCISES

1. Describe how the ontology developed in Part II (Classification of agents and behavior) would need to be expanded in order to serve as a basis for developing health behavior theories.
2. Discuss how health behavior and the ten behavior components are related to the ideas of “computation”, “information”, and “entropy”.

SOLUTIONS

1. To provide a basis for developing health behavior theory, the ontology would need to define the constructs used in health behavior theories, and how those constructs relate to the agent roles and behaviors in the ontology.
2. Boiled down to essentials, health behavior is merely a computation that transforms input information into output information, in conformance with the laws of entropy. Getting the input, producing the output, and sending the output are included in the ten behavior components.

PART V: METHODS AND TOOLS

Our civilization runs on software. Yet the art of creating it continues to be a dark mystery, even to the experts, and the greater our ambitions, the more spectacularly we seem to fail.

Scott Rosenberg¹

Ideally, the variation in the predicted impacts among models of a proposal should itself yield information about the degree of uncertainty surrounding the proposal. Policy analysts should be able to choose among estimates according to their own assessment of this evidence. ... As typically presented, however, estimates do not fulfill any of these functions, and policy analysts cannot choose among them by comparing their assumptions. ... Indeed, it is almost impossible to understand why estimates based on different models differ. ... This lack of comparability among models undermines the modeling enterprise. The resulting variability suggests that the models yield no genuine information. Worse, it raises the suspicion that estimates are made to accommodate the preferences of the estimator's patrons.

Sherry Glied et al²

Policymakers are often faced with many complex policy options and, as a consequence, need tools to distinguish among these options and to understand their effects and costs. The forecasting models that policymakers depend on to estimate these effects are numerous and varied and often produce inconsistent and undependable results. ... Furthermore, the models are often black boxes, so the users of the results, such as myself, a congressional staffer, have no idea what data the models used or what assumptions they were based on. ... Therefore, it would be helpful to know the costs and effects of different proposals under agreed-upon standards before they are sent to the CBO for scoring. The congressional staff want accurate, reliable results. Part of increasing reliability is building better models and understanding data and empirical constraints. Over time, modeling could improve.

Linda Fishman³

¹ Rosenberg (2008): "Dreaming in code: Two dozen programmers, three years, 4,732 bugs, and one quest for transcendent software".

² S. Glied, Remler, & Zivin (2002): "Inside the sausage factory: improving estimates of the effects of health insurance expansion proposals".

³ Fishman (2003): "Just feed me the sausage: one congressional staffer's view".

INTRODUCTION

Software is hard.

Donald Knuth¹

A central goal of this work is to inspire and enable you to develop effective agent-based simulation models of health systems, so that you will help stakeholders solve real-world problems. Part V describes the methods and tools you will need to build such models.

It has four chapters:

- **Agent-based modeling method:** Proposes a complete method for creating agent-based simulation models of health systems.
- **Simulation modeling guidelines:** Provides good practice guidelines for *how* you should carry out the modeling method.
- **Agent-based modeling tools:** Describes the tools you will need to develop agent-based simulation models.
- **Sample agent-based models:** Describes three agent-based models that I developed using this part's methods, guidelines, and tools.

A complete modeling method for creating agent-based simulation models of health systems has not previously existed. Neither has a relevant set of modeling guidelines. The method and guidelines that I suggest in this part are new and, consequently, provisional. They need to be tested, elaborated, and then adopted as a standard. In Part VI (Filling the gaps) I discuss how this can be accomplished.

I hope you will use the material in this part to build models that will help solve our urgent healthcare problems, and improve the health of millions. I also hope you will have fun.

¹ Knuth (1996). Donald Knuth is author of the influential book *The Art of Computer Programming*, and one of computer science's most respected gurus.

CHAPTER THIRTEEN: AGENT-BASED MODELING METHOD

As multiagent systems become more established in the collective consciousness of the computer science community, we might expect to see increasing effort devoted to devising methodologies to support the development of agent systems. Such methodologies have been highly successful in the object-oriented community.

Michael Wooldridge¹

A. INTRODUCTION

This chapter presents a simple method for you to build, use, and maintain agent-based models for simulating health systems.

Every modeler follows some modeling method, but, especially for agent-based simulation modeling, the methods are often ad hoc and implicit. In 2004 two software engineering professors interviewed two hundred software development team leaders from a cross-section of industries about their development practices. They reported “the shock and disappointment we felt at finding that the most dominant practice was none at all—a practice (if it can be called such) reported by a full third of the survey participants”.²

If, however, you follow a well-planned and explicit method, such as the one I suggest here, it is far more likely that you will produce models on schedule, within budget, and with high quality, and it is more likely that your users will find them understandable, reliable, and useful.

Although there are many software development methods, to my knowledge the method I describe in this chapter is the first complete method specifically designed for building agent-based models to simulate health systems (see the sidebar).



Pause to reflect

Take a moment to consider what you think a method for building agent-based simulation models should include.

Do you think a method is even necessary? Why?

Objects are not agents

Object-oriented programming (OOP, pronounced “oops” without the “s”) is a relatively new way to develop computer programs, based on the concept of an “object”. An object is a collection of computer code that can be viewed as an independent entity, with its own data and actions (called “methods” in OOP). Objects can communicate with each other by sending messages back and forth.

Although an object may seem to be the same thing as an “agent” in agent-based simulation modeling, it is not. Whereas an agent is autonomous and can control its behavior, an object cannot. An object X can make another object Y perform some action A merely by executing Y’s method for A. But if X and Y were agents, X would have to request Y to perform A, and Y—being autonomous—might refuse.

Moreover, an agent’s behavior is flexible. Depending on its environment, an agent reacts in different ways. By contrast, an object is generally not designed for such flexible behavior.

Because agents and objects are different, methods for designing and building OOP models—of which there are many—are not necessarily suitable for agent-based programming.

¹ Wooldridge (2009)

² Laplante & Colin (2004)

B. METHOD OVERVIEW

The method includes six major processes:

1. **Manage the project.** The first process manages the project. It continues for the project's duration.
2. **Develop the model.** The second process develops a computer model that is ready to use.
3. **Evaluate the model.** In the third process, an independent third party evaluates the model and its documentation.
4. **Implement the model.** This process trains users and installs the model.
5. **Operate the model.** This process includes running the model, analyzing the results, documenting the work, and preparing a results report.
6. **Maintain the model.** This process enhances, repairs, and archives the model.

C. THE METHOD IN DETAIL

Following is a more detailed description of the method's processes:

1. Manage the project

The method's first process includes:

- planning the modeling project
- drafting the modeling contract with the sponsor
- allocating human and material resources
- monitoring compliance with guidelines
- monitoring model usage
- providing access to the model
- collaborating with stakeholders
- measuring the project's progress

Although the tasks for this process are largely self-explanatory, the last one bears more explanation:

- As the SEI CMMI indicates (see sidebar), modeling projects that are managed according to quantitative goals have a higher maturity level and are more likely to succeed. Therefore, as part of this first process, it is important to set quantitative goals and to measure how well the modeling project meets these goals.

CMMI maturity levels

The Carnegie Mellon Software Engineering Institute (SEI) has developed processes to help organizations develop, implement, and maintain high-quality software. It is called CMMI (Capability Maturity Model Integration). The CMMI first assesses the current maturity level of an organization. There are five maturity levels:

1. Initial: The organization's processes are usually ad hoc and chaotic, and the organization does not provide a stable environment to support structured processes. Success in these organizations depends on the competence and heroics of the organization's people, and not on the use of proven processes. Maturity Level 1 organizations are characterized by a tendency to overcommit, to abandon processes in times of crisis, and to fail to repeat successes.

2. Managed: The organization's processes are planned and executed in accordance with policy; the processes employ skilled people who have adequate resources to produce controlled outputs; they involve relevant stakeholders; are monitored, controlled, and reviewed; and are evaluated for adherence to process standards.

3. Defined: The organization's processes are well characterized and understood, and are described in standards, procedures, tools, and methods. Processes are described more rigorously and managed more proactively than in Level 2.

4. Quantitatively managed: The organization establishes quantitative objectives for quality and performance and uses them as criteria in managing processes.

5. Optimizing: The organization continually improves its processes based on a quantitative understanding of the common causes of variation inherent in processes.¹

¹ To find out more about CMMI, go to the Carnegie Mellon SEI website, "CMMIinstitute.com".

C. THE METHOD IN DETAIL continued

1. Manage the project continued

The creator of CMMI, Watts Humphrey, informally sketched what organizations look like at the various maturity levels: “An organization at Level 1 is basically not doing much of anything. At Level 2, they’re doing some planning, tracking, configuration management, they make some noises about quality assurance, that kind of stuff. A Level 3 organization begins to define processes—how they work, how they get things done, trainable things. At Level 4 they’re using measurements. They have a framework for actually tracking and managing what they do, something statistically trackable. Level 5 organizations have a continuously improving process.”¹

Organizations that implement CMMI have seen 20 percent reductions in development costs, 37 percent improvements in scheduling, 62 percent improvements in productivity, 50 percent improvements in quality, 14 percent improvements in customer satisfaction, and 4.7:1 ROI gains.² A formal quantitatively based management process can be a modeling method’s most potent process, but it is often overlooked.

2. Develop the model

The second process develops a computer model that is ready to use. It includes the following tasks:

- **Requirements.** Determine user requirements for the model.
- **Model type.** Determine the type of model to employ.
- **Design.** Design the model.
- **Construction.** Construct it for simulation with a computer.
- **Validation and verification.** Test the model.
- **Documentation.** Document the requirements, design, construction, and test results.

¹ Rosenberg (2008)

² These are median measures. See the “CMMI Executive Overview” by the Carnegie Mellon University (2006) and “Demonstrating the impact and benefits of CMMI: an update and preliminary results” by Dennis Godenson and Diane Gibson, published by the Carnegie Mellon Software Engineering Institute (2003).

C. THE METHOD IN DETAIL *continued*

2. Develop the model *continued*

Although there are many methods for developing software, there are only a few for developing agent-based models, most of which are relatively immature. The sidebar describes three of the most mature methods. They emphasize that a model should be developed in distinct phases, by a team with appropriate expertise for each phase.

Requirements

Using structured interviews and questionnaires, the modeler elicits from sponsors and users the following information about the desired model:

- **Description.** A general description.
- **Questions addressed.** The questions that the model should answer. These questions should be specific and concrete. The modeler should also determine how one will know when the questions have been answered. Provide the desired answer format (graphs, charts, quantitative information, etc.), the desired precision, and examples of good answers. Also, provide the history of the questions, why the questions are important, the audience for the answers, and how the audience will use the answers.
- **Interested stakeholders.** Stakeholders who are interested in the model or who might be affected by the model.
- **Agents and their behaviors.** Health system agents that the model will include, together with their behaviors and interrelationships. A good way to discover the model's agents is to focus on nouns in the model's questions, along with other related entities that have goals or can make decisions.
- **Output.** Desired model output. The output can range from simple numeric values to charts to complex visualizations. Visualizations are particularly important, because they are what will stick in the user's mind.
- **Simplifying assumptions.** Assumptions to simplify the model.
- **Parameters.** Parameters that the user would like to vary, together with the limits and default value for each.

Agent-based development methods

There are several development methods created especially for agent-based models. Of these, following are three of the most prominent:

Gaia

The Gaia method addresses three initial stages of model development: requirements, analysis, and design. During the requirements stage, the modeling team captures the sponsor's requirements. In the analysis stage they identify the roles within the system being modeled, determine how the roles interact, and develop a conceptual analytic model of the system. In the design phase, the team transforms the analytic model into a platform-specific model design that is ready for implementation.¹

Prometheus

The Prometheus method is in three stages: system specification, architectural design, and detailed design. In the system specification stage, the modeling team identifies the goals and basic functions of the system being modeled, as well as the interface between the system and its environment. In the architectural stage, the team identifies the agents within the system, interactions among the agents, and the system's structure. In the detailed design stage, the team defines the agents' internal processes.²

Tropos

This method has five stages: early requirements, late requirements, architectural design, detailed design, and implementation. In its implementation stage, the team implements the model according to the design developed in the requirements and design stages.³

¹ Zambonelli, Jennings, & Wooldridge (2003)

² Padgham & Winikoff (2004)

³ Bergenti, Gleizes, & Zambonelli (2004); Bresciani, Perini, Giorgini, Giunchiglia, & Mylopoulos (2004); www.troposproject.org.

C. THE METHOD IN DETAIL continued

2. Develop the model continued

Model type

Based on the requirements, the modeler determines the appropriate type of model to build. If it appears that the model must have many of the following characteristics, it may be appropriate to employ an agent-based simulation model:

- **Autonomous decision-making agents.** Agents in the simulation make decisions autonomously.
- **Heterogeneous agents.** The agents have varied characteristics or behaviors.
- **Dynamic.** The simulation is dynamic. That is, its former states influence its future states.
- **No central controller.** There is no central controller managing the system being simulated.
- **Multiple simultaneous processes.** The system being simulated cannot be expressed as one process. If this were possible, then another modeling approach, such as discrete-event simulation, might be more appropriate. Rather, there are many independent processes (agent behaviors) occurring simultaneously.
- **Aggregate functions do not apply.** The situation being studied does not lend itself to mathematical formulation. That is, the complexity of agent interactions cannot be captured by aggregate mathematical functions. If this were possible, then another modeling approach, such as system dynamics, might be more appropriate.
- **Spatial factors are important.** The spatial location of agents is important.

In their book “Managing business complexity”, Michael North and Charles Macal discuss differences between agent-based models and other model types, such as system dynamics, discrete event, participatory simulation, and optimization.¹

¹ North & Macal (2007)

C. THE METHOD IN DETAIL continued

2. Develop the model continued

Model type continued

Even though agent-based models are an important new way to address many health system problems, they are not a panacea. Following are some of their limitations:

- **Limited intelligence.** Even though the agents in agent-based models represent real-life entities, they do not have real-life intelligence. Just as many people have been overly optimistic about the potential for Artificial Intelligence (AI) to model human intelligence, it is easy to be overly optimistic about the intelligence of agents in agent-based models.
- **Limited behavior.** Even though agents in agent-based models are meant to mimic the behavior of real-life agents, they often cannot, mainly because we do not know enough about real-life behavior.
- **New technology hype.** Even though agent-based modeling has recently effectively addressed a wide range of problems, and thus has been hyped as a powerful new technology, it is easy to overstate its applicability. There are many questions that traditional model types (such as discrete event, system dynamics, and cell-based tabular models) can address as effectively as, or more effectively than, agent-based models.
- **Expense.** Modeling agents at the individual level, together with their behaviors and inter-relationships, can be time-consuming and expensive. Other model types can be less expensive to build and maintain.
- **Lack of analytic methods.** We do not have adequate methods to help us understand and optimize agent-based modeling results. I discuss this limitation in Chapter sixteen (Sample agent-based models).
- **Slow adoption.** Although there has been much hype about agent-based modeling, it has not yet become mainstream. Perhaps due to the limitations above, the agent-based modeling community is small and concentrated in academic and experimental settings. Commercial applications are relatively rare.¹

¹ For an excellent discussion of the limitations of agent-based modeling, see Chapter 9 (Methodologies) of Wooldridge (2009).

C. THE METHOD IN DETAIL continued

2. Develop the model continued

Design

The next phase is to develop a conceptual design of the model. A conceptual design is a design that is independent of the computer platform and programming language with which the model will be developed. The conceptual model should fully describe the model that will answer the user questions. Because it should theoretically be possible to implement the model using any technology, in this phase the modeler can focus on the model's solution, and not be hampered by any particular technology.

In developing a conceptual design, the modeler should produce:

- **Message flow diagram.** A diagram showing how messages flow among the model's agents
- **Behavior schedule.** A chart showing the behaviors for each agent and how they are scheduled during a simulation
- **Behavior descriptions.** A detailed description of each component of an agent's behavior, including its "Input messages", "Get input" processes, "Output messages", "Send output" processes, "Attributes", "Goals", "Experience", "Rules", and "Produce output" processes
- **Behavior diagrams.** A diagram showing how the agent's behaviors are interrelated, and the data stores that are used

Of course, the modeler should also provide any other diagrams or descriptions that help to fully describe the model design.

Construction

Based on the model type selected and the conceptual design, the programmer constructs the model.

C. THE METHOD IN DETAIL continued

2. Develop the model continued

Verification and validation

The model is thoroughly tested, using formal “verification and validation” processes (see the sidebar).

According to Watts Humphrey, the creator of CMMI, in the typical computer model there is a defect (often affectionately called a “bug”) in every seven to ten lines of computer code. Although some defects will be more important than others, it is important to find and track all defects, and to fix the important ones as quickly as possible.^R

Documentation

The user requirements, model type decision, design, construction, and testing results should be documented, so that another team could easily take up the model and maintain it.

Donald Knuth, the widely acknowledged guru of computer programming, advocates an approach to construction documentation called “literate programming”. About this he writes, “Instead of imagining that our main task is to instruct a computer what to do, let us concentrate rather on explaining to human beings what we want a computer to do. The practitioner of literate programming can be regarded as an essayist, whose main concern is with exposition and excellence of style. Such an author, with thesaurus in hand, chooses the names of variables carefully and explains what each variable means. He or she strives for a program that is comprehensible because its concepts have been introduced in an order that is best for human understanding, using a mixture of formal and informal methods that reinforce each other.”²

Verification and validation

Verification and validation (V&V) are often confused with each other.¹ Model verification involves both externally directed tasks and internally directed tasks. Externally, verification ensures that the model is an accurate reflection of stakeholder needs, that design accurately follows requirements, and that construction accurately follows design. Internally, it ensures that the model is internally consistent and without defects.

Validation involves two externally directed tasks. One ensures that the model is an accurate reflection of the real world, and the other ensures that experts assess the model as reasonable, practicable, and relevant.

It is good practice to include structured V&V processes, such as structured walkthroughs or formal audits, at each major step of model development such as after requirements, design, and construction. The V&V team should include people who are independent from those who produced the work being reviewed.

¹ They can also be confused with the epidemiologic concepts of internal and external validity, which relate to proper demonstration of cause-effect relationships between variables in scientific studies (internal validity) and to whether such relationships can be generalized (external validity).

² Knuth (1992)

C. THE METHOD IN DETAIL continued

3. Evaluate the model

The third process is to have a third party appraise your model. It includes examining the model to determine if:

- it achieves its goals and answers the questions it is supposed to answer
- its assumptions are reasonable
- its model type is appropriate
- its levels of detail and complexity are appropriate
- it has been verified and validated
- the results are reasonable
- it is easy to use
- its documentation is clear and complete
- its processing speed is acceptable

The third party issues a report documenting its findings.

4. Implement the model

This process involves preparing the model for operation. It includes training users and installing the model. For information about *how* to implement this method and the next two methods, see Guideline Two (Follow generally accepted good practice guidelines for software engineering) in Chapter fourteen (Simulation modeling guidelines).

5. Operate the model

This process includes running the model, analyzing the results, documenting the work, and preparing a results report. It is not enough to solve a problem. In order for the solution to be useful, others must understand the solution at an intuitive level. Therefore, especially for health system decision making, a clear, well-documented results report is critical for agent-based modeling success.

6. Maintain the model

This process includes enhancing, repairing, and archiving a model. For most long-lived software, this process is the most expensive.

C. THE METHOD IN DETAIL continued

Even though I have presented the six processes of this modeling method—as well as their sub-processes—in sequential order, in practice they are not strictly sequential. Rather, they are often iterative. For example, during the third process (Evaluate the model) problems may be found that require more work in the second process (Develop the model). Similarly, the sub-processes of the second process (Develop the model) are often iterative. For example, the third sub-process (Design) may lead to reconsideration of the first process (Requirements).

D. ISSUES AND FUTURE DIRECTIONS

The primary issue associated with the modeling method is that a complete method for agent-based modeling of health systems did not previously exist. One reason for this is that agent-based methodologies in general are very young. Addressing agent-based modeling methodologies, Michael Wooldridge, one of the pioneers of agent-based modeling, recently wrote, “This work is, at the time of writing, rather tentative—not much experience has yet been gained with them.”²

E. TO LEARN MORE

One of the most interesting books about software development is titled “Dreaming in code” by Scott Rosenberg.³ Rosenberg provides a close-up look at a famous group of software developers—led by Lotus 1-2-3 creator Mitch Kapor—that spent years and millions to develop a new product that failed. In Chapters nine and ten, he reviews the captivating history of software development methodologies.

An insightful and beautifully written presentation of what we know about computer programming is Donald Knuth’s “The art of computer programming”⁴ (see the sidebar).

Software is hard

Donald Knuth is a professor emeritus at Stanford University who created the typesetting system TeX and the font design program Metafont. He is also a guru of computer programming, and has written and lectured extensively about it. He has said:

“What were the lessons I learned from so many years of intensive work on the practical problem of setting type by computer? One of the most important lessons, perhaps, is the fact that *software is hard*. From now on I shall have significantly greater respect for every successful software tool that I encounter. During the past decade I was surprised to learn that the writing of programs for TeX and Metafont proved to be much more difficult than all the other things I had done (like proving theorems or writing books). The creation of good software demands a significantly higher standard of accuracy than those other things do, and it requires a longer attention span than other intellectual tasks.

“A great deal of technical information must be kept in one’s head, all at once, in high-speed random-access memory somewhere in the brain ... The amount of technical detail in a large system is one thing that makes programming more demanding than book-writing. Another is that programming demands a significantly higher standard of accuracy.”¹

¹ From Donald Knuth’s lectures, presented in Rosenberg (2008)

² Wooldridge (2009)

³ Rosenberg (2008)

⁴ Knuth (2005)

E. TO LEARN MORE continued

To learn more about software development standards and practices, read the excellent book titled “Code complete” by Steve McConnell.¹ It shows you how to write high-quality easily communicated computer code. Another classic about software development is “The mythical man-month” by Frederick Brooks.² For more thorough, but more academic, grounding in software development, read “Fundamentals of software engineering” by Carlo Ghezzi and others.³

For more information about verification and validation for agent-based models, and about agent-based modeling in general, read the book “Managing business complexity” by Michael North and Charles Macal.⁴

For an interesting discussion of agent-based modeling methods, see “Design of agent-based models” by Tomáš Šalamon.⁵

F. REVIEW AND A LOOK AHEAD

In this chapter, I introduced a complete method for building agent-based models for simulating health systems. In the next chapter, we will look at guidelines for *how* you should implement the method.

(Don’t forget to take a look at the exercises for this chapter. They start on the next page.)

¹ McConnell (2004)

² Brooks (1995)

³ Ghezzi, Jazayeri, & Mandrioli (2003)

⁴ North & Macal (2007)

⁵ Salamon (2011)

EXERCISES

1. Consider a computer model that you or someone you know recently developed. (It doesn't have to be an agent-based model, and it may be a simple model.) First, describe the method used to develop the model. Then, compare that method to the method described in this chapter. If the method in this chapter had been followed, do you think the resulting model would have been better? Why?
2. A well-known former Microsoft project manager, Joel Spolsky, created a different kind of software development method. He calls it the Joel Test. It asks the following 12 questions:
 - Do you use source control? [That is, do you manage the versions of your computer code?]
 - Can you make a build in one step? [Can you compile your application in one step?]
 - Do you make daily builds?
 - Do you have a bug database?
 - Do you fix bugs before writing more code?
 - Do you have an up-to-date schedule?
 - Do you have a spec? [A spec is a detailed plan for what the code should do.]
 - Do programmers have quiet working conditions?
 - Do you use the best tools that money can buy?
 - Do you have testers?
 - Do new candidates write code during their interview?
 - Do you do hallway usability testing? [Chatting around the water cooler.]

Spolsky says that a score of 12 is perfect, that 11 is tolerable, but that 10 or lower indicates a serious problems.

What do you think about this method? Would it work for you?

SOLUTIONS

1. Solution vary.
2. Solution vary.

CHAPTER FOURTEEN: SIMULATION MODELING GUIDELINES

Despite the widespread use of formal methods to provide information to the legislative debate, neither the policy analysis tools employed nor the estimates they produce have been subject to much explicit evaluation of their utility or accuracy.

National Research Council
Panel to evaluate models for social welfare programs³

A. INTRODUCTION

This chapter proposes seven good practice guidelines for building and using simulation models for health systems research and policymaking.

A comparable set of guidelines has never been developed. This is particularly puzzling, because the development of such guidelines has long been strongly recommended. For example, fifteen years ago, a distinguished panel of the U.S. National Research Council evaluated the role of micro-simulation modeling for social welfare programs, including healthcare programs. In their two-volume report, they wrote, “We recommend that policy analysis agencies set standards of good practice for the development of future micro-simulation models.”⁴ Such standards were never established.

Others have found good practice guidelines helpful. For example, the field of atmospheric science and the U.S. Department of Defense found that guidelines played a pivotal role in helping their simulation modeling teams to mature (see the sidebar).

Comprehensive guidelines

The seven guidelines presented in this chapter apply to simulation models of every type used for health systems research and policy modeling, and to all aspects of modeling—including management, model development, evaluation, implementation, operation, and maintenance. However, they do not cover either technical details of modeling, or the technical specifics of models themselves, subjects perhaps best left to the individual judgment of modelers.

The maturation of modeling

Good practice guidelines played a key role in the maturation of modeling in the field of atmospheric science, and for the U.S. Department of Defense (DOD).

Years ago, atmospheric science models were highly diverse, as were the members of the atmospheric modeling community—much like health systems research and policy modelers today.

Ongoing lack of comparability, interoperability, and credibility of models led to a consensus-building process within the community, and crystallized in 1995 as a set of good practice guidelines.¹ The quality of atmospheric modeling is now much improved, and has increased the credibility and influence of atmospheric modelers in policy debates about vital public issues such as greenhouse gases.

Similarly, in the early 1990’s, the U.S. Department of Defense recognized that its immense number of computer models had many commonly shared problems, such as lack of interoperability, reusability, and credibility.

In 1995, it developed a plan to reorganize its modeling capabilities, and established the Defense Modeling & Simulation Office (DMSO), which developed and promulgated modeling good practice guidelines.² As a result, the DOD’s modeling capabilities are now among the world’s most advanced.

¹ Ireland, Jones, Griffiths, Ng, & Nelson (2004)

² Under Secretary of Defense for Acquisition and Technology (1995)

³ Citro, Hanushek, & National Research Council (U.S.). Panel to Evaluate Microsimulation Models for Social Welfare Programs (1991)

⁴ Citro, et al. (1991)

A. INTRODUCTION *continued***How the guidelines were developed**

To develop the guidelines, I performed a comprehensive literature search, using a structured search methodology, to find published resources for standards, guidelines, best practices, and principles related to health systems research and policy simulation modeling.

From this search, I found only three publications that include guidelines specifically for health systems research and policy simulation modeling. But even when their recommendations are combined, these publications cover only a small fraction of the processes involved in modeling. They are far from complete. Even so, it appears that many health systems research and policy modelers either do not know about, do not accept, or simply choose not to implement the guidelines.

Guidelines from other fields

Neither is a complete set of guidelines available from other related fields, such as healthcare economic evaluation. The limited guidelines that are available do not address many of the special needs of health system stakeholders.

Modeling guidelines from unrelated fields and organizations, such as the U.S. Department of Defense and the U.S. Department of Energy—even though they are comprehensive and well-tested—cannot be adopted for health systems research and policy simulation modeling, because they are either too specific for a particular field, or far too detailed.

This chapter first presents the proposed seven good practice guidelines. It then discusses the potential benefits of using such guidelines, and provides resources to learn more about them.

B. SEVEN GOOD PRACTICE GUIDELINES—OVERVIEW

The following table summarizes the seven good practice guidelines for constructing and using simulation models for health systems research and policymaking. The table also shows how each guideline relates to the processes of the agent-based modeling method presented in the previous chapter.

Good practice guidelines	Agent-based modeling method processes					
	Management	Development	Evaluation	Implementation	Operation	Maintenance
1. Assemble appropriate teams.	●					
2. Follow generally-accepted good practice guidelines for software engineering.	●	●	●	●	●	●
3. Explicitly include in the model relevant agents and outcomes.		●				
4. Choose a model type that is consistent with stakeholder requirements.		●				
5. Employ unbiased, relevant, diverse, and complete data sources, and use credible methods to collect, assess, and manipulate the data.		●				
6. Obtain an independent evaluation of the model.			●			
7. Prepare a complete clearly-written report about the modeling results that is peer reviewed and available for scrutiny.					●	

As you can see, these guidelines are comprehensive; they address all the processes of the comprehensive agent-based modeling method. I do not know any other set of guidelines for health systems simulation that is as comprehensive.

C. SEVEN GOOD PRACTICE GUIDELINES—DETAILS

Following is a detailed presentation of each guideline.

Guideline 1: Assemble appropriate teams.

Assemble appropriate teams to carry out each of the basic modeling processes (see the sidebar). In particular:

Form a project steering group

Form a project steering group to guide all phases of the modeling project. Members of the group should include a representative from the stakeholder for whom the work is being done, a representative of the model’s end users, as well as representatives from key areas of the health system being modeled. The group should meet at regular intervals to discuss project management issues, and to review the project’s work products. One member of the group should be appointed chairperson. An important responsibility of the chairperson is to maintain the project’s political neutrality.

In addition to providing guidance, members of the project steering group provide access to data needed for the model as well as to key personnel for model development, evaluation, implementation, operation, and management. Involving such a group increases the model’s credibility.¹

Involve stakeholders

Involve stakeholders—individuals such as policymakers and end users, as well as representatives of relevant organizations—in all phases of the modeling lifecycle. In particular, involve stakeholders in the requirements and design tasks of the model development process. It is important to ensure that relevant stakeholders for the project’s latter phases, such as end users, provide input to the earlier requirements and design decisions that will affect them.²

Basic modeling processes

As we saw in the previous chapter, no matter what software or methodology a modeler employs, each simulation model used for health systems research and policymaking goes through—either explicitly or implicitly—the following basic modeling processes:

1. **Management.** The first process involves the general management of the model and its results. It includes project planning, drafting the modeling contract with the sponsor, allocating human and material resources, monitoring compliance with guidelines, monitoring model usage, providing access to the model, and collaborating with other stakeholders. This process continues throughout a model’s lifecycle.
2. **Development.** The second process involves development of a final computer model that is ready for implementation. It includes determining the user requirements for the model, designing the model, constructing it, documenting it, and testing it.
3. **Evaluation.** This process involves third-party evaluation of the model. It includes analyzing the model and issuing an evaluation report.
4. **Implementation.** This process involves preparing the model for operation. It includes training users and installing the model.
5. **Operation.** This process involves operating the model, and includes running the model, analyzing the results, documenting the work, and preparing a results report.
6. **Maintenance.** This process includes enhancing, repairing, and archiving a model.

¹ Harper (2004)

² Academy of Managed Care Pharmacy (AMCP) (2005); Drummond & Jefferson (1996); House & McLeod (1977); Philips, Bojke, Sculpher, Claxton, & Golder (2006); Software Engineering Institute (2006)

C. SEVEN GOOD PRACTICE GUIDELINES—DETAILS *continued***Guideline 1: Assemble appropriate teams** *continued***Employ teams with appropriate skills**

To carry out each process in a model's lifecycle, employ a team with appropriate skills. In particular:

Name a project manager for the overall project. The project manager is responsible for the model's quality, documentation, and reporting; for managing the project's development, implementation, and maintenance teams; and for ensuring compliance with modeling guidelines.¹

For the development process, include people with software engineering training and expertise. Because the primary task of development work is to build high-quality software, the development team should include people with training and expertise in building software. In particular, the team should include individuals with expertise and experience in formal software requirements definition, conceptual design, and construction. The team should also include individuals with experience in healthcare data analysis and databases, and members with experience and credentials in health systems research or policy modeling. Ideal team members are people with degrees and experience in software engineering. Such members will increase the model's quality and credibility.²

For the operation process, choose team members without political biases. If the model is being operated to obtain results for a sponsored study, the operation team members should be independent of the study's sponsors. And, they should be trained how to properly use the model. The operation team's composition may affect whether the results can be published. Some journals do not publish manuscripts from authors who receive financial support from the study sponsor.³

¹ GAO (1998); Law (2006); Task Force on Principles for Economic Analysis of Health Care Technology (1995)

² GAO (1998); Task Force on Principles for Economic Analysis of Health Care Technology (1995)

³ Armstrong (2001); Citro, et al. (1991); John Sterman (2000); Task Force on Principles for Economic Analysis of Health Care Technology (1995)

C. SEVEN GOOD PRACTICE GUIDELINES—DETAILS *continued*

Guideline 2: Follow generally-accepted good practice guidelines for software engineering.

For all the basic modeling processes (management, development, evaluation, implementation, operation, and maintenance) follow published and generally-accepted good practice guidelines for software engineering, including structured processes for:

- Documentation;¹
- Eliciting model requirements from stakeholders;²
- Producing the conceptual design;³
- Software construction;⁴
- Database construction;⁵
- Model implementation and maintenance;⁶ and
- Verification and validation of model requirements, conceptual design, and construction⁷ (see the sidebar).

Although many academic researchers and governmental modelers consider their models exempt from software engineering standards, such a perspective is not good practice. Every simulation model for health systems research or policymaking, no matter its size or who prepares it, is software that should be prepared according to software engineering standards. The primary measure of software success is the degree to which it meets its intended purpose. Software engineering standards are the accepted way to discover, document, and achieve that purpose.

Verification and validation

A reminder from the previous chapter:

Externally, “**verification**” ensures that the model is an accurate reflection of stakeholder needs, that design accurately follows requirements, and that construction accurately follows design. Internally, it ensures that the model is internally consistent and without defects.

“**Validation**” involves two externally directed tasks. One ensures that the model is an accurate reflection of the real world, and the other ensures that experts assess the model as reasonable, practicable, and relevant.

¹ Citro, et al. (1991); GAO (1998); Gass & Thompson (1980); Ireland, et al. (2004); Law (2006); Philips, et al. (2006); Software Engineering Institute (2006); John Sterman (2000); Toder et al. (2000); M. C. Weinstein et al. (2003)

² House & McLeod (1977); Software Engineering Institute (2006)

³ Software Engineering Institute (2006)

⁴ Law (2006); Software Engineering Institute (2006); Toder, et al. (2000)

⁵ GAO (1998); Software Engineering Institute (2006)

⁶ Armstrong (2001); Citro, et al. (1991); GAO (1998); Software Engineering Institute (2006)

⁷ Akehurst et al. (2000); American Diabetes Association Consensus Panel (ADACP) (2004); Armstrong (2001); Baladi, Menon, & Otten (1998); Buxton et al. (1997); Citro, et al. (1991); Eddy (1985); S. Glied, et al. (2002); Halpern, Luce, Brown, & Geneste (1998); Ireland, et al. (2004); Law (2006); McCabe & Dixon (2000); Philips, et al. (2006); Sculpher, Fenwick, & Claxton (2000); Sendi, Craig, Pfluger, Gafni, & Bucher (1999); Software Engineering Institute (2006); Sonnenberg et al. (1994); Soto (2002); John Sterman (2000); M. C. Weinstein, et al. (2003)

C. SEVEN GOOD PRACTICE GUIDELINES—DETAILS continued

Guideline 2: Follow generally-accepted good practice guidelines for software engineering continued

Examples of published and generally-accepted good practice guidelines for software engineering are IEEE software engineering standards and Carnegie Mellon’s Software Engineering Institute (SEI) CMMI (Capability Maturity Model Integration) for Development.¹

Ease of use

Design the model to be easy to use, reuse, share, test, and maintain:²

- Avoid unnecessary complexity. Simpler models can reduce costs and the likelihood of mistakes. Simpler models are also more appropriate when uncertainty is high and data is scarce. However, absence of data is not in itself a justification for simplifying a model. A model should make explicit assumptions that can be challenged, and modelers should explore the impact of assumptions through sensitivity analysis.
- Design the model with flexibility to serve a wide audience. For example, the design should allow users to change model variables.
- The model should employ a hierarchical modular design, to facilitate unit testing, and reuse of model components. Object-oriented design methods and computer languages are well-suited for hierarchical modular design.

Large models

For a large model (one that requires more than about 100,000 lines of new computer code³) prepare and maintain the following documentation: a project plan, including definition of the project lifecycle; a project schedule; a documentation and reporting plan; the resources necessary to complete the project; a project budget; a feasibility study; a project risk profile that describes the project’s risks; a risk management strategy; a plan for stakeholder involvement, and a plan for monitoring model use.

¹ To find these standards, go to the IEEE website, “www.ieee.org”, and the Carnegie Mellon SEI website, “www.sei.cmu.edu”.

² Armstrong (2001); Barton, Bryan, & Robinson (2004); Buxton, et al. (1997); Citro, Hanushek, & National Research Council (U.S.). Panel on Retirement Income Modeling. (1997); Halpern, et al. (1998); Harper (2004); McCabe & Dixon (2000); Sculpher, et al. (2000); Sonnenberg, et al. (1994); Soto (2002); John Sterman (2000); Toder, et al. (2000); M. C. Weinstein, et al. (2003)

³ Jones (1995) and Boehm (1984)

C. SEVEN GOOD PRACTICE GUIDELINES—DETAILS *continued***Guideline 3: Explicitly include in the model relevant agents and outcomes.**

Explicitly include all agents (such as patients, insurers, governmental bodies, healthcare providers, etc.) relevant to the health system research or policymaking proposal being modeled. Also explicitly include all these agents' characteristics and behaviors relevant to the proposal being modeled. Agents, their characteristics, and their behaviors should be chosen to reflect underlying real-world entities and their real-world characteristics and behaviors.

Also, include in the model all relevant outcomes, using appropriate, complete, and unbiased outcome measures. In general, both economic costs and population health outcomes should be included.

Relevant agents

All relevant agents, agent characteristics, and entity behaviors should be explicitly defined. In particular, population heterogeneity should be explicitly recognized. Agents that may change significantly over the modeling time horizon should be included explicitly in the model as endogenous agents.

For most health systems research and policymaking models:

- Agents, agent characteristics, and agent behaviors should not be omitted simply because of a lack of data.
- A person's characteristics should include quality of life as well as length of life (age). In the baseline case, a utility scale for health states should be used that reflects quality of life as well as longevity.
- Agents should be capable of incorporating cyclical and random characteristics.
- Relevant agent subgroups should be explicitly modeled.
- Agents, agent characteristics, and agent behaviors should not be automatically assumed to carry forward into the future. Rather, theory and empirical research should inform the changes in agents and agent characteristics.
- Agents, agent characteristics, and agent behaviors may be included in the model to enhance the model's reflection of the real world, even if they do not materially affect the model's results. Such inclusion should be balanced with the model's ease of use and stakeholder needs.

C. SEVEN GOOD PRACTICE GUIDELINES—DETAILS continued

Guideline 3: Explicitly include in the model relevant agents and outcomes

continued

Relevant agents continued

- Interrelated characteristics and behaviors among agents should be reflected. For example, if the relationship between characteristic X_a and behavior Y_a of agent a is related to characteristic X_b of agent b, the model should reflect that interrelationship.
- Use causal chains to model serial causes and effects. For example, if X causes Y which then causes Z , this should be modeled as a causal chain rather than as simultaneous equations.
- Agent behaviors should be based on either empirical evidence or domain expertise. However, this does not mean that all causal linkages must have been proven.
- If applicable, agent behaviors should include second-order effects (reactions to results of the agent's actions).
- Individual and family-level behaviors should reflect correlation patterns within individual and family groups, and even within birth cohorts and geographic areas.
- If relevant, behaviors related to social healthcare programs such as Medicare and Medicaid, should be explicitly modeled.

When modeling health insurance policy proposals:

- Modelers should explicitly define the agents eligible for health insurance.
- Modelers should explicitly define agent characteristics such as race, immigration status, and asset test results, and describe how such characteristics are used to determine eligibility for health insurance reform programs and how they affect agent behaviors.

The need to simplify the model to increase its understandability and practicability should be balanced with the need for detail to reflect real-world health systems accurately.¹

¹ The following resources support the agent-related recommendations in Guideline 3. Regarding agents and their characteristics: American Diabetes Association Consensus Panel (ADACP) (2004); Armstrong (2001); Citro, et al. (1997); GAO (1998); Gold, Siegel, Russell, & Weinstein (1996); Harper (2004); Sculpher, et al. (2000); Sonnenberg, et al. (1994); Soto (2002); Toder, et al. (2000); M. C. Weinstein, et al. (2003). Regarding agent behaviors: American Diabetes Association Consensus Panel (ADACP) (2004); Armstrong (2001); Halpern, et al. (1998); Philips, et al. (2006); Soto (2002); Toder, et al. (2000); M. C. Weinstein, et al. (2003). Regarding second-order effects: Citro, et al. (1997); Toder, et al. (2000); M. C. Weinstein, et al. (2003)

C. SEVEN GOOD PRACTICE GUIDELINES—DETAILS *continued*

Guideline 3: Explicitly include in the model relevant agents and outcomes
continued

Relevant outcomes

Determining relevant outcomes is especially important when outcomes are not obvious or when failure to consider a particular outcome might bias the results.

In general, for health systems research and policymaking models:

- Outcomes should be disaggregated to identify outcomes for sub-groups of interest.
- The components of cost (such as direct costs and indirect costs) should be provided in addition to aggregate cost.
- Incremental costs (such as incremental cost per life year gained) should be provided in addition to aggregate costs.
- Evaluations of effectiveness should include both beneficial and harmful effects of a research or policy proposal.
- Decisions about which costs and health outcomes to include should strike a balance between expense and difficulty on the one hand and potential importance on the other.
- Health-related quality of life measures should reflect the effects of morbidity on productivity and leisure.
- Costs should reflect the marginal resources consumed.
- Resource costs over time should be aggregated in constant dollars that remove general price inflation.
- Direct medical and non-medical costs should be included, as well as indirect costs such as productivity changes. Short-term and long-term costs should also be included.

Outcome measures should include the most important consequences for the population being evaluated.¹

¹ The following resources support the outcome-related recommendations in Guideline 3. Citro, et al. (1997); Drummond & Jefferson (1996); Gold, et al. (1996); Ofman (2003); Soto (2002); Task Force on Principles for Economic Analysis of Health Care Technology (1995)

C. SEVEN GOOD PRACTICE GUIDELINES—DETAILS *continued*

Guideline 4: Choose a model type that is consistent with stakeholder requirements.

The modeler should choose a model type that is consistent with stakeholder requirements. There are many simulation model types used for health systems research and policy modeling, including agent-based models, cell-based models, discrete-event simulation models, macroeconomic models, micro-simulation models, and system dynamics models. Each model type has advantages and disadvantages that make it more or less appropriate for modeling a particular health policy proposal. For example, the sidebar gives characteristics of a simulation proposal for which an agent-based model type may be advantageous.

An important issue to address in selecting a model type is whether individual entities of the model need to be autonomous. Where interactions among independent entities are important, agent-based models, discrete-event models, and system dynamics models may be preferable to other model types.

Another issue to address is whether the model should be deterministic or stochastic. In many cases, it is reasonable to use only a point estimate or a range of values for the likelihood of a given event, and thus a deterministic model is appropriate. A stochastic model is appropriate when Monte Carlo simulation techniques can be used to evaluate the uncertainty of events.

It is a good idea to ask an independent panel of unbiased experts to rate potential model types for the proposal to be modeled. The chosen model type should be explicitly justified, taking into account the characteristics of the proposal, the opinion of experts, a literature review of model types used for similar proposals, and the anticipated development cost and budget.¹

Reasons for choosing an agent-based model type

As we saw in the previous chapter, if a health systems research or policy simulation modeling proposal has many of the following characteristics, it may be appropriate to employ an agent-based model type:

Many autonomous decision-making agents.

Agents in the simulation make decisions autonomously.

Heterogeneous agents. The agents have varied characteristics or behaviors.

Dynamic. The simulation is dynamic. That is, its former states influence its future states.

No central controller. There is no central controller managing the system being simulated.

Multiple simultaneous processes. The system being simulated cannot be expressed as one process. If this were possible, then another modeling approach, such as discrete-event simulation, might be more appropriate. Rather, there are many independent processes (agent behaviors) occurring simultaneously.

Aggregate functions do not apply. The situation being studied does not lend itself to mathematical formulation. That is, the complexity of agent interactions cannot be captured by aggregate mathematical functions. If this were possible, then another modeling approach, such as system dynamics, might be more appropriate.

Spatial factors are important. The spatial location of agents is important.

¹ The following resources support the recommendations in Guideline 4: Armstrong (2001); Sonnenberg, et al. (1994); Soto (2002); Toder, et al. (2000); Barton, et al. (2004); Halpern, et al. (1998); Philips, et al. (2006); Harper (2004); McCabe & Dixon (2000); Philips, et al. (2006); Sculpher, et al. (2000); Software Engineering Institute (2006)

C. SEVEN GOOD PRACTICE GUIDELINES—DETAILS continued

Guideline 5: Employ unbiased, relevant, diverse, and complete data sources, and use credible methods to collect, assess, and manipulate the data.

Employ credible, unbiased, relevant, diverse, and complete data sources to derive and populate agent characteristics (attributes) and behaviors. Also, employ credible and structured methods to collect, assess, and manipulate such data. ¹

Data sources

Regarding data sources:

- Avoid biased data sources, such as data from people committed to particular viewpoints or rewarded for certain outcomes.
- Base data from the literature only on peer-reviewed sources.
- Only use expert judgment to fill in data where other credible data sources do not exist, and when using expert judgment, include only the most credible current professional judgment.
- Ensure that the data are logical, consistent, and realistic.
- Do not permit study sponsors to force the use of invalid or unrealistic data.
- Obtain estimates of health outcomes and costs from the best-designed and least-biased sources relevant to the proposal and to the population under evaluation.
- Never base data on a selective sub-sample of studies.
- Find alternative ways to measure the same thing, especially if biases are likely. If unbiased data sources are not available, find sources with differing (and hopefully compensating) biases. Analogous data sources can also prove useful. Observational studies, retrospective data, and expert opinion can be used as data sources, in addition to random controlled trials.

In general, all practically available relevant data sources, rather than a selected subset of sources, should be used.

¹ The following resources support the data source recommendations in Guideline 5: Armstrong (2001); Barton, et al. (2004); Halpern, et al. (1998); Harper (2004); McCabe & Dixon (2000); Philips, et al. (2006); Sculpher, et al. (2000); Software Engineering Institute (2006); Sonnenberg, et al. (1994); Soto (2002); Toder, et al. (2000). The following resources support the credible methods recommendations. Credible methods to collect data: Armstrong (2001); Harper (2004). Credible methods to assess data quality: Harper (2004); Philips, et al. (2006); M. C. Weinstein et al. (2001). Collecting expert opinion: Armstrong (2001); Halpern, et al. (1998); M. C. Weinstein, et al. (2001). Credible methods to clean and adjust data, and adjusting for systematic and unsystematic events: Armstrong (2001). Pooling data: Armstrong (2001); M. C. Weinstein, et al. (2001)

C. SEVEN GOOD PRACTICE GUIDELINES—DETAILS continued

Guideline 5: Employ unbiased, relevant, diverse, and complete data sources, and use credible methods to collect, assess, and manipulate the data continued

Methods

Regarding data methods:

- Employ credible and systematic procedures, such as the Delphi or Nominal Group techniques, to collect expert opinion. When collecting expert opinion: Pretest the experts' questions on a sample of potential respondents to ensure that they are understood and are relevant; frame the questions in alternative ways (sometimes even small changes in wording can lead to substantial changes in responses); have the experts justify their responses in writing; provide numerical scales with several categories for experts' answers; and obtain information from a heterogeneous group of experts. It is important to include individuals with substantial credibility in their fields, as well as individuals from a range of practice settings and geographic locations.
- Employ structured processes to clean and adjust data. Only clean and adjust data when there are specific reasons for the revisions. Cleaning the data involves correcting mistakes, reflecting changed definitions, and managing missing information. It is good practice to keep a detailed log of data cleaning and adjustment work.
- Pool similar types of data using appropriate methods. Appropriate methods for pooling data include systematic meta-analysis. The Cochrane Collaboration¹ and others have developed guidelines for systematic meta-analysis. When pooling, it is good practice to weight more relevant data more heavily.
- Use statistical techniques or domain knowledge to adjust for systematic and unsystematic events. Systematic events include seasonal and holiday changes. Unsystematic events include events such as hurricanes that adversely affect population health status in a region.

¹ See "www.cochrane.org"

C. SEVEN GOOD PRACTICE GUIDELINES—DETAILS continued

Guideline 6: Obtain an independent evaluation of the model

Employ an independent team to evaluate the model, prior to the model's use. Many health policy models are of such complexity that evaluation by an individual is inadequate. In such cases, the evaluation team should be multidisciplinary, consisting of personnel knowledgeable in computer science, statistics, the functional areas being modeled, and the environment of the policy decision maker. The model should be evaluated prior to its use, in order to uncover its defects before it is operational.¹

Based on existing documentation, the evaluation team should:

- Employ structured processes to evaluate the model, its data, and its documentation. In evaluating data, the concern is two-fold: (1) the accuracy, completeness, impartiality, and appropriateness of the original data; and (2) the manner in which the model transforms the original data.
- Attempt to replicate the model's results, and analyze the sensitivity of results.
- Assess the validity of results, the quality of the model's development processes, the model's biases, and the model's availability, usability, and maintainability. Factors that affect a model's usability include the availability of data, how easy it is to understand the model's output, the presentation format, how easy it is to transfer the model to another computer system, the model's size, and the time and cost to run a typical simulation.
- Prepare a publicly available report describing the evaluation methodology and findings. The evaluation report should include: The results of the evaluation analysis; a description of the model's design and assumptions; an analysis of the accuracy and appropriateness of the model's data; a statement about whether the model's assumptions, data, computations, and assigned role in the decision process are appropriate and accurate; an assessment of the model's interfaces; a description of when the model should and should not be used; and a description of the model's defects.

¹ The following resources support the recommendations in Guideline 6: Multidisciplinary team for evaluation: Armstrong (2001); Gass & Thompson (1980); Ireland, et al. (2004); Soto (2002); John Sterman (2000); Task Force on Principles for Economic Analysis of Health Care Technology (1995); M. C. Weinstein, et al. (2001). Structured evaluation processes, sensitivity assessment, development process assessment, and evaluation report: Gass & Thompson (1980). Replication of model results: Armstrong (2001); Gass & Thompson (1980); John Sterman (2000). Validity assessment: Citro, et al. (1991); Gass & Thompson (1980)

C. SEVEN GOOD PRACTICE GUIDELINES—DETAILS continued

Guideline 7: Prepare a complete, clearly-written, report about the modeling results that is peer reviewed and available for scrutiny.

When reporting the modeling results, write the report in a simple and understandable way (avoiding jargon and technical language), describing the background, purpose, and scope of the analysis, as well as the background of and rationale behind the model used.¹

Background, purpose, scope, and rationale

In the background section of the report, include: The health systems research or policymaking proposal being modeled and how it was developed; the purpose of the analysis; settings to which the results apply; decisions the results can affect; how the model was developed; the model's purpose and the decisions that may be affected by its results; the model's scope; the model's perspective; and model limitations and their implications.

Specify the research or policymaking proposal being modeled in detail. Avoid excluding or understating any pertinent components, and justify all components that are excluded from the description. Also, specify the background and context of the proposal being modeled. It is also good practice to include alongside the proposals being modeled a few extreme proposals that represent the ends of the spectrum on which alternative proposals lie (such as extremely rich and sparse program designs). Such extreme proposals can serve as anchor points against which other proposals can be compared.

Once the proposal being modeled has been described, it is important to describe the context for the analysis. In particular, the report should describe the boundaries of the analysis, including a list of the effects and outcomes that have and have not been taken into account. If there are potential unintended consequences that have been excluded from the analysis, they should be described together with a rationale for their exclusion. This information is best provided in conjunction with a description of the background and rationale behind the model and its entities.

¹ The following resources support the recommendations in Guideline 7: Simple and understandable style: Armstrong (2001); Ireland, et al. (2004). Background description: Armstrong (2001); Citro, et al. (1997); Eddy (1985); Gold, et al. (1996); Law (2006); Nuijten et al. (1998); Sculpher, et al. (2000); Sonnenberg, et al. (1994); Soto (2002); Halpern, et al. (1998); Philips, et al. (2006); Drummond & Jefferson (1996); Ofman (2003); McCabe & Dixon (2000); John Sterman (2000)

C. SEVEN GOOD PRACTICE GUIDELINES—DETAILS *continued*

Guideline 7: Prepare a complete, clearly-written, report about the modeling results that is peer reviewed and available for scrutiny *continued*.

Results

Describe all relevant results.² In particular:

- Report important findings, regardless of the result.
- Describe the results of sensitivity analyses of key assumptions and parameters, as well as the methods used to analyze sensitivity.
- Present results in both disaggregated and aggregated form, and provide intermediate results. If changes in productivity or other indirect costs are included, they should be reported separately from other costs, and their relevance discussed. Similarly, results for important population subgroups should be reported separately, and quantities of resources should be reported separately from resource unit costs.
- Assess the uncertainty of results, including second-order uncertainty if applicable, and describe the methods used to assess uncertainty. Assessments of uncertainty can help decision makers understand how model results can affect decisions, and can indicate the need for contingency plans. Examples of methods for reporting uncertainty are prediction intervals and confidence intervals (see the sidebar).
- Compare the results to results from other researchers.
- Disclose any biases in the results, including biases present by design, and disclose the impact of the biases on model results.
- Disclose subjective adjustments of model results.
- Describe research in progress that could alter the results.
- Give reasons why the results may be wrong.
- Explain why results appear to be valid.

The uncertainty of simulation results

The estimation of uncertainty in health system simulation models has been much neglected. When estimates of uncertainty have been made, the methods used—such as “low”, “intermediate”, and “high” scenarios—often have had little scientific basis.

Concerning simulation models of health reform proposals, Sherry Glied and Nicholas Tilipman recently wrote, “Unfortunately, because modeling of health care reform proposals arose in the context of the budget process, where a single figure must appear, there is no tradition of placing confidence estimates on models. Nevertheless, consumers of modeling results should ... recognize that estimates, especially for large-scale program changes, inevitably carry wide confidence bounds.”¹

¹ S. Glied & Tilipman (2010)

² The following resources support the results recommendations in Guideline 7: Important findings: Soto (2002); Drummond & Jefferson (1996); Eddy (1985); GAO (1979); Nuijten, et al. (1998); Ofman (2003). Disaggregated and aggregated reporting: Soto (2002); Drummond & Jefferson (1996). Intermediate results: Nuijten, et al. (1998). Comparing to other researchers: Armstrong (2001); S. Glied, et al. (2002); Gold, et al. (1996); M. C. Weinstein, et al. (2003); Halpern, et al. (1998); Drummond & Jefferson (1996); Buxton, et al. (1997); John Serman (2000); Citro, et al. (1997); Ireland, et al. (2004); Nuijten, et al. (1998); GAO (1979); Akehurst, et al. (2000). Biases: Halpern, et al. (1998). Subjective adjustments: Armstrong (2001); John Serman (2000). Research in progress: Eddy (1985). Reasons why results may be wrong: Armstrong (2001). Results validity: Soto (2002). Assessment of uncertainty: Armstrong (2001); American Diabetes Association Consensus Panel (ADACP) (2004); Citro, et al. (1997); Soto (2002); Philips, et al. (2006); Citro, et al. (1991). Sensitivity analysis: American Diabetes Association Consensus Panel (ADACP) (2004); Citro, et al. (1997); Gold, et al. (1996); Toder, et al. (2000); Barton, et al. (2004); Buxton, et al. (1997); Eddy (1985)

C. SEVEN GOOD PRACTICE GUIDELINES—DETAILS continued

Guideline 7: Prepare a complete, clearly-written, report about the modeling results that is peer reviewed and available for scrutiny continued.

Results continued

Transparency

When reporting modeling results, make the model and data transparent, and provide sufficient details to enable others to replicate the results.¹

Although the standards for transparency and replicability are still being debated, there is general agreement on a few basic principles. First, the model should be clearly disclosed. Modelers are expected to clearly describe the operations performed on the data to obtain the model's results. In particular, causal relationships between first-order impacts and ultimate outcomes should be described. A detailed description of the model should allow other modelers to replicate, in principle, the model's results. That the replication may be impractical is irrelevant.

Some researchers feel that an ability to replicate only in principle is not sufficient, and prefer to make their models easily replicable by making the source code publicly available. Such source code may be made available to researchers who ask for it, with the stipulation that it cannot be redistributed. Alternatively, the source code may be distributed—perhaps on a website through the Internet—with an open source license that allows for distribution, modification, and derived work. Public accessibility facilitates a model's evaluation, debugging, and enhancement. However, this benefit has to be weighed against the potentially serious disruption of incentives and funding opportunities for the researchers who created the model. Researchers may be less inclined to invest the effort required to build complex models if they have to give them away and are unable to reap the benefits of their work.

¹ The following resources support the transparency recommendations in Guideline 7: General: Armstrong (2001); Citro, et al. (1997); Sonnenberg, et al. (1994); Soto (2002); Toder, et al. (2000); John Sterman (2000); Citro, et al. (1991); Akehurst, et al. (2000); J. Sterman (2001); Pignone (2005). Publicly available model: Sonnenberg, et al. (1994); Soto (2002); John Sterman (2000). Publicly available source code: Toder, et al. (2000). Model website: John Sterman (2000).

C. SEVEN GOOD PRACTICE GUIDELINES—DETAILS continued

Guideline 7: Prepare a complete, clearly-written, report about the modeling results that is peer reviewed and available for scrutiny continued.

Transparency continued

The second agreed-upon principle is that data sources should be clearly disclosed. Other researchers should, at least in principle, be able to access the same data that were used for the analysis. Where the data is proprietary, information can be provided to the public that explains how proprietary data can be acquired. In all cases, descriptive tables (or otherwise condensed versions) of the proprietary data will help to make the data transparent.

Assumptions

When reporting results, describe and justify all assumptions and model parameters.¹ In particular:

- Report the results of a literature search for relevant assumptions, and how the recommended assumptions found in the literature relate to the model’s assumptions;
- Describe how assumptions recommended in the literature have been adjusted; and
- Avoid assumptions that are biased in favor of vested interests, and explain why the model’s assumptions are considered unbiased.

Scenarios

When reporting modeling results, include the following scenarios:²

- A baseline scenario;
- A standard reference scenario (if available); and
- At least two alternative scenarios.

The baseline scenario reflects the current state of affairs, the “status quo”.

¹ The following resources support the assumptions recommendations in Guideline 7: Armstrong (2001); Gold, et al. (1996); Harper (2004); John Sterman (2000); GAO (1979).

² The following resources support the scenario recommendations in Guideline 7: Armstrong (2001); S. Glied, et al. (2002); Gold, et al. (1996); Eddy (1985).

C. SEVEN GOOD PRACTICE GUIDELINES—DETAILS continued

Guideline 7: Prepare a complete, clearly-written, report about the modeling results that is peer reviewed and available for scrutiny continued.

Scenarios continued

The standard reference scenario is one that employs standardized assumptions, policy provisions, data, and methodology. Such a case enhances comparability across studies for various models. It should take a societal perspective, and include both population health outcomes as well as cost results. There are currently few widely agreed standard reference cases for health system modeling.

The alternative scenarios should reflect different assumptions regarding uncontrollable elements in the environment. Additional scenarios help decision makers develop contingency plans for alternative environments.

Disclosure

When reporting modeling results, give the names and affiliations of the modeling team members, and disclose potential team member biases and conflicts of interest. Disclose the sponsors of the model, as well as funding amounts. Biases include strongly held political views and close association with sponsors, such as through direct financial ties, or indirect stock ownership. Give the contact information for the primary investigator, so that others can receive more information about the modeling results.¹

Peer review and scrutiny

Make the report easily available for scrutiny and comment, and subject it to peer review.² The report should reference the model's development, evaluation, and maintenance reports, which should also be publicly available.

Modeling reports should be freely available to anyone for examination and research. Public accessibility facilitates modeling evaluation and improvement.

¹ The following resources support the disclosure recommendations in Guideline 7: Disclosure of modeling teams: Armstrong (2001); Soto (2002); Nuijten, et al. (1998); GAO (1979). Disclosure of the study sponsors: Ofman (2003); GAO (1979).

² The following resources support the peer review and scrutiny recommendations in Guideline 7: Public availability of reports: Armstrong (2001); Citro, et al. (1997); Sonnenberg, et al. (1994); Soto (2002); Toder, et al. (2000); John Sterman (2000); Citro, et al. (1991); J. Sterman (2001); Pignone (2005). Peer review: Soto (2002).

D. BENEFITS OF THE GUIDELINES

Implementing good practice guidelines such as the seven proposed in this chapter would produce both shorter-term and longer-term benefits for health system stakeholders.

Shorter-term benefits

The most immediate benefit is to improve the credibility of modeling results. Improved credibility is particularly important, because health systems research and policy modeling results are often perceived as not credible and unreliable. Several stakeholder problems stem from this perceived lack of credibility: Policymakers are reluctant to rely on modeling results to formulate or promote policies; funding sources are disinclined to fund the development of new models or the maintenance of legacy models; and publishers are cautious about publishing modeling results.

Implementing the guidelines would improve modeling credibility by:

- Improving modeling quality and reliability;
- Improving comparability of modeling results; and
- Improving the professional status of modelers.

Improving modeling quality and reliability

Guideline 1 directs modelers to assemble appropriate teams, including a project steering group to guide the overall development and use of models. Many health system modeling groups do not include people with skills that are necessary to develop high-quality models. For example, many groups do not include people with expertise in software engineering. Also, it appears that most such groups are not guided by a project steering group. Following Guideline 1 would increase the quality and credibility of simulation models.

Guideline 2 encourages modelers to employ structured processes—based on software engineering standards—to manage, develop, evaluate, implement, operate, and maintain health systems simulation models. Many, if not most, health systems modeling groups employ ad hoc processes, rather than structured processes, to manage, develop, implement, operate, and maintain models.

D. BENEFITS OF THE GUIDELINES *continued*

Shorter-term benefits *continued*

Improving modeling quality and reliability *continued*

It also appears that many such groups do not use structured verification and validation processes (such as structured walkthroughs) to develop models (see the sidebar). And they often do not adequately document their work. The Carnegie Mellon Software Engineering Institute has demonstrated that the use of structured processes—including structured verification, validation, and documentation processes—increases the quality and reliability of software products.

Guideline 3 directs modelers to include in their models all relevant agents and outcomes. Many health system models focus only on a portion of the agents affected by a proposal, and they focus only on economic effects rather than also incorporating population health outcome effects when such effects would be relevant. Such bias can reduce the perceived quality of modeling results.

Guideline 6 encourages modelers to seek an independent evaluation of their work. It is rare for modeling groups to seek an independent evaluation, even though such a step would demonstrate the model’s quality and reliability, and thus enhance its credibility.

Improving comparability of modeling results

In the history of health systems modeling, there are few in-depth model comparisons. In fact, from my literature search, I identified only four. None of these model comparisons successfully identified the reasons for divergent results in the models they studied:

- Sherry Glied and colleagues attempted to compare results of three healthcare reform models, and concluded “it is almost impossible to understand why estimates based on different models differ”.² She did not report, though, that she also attempted to compare the three models’ results when the models were applied to a standard reference healthcare reform scenario. The results turned out to be so divergent that the modelers asked her not to publish the results; she didn’t.³

Model validation

A National Research Council panel wrote, “Despite the widespread use of formal models to provide information to the legislative debate, neither the policy analysis tools employed nor the estimates they produce have been subject to much explicit evaluation of their utility or accuracy.

“Our strongest recommendation to policy analysis agencies, for these and other kinds of models, is to invest the needed resources to make validation an integral part of the policy estimation process. Without systematic and rigorous evaluation of models and their inputs and outputs, no one can know their quality today or make informed choices about how best to allocate scarce investment resources to improve their quality and usefulness for tomorrow.”¹

¹ Citro, et al. (1991)

² S. Glied, et al. (2002)

³ Personal communication with Sherry Glied on March 6, 2006.

D. BENEFITS OF THE GUIDELINES continued**Shorter-term benefits** continued*Improving comparability of modeling results* continued

- In its 1993 report titled *An Inconsistent Picture*, the U.S. Office of Technology Assessment (OTA) noted the widely divergent results of several models assessing the Clinton healthcare reform initiatives: “There is a startlingly wide range of estimates of the impact of the selected approaches to health care reform on the areas of the economy”.¹ Yet, when the OTA was asked to explain the differences, it could not, mainly because many models were proprietary and would not release key information.
- Attempts outside of the U.S. have not fared better. In 1999, a European panel tried to compare results of a Canadian micro-simulation model, POHEM, with results from a Dutch macro-simulation model, PREVENT. Their main conclusion was that the results were not comparable.²
- Pignone and colleagues critically compared the results of five cost-effectiveness models of colorectal cancer screening. They concluded, “... The multiple differences between studies and the limited data available in the published reports on the analyses made it difficult to determine with confidence the sources of variation between studies.” But, they didn’t stop there. They convinced the National Cancer Institute and the National Academy of Sciences to ask the modelers to perform a series of model runs using standardized assumptions and inputs, to determine how divergent the results would then be. The result? “Full standardization removed many, but not all, of the differences in costs. In terms of effectiveness (life-years saved), substantial differences remained after full adjustment, suggesting that variables for which we did not adjust, such as model structure or natural history assumptions, may account for much of the variation observed.” As a result of this work, the authors recommended that modelers should follow modeling good practice guidelines for development and reporting.³

¹ Office of Technology Assessment (1993)

² Gunning-Schepers (1999)

³ Pignone (2005)

D. BENEFITS OF THE GUIDELINES *continued*

Shorter-term benefits *continued*

Improving comparability of modeling results *continued*

With notable exceptions, it is usually difficult—and often impossible—to understand how current health systems research and policy simulation models work, much less to reproduce their results. In general, models are not fully explained in published reports, neither the models nor their data sets are publicly available, and modeling reports employ a variety of often contradicting terminology. Health system modeling is far from transparent.

Guideline 7 encourages inter-model comparisons and transparency, and directs modelers to provide publicly available detailed reports—along with adequate data and sufficient operational details—to enable third parties to evaluate a model and reproduce its results. It also encourages modelers to employ standard vocabulary, avoid jargon, and quantify the uncertainty of results.

If Guideline 7 were widely implemented, the number of inter-model comparisons would likely increase, as would the number of successful comparisons.

Improving the professional status of modelers

While most individual health system simulation modelers are professionals, the community of modelers as a whole is not perceived as, and does not act like, a profession (see sidebar).

The community of health system modelers lacks most of the attributes that distinguish professional groups. Whereas most professional groups (such as physicians, attorneys, economists and actuaries) are cohesive, collaborative, credentialed, governed by standards of practice, proactive, innovative, stable, and have established publishing and conference forums, health systems modelers lack these.

A modeling profession?

In her article titled “Just feed me the sausage”, congressional staffer Linda Fishman wrote:

“... [W]e need an independent means of voluntarily creating and enforcing standards. One way to do this would be to encourage modeling to develop as a profession of its own standing, similar to actuarial science. Actuaries, who come to the profession from many academic backgrounds (as in modeling) and some of whom are estimators or modelers, adopt a code of conduct and a code of standard practices to which they must adhere or risk being disciplined by the profession.

“The purpose of a standard is to give actuaries guidance and a description of recommended practices, actuarial methods, and assumptions and information that should be communicated to users of reports concerning social ‘insurance’.

“... For example, actuaries certify an estimate according to generally accepted practice so that policy makers can have more confidence in it. It takes many hours of rigorous study followed by a series of exams to become an actuary. But there is no such requirement to become an estimator.”¹

¹ Fishman (2003)

D. BENEFITS OF THE GUIDELINES continued**Shorter-term benefits** continued*Improving the professional status of modelers* continued

Health system modelers are fragmented and rarely collaborate. They include people from widely diverse educational backgrounds, such as economists, social scientists, and medical personnel. They work in a variety of settings, including academic institutions, government agencies, consulting firms, and think tanks. They spring from a variety of historical modeling lineages, such as macro-economics, system dynamics, micro-simulation, discrete-event, cell-based, and agent-based modeling. They speak different modeling languages. And they rarely communicate or collaborate with one another or with other stakeholders.

A National Research Council panel noted, “Indeed, for health care policy, it appears to us that communication and turf problems have hampered effective coordination of modeling, database construction, and behavioral research needed to support policy analysis”.¹ Another National Research Council panel noted, “In the area of projection modeling, there are as yet no success stories of effective collaboration of agencies and their contractors with the academic community more broadly.”²

There is no professional training program for health system modeling, and no professional credential. Although PhDs in economics, public health, and social science are often employed in this work, such PhD programs do not teach the skills required for health system modeling. Neither do actuarial or medical programs. For example, none of these programs teaches even the basics of software engineering. The result is researchers who are unprepared to deal with large software development projects. Such lack of training may discourage talented and creative minds from engaging in health system modeling. Those who dare to engage in such research may have to painfully and inefficiently learn the lessons of disciplines such as software engineering.

¹ Citro, et al. (1991)

² Citro, et al. (1997)

D. BENEFITS OF THE GUIDELINES continued**Shorter-term benefits** continued*Improving the professional status of modelers* continued

Health system modelers are generally reactive, responding to the momentary needs of healthcare policy leaders and fluctuations in research funding sources, rather than proactively building models to generate new insights about health systems. Innovation is rare. A National Research Council panel observed, "...because the policy community that actively works with micro-simulation models today is largely limited to a small number of expert staff in a few firms and agencies, there are few avenues for new ideas and perspectives—either from users in the agencies, academic researchers, or others—to lead to improvements in models and the estimates they produce".¹ The same comment applies to health system modelers from all modeling lineages.

With few exceptions, health system models and modeling teams come and go. Time and again, millions are spent on intense modeling efforts, only to be abandoned after policy needs change or funding runs out. Indeed, two massive health policy models, one in Germany and one in the U.S. financed by the Health Resources Administration, were never completed. A National Research Council panel noted, "Examples of models that foundered because the goals were far too ambitious, particularly given the restricted capabilities of the computer hardware and software technology available at the time, litter the history of micro-simulation model development in the United States."²

Physicians, attorneys, economists, and actuaries have well-established journals to publish their work, and frequent conferences to attend. But health systems modelers generally have no such forums. If their work is published at all (some leading medical and healthcare journals, such as the *New England Journal of Medicine*, decline to publish computer modeling results³) it is in a hodgepodge of journals and conference reports. Neither are there any conferences for health system modelers from various modeling lineages to meet and exchange ideas.

¹ Citro, et al. (1991)

² Citro, et al. (1991)

³ Kassirer & Angell (1994)

D. BENEFITS OF THE GUIDELINES *continued*

Shorter-term benefits *continued*

Improving the professional status of modelers *continued*

Lastly, there are no generally accepted standards for health system modeling. The lack of standards is particularly curious and risky, because health system research and policy models are often large (thus subject to significant defects) and can dramatically affect society through their impact on healthcare decision making. This lack of standards is the inspiration for this chapter.

Although the seven guidelines by themselves will not create a modeling profession, they can contribute to the creation of one:

- Guidelines can help to provide common terminology and common work processes to facilitate communication and collaboration among modelers.
- They establish a standard of practice and ethics.
- They educate practitioners about good modeling practices, and provide a basis for formal training programs and credentialing.

Longer-term benefits

The benefit of improved modeling credibility promises, over the longer term, to lead to other benefits of greater social significance.

An important potential longer-term benefit is that policymakers would use models more often to develop and promote their policies. In the complex world of health care, modeling is the only practical way for policymakers to understand the potential impact of proposed policies (see the sidebar).

Yet, especially in the U.S., healthcare policymakers are reluctant to rely on this tool. Many reasons have been offered to explain this reluctance, including sheer ignorance, perceived lack of relevance, distrust of modeler motives, political factors, regulatory factors, fear of lawsuits, and even the American love of freedom from constraint. ²

Modeling, a way to understand complex systems

“Policies to promote public health and welfare often fail or worsen the problems they are intended to solve. Evidence-based learning should prevent such policy resistance, but learning in complex systems is often weak and slow. Complexity hinders our ability to discover the delayed and distal impacts of interventions, generating unintended ‘side effects’.

“Yet learning often fails even when strong evidence is available: Common mental models lead to erroneous but self-confirming inferences, allowing harmful beliefs and behaviors to persist and undermining implementation of beneficial policies. When evidence cannot be generated through experiments in the real world, virtual worlds and simulation become the only reliable way to test hypotheses and evaluate the likely effects of policies. Most important, when experimentation in real systems is infeasible, simulation is often the only way we can discover for ourselves how complex systems work. Without the rigorous testing enabled by simulation, it becomes all too easy for policy to be driven by ideology, superstition, or unconscious bias.” ¹

¹ J. D. Sterman (2006)

² Neumann (2004)

D. BENEFITS OF THE GUIDELINES continued

Longer-term benefits continued

One important reason for this reluctance is modeling's current lack of credibility. For example, policymakers still remember the adverse effect of modeling on the Clinton healthcare reform initiative. During the summer of 1993, in what may have been a crucial blow to Clinton healthcare reform, the nation's elites abandoned healthcare reform, partly because they had become nervous about its cost.¹ Contributing to this nervousness was the lack of consistency among modeling results and the inability to explain these inconsistencies.

Improved modeling credibility should encourage policymakers to use models more extensively, thereby producing better-quality healthcare policies that, it is reasonable to hope, will improve population health (the ultimate goal). Improved credibility should also encourage funding sources to fund the development of more simulation models, and publishers to publish more modeling results.

E. ISSUES AND FUTURE DIRECTIONS

The guidelines that I presented in this chapter are proposed guidelines. Over time they need to be more fully developed and tested by health systems simulation modelers as well as stakeholders, to ensure their usefulness and practicability.

F. TO LEARN MORE

Guideline 2 encourages health systems modelers to follow software engineering practices. To learn more about software engineering standards and practices, read the excellent book titled "Code complete" by Steve McConnell.² It shows you how to write high-quality easily communicated computer code. Another classic about software engineering is "The mythical man-month" by Frederick Brooks.³ For more thorough, but more academic, grounding in software engineering, read "Fundamentals of software engineering" by Carlo Ghezzi and others.⁴

¹ Starr (1995)

² McConnell (2004)

³ Brooks (1995)

⁴ Ghezzi, et al. (2003)

G. REVIEW AND A LOOK AHEAD

In this chapter, I noted that, curiously, the practice of health system simulation modeling does not have a set of comprehensive good practice guidelines. I then proposed a set of seven such guidelines, and discussed the benefits that health system stakeholders might reap if modelers would implement them.

In the next chapter, we will look at methodologies to use for developing agent-based simulation models.

(Don't forget to take a look at the exercises for this chapter. They start on the next page.)

EXERCISES

1. Find a report about the results of a health system simulation model, and determine if the modelers followed the seven good practice guidelines.
2. Identify a health system simulation model that your organization has developed, and determine if its modelers followed the seven good practice guidelines. If the model's sponsors or users have encountered any problems with the model, determine if any of these might have been avoided by following the guidelines.

SOLUTIONS

1. Jonathan Gruber of Massachusetts Institute of Technology (MIT) developed a micro-simulation model to analyze the impact of using federal tax credits to expand health insurance coverage. Information about the model and its use is found in three publications: two journal articles about the model's results and one technical report about the model and its results.¹

In 2006, Modern Healthcare Magazine named Dr. Gruber the 19th most powerful person in health care in the U.S. He was associate head of the Department of Economics at the MIT, a professor of economics at MIT, and director of the National Bureau of Economic Research's Program on Children. He served as a senior health policy advisor during the development of the Clinton administration's healthcare reform proposal.

The table on the following page shows how well the Gruber model complies with the seven good practice guidelines.

¹ Gruber (2000a); Gruber (2000b); Gruber & Levitt (2000)

SOLUTIONS continued

Solution 1 continued

Guidelines	Gruber model compliance
1. Assemble appropriate teams.	Not reported
2. Follow generally-accepted good practice guidelines for software engineering.	Not reported
3. Explicitly include in the model relevant agents and outcomes.	Partially compliant. Excluded agents and excluded behaviors are not justified.
4. Choose a model type that is consistent with stakeholder requirements.	Not compliant. No explanation is given for the model type chosen.
5. Employ unbiased, relevant, diverse, and complete data sources, and use credible methods to collect, assess, and manipulate the data.	Not compliant. Evidence that the data sources are complete and credible is not given. It appears that only ad hoc methods were used to collect expert opinion.
6. Obtain an independent evaluation of the model.	Not compliant. It appears that an independent evaluation was not obtained.
7. Prepare a complete clearly written report about the modeling results that is peer reviewed and available for scrutiny.	Partially compliant. The following were not reported: background and context; settings to which the results apply; model limitations and their implications; and decisions the results can affect. The model scope was not justified. Sensitivity analyses were not performed. An assessment of uncertainty was not reported. Results were not placed in the context of current research and policy analysis. Reasons why the results may be wrong were not given. Sufficient details were not given to enable replication of results. The modeling team members were not reported, the sponsor was not reported, and potential biases and conflicts were not reported. Not all assumptions are given and most of those given are not justified.

As the table illustrates, for the most part the Gruber model does not comply with the guidelines. (Of course, it is not fair to judge this model against guidelines that did not exist when the model was developed and operated. The table is given only as an example.)

2. You might use a table similar to the one above to analyze your organization's model.

CHAPTER FIFTEEN: AGENT-BASED MODELING TOOLS

We can conclude that although there are a high number of possible tools for agent-based simulation, most of them are suitable for education, research, and experimental purposes, and there is a lack of systems that can be used for big, real-world simulations.

Tomáš Šalamon¹

A. INTRODUCTION

In this chapter, I introduce you to the tools I used to carry out the agent-based modeling method described in Chapter thirteen (Agent-based modeling method) in order to build and analyze the three sample models described in Chapter sixteen (Sample agent-based models).

The tools I used to build and analyze the sample models are:

- **Repast Symphony:** an agent-based modeling environment
- **Eclipse:** a software development environment
- **Java:** an object-oriented computer programming language
- **Excel and VBA:** a Microsoft spreadsheet program (Excel) and its computer programming language, Visual Basic for Applications (VBA)
- **Windows PC:** A personal computer (PC) with the Microsoft Windows operating system

This is the minimum toolset you will need to build and analyze a substantive agent-based simulation model. I devote a section of this chapter to each of these tools, and then in a final section I describe other tools that you may find helpful, such as Bugzilla, a software defect tracking system.

As you will see, these tools are mature and powerful enough for you to develop substantive agent-based simulation models to help solve real-world health systems problems. However, as with any set of powerful tools, you will need to devote time to learn how to use them.

¹ This comment concludes a review of agent-based modeling tools in Salamon (2011).

B. REPAST SIMPHONY

The foremost agent-based modeling environment for social simulation, Repast Symphony, is a free and open source agent-based modeling environment. In this section I will introduce you to Repast Symphony, which from here on I'll simply call Repast.²

The name Repast is an acronym for "Recursive Porous Agent Simulation Toolkit". Nick Collier, one of Repast's creators, explains the name: "Our goal with Repast is to move beyond the representation of agents as discrete, self-contained entities in favor of a view of social actors as permeable, interleaved and mutually defining, with cascading and recombinant motives. We intend to support the modeling of belief systems, agents, organizations and institutions as recursive social constructions."³

In 2000, University of Chicago researchers Nick Collier, Michael North, and David Sallach conceived Repast as an extension of the then-dominant agent-based modeling environment "Swarm". Since then, these researchers have moved to the Argonne National Laboratory (see the top sidebar) Center for Complex Adaptive Agent Systems Simulation. Together with a team of nearly twenty researchers, they have developed Repast into a full-fledged stand-alone simulation environment. The team is led by Michael North. Dr. North has appeared on the cover of *Science*, has written or co-written over fifty journal articles, and holds ten college degrees, including an MBA and a PhD.

Repast's development is managed by a volunteer board of directors from government, academia, and business, called the Repast Organization for Architecture and Design (ROAD). Its mission is to develop a reusable software infrastructure to support rapid social science discovery. It is succeeding (see the bottom sidebar).⁵

Argonne

Located outside of Chicago, with over 1,250 scientists and engineers, Argonne National Laboratory is one of the U.S. Department of Energy's largest national laboratories for scientific and engineering research.

Its mission is to integrate world-class science, engineering, and user facilities to deliver innovative research and technologies, and to create new knowledge that addresses the scientific and societal needs of the nation.¹

Repast contributes to this mission, because it is an innovative world-class modeling environment that enables researchers to address national scientific and social needs.

Most suitable framework

Among the many positive reviews of Repast, in 2004, Tobias and Hofmann wrote:

"We can conclude with great certainty that according to the available information, Repast is at the moment the most suitable simulation framework for the applied modeling of social interventions based on theories and data."⁴

This statement remains true today.

¹ From the Argonne website, www.anl.gov.

² Repast's home page is "repast.sourceforge.net". "Open source" means that Repast's computer code is openly available, so that you can change it to suit a particular purpose. In addition to Repast Symphony, Argonne also provides a version of Repast to use on supercomputers and computer clusters, "Repast HPC" (Repast for High Performance Computing). Although Repast HPC can only be programmed in C++, all other comments in this introduction apply also to it.

³ Collier, Howe, & North (2003)

⁴ Tobias & Hofmann (2004)

⁵ To learn more about Repast's history and purpose, see Collier (2001) and Samuelson & Macal (2006).

B. REPAST SIMPHONY *continued*

Purpose

To appreciate Repast’s purpose, pretend that you are head of a large hospital’s emergency department. You have a simple idea to modify the physical arrangement of the department’s waiting room to make it safer in case of fire, and you would like to convince the hospital to make the change.

How might you demonstrate the benefits of your idea? One way would be to prepare a film showing what might happen in a fire, before and after your modification. To do this, you would need:

- **Actors:** Actors who would imitate how patients and staff would behave in a fire.
- **Script:** A realistic script of fire behaviors for the actors to follow.
- **Set:** A set like the waiting room, for the actors to perform their parts.
- **Director:** A director who tells the actors when the fire scenes occur, such as when the fire breaks out, when smoke fills the room, etc.
- **Observation booth:** A place from which to direct, observe, and record what happens.
- **Recording equipment:** Video and audio equipment to record what happens.
- **Analytic tools:** Tools to measure what happens (number of fatalities, average exit time, etc.) and to assemble the “before” and “after” films.
- **Screening room:** A way to show the film to decision makers.

Carrying out such a plan would be prohibitively expensive. Moreover, many similar social experiments are flatly impossible.

From its outset, the purpose of Repast has been to provide a viable way to perform such social experiments. Its developers describe Repast as a “software infrastructure to support rapid social science discovery based on computational experimentation”.¹



Pause to reflect

Take a moment to plan what you would need in order to shoot and present such a “before” and “after” film.

Why do hospitals and other organizations not make decisions in this way?

¹ North et al. (Submitted 2012).

B. REPAST SIMPHONY continued

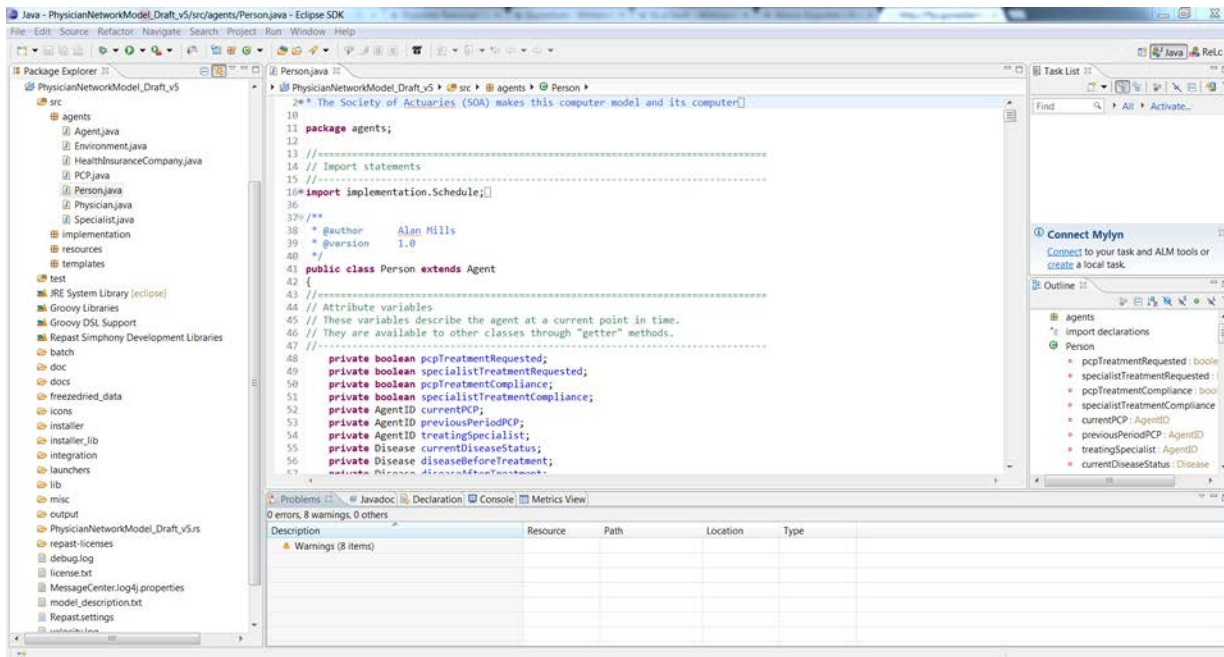
Purpose continued

As we will explore in the next section, Repast provides all the components that you would have needed for your fire safety film, but in a computer environment rather than in real life.

Modules

To help you develop your social experiments (or “agent-based simulations”, as I will now refer to them) Repast seamlessly integrates the following modules:

- **Design and development:** Repast provides a way for you to design and write the “script” (here called a “program” of “computer code”) that will govern how agents in your simulation will behave. It does this with the widely used tool “Eclipse”. Using Eclipse, you can write your Repast program in any of a variety of programming languages, including Java, C++, C#, and Python. The figure below shows the Eclipse development environment for Repast, which I will describe in Section C (Eclipse) below.



B. REPAST SIMPHONY continued

Modules continued

- Core management:** After you complete your simulation’s “script”, the core management module provides the tools you need to run the simulation. These core tools correspond to the actors, the set, and the director in our film example. This module provides the agents for your simulation, schedules their behaviors, manages their relationships (such as friend or family networks), manages the “contexts and projections” for the simulation’s “set” (see the sidebar), generates random numbers you may need, and performs many administrative tasks to help your simulation run smoothly. You can tell Repast how to manage your simulation either through Eclipse or through the Repast user interface, which we will explore next.
- User interface:** Corresponding to the “control booth” in our fire example, the Repast user interface (shown below) performs several functions. First, it provides a place to enter simulation parameters, such as the annual incidence of a particular disease. Second, it enables you to easily tell Repast how to collect and manage simulation results data, without resorting to a computer programming language. (Data management is a separate module, discussed below.) Third, the user interface provides access to many tools to visualize and analyze simulation results. (The data analysis module is also discussed below.) Fourth, it allows you to control the simulation: to turn it on, pause it, slow it down, speed it up, or stop it.

Contexts and projections

Two key concepts in Repast are “contexts” and “projections”. They both relate to how Repast manages the space (the “set”) in which your agents will act.

A “context” is a container that holds a collection of agents. By referring to contexts, you can easily tell Repast what to do with groups of agents. For example, you might want to put a certain group of agents in Health System A, and another group in Health System B. To accomplish this, you could use two contexts for the two hospitals.

Contexts can be hierarchical. For example, in Health System A you might have two hospitals, Hospital X and Hospital Y, each of which could be a separate context, and each of which might have a separate collection of employee or patient agents.

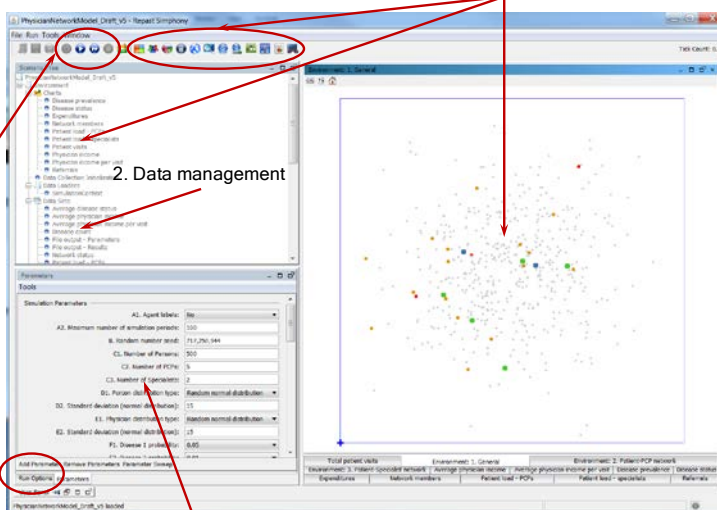
A “projection” is a relationship among a subset of the agents in a context. For example, a subset of the patients of Hospital X might be a family. The family relationship could be represented by a network projection.

Repast also provides particularly robust GIS (geographic information systems) projections that enable agents to act on realistic geographic surfaces such as mountains, cities, and even other planets.

3. Visualization and analysis

2. Data management

4. Simulation control



1. Parameter entry

B. REPAST SIMPHONY continued

Modules continued

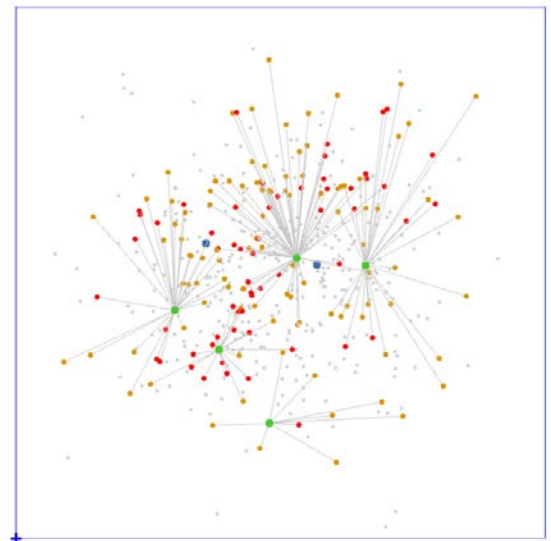
It is also possible to bypass the user interface and run your simulations in “batch mode”. This ability is useful if you want to quickly run many consecutive simulation runs, such as to test the sensitivity of simulation parameters. You can run Repast in batch mode using Repast’s “parameter sweep” feature, whereby it performs a series of simulations with varying parameters.

- Data management:** The Repast data collection module collects and stores information about the simulation as it runs. It is the counterpart of the video and audio recording equipment in our film example. Through the user interface, you have wide latitude to define how data is collected. You do this in two steps. First, you define data sets to collect by specifying the data items to collect and when they should be collected. Next, you define where and how these data sets should be saved. You can then analyze these data sets using Repast’s analytic tools (discussed next) or other analytic tools.

Repast also enables you to save (or “freeze”) the entire state of a simulation through its “freezedrying” feature. This feature is useful if you need to stop a long simulation run before it finishes. The “freezedrying” feature allows you to start the simulation again from where you stopped.

- Analysis:** Repast provides many tools to analyze simulation data collected by the data management module. With the user interface, you can visualize the simulation agents in any context or projection (see the example at top right). As the simulation progresses, you can “probe” individual agents (the middle example), or you can create time series charts and histograms to view results (the bottom example). The examples are from the Physician Network Model presented in Chapter sixteen (Sample agent-based models).

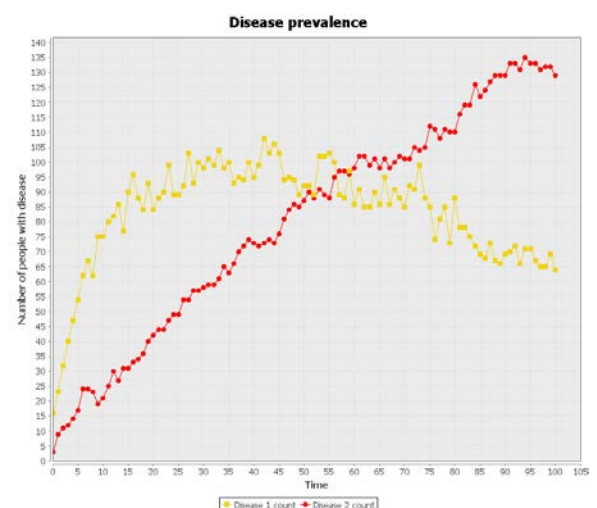
In addition, Repast can make a QuickTime movie of a simulation as it runs.



Person224

1. Disease:	1	
2a. Goal 1:	Convenience	
2b. Goal 2:	Conformance	
2c. Goal 3:	Treatment	
3. Current PCP:	PCP2	
4a. Treatment requested - PCP:	<input type="checkbox"/>	
4b. Treatment recommendation received - PCP:	None	
4c. Treatment compliance - PCP:	<input type="checkbox"/>	
5a. Treatment requested - Specialist:	<input type="checkbox"/>	
5b. Treatment recommendation received - Specialist:	None	
5c. Treatment compliance - Specialist:	<input type="checkbox"/>	

Locations: Space: 50.12128, 53.23084



B. REPAST SIMPHONY continued

Modules continued

In addition to its own analytic tools in the user interface, Repast provides access to powerful third-party analytic tools that are free and open source, including:

- **GRASS GIS** for managing and analyzing geospatial data
- **iReport** for preparing web-based reports
- **JoSQL** for analyzing and manipulating databases
- **JUNG** for analyzing and visualizing networks
- ***ORA** for analyzing networks
- **Pajek** for analyzing and visualizing networks
- **R** for analyzing and visualizing numerical data
- **VisAD** for visualizing and sharing numerical data
- **Weka** for data mining²

Even though they are free and open source, these tools are not toys. For example, with nearly one million users (some say two million) R threatens to put the SAS Institute out of business (see the sidebar). In Chapter sixteen (Sample agent-based models) I provide examples using R to analyze simulation data.

- **Stand-alone model execution:** Repast provides a module to prepare a stand-alone version of your simulation model, so that others (such as decisions makers) can run it outside of the Repast environment. In our film example, this module is the counterpart of the screening room in our film example.

Michael North and his team designed Repast so that these modules function independently. This design allows you to replace a Repast module with your own module (such as from a “legacy” software system that your company has), and enables the Repast team to upgrade a module without affecting the rest of Repast.³

R

According to its website, R is a “language environment for statistical computing and graphics”. But according to thousands of researchers, statisticians, and business analysts, it is much more. A research scientist at Google said, “R is really important to the point that it’s hard to overvalue it. It allows statisticians to do very intricate and complicated analyses without knowing the blood and guts of computing systems.”¹

Companies as diverse as Google, Pfizer, Merck, Bank of America, and Shell rely on R for data analysis.

R includes sophisticated packages to:

- manage and store data
- analyze data
- visualize data

Thanks to the work of hundreds of researchers around the world, R now has about 2,000 special programs (called “packages”) for data management and analysis. These include packages to calculate environmental trends, analyze speech patterns, analyze the human genome, and analyze financial derivatives. And the number of packages continues to grow.

For an entertaining article about R from the New York Times, see Vance (2009).

¹ Vance (2009)

² To learn more about these tools, visit their web sites: GRASS GIS: “grass.osgeo.org”; iReport: “community.jaspersoft.com”; JoSQL: “josql.sourceforge.net”; JUNG: “jung.sourceforge.net”; *ORA: “www.casos.cs.cmu.edu/projects/ora”; Pajek: “pajek.imfm.si”; R: “www.r-project.org”; VisAD: “www.ssec.wisc.edu”; Weka: “www.cs.waikato.ac.nz”

³ A detailed description of the Repast modular “plugin” architecture may be found in North, et al. (Submitted 2012).

B. REPAST SIMPHONY continued

User community members and their work

As of 2012, Repast has about 7,000 regular users.¹ And the number is steadily growing.

As a rough indication of Repast user growth, the chart at right shows the annual number of inquiries sent to the user group forum.²

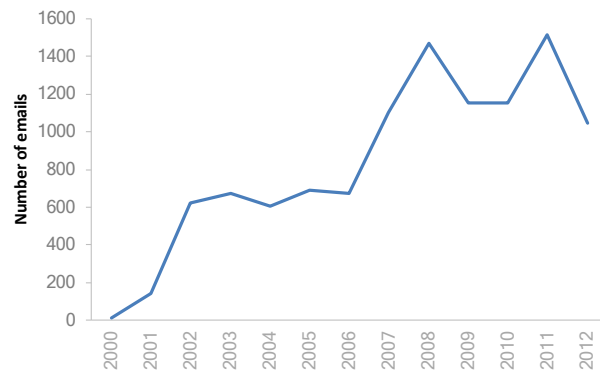
A high-profile Repast user is the University of Michigan’s Center for the Study of Complex Systems (CSCS). In 2011, CSCS teamed with Argonne to develop many Repast demonstration models for the 2011 Google Summer of Code.³

Repast users have developed a wide variety of applications that go far beyond mere demonstration models, including simulations of consumer markets, chemical reactor networks, disease epidemics, the Los Angeles market for hydrogen automobile fuel, the emergence of coordination among social agents, ancient pedestrian traffic, and electricity markets. A simulation of consumer markets for the company P&G directly influenced its management decisions and led to substantial cost savings.⁴ But, surprisingly, aside from simulations of disease epidemics, it appears that Repast users have not used Repast to model health systems.

User license

Argonne offers Repast under one of the most generous and simple user licensing agreements, called the “New BSD” (Berkeley Software Distribution) license. In effect, the license permits you to modify and distribute Repast in any way, including bundling it with for-profit software, as long as:

- the Argonne copyright, conditions, and disclaimers are included
- Argonne’s name is not used to endorse the resulting product⁵



¹ From a conversation with Michael North in December 2012.

² The history of forum inquiries is at “sourceforge.net/mailarchive/forum.php?forum_name=repast-interest”.

³ The results of this work can be found at “code.google.com/p/repast-demos”

⁴ North, et al. (Submitted 2012)

⁵ To see the license, go to: “repast.sourceforge.net/repast-license.html”.

B. REPAST SIMPHONY continued

Documentation and support

Argonne offers strong support to help you learn how to use Repast:

- **Documentation:** Repast documentation includes getting started guides, frequently asked questions, a reference guide, and guides about special Repast features such as data collection and “parameter sweeps”.¹
- **API and computer code:** Argonne provides a “Javadoc”-generated guide to Repast’s computer code. This resource is called the “Application Programming Interface” (API) and is useful if you want to access Repast’s features through programming, or if you want to change Repast’s code. For more information about Javadoc and the API, see the sidebar. Repast’s computer code is clearly written, amply documented, and easy to follow.²
- **Sample applications:** Many sample Repast applications are available, including the many applications mentioned above that were produced for the Google Summer of Code.³
- **User forum:** Repast has an active user forum, where you can obtain answers to your questions.⁴
- **Workshops:** Every year Argonne hosts workshops about Repast at the Argonne facility. These have a high teacher-to-student ratio, and—I can say from experience—are useful and fun.⁵
- **Papers:** Many researchers have written papers about their work with Repast.⁶

Perhaps the most disappointing aspect of Repast support is the lack of a full-blown user manual. Repast beginners and veterans alike would benefit from a comprehensive, up-to-date, and internally consistent manual.

Javadoc and the Repast API

Just as we can view Mozart’s work as a collection of musical phrases organized into movements (Allegro vivace, Andante catabile, etc.) within separate pieces of music (such as the Jupiter Symphony), Repast can be viewed as a collection of computer code organized into “classes” within “packages”.

Repast consists of about two hundred packages and thousands of classes. The API organizes these in a way that makes them easy to explore. For example, as shown below, one view of the API shows all the Repast packages (1), all the classes within a selected package (2), and information about a particular class (3).



The API is automatically generated with a Java language feature called “Javadoc” (Repast is written in the Java language), based on special comments that the programmer inserts in the computer code.

¹ For the complete collection of Repast Symphony documentation, go to: “repast.sourceforge.net/docs.html”.
² To obtain the Repast Symphony API, in either HTML or zipped format, go to “repast.sourceforge.net/docs.html”.
³ To view a collection of Repast sample applications, go to “code.google.com/p/repast-demos”.
⁴ To join the user group forum, go to “https://lists.sourceforge.net/lists/listinfo/repast-interest”.
⁵ To learn more about Argonne’s workshops, go to “www.dis.anl.gov/conferences/abms/info.html”.
⁶ For a sample of these papers, go to “repast.sourceforge.net/papers.html”.

B. REPAST SIMPHONY continued

Competitive modeling environments

For specialized business purposes—especially when agent-based simulation is combined with discrete event or system dynamics simulation—researchers use a software package called “AnyLogic”. However, AnyLogic is not free or open source.¹

To learn agent-based modeling, the agent-based environment “NetLogo” was once a strong competitor, but with the addition of the ReLogo language to Repast, NetLogo now offers little advantage over Repast other than its well-developed user documentation.²

Wikipedia lists and compares about 75 agent-based modeling packages, including Repast, NetLogo, and AnyLogic.³ In addition, it cites several comparative studies.

Future directions

In speaking with Michael North, I mentioned my dream for simulating health systems: a modeling environment in which a modeler or decision maker can choose health system agents from a library of agents, choose agent behaviors from a behavior library, and then let the agents loose on a simulated playing field (chosen from a library of possibilities) to see what they do.

He said that such an environment was part of the original plan for Repast. I then asked if he thought we would ever see such a thing.

In his typically reserved and respectful way, he said, “That’s a very good question.” After an enigmatic pause he continued, “The answer is yes ... sooner than you might think.”

¹ To find out more about AnyLogic, go to “www.anylogic.com”.

² To explore the NetLogo environment, go to “ccl.northwestern.edu/netlogo”.

³ For the comparison, go to “en.wikipedia.org/wiki/Comparison_of_agent-based_modeling_software”.

C. ECLIPSE

With over 6 million users and 65 percent of the Java development market share, Eclipse is one of the most respected and widely used integrated development environments (IDE). It is free and open source, and recently won a prestigious award (see the sidebar).

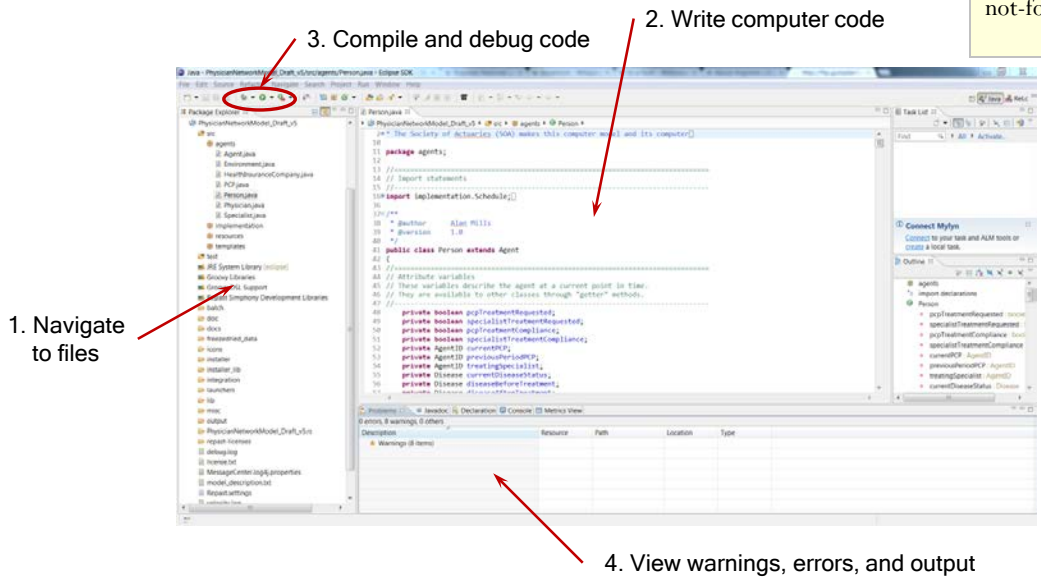
A typical IDE provides a computer programmer with an editor for writing computer code, a way to run the code, and a debugger for finding and repairing code defects. Eclipse provides these and more.

The diagram below shows what the Eclipse interface looks like as you use it to write and run Java code. On the left is a navigation pane to help you locate files and find out information about them. In the center is where you write the computer code. Eclipse provides many aids to help you write code quickly and error-free. On the top are ways to easily execute the code and debug it. The bottom center pane is an area that shows you errors and warnings about your code, as well as the console output as you run the code. Eclipse has many additional features that help you develop Repast models efficiently. Repast comes packaged with Eclipse.

2011 ACM Award

In 2012, The Association for Computing Machinery (ACM) recognized Eclipse with the 2011 ACM Software Systems Award. The award is given to an institution or individuals recognized for developing software systems that have had a lasting influence. In granting the award the ACM said:

“Created by IBM, Eclipse changed the way builders think about tools by defining a set of user interaction paradigms for which domain-specific variants are plugged in and customized for their tool. Conceived to address perceived shortcomings in proprietary software development tools, Eclipse allowed developers to seamlessly integrate their own extensions, specializations, and personalizations. It revolutionized the notion of an Integrated Development Environment (IDE) by identifying the conceptual kernel underlying any IDE. Eclipse was designed as an open, extensible platform for application development tools with a Java IDE built on top. In 2004 Eclipse became a not-for-profit corporation.”¹



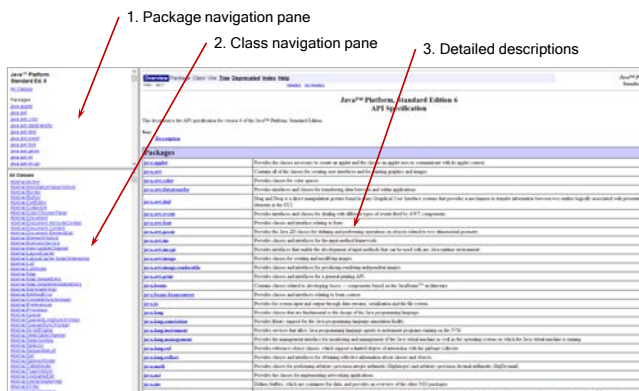
To learn more about Eclipse, read the book “Eclipse IDE 3.7” by Lars Vogel or watch the series of 16 tutorial videos at “eclipsetutorial.sourceforge.net”.²

¹ The Association for Computing Machinery (2012)
² The Eclipse website is “www.eclipse.org”.

D. JAVA

With over 10 million users—including corporate giants such as Google—Java is one of the most popular computer languages, and is the language I used to program the Repast simulations. It is an object-oriented language that provides many benefits other languages don't:

- **Write once, run anywhere.** Java enables a programmer to write code once and run it on any computer, rather than having to compile it separately for each different operating system.
- **Tight memory management.** Java manages computer memory well, avoiding undesirable memory leaks that have plagued languages such as C and C++. Such leaks can cause problems that are difficult to find and repair, especially in agent-based simulations.
- **Easy to learn.** Because its syntax is logical and similar to other common languages such as C++, Java is relatively easy to learn. In addition, Java is well supported and documented, with many educational books, videos, and classes.
- **Free and open source.** All of Java's core code is available under a free and open-source distribution license.
- **Easily documented.** Java comes with a documentation generator called Javadoc that produces and manages code documentation in HTML format. Java's own documentation, called the Java Application Programming Interface (API) is produced by Javadoc:



To learn how to program in Java read “Head first Java” by Kathy Sierra and Bert Bates¹ or “Java the complete reference” by Herbert Schildt.² Another good way to learn Java is to watch the series of 16 tutorial videos at “eclipsetutorial.sourceforge.net”.³

¹ Sierra & Bates (2005)

² Schildt (2011)

³ The Java web site is “www.java.com”. To learn Java, take a look at “www.java.com/en/java_in_action/bluej.jsp”.

E. EXCEL AND VBA

Microsoft's Excel is a ubiquitous spreadsheet application. I used its 2D and 3D charting capabilities to analyze Repast simulation results, and I used its programming language—called Visual Basic for Applications (VBA)—to manipulate Repast output for analysis.

To learn Excel and VBA, read “Excel 2010 bible” by John Walkenbach.¹

F. WINDOWS PC

Although I used a personal computer (PC) with a Windows operating system to develop, run, and analyze the Repast simulations, all the tools described in this chapter also run on the Mac operating system (Mac OS).

For best results with Repast, it is a good idea to use a 64-bit computer with a current-generation processor, and at least 8GB of random-access memory (RAM).

G. OTHER TOOLS

There are other tools you may find helpful, especially for larger simulation models:

- **Analysis.** Don't forget to use the graphical analysis tools supplied with Repast as well as the analytical tools available through its user interface, such as:
 - **Pajek** for analyzing and visualizing networks
 - **R** for analyzing and visualizing numerical data
- **Defect tracking.** To keep track of defects in your computer code, consider using Bugzilla. It is free. For more information, go to “www.bugzilla.org”. Bugzilla is available as an Eclipse plugin.
- **Version control.** To manage versions of your computer code and documentation—especially if more than one programmer is involved in your project—consider using Apache Subversion as a plugin for Eclipse. It is free. For more information, go to “www.eclipse.org/subversive”.

¹ Walkenbach (2010)

G. OTHER TOOLS continued

- **Design.** You may recall from Chapter thirteen (Agent-based modeling method) that there is a method called Prometheus that was developed especially for agent-based modeling. This method has an Eclipse-based tool named PDT (Prometheus Design Tool) to help you design an agent-based model. To learn more about Prometheus and PDT, read “Developing intelligent agent systems” by Lin Padgham and Michael Winkoff.¹

H. ISSUES AND FUTURE DIRECTIONS

The primary issue related to these tools is that they take time to learn. To help you learn these tools, we need to develop workshops devoted to agent-based health systems simulation. More about this in Part VI (Filling the gaps).

I. TO LEARN MORE

To learn more about agent-based simulation tools—and for another perspective about Repast Symphony and Java—read Appendix B (Agent-based modeling software) of “Design of agent-based models” by Tomáš Šalamon.² The book is an interesting and useful introduction to agent-based simulation modeling.

J. REVIEW AND A LOOK AHEAD

In this chapter, I introduced the tools that I used to develop the three sample agent-based models described in Chapter sixteen (Sample agent-based models). This is the toolset that I recommend for you to build substantive agent-based simulation models to solve real-world health systems problems.

In the next chapter, we will explore the three sample agent-based models.

(Don’t forget to take a look at the exercises for this chapter. They start on the next page.)

¹ Padgham & Winikoff (2004). The download site for PDT is “www.cs.rmit.edu.au/agents/pdt/pdt.shtml”.

² Salamon (2011)

EXERCISES

1. Download and install the latest versions of Java and Repast Symphony. (Note that Eclipse will come along with Repast.)
2. Go through the “Repast Java getting started” guide. Be sure to build the model described in the guide.

SOLUTIONS

1. To download Java, go to “www.java.com/en/download”. To download Repast Symphony (and Eclipse) go to “repast.sourceforge.net/download.html”. For more information about this, see the document “Getting started with the agent-based models” on the webpage for this report.
2. The guide is found at “repast.sourceforge.net/docs.html”.

CHAPTER SIXTEEN: SAMPLE AGENT-BASED MODELS

Just as the community of biologists had to learn to fully exploit the microscope when it was first invented, so we have only begun to explore the uses and limits of the artificial society as a scientific tool.

Joshua Epstein and Robert Axtell¹

A. INTRODUCTION

In this chapter, we will look at three problems that health systems face, and explore how agent-based models can help solve them. But the chapter's purpose is not about these specific problems or their solution. Rather, my aim is to introduce you to three sample agent-based models that, I hope, will provide templates and inspiration for you to start building your own agent-based models, models that will help solve the health system problems that concern you.

I call these sample models the “Physician Network Model”, the “Workplace Wellness Model”, and the “Adverse Selection Model”. They are simple enough to ease you gently into the art of agent-based model construction, yet, I hope, robust enough for you to find them interesting and useful.

B. PHYSICIAN NETWORK MODEL

The question addressed by the Physician Network Model is one that many health insurance companies ask: How can a group of physicians—a “physician network”—be optimized to best serve the health needs of a community? That is, what is the best size and configuration of such a network? Our simple agent-based model will help us see that the question itself is too narrow.

In exploring this model, we will first look in more detail at the question it addresses, and why an agent-based model is suitable to address it. We will then look at the model's agents and their behaviors. Lastly I will show you how to run the model, and we will look at the answers it provides.

Appendix A describes the model in detail. The model itself—in two formats—is available for you to download and explore.²

¹ Joshua M. Epstein & Axtell (1996)

² To download the model, go to the web page for this report, found on the Society of Actuaries' website “www.soa.org”.

B. PHYSICIAN NETWORK MODEL continued

1. The question

The model addresses the following question: How can the characteristics of a network of primary care physicians (PCPs) and specialists be modified to optimize:

- its **“carrying capacity”** (the number of patients it serves),
- **healthcare expenditures** associated with its services, and
- the **population health** of its community?

The model simulates how a network of PCPs and specialist physicians serves a community of people. As inhabitants become sick and are treated by network physicians, the model traces the interactions among the inhabitants, the physicians, and a company providing the community’s health insurance.

2. Suitability of agent-based modeling

An agent-based model is suitable to address this question, for the following reasons:

- **There are many autonomous decision-making agents.** All of the agents relevant to the question (the inhabitants, the physicians, and the insurance company) make decisions autonomously.
- **Agents are heterogeneous.** Because they vary by geographic location and goal priorities, the physicians and community inhabitants are heterogeneous.
- **The system is dynamic.** The health system underlying the question is dynamic. That is, a former state of agent interactions influences future states. For example, treatments provided by a PCP in one period affect the PCP’s status in the health insurer’s network, as well as the number of inhabitants who choose the PCP as their physician, in the next period.
- **There is no central controller.** There is no central controller managing the system being studied. Health systems in general do not have central controllers.
- **Multiple simultaneous processes.** The system being studied cannot be expressed as one process. If this were possible, then another modeling approach, such as discrete-event simulation, might be more appropriate. Rather, there are many independent processes (agent behaviors) occurring simultaneously.

B. PHYSICIAN NETWORK MODEL continued

2. Suitability of agent-based modeling continued

- **Aggregate functions do not apply.** The situation being studied does not lend itself to mathematical formulation. That is, the complexity of agent interactions cannot be captured by aggregate mathematical functions. If this were possible, then another modeling approach, such as system dynamics, might be more appropriate.
- **Spatial factors are important.** In the health system being considered, the spatial location of agents is important. For example, a person can decide whether to visit a physician based on the physician's geographic location.

3. Agents and their behavior

The model includes the following agents and behaviors:

- **Person:** An individual inhabitant of the community. A Person assesses the quality of physician performance, chooses a primary care physician, requests treatment from a physician, and complies with treatment recommendations.
- **Primary care physician (PCP):** A physician in the network who provides the first line of health care. The PCP recommends treatment for a Person, refers a Person to a Specialist, and submits claims to the Insurance Company.
- **Specialist:** A physician in the network who focuses on a specialized area of medicine. A Specialist recommends treatment for a Person, and submits claims to the Insurance Company.
- **Insurance Company:** A health insurance company that pays claims to PCPs and Specialists, assesses the performance quality of PCPs and Specialists, and determines which PCPs and Specialists will remain in the network. All people in the community have health insurance through the Insurance Company.
- **Environment:** The container for the model's agents. The Environment creates the simulation's agents, schedules agent behaviors, and manages the passing of messages among agents.

Appendix A provides details about these agents and their behaviors, how they communicate, the model's simplifying assumptions, and how the model can be tested.

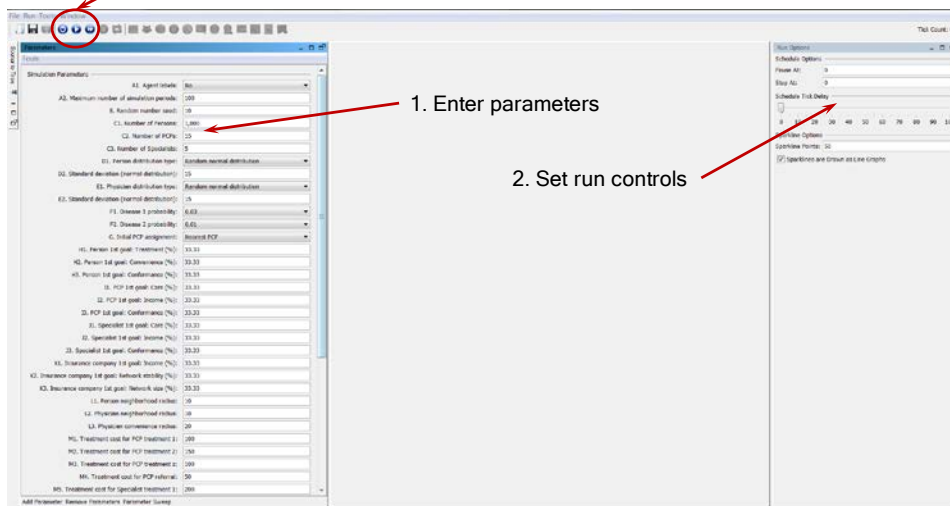
B. PHYSICIAN NETWORK MODEL continued

4. Running the model

After launching the model, you will see the Repast “user interface”, shown below.¹ With it you will:

- **Enter parameters.** On the left side of the user interface the model’s parameters are listed. You can change any of these, in order to run the model under alternative scenarios. But because the model opens with valid default parameters, you do not have to change any parameters. Appendix A describes the model’s parameters in detail.²
- **Set run controls.** On the right side of the user interface is a window to help you control how the model runs. The most useful of these controls is the “Schedule Tick Delay”. If you need to slow down a simulation, move its pointer to the right.
- **Initialize run, start run, step run.** The three buttons shown at the top are to initialize the model (“Initialize Run”), to start it (“Start Run”), and to run it one step at a time (“Step Run”). If you hover the mouse pointer over one of these buttons, its name appears. You start a simulation by clicking on the “Initialize Run” button. You can then either run it step by step by clicking on “Step Run”, or let it run through all its steps automatically by clicking on “Start Run”.

3. Initialize run, start run, step run



¹ You can launch the model either by importing it into Eclipse, and running it from the Eclipse environment, or by installing its stand-alone version. Both versions of the model, together with detailed instructions for launching them, are available from the web page for this report, found on the Society of Actuaries’ website “www.soa.org”.

² The model can run with the default values chosen, as it does for the simulation results in this chapter.

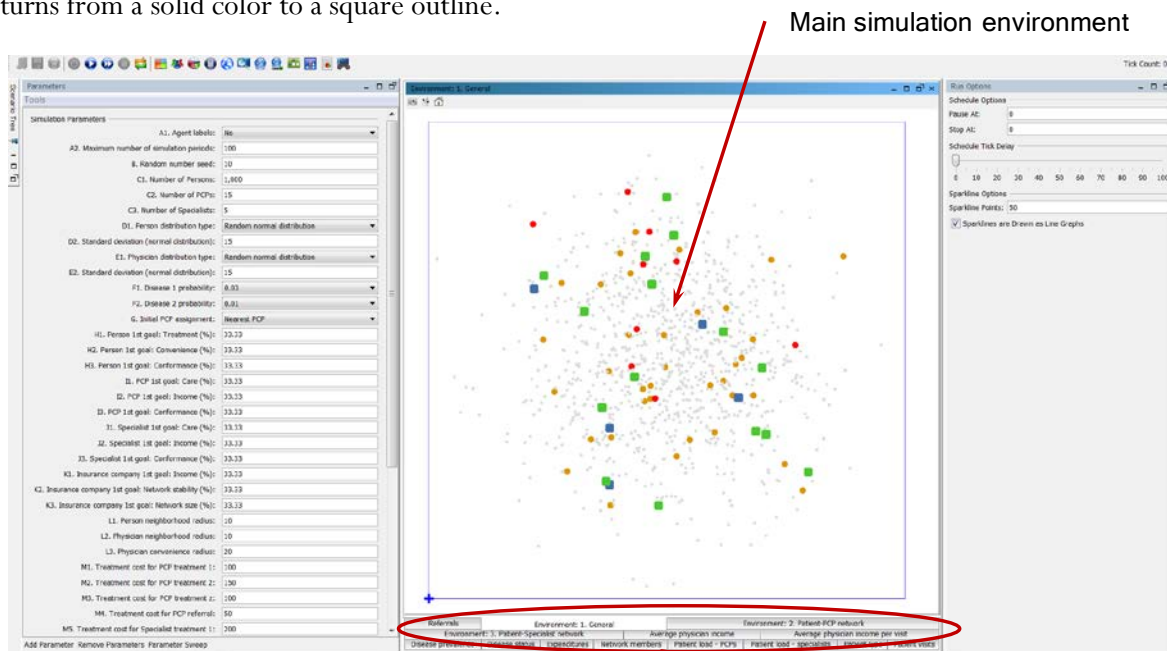
B. PHYSICIAN NETWORK MODEL continued

5. Results

When you initialize the model, the main simulation environment appears in the middle of the user interface, as shown below.¹ Here, the community’s 1,000 inhabitants (Person agents) are represented by disks. Small grey disks are inhabitants free of disease, large mustard-colored disks are those with “Disease 1”, and large red disks are those with “Disease 2”.

The community’s 15 PCPs are represented by green squares, and the 5 Specialists by blue squares. The Insurance Company is represented by the blue cross in the lower left corner.

As the simulation progresses, if the disease status of a Person agent changes, the Person’s disk changes color. Also, if a physician is dropped from the Insurance Company network, the physician’s square turns from a solid color to a square outline.



Charts and other environments

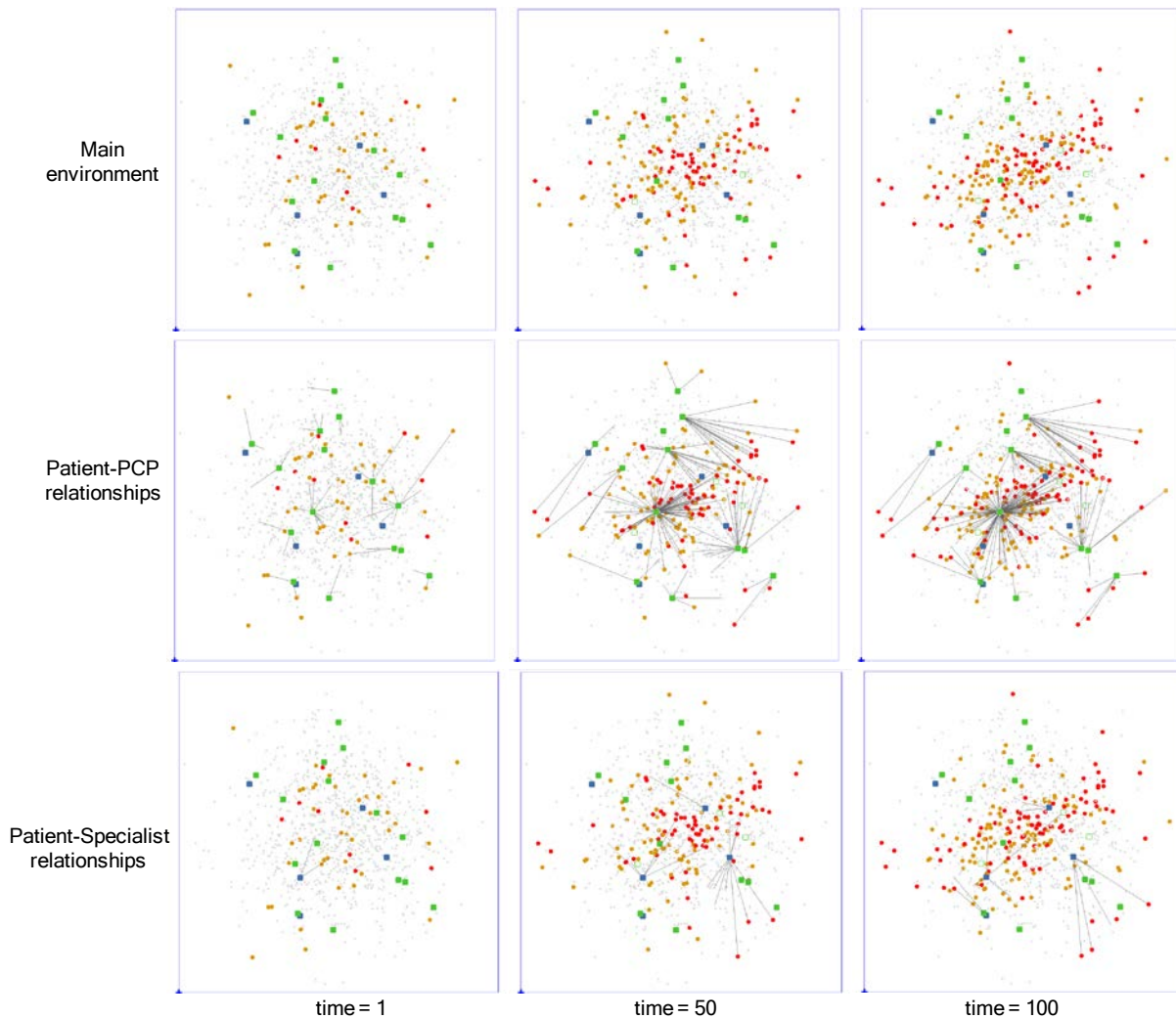
At the bottom are tabs for the model’s charts and other environments. Let’s now run a simulation and explore these.

¹ For some models, it may take a few seconds for the simulation environment to appear. Be patient. To make the space wider for a simulation environment, you can click and drag the edges of the left and right panels to make them narrower. To move the environment around, hold the right mouse button down and move the mouse. To zoom in, use the mouse wheel or its equivalent for your computer.

B. PHYSICIAN NETWORK MODEL continued

5. Results continued

The following series of views shows the main environment at times 1, 50, and 100.¹ Also shown are the two other environments—one showing the patient-PCP relationships and the other showing the patient-Specialist relationships—at the same times.



As time passes, the number of diseased people in the community increases. And they seem to cluster in the middle, particularly around one PCP with whom many inhabitants have a patient-doctor relationship. Also, three PCPs have been dropped from the network.

¹ Unless noted otherwise, all the Physician Network Model simulations in this chapter are run with the model’s default parameters and a random number seed of “10”.

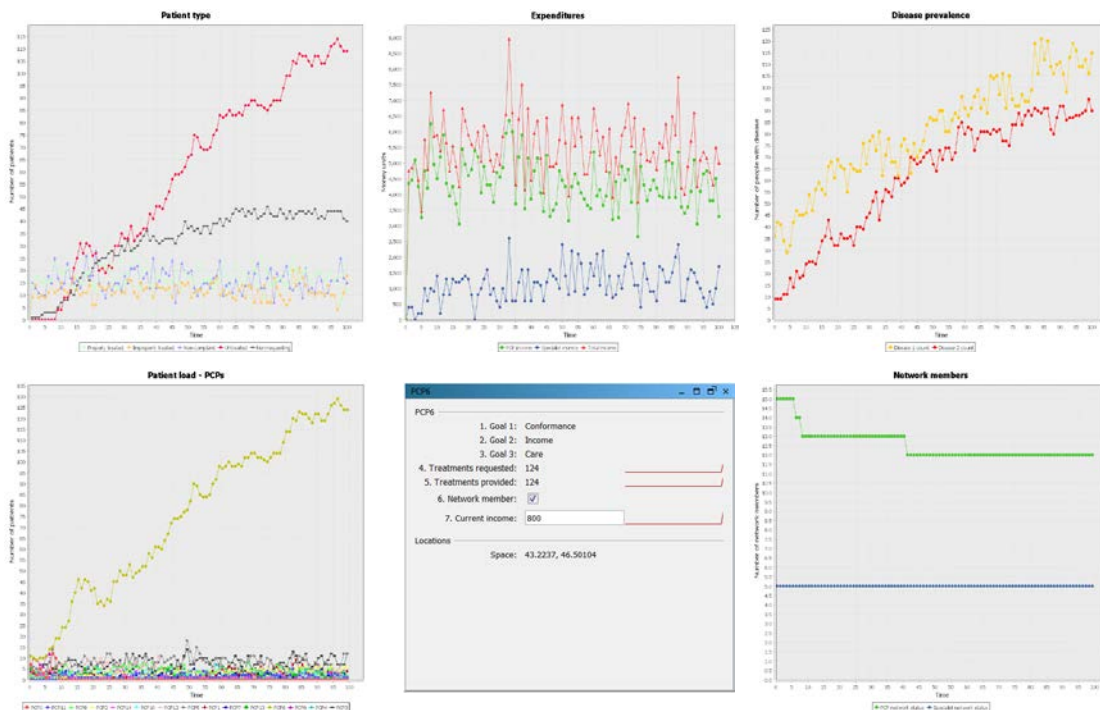
B. PHYSICIAN NETWORK MODEL continued

5. Results continued

The charts below provide more information. The upper left chart (“Patient type”) shows that one type of patient, the “untreated” patient (a patient who cannot visit a PCP, because the PCP is overloaded with patients and cannot provide treatment—see the table at right) is increasing. During period 100, nearly 110 patients are left untreated. The lower left chart shows that one PCP is overloaded. During period 100, this PCP had nearly 125 treatment requests, but had a patient capacity of only 15. The bottom middle panel shows a “probe” of this PCP (obtained by double-clicking on it); the PCP is PCP number 6, with first and second goals of “Conformance” and “Income” (rather than patient care).

Patient type	Treatment requested	Treatment received	Compliant	Treatment effective
1. Properly treated	Yes	Yes	Yes	Yes
2. Improperly treated	Yes	Yes	Yes	No
3. Non-compliant	Yes	Yes	No	NA
4. Untreated	Yes	No	NA	NA
5. Non-requesting	No	NA	NA	NA

The top middle chart shows that expenditures for PCPs (green) and Specialists (blue) remain relatively level. The top right chart shows that the numbers of people with Disease 1 (mustard) and Disease 2 (red) are increasing. And the bottom right chart shows that the number of PCPs in the network is declining.



This is not a happy community. People are getting sick, many cannot see a physician, and physicians are being dropped from the network.

B. PHYSICIAN NETWORK MODEL continued

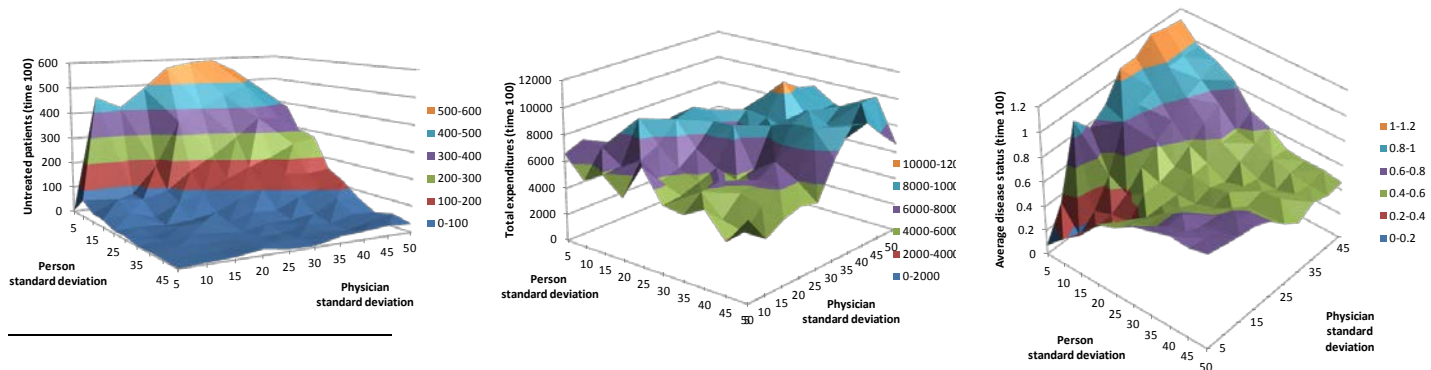
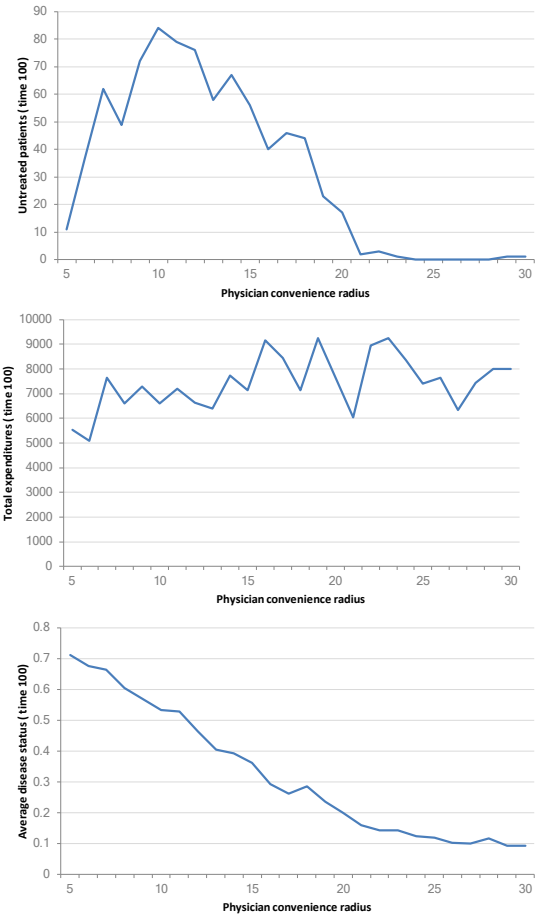
5. Results continued

In the top left chart on the previous page, you may have noticed that the number of “non-requesting” patients is also increasing. A non-requesting patient is one who does not even attempt to visit a physician, because physicians are too far away. This behavior is determined largely by the “physician convenience radius” parameter, which in our simulation is 20. (For comparison, the width and height of the community environment is 100.)

The charts at right show that if we increase the radius that a patient will travel to visit a physician, the number of untreated patients decreases, the average disease status decreases, and total expenditures rise only slightly. Therefore, a plan to increase the community’s health might include an incentive to encourage people to travel farther to visit physicians. Alternatively, physicians in the network should be chosen so that patients do not have to travel far to visit them.

Does it matter how concentrated or dispersed patients and physicians are? The charts below show the number of untreated patients, total expenditures, and average disease status as functions of patient and physician “standard deviation”. In our simulation, patients and physicians are distributed across the environment according to the “normal” probability distribution. With higher standard deviations for this distribution, people and physicians are more dispersed. For both people and physicians, our simulation has a standard deviation of 15.

The charts below show that in a community with inhabitants who have a standard deviation of 15, the best physician standard deviation is 25 to 30.¹ Thus, again, the location of network physicians is important.

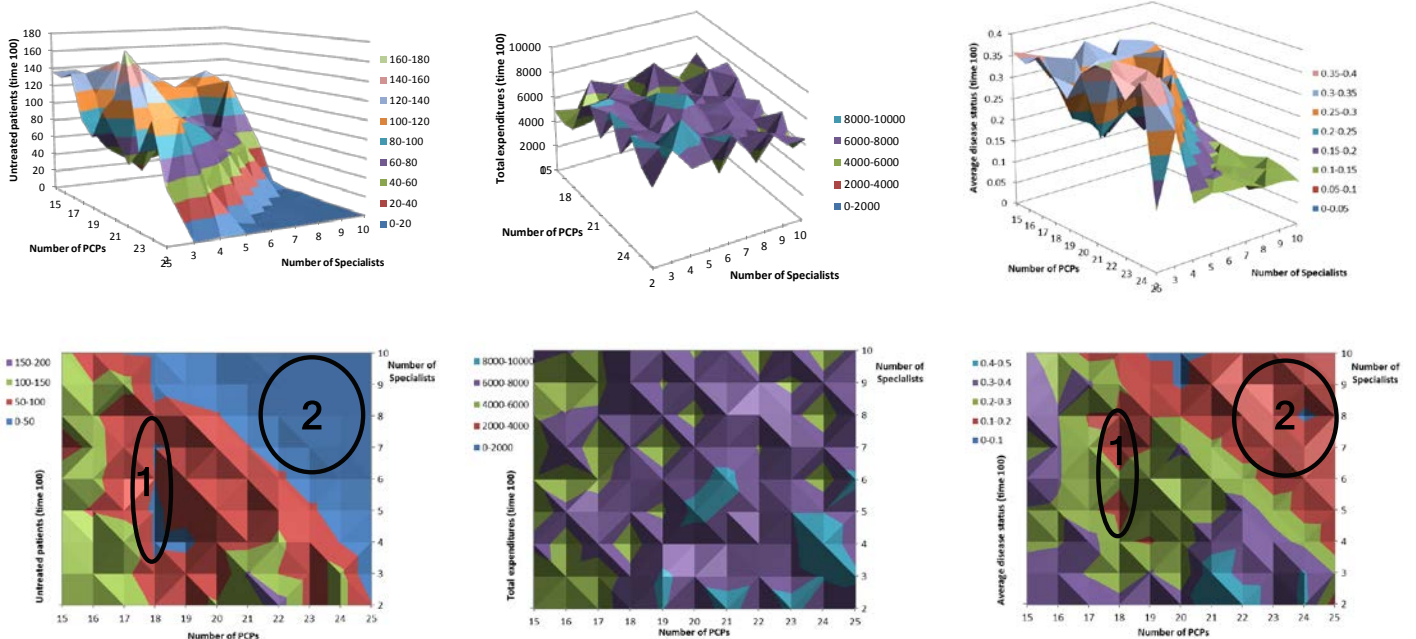


¹ The charts on this page were produced using the “parameter sweep” feature of Repast Simphony, together with the charting capability of Microsoft Excel.

B. PHYSICIAN NETWORK MODEL continued

5. Results continued

In the community, there are 15 PCPs and 5 Specialists. Is this enough?
The six charts below suggest that it isn't.



These charts show how the number of untreated patients, total expenditures, and the average disease status vary by the number of PCPs and Specialists. The top row is 3D charts and the bottom is topographical charts.

They show that there are two ways to decrease the number of untreated patients and the average disease status. The first way (denoted by “1” on the topographical charts) is to increase the number of PCPs to about 18 while keeping the number of Specialists between 4 and 7.

The second way is to increase the number of PCPs to 20 to 25 and increase the number to Specialists to 7 to 10. Both ways would leave total expenditures unchanged.¹ However, the second way may be preferable, because it is a larger area and thus would be more resilient to variance. The second area is thus a more “robust” solution.

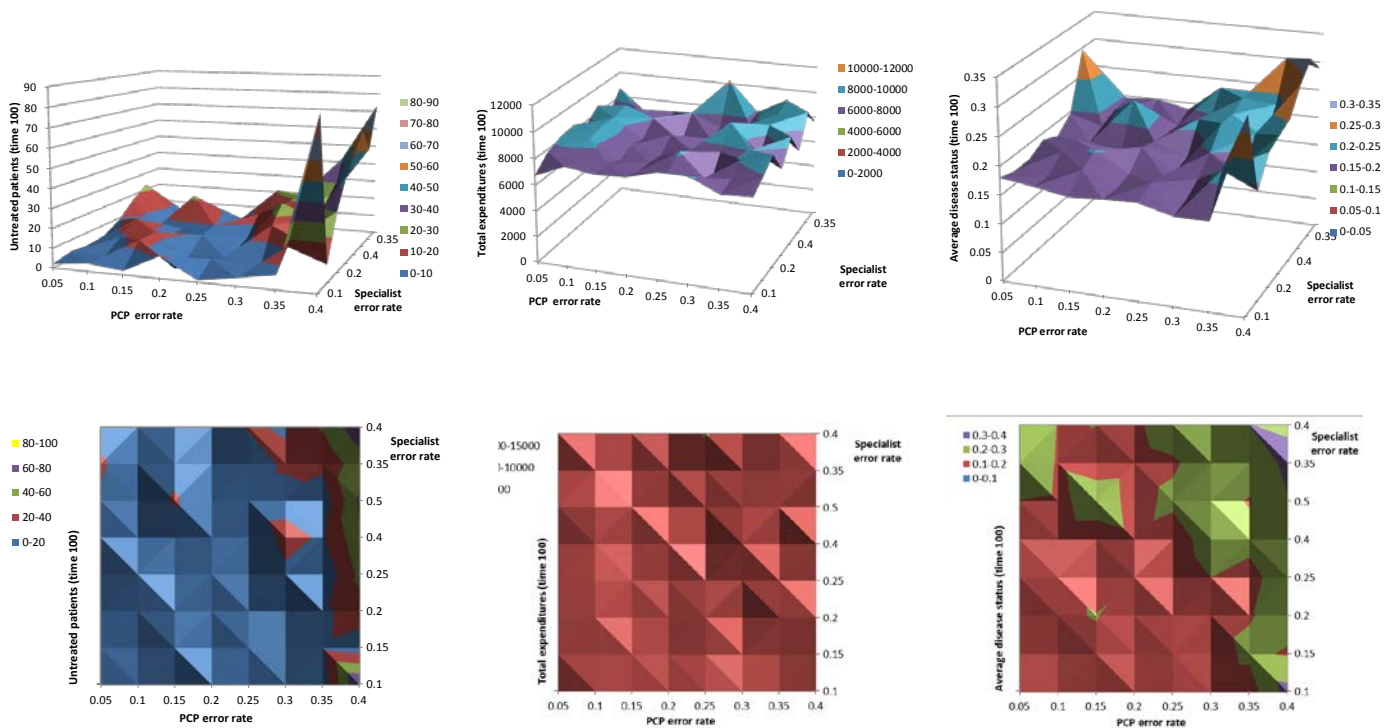
¹ It makes sense that the number of untreated patients and the average disease status should fall if the numbers of PCPs and Specialists rise.

B. PHYSICIAN NETWORK MODEL continued

5. Results continued

The physician error rate can also have a dramatic impact on results. The current error rate of network PCPs is 0.30, while the Specialist error rate is 0.20. The charts below show that the Specialist rate is in an acceptable range, but that the PCP rate is at a point leading to markedly increased numbers of untreated patients and worse average disease status.¹

Again, it is interesting that total expenditures are relatively unresponsive to changes in the model’s parameters.



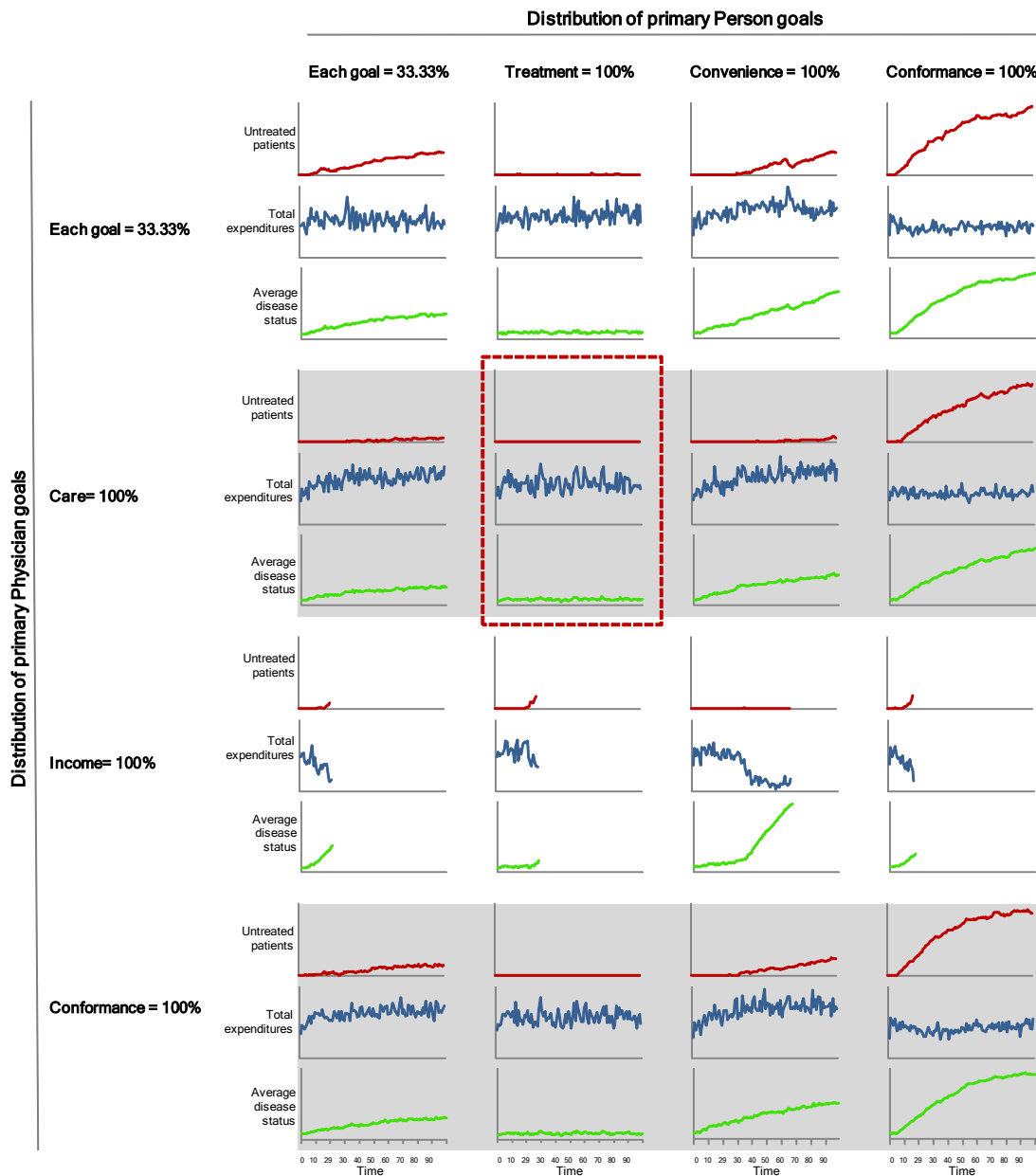
Next, let’s explore how behavioral goals affect results. The set of charts on the next page is a “lattice chart” (also called a “trellis chart” and a “panel chart”) showing how the results vary for different combinations of physician and patient behavior goals.

¹ This result makes sense. As the PCP error rates fall, the average disease status should fall and the number of PCPs left in the physician network should rise. The larger number of PCPs would then lead to fewer untreated patients.

B. PHYSICIAN NETWORK MODEL continued

5. Results continued

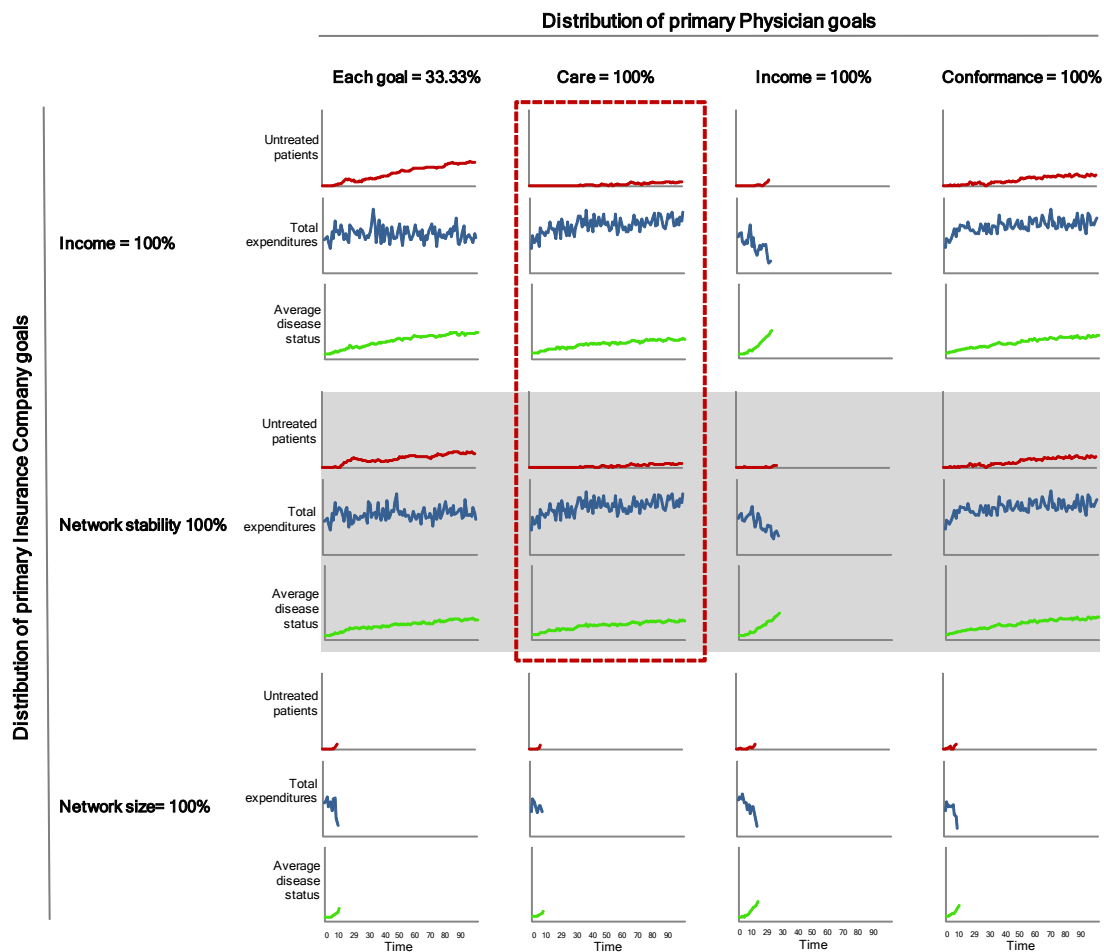
As the lattice chart below demonstrates, patients who have a primary goal of “Treatment” (the patient emphasizes treatment over convenience and conformance with other people), together with physicians who have a primary goal of “Care” (the physician emphasizes good patient care over income and conformance with other physicians) leads to a low number of untreated patients, level expenditures, and low average disease status.



B. PHYSICIAN NETWORK MODEL continued

5. Results continued

Similarly, the lattice chart below shows that a physician primary goal of “Care” combined with Insurance Company primary goals of “Income” or “Network stability” lead to the most favorable results.¹



These results make sense. One would expect to obtain the best result if patients and physicians focus on health care, rather than on goals such as conformance, convenience, or income.

Thus, efforts to change the healthcare goals of people, physicians, and health insurance companies could have a markedly positive impact on community health.

¹ The lattice charts were prepared with the “parameter sweep” feature of Repast Symphony together with the charting capability of Microsoft Excel. You may notice that several of the chart lines do not continue to time 100. This is because the number of PCPs in the physician network is reduced to zero before time 100.

B. PHYSICIAN NETWORK MODEL continued

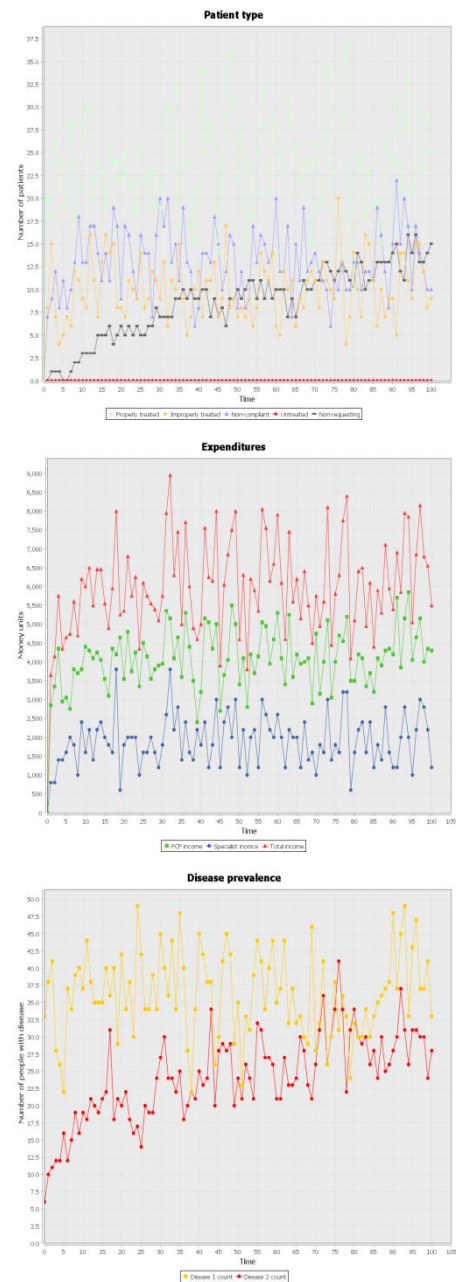
5. Results continued

Of course, even with our simple example there are many other parameter combinations to explore. But what would happen if we merely implemented the changes we have already explored?

Let's:

- increase the physician convenience radius from 20 to 25 (by providing patients better transportation alternatives, for example)
- increase the physician location standard deviation from 15 to 25 (say by choosing network physicians whose offices are geographically further apart)
- increase the number of PCPs from 15 to 20, and the number of Specialists from 5 to 7 (by increasing the number of physicians allowed into the network)
- decrease the PCP error rate from 0.30 to 0.20 (say by offering incentives for reducing error rates, or by providing training)
- increase the percentage of people with a primary goal of “Treatment” from 33.33 percent to 50 percent, and decrease the two other goals to 25 percent each (by offering health education classes, for example)
- increase the percentage of physicians with a primary goal of “Care” from 33.33 percent to 50 percent, and decrease the two other goals to 25 percent each (by offering incentives for greater emphasis on treatment, or by providing training)
- increase the likelihood of the insurance company having a primary goal of “Network stability” from 33.33 percent to 100 percent (say by educating the company’s executives).

The charts to the right show the results. There is no longer a problem with untreated patients, the incidence of Disease 1 is level, the incidence of Disease 2 rises only slightly, and expenditures are level. In addition, there have been no reductions in the number of physicians in the network, and no physician is overworked. Although there is still work to do, the community’s patients and physicians will now be happier. The insurance company should be happy as well.



B. PHYSICIAN NETWORK MODEL continued

5. Results continued

Let's pause to consider what agent-based modeling has helped us accomplish. By modeling the interplay of agent behaviors—from the bottom up—we have not only answered the original question, but, more importantly, we have come to understand that the question is too narrow.

Rather than ask how a particular facet of the health system (such as the physician network) could be modified to better serve the community, it is better to ask how the system as a whole—including the behaviors and characteristics of all its agents—can be modified to improve health care access, health system expenditures, and population health. The model shows us that modifying several factors throughout the system is more powerful than focusing on a particular part of the system such as the physician network. The problem is the system as a whole, not one of its facets. And the solution is the system as a whole.

To effectively address this more apt—but more complex—question, we need optimization techniques and tools that can assess the potential impact of billions of parameter combinations together with their associated risks. Such tools and techniques do not yet exist.⁵ Thus, agent-based simulation unfolds a new universe of statistical and risk analysis possibilities, one ripe for you to explore.

Comparison to other models

In the public domain there appears to be no model that is comparable to the Physician Network Model.



Pause to reflect

Take a moment to ponder how the agent-based model helped to answer the original question.

Given what you now know, do you think the original question is the right question? Why?

C. WORKPLACE WELLNESS MODEL

The Workplace Wellness Model addresses a common question that many employers ask: what is the optimal design for a workplace wellness program? Our agent-based model helps us understand the many intertwined considerations that underlie this question.

To explore this model, we will first look in detail at the question it addresses, and why an agent-based model is suitable to address it. We will then review the model's agents and their behaviors. Lastly I will show you how the model addresses the question.

The model is described in detail in Appendix B. The model itself—in two formats—is available for you to download and explore.¹

1. The question

The Workplace Wellness Model simulates the behavior of employees working for an employer that provides a workplace wellness program. The employer's program promotes employee exercise. Its goal is to reduce the number of overweight and obese employees, thereby reducing the incidence of Type 2 diabetes among employees, reducing the employer's medical expenditures for diabetes care, reducing the number of days of absenteeism and presenteeism (staying at work while sick and unproductive), and lengthening the span of employee careers.

The model traces:

- the number of employees who participate in the program and their average age
- the number of employees who are normal weight, overweight, and obese
- the prevalence of diabetes and average BMI²
- program costs
- the employer's medical expenditures for diabetes care
- the number of absenteeism and presenteeism days due to diabetes
- the number of employees who terminate or retire
- the number of years employees work before terminating or retiring

¹ To download the model, go to the web page for this report, found on the Society of Actuaries website “www.soa.org” under Research > Completed research projects > Health.

² BMI stands for “Body Mass Index” and is equal to weight (in pounds) divided by height (in inches) squared, times the constant 703.

C. WORKPLACE WELLNESS MODEL continued

1. The question continued

Specifically, the model addresses the following questions:

1. How do various wellness program designs affect:
 - **Medical expenditures.** The employer's medical expenditures for diabetes care
 - **Program costs.** The employer's costs to administer the program?
 - **Absence.** Employee absenteeism and presenteeism due to diabetes
 - **Health.** Employee health (measured by diabetes prevalence and average BMI)
 - **Career length.** The number of years employees work until termination or retirement?

And how do such effects evolve over time?

2. What wellness program design optimizes the combination of:
 - **Expenditure reduction.** The reduction in employer medical expenditures for diabetes care, offset by program costs
 - **Absence improvement.** Improvement in absenteeism and presenteeism
 - **Health improvement.** Improvement in employee health
 - **Career length improvement.** Improvement in the number of years that employees work

2. Suitability of agent-based modeling

An agent-based model is suitable to address this question, for the following reasons:

- **There are many autonomous decision-making agents.** The employee agents make decisions autonomously.
- **Agents are heterogeneous.** Because they vary by workplace location, age, and goal priorities, the employee agents are heterogeneous.
- **The system is dynamic.** The workplace wellness program is dynamic. That is, its former states influence its future states. For example, the number of people who participate in one year influences the number of people who choose to participate in the next.

C. WORKPLACE WELLNESS MODEL continued

2. Suitability of agent-based modeling continued

- **There is no central controller.** There is no central controller managing the evolution of a workplace wellness program. No one dictates program participation, compliance, or how employers structure their programs.
- **Multiple simultaneous processes.** A workplace wellness program cannot be expressed as one linear process. If this were possible, then another modeling approach, such as traditional discrete simulation, might be more appropriate. Rather, the employees engage in many independent behaviors simultaneously.
- **Aggregate functions do not apply.** A workplace wellness program does not lend itself to mathematical formulation. That is, the complexity of agent interactions cannot be captured by traditional aggregate mathematical functions. If this were possible, then another modeling approach, such as system dynamics, might be more appropriate.
- **Spatial factors are important.** Because Employees can base their wellness program participation and compliance behavior on the corresponding behavior of their neighbors, the spatial location of Employees in the population is important.

3. Agents and their behaviors

The model includes the following agents and behaviors:

- **Employee:** An individual employee of the Employer. An Employee decides whether to participate in the wellness program, decides whether to comply with the program's exercise recommendations, progresses along three "stages of change" (Ignorance, Awareness, Implementation)¹ for maintaining an exercise regimen, decides whether to terminate employment in order to work elsewhere, and decides when to retire.

¹ The model implements a hypothetical three-stage model of behavior change for maintaining an exercise regimen. According to this model, an Employee progresses from Stage I (Ignorance) to Stage II (Awareness) to Stage III (Implementation) in discrete steps, with different factors influencing the Employee's progression from stage to stage. This model is a simplification of "stage of change" models in the research literature, such as the "transtheoretical model", the "caution adoption process model", and the "health action process" model. For more information about "stage of change" health behavior models, see Chapter 6 of the book "Predicting health behavior" by Mark Conner and Paul Norman (published in 2005 by Open University Press).

C. WORKPLACE WELLNESS MODEL continued

3. Agents and their behaviors continued

- **Employee continued:** The Employee also changes body weight, develops diabetes, incurs medical expenses for diabetes, has days of absence from work, and has days of presenteeism.
- **Employer:** The model's user plays the role of the Employer. The Employer decides the type of wellness program to implement. As part of the wellness program, the Employer decides:
 - **Target population.** The employee body weight categories to target with the program.
 - **Design intensity.** The intensity of the program design (see below).
 - **Choice architecture.** Whether to reflect in the program's design and marketing what we have learned about human decision making from behavioral economics (see below).
 - **Incentives.** The level of program incentives to reward employees who comply with program requirements.

There are three types of wellness program design: “None”, “Level 1”, and “Level 2”. The Level 2 program is more effective than the Level 1 program in getting employees to join the program and exercise, but it is more costly. For example, a Level 1 program might supply employees with written information about how exercising reduces obesity, while a Level 2 program might provide such information in a video format, together with a weight screening program and an online health risk assessment.

There are three levels of reflecting results from behavioral economics (that we will call the “choice architecture intensity”): “None”, “Level 1”, and “Level 2”. Level 2 is more effective than Level 1 in getting employees to join the program and comply with its recommendations, but is more costly. For example, Level 1 might involve presenting program choices (such as whether or not to join) in an order and with defaults that encourage participation. Level 2 might also incorporate what we know about behavioral economics factors such as “focusing”, “anchoring”, etc. throughout the program's marketing and educational materials.

C. WORKPLACE WELLNESS MODEL continued

3. Agents and their behaviors continued

There are three levels of incentives: “None”, “Level 1”, and “Level 2”. Level 2 incentives are more effective than the Level 1 incentives in getting employees to join the program and exercise, but are more costly.

Program design type, choice architecture intensity, and program incentive levels are independent: For each program design type, the Employer can choose any level of intensity for choice architecture and incentives.

Appendix B provides details about these agents and their behaviors, as well as the model’s simplifying assumptions.

4. Running the model

As with the Physician Network Model, to run the Workplace Wellness Model, you enter parameters in the user interface, set run controls, initialize the run, and then start the simulation.¹

The parameters include information about the program design and its costs, information about the number and type of employees, disease rates (such as diabetes incidence, prevalence, and remission), termination rates, and administrative settings (such as the random number seed and the output file name).

A complete description of the model parameters is in Appendix B.

5. Results

When you initialize the model, the main simulation environment appears in the middle of the user interface. The employees are represented by disks located in a work environment. The distance between disks represents the relational closeness of co-workers.

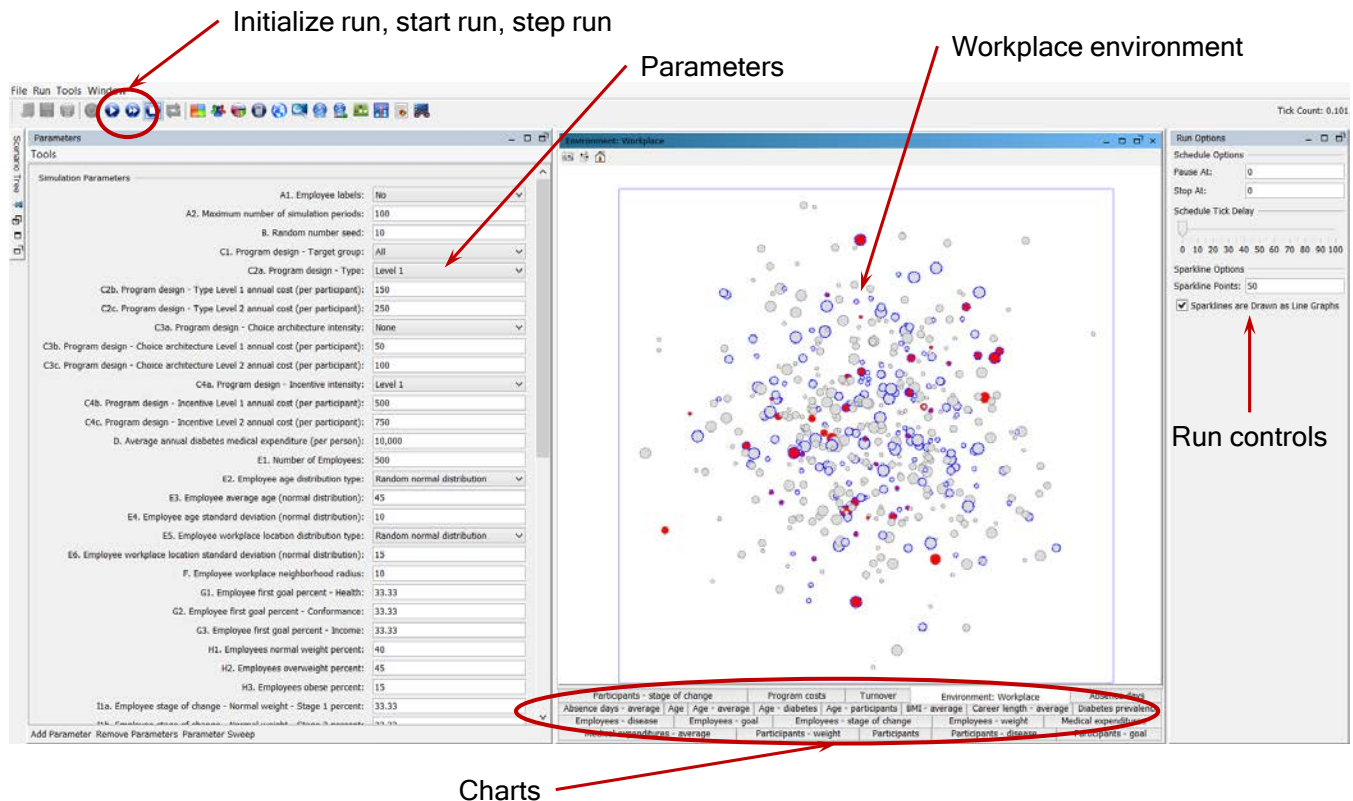
¹ For more detailed information about running the model, see Subsection 4 (Running the model) of the Physician Network Model description earlier in this chapter.

C. WORKPLACE WELLNESS MODEL continued

5. Results continued

As shown below, employees with diabetes are colored red, and those without diabetes are grey. The size of the disk corresponds to the Employee’s weight category. Employees with small disks are normal weight, those with larger disks are overweight, and those with the largest disks are obese. Disks with a blue border represent Employees in the wellness program; those with a black border are not in the program.

As the simulation progresses, Employees age, join or leave the wellness program, contract diabetes or enjoy remission, gain or lose weight, and terminate or retire. Disks of Employees who terminate or retire are first colored white, and are then removed from the workplace environment.¹

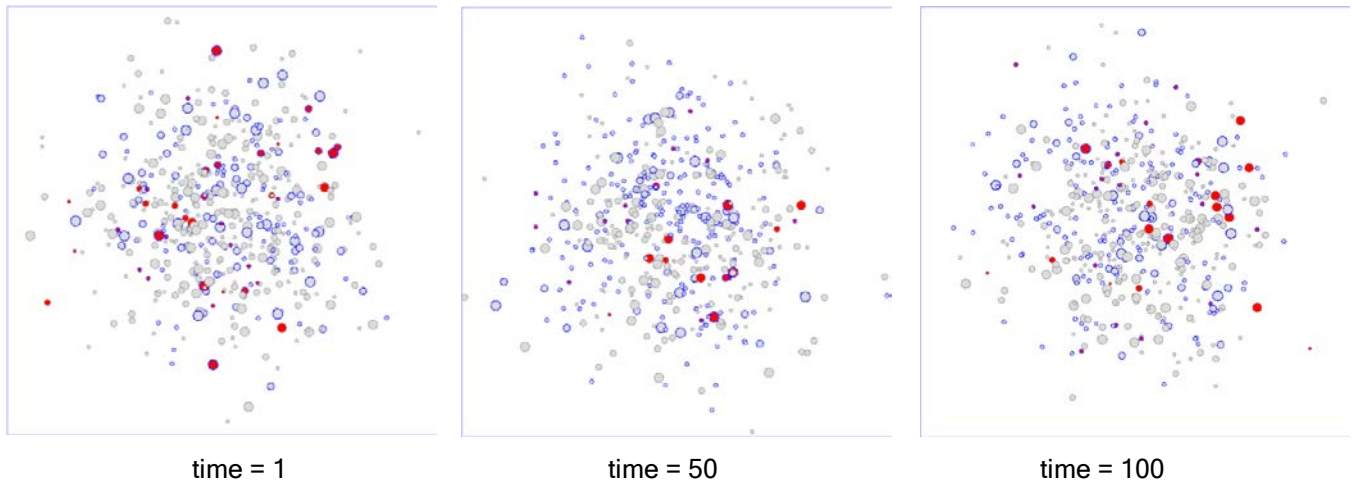


¹ Unless noted otherwise, all the Workplace Wellness Model simulations in this chapter are run with the model’s default parameters and a random number seed of “10”.

C. WORKPLACE WELLNESS MODEL continued

5. Results continued

The following series shows the workplace environment at times 1, 50, and 100.



As time passes, the number of program participants (disks outlined in blue) appears to increase and the number of employees with diabetes (red disks) appears to decrease.

On the next page are charts that provide more information about this default scenario (see the sidebar). They show that, as time passes, total medical expenditures decrease from about 500,000 to about 325,000, a savings of about 175,000. Program costs increase from 0 to about 150,000, producing a net savings of about 25,000. The charts show that the number of annual absence days decreases from about 1,400 to about 900, an improvement of about 500 days. If each absence day is worth 100, then for the employer the program appears to generate a savings of about 75,000.

The charts also show that diabetes prevalence decreases, the number of employees who have normal weight increases, the number overweight decreases, and the number of obese employees decreases. The average BMI also decreases from about 26 to about 24. Thus, under this scenario, employees appear to be getting healthier.

Default scenario

The default scenario has the following key characteristics:

Program design

- **Employees targeted:** All employees
- **Program design type:** Level 1
- **Type level 1 annual cost:** 150
- **Choice architecture intensity:** None
- **Incentive intensity:** Level 1
- **Intensity level 1 annual cost:** 500

Other

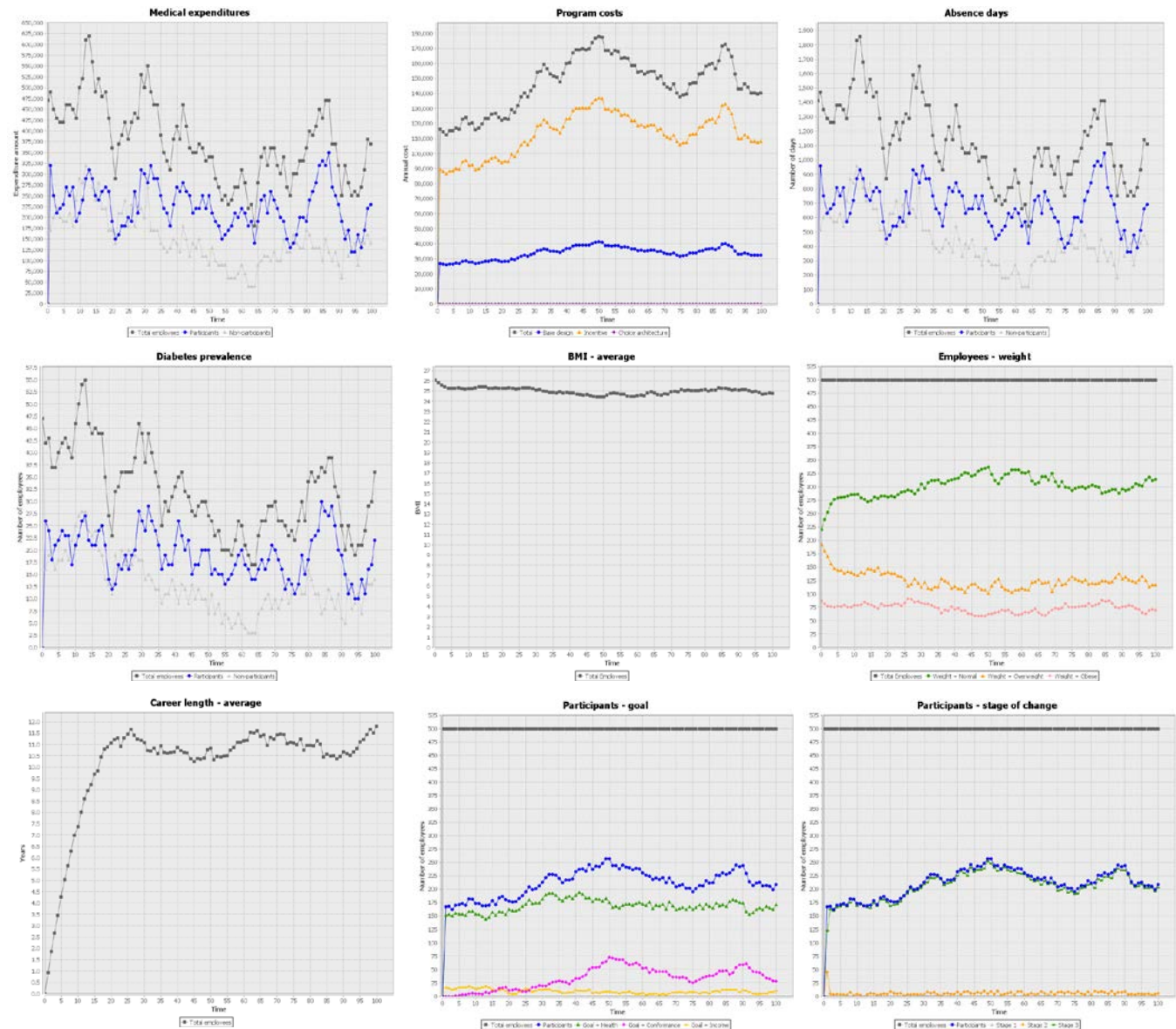
- **Annual medical expenditures for diabetes (per person):** 10,000
- **Number of employees:** 500
- **Employees normal weight percent:** 40
- **Employees overweight percent:** 45
- **Employees obese percent:** 15
- **Retirement age:** 65

For definitions of these parameters, and a list of all parameters, see Appendix B.

C. WORKPLACE WELLNESS MODEL continued

5. Results continued

The bottom middle chart shows how the number of participants with each of the three goals “Health”, “Conformance”, and “Income”¹ changes during the simulation. It shows that number of participants with the goal “Conformance” increases, while the number with the other two goals remains relatively steady. The bottom right chart shows that throughout the simulation most participants are at stage of change III (“Implementation”). Not bad, but is there a better design?



¹ For more information about employee goals in the Workplace Wellness Model, see Appendix B.

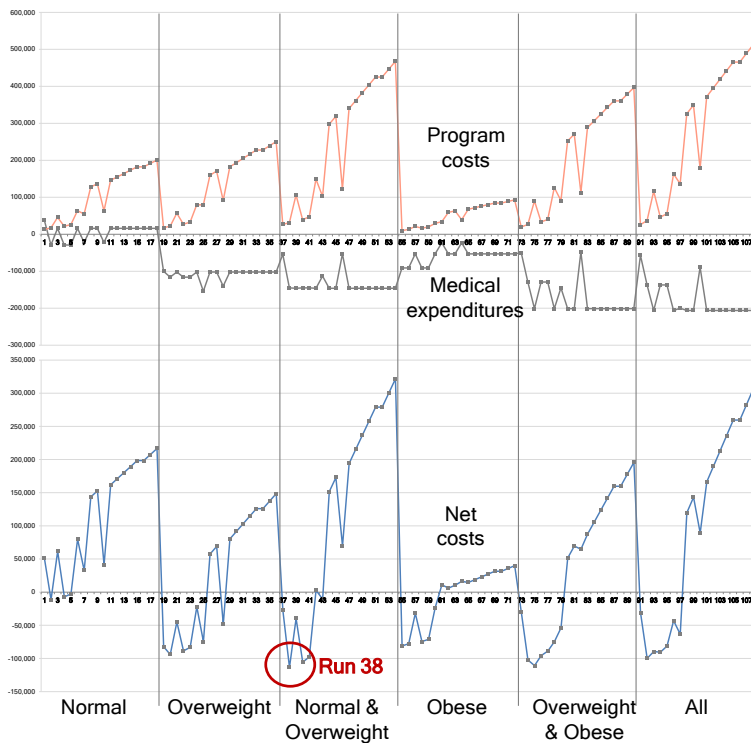
C. WORKPLACE WELLNESS MODEL continued

5. Results continued

The chart below shows the program costs, medical expenditure savings, and the net costs (program costs + medical expenditure savings) for 108 simulations, one for each permutation of the program design parameters:

- **Target group.** The weight category or categories that the employer targets with the program. Choices: Normal, Overweight, Normal and Overweight, Obese, Overweight and Obese, and All.
- **Design type.** The type of program that the employer implements. Choices: Level 1 and Level 2 (1 and 2 in the table at right).
- **Choice architecture intensity.** The choice architecture intensity that the employer implements. Choices: None, Level 1, and Level 2 (0, 1, 2 in the table at right).
- **Incentive intensity.** The incentive intensity that the employer implements. Choices: None, Level 1, and Level 2 (0, 1, 2 in the table at right).

Run	Target group	Design		
		CA	Level	Incentive
1	Normal	1	0	0
2	Normal	1	1	0
3	Normal	1	2	0
4	Normal	2	0	0
5	Normal	2	1	0
6	Normal	2	2	0
7	Normal	1	0	1
8	Normal	1	1	1
9	Normal	1	2	1
10	Normal	2	0	1
11	Normal	2	1	1
12	Normal	2	2	1
13	Normal	1	0	2
14	Normal	1	1	2
15	Normal	1	2	2
16	Normal	2	0	2
17	Normal	2	1	2
18	Normal	2	2	2
19	Overweight	1	0	0
20	Overweight	1	1	0
21	Overweight	1	2	0
22	Overweight	2	0	0
23	Overweight	2	1	0
24	Overweight	2	2	0
25	Overweight	1	0	1
26	Overweight	1	1	1
27	Overweight	1	2	1
28	Overweight	2	0	1
29	Overweight	2	1	1
30	Overweight	2	2	1
31	Overweight	1	0	2
32	Overweight	1	1	2
33	Overweight	1	2	2
34	Overweight	2	0	2
35	Overweight	2	1	2
36	Overweight	2	2	2
37	Normal & Overweight	1	0	0
38	Normal & Overweight	1	1	0
39	Normal & Overweight	1	2	0
40	Normal & Overweight	2	0	0
41	Normal & Overweight	2	1	0
42	Normal & Overweight	2	2	0
43	Normal & Overweight	1	0	1
44	Normal & Overweight	1	1	1
45	Normal & Overweight	1	2	1
46	Normal & Overweight	2	0	1
47	Normal & Overweight	2	1	1
48	Normal & Overweight	2	2	1
49	Normal & Overweight	1	0	2
50	Normal & Overweight	1	1	2
51	Normal & Overweight	1	2	2
52	Normal & Overweight	2	0	2
53	Normal & Overweight	2	1	2
54	Normal & Overweight	2	2	2
55	Obese	1	0	0
56	Obese	1	1	0
57	Obese	1	2	0
58	Obese	2	0	0
59	Obese	2	1	0
60	Obese	2	2	0
61	Obese	1	0	1
62	Obese	1	1	1
63	Obese	1	2	1
64	Obese	2	0	1
65	Obese	2	1	1
66	Obese	2	2	1
67	Obese	1	0	2
68	Obese	1	1	2
69	Obese	1	2	2
70	Obese	2	0	2
71	Obese	2	1	2
72	Obese	2	2	2
73	Overweight & Obese	1	0	0
74	Overweight & Obese	1	1	0
75	Overweight & Obese	1	2	0
76	Overweight & Obese	2	0	0
77	Overweight & Obese	2	1	0
78	Overweight & Obese	2	2	0
79	Overweight & Obese	1	0	1
80	Overweight & Obese	1	1	1
81	Overweight & Obese	1	2	1
82	Overweight & Obese	2	0	1
83	Overweight & Obese	2	1	1
84	Overweight & Obese	2	2	1
85	Overweight & Obese	1	0	2
86	Overweight & Obese	1	1	2
87	Overweight & Obese	1	2	2
88	Overweight & Obese	2	0	2
89	Overweight & Obese	2	1	2
90	Overweight & Obese	2	2	2
91	All	1	0	0
92	All	1	1	0
93	All	1	2	0
94	All	2	0	0
95	All	2	1	0
96	All	2	2	0
97	All	1	0	1
98	All	1	1	1
99	All	1	2	1
100	All	2	0	1
101	All	2	1	1
102	All	2	2	1
103	All	1	0	2
104	All	1	1	2
105	All	1	2	2
106	All	2	0	2
107	All	2	1	2
108	All	2	2	2

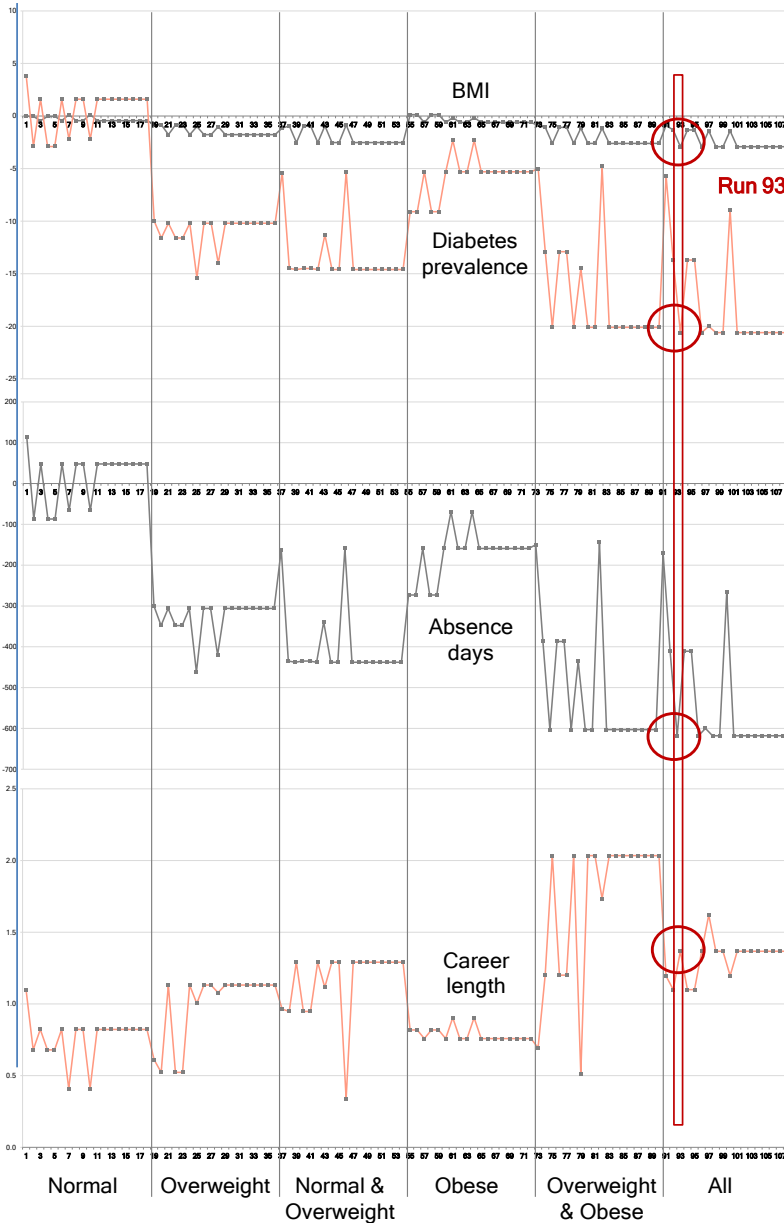


As the chart shows, from a purely economic perspective, it appears that the most favorable program design is from Run 38: targeting Normal weight and Overweight employees with a Level 1 design type, Level 1 choice architecture, and no incentives. But is this the best overall design?

C. WORKPLACE WELLNESS MODEL continued

5. Results continued

Perhaps not. As the chart below shows, Run 93 minimizes BMI, diabetes prevalence, and absence days. It also significantly improves career length. The program design for Run 93 covers all employees, and implements a design type of Level 1, a choice architecture of Level 2, and no incentives. It improves employee health and lengthens their working career. But is it cost-effective?

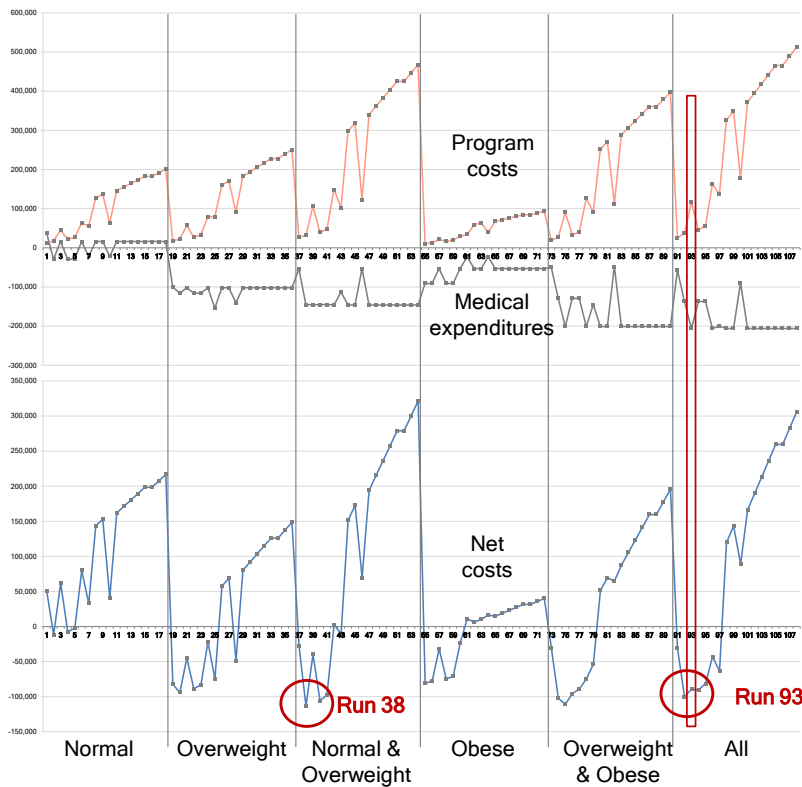


Run	Target group	Design		
		CA	Incentive	Level
1	Normal	1	0	0
2	Normal	1	1	0
3	Normal	1	2	0
4	Normal	2	0	0
5	Normal	2	1	0
6	Normal	2	2	0
7	Normal	1	0	1
8	Normal	1	1	1
9	Normal	1	2	1
10	Normal	2	0	1
11	Normal	2	1	1
12	Normal	2	2	1
13	Normal	1	0	2
14	Normal	1	1	2
15	Normal	1	2	2
16	Normal	2	0	2
17	Normal	2	1	2
18	Normal	2	2	2
19	Overweight	1	0	0
20	Overweight	1	1	0
21	Overweight	1	2	0
22	Overweight	2	0	0
23	Overweight	2	1	0
24	Overweight	2	2	0
25	Overweight	1	0	1
26	Overweight	1	1	1
27	Overweight	1	2	1
28	Overweight	2	0	1
29	Overweight	2	1	1
30	Overweight	2	2	1
31	Overweight	1	0	2
32	Overweight	1	1	2
33	Overweight	1	2	2
34	Overweight	2	0	2
35	Overweight	2	1	2
36	Overweight	2	2	2
37	Normal & Overweight	1	0	0
38	Normal & Overweight	1	1	0
39	Normal & Overweight	1	2	0
40	Normal & Overweight	2	0	0
41	Normal & Overweight	2	1	0
42	Normal & Overweight	2	2	0
43	Normal & Overweight	1	0	1
44	Normal & Overweight	1	1	1
45	Normal & Overweight	1	2	1
46	Normal & Overweight	2	0	1
47	Normal & Overweight	2	1	1
48	Normal & Overweight	2	2	1
49	Normal & Overweight	1	0	2
50	Normal & Overweight	1	1	2
51	Normal & Overweight	1	2	2
52	Normal & Overweight	2	0	2
53	Normal & Overweight	2	1	2
54	Normal & Overweight	2	2	2
55	Obese	1	0	0
56	Obese	1	1	0
57	Obese	1	2	0
58	Obese	2	0	0
59	Obese	2	1	0
60	Obese	2	2	0
61	Obese	1	0	1
62	Obese	1	1	1
63	Obese	1	2	1
64	Obese	2	0	1
65	Obese	2	1	1
66	Obese	2	2	1
67	Obese	1	0	2
68	Obese	1	1	2
69	Obese	1	2	2
70	Obese	2	0	2
71	Obese	2	1	2
72	Obese	2	2	2
73	Overweight & Obese	1	0	0
74	Overweight & Obese	1	1	0
75	Overweight & Obese	1	2	0
76	Overweight & Obese	2	0	0
77	Overweight & Obese	2	1	0
78	Overweight & Obese	2	2	0
79	Overweight & Obese	1	0	1
80	Overweight & Obese	1	1	1
81	Overweight & Obese	1	2	1
82	Overweight & Obese	2	0	1
83	Overweight & Obese	2	1	1
84	Overweight & Obese	2	2	1
85	Overweight & Obese	1	0	2
86	Overweight & Obese	1	1	2
87	Overweight & Obese	1	2	2
88	Overweight & Obese	2	0	2
89	Overweight & Obese	2	1	2
90	Overweight & Obese	2	2	2
91	All	1	0	0
92	All	1	1	0
93	All	1	2	0
94	All	2	0	0
95	All	2	1	0
96	All	2	2	0
97	All	1	0	1
98	All	1	1	1
99	All	1	2	1
100	All	2	0	1
101	All	2	1	1
102	All	2	2	1
103	All	1	0	2
104	All	1	1	2
105	All	1	2	2
106	All	2	0	2
107	All	2	1	2
108	All	2	2	2


C. WORKPLACE WELLNESS MODEL continued

5. Results continued

The chart below shows that the net cost of the program design for Run 93 is nearly as low as that for Run 38. Thus, the Run 93 program design looks like a good choice.



But is it the best choice? To answer this question, we would have to explore how robust it is to changes in environmental parameters. We will do this in the exercises.



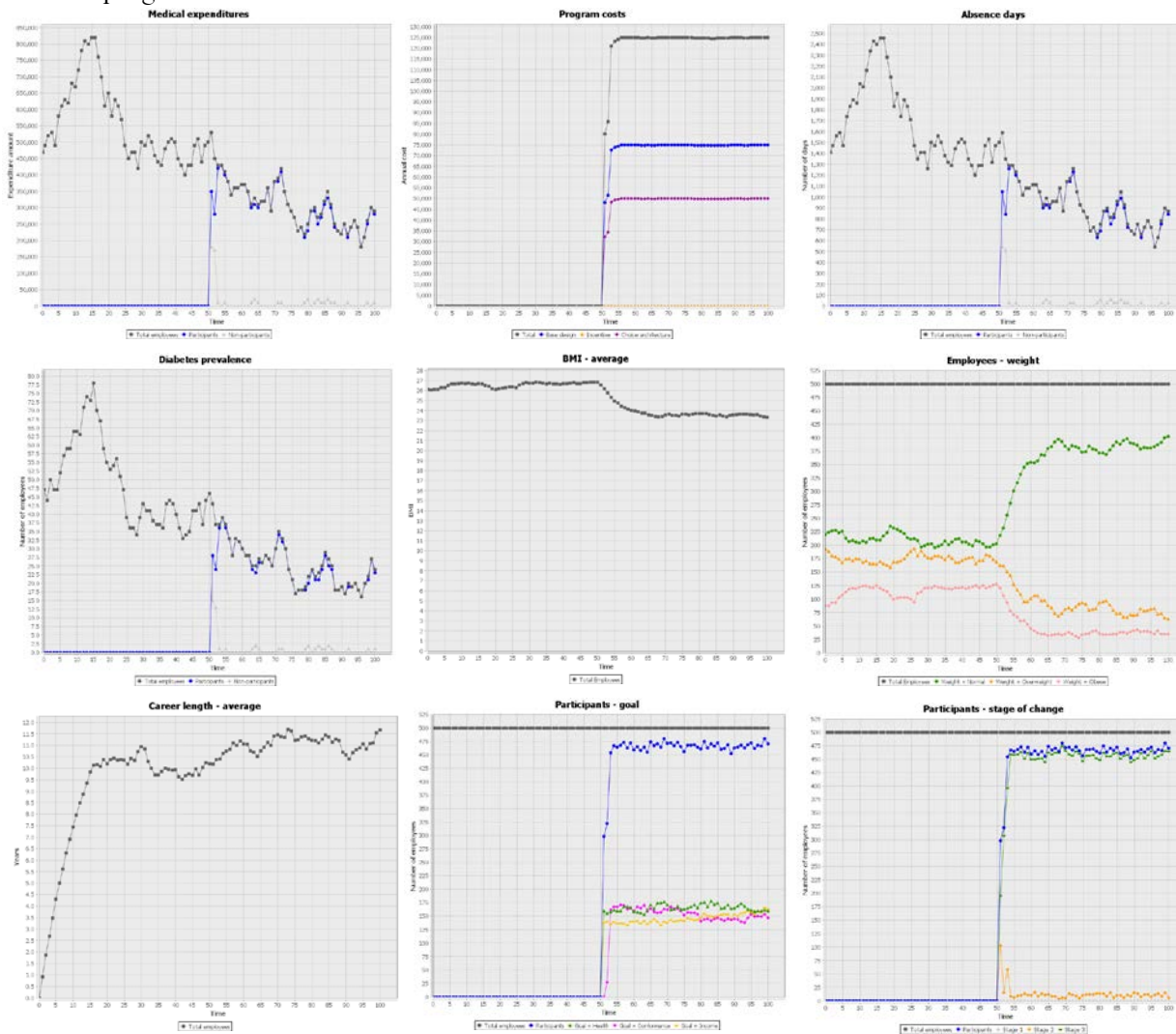
Pause to reflect

Take a moment to take stock. Has the model answered the questions it is supposed to answer? Do you think another type of model would have been able to provide such answers?

C. WORKPLACE WELLNESS MODEL continued

5. Results continued

As you paused, you probably noticed that we have not yet addressed how the wellness program's effects evolve over time. The charts below do this. For the first 50 time periods, they show results with no wellness program. Then, at time 50, the employer implements the wellness program of Run 93.



The charts highlight a conundrum common to workplace wellness programs: Some employee health measures (such as BMI, weight category, stage of change, and diabetes incidence) can respond quickly to program interventions, but other measures, such as medical expenditure savings, absence days, career length improvement, and diabetes prevalence take time. And, of course, program costs start accruing immediately.

D. ADVERSE SELECTION MODEL

Starting in 2014, most states will start providing Health Insurance Exchanges (“Exchanges”), that—in President Barack Obama’s words—will be “a market where Americans can one-stop shop for a health care plan, compare benefits and prices, and choose the plan that’s best for them.” Exchanges are part of the Patient Protection and Affordability Care Act (ACA) that the US Congress passed in 2010, with the aim of increasing the number of Americans covered by health insurance. The ACA has two other important provisions:

- In offering health insurance, insurance companies can no longer discriminate against people in poor health. In order to protect such companies from adverse selection (see the sidebar) states must provide “risk adjustment”, a mechanism that reallocates premium income from insurance companies with healthier enrollees to companies with sicker enrollees, in order to equalize health expenditure risk among the companies, and to remove incentives for health insurers to seek only the healthiest enrollees.
- It also requires each state—or the federal government on behalf of a state—to review the increases in health insurance premiums that insurers propose, and determine if they are reasonable. Thus, states can limit how much insurers can increase their health insurance premiums.

States, health insurers, provider networks, and many others are wondering how Exchanges will change the U.S. healthcare system. Will the number of uninsured individuals decrease? Will state risk adjustment agencies and the individual mandate adequately dampen the potentially harmful effects of adverse selection? With state premium limits, can insurers stay profitable?

The Adverse Selection Model addresses these questions by helping us understand the interrelated behaviors of the many agents involved in them. To explore this model, we will first look in detail at the questions it addresses, and why an agent-based model is suitable to address them. We will then review the model’s agents and their behaviors. Lastly I will show you what the model has to say about the questions.¹

Adverse selection

Adverse selection is when individuals who have higher exposure to health risks purchase insurance policies with more coverage or higher expected payments.

With adverse selection, the true health risk of an individual is private information, unknown to the health insurer. The phenomenon could be “adverse” for a health insurer: if only unhealthy people were to purchase high-coverage insurance from an insurer, that insurer might have to pay out more in healthcare expenditures than it would obtain in premiums, and could go out of business.

Through careful policy design, pricing, and marketing, insurers have traditionally been careful to ameliorate the potentially harmful effects of adverse selection. However, with ACA, insurers will no longer be able to use such tools to discriminate against sicker people, and will need to rely on state risk adjustment to even out the effects of adverse selection.

To further help health insurers minimize the potentially harmful effects of adverse selection, the ACA also requires most people—both sick and healthy—to obtain health insurance, or pay a penalty tax. This is the so-called “individual mandate” that the Supreme Court decided the federal government could legally implement.

¹ The model is described in detail in Appendix C. The model itself—in two formats—is available for you to download and explore. To download the model, go to the web page for this report, found on the Society of Actuaries’ website “www.soa.org” under Research > Completed research projects > Health.

D. ADVERSE SELECTION MODEL continued

1. The questions

The Adverse Selection Model simulates how uninsured people purchase individual health insurance from an Exchange. For each time period of the simulation, it simulates the interrelated behaviors of the following agents: uninsured inhabitants of a community (called “Person” agents in the model), two competing health insurance companies (Health Insurance Companies A and B), a state-run Exchange (Exchange), a state insurance commissioner (Premium Rate Limit Agency), a state risk adjustment agency (Risk Adjustment Agency) that reallocates premium income among insurance companies to maintain health expenditure risk equity among them, a federal government penalty tax agency (Penalty Tax Agency), and two networks of healthcare providers (Provider Networks A and B), one for each health insurance company.

Specifically, the Adverse Selection Model is designed to address the following questions:

1. How can state agencies and the federal government work together to minimize the number of uninsured people?
2. In an Exchange environment, how can a health insurance company:
 - **minimize** adverse selection?
 - **maximize** its profit for health insurance offered through an Exchange?
 - **maximize** its market share for health insurance offered through an Exchange, while maintaining profitability?

D. ADVERSE SELECTION MODEL continued

1. The questions continued

To address these questions, for each time period of the simulation the model traces the following results:¹

- **Percentage insured.** The percentage of Person agents who purchase insurance from the Exchange.
- **Disease status.** The population's average disease status.
- **Insurer accumulated profit.** Each Health Insurance Company's accumulated profits.
- **Insurer market share.** Each Health Insurance Company's market share (the number of Person agents it covers divided by total covered Person agents)
- **Adverse selection.** The number of Person agents who adversely select a health plan. For the purpose of the model, a Person adversely selects a health insurance plan when the Person determines that the Person's health is grave and chooses a "rich" plan (one without co-payment), rather than a lower-cost plan with co-payment.

However, as you will see, the model provides many more results (including over 35 charts) that are needed to understand and address the questions.

¹ The model provides many more results than the ones shown here. For the complete list of results, see Section A.5 (Model overview—output) of the detailed description in Appendix C.

D. ADVERSE SELECTION MODEL continued

2. Suitability of agent-based modeling

An agent-based model is suitable to address these questions, for the following reasons:

- **There are many autonomous decision-making agents.** All agents in the simulation make decisions autonomously, and there are many agents.
- **Agents are heterogeneous.** Because they vary by geographic location, income, and health status, the Person agents are heterogeneous. Depending on how the user sets the model's parameters, the Health Insurance Company agents can also have different attributes and thus be heterogeneous.
- **The system is dynamic.** The simulation is dynamic. That is, its former states influence its future states. For example, the type of insurance that Person agents purchase in one period influences the type of insurance that Person agents will purchase in the next period. As another example, the level of insurance company profits in a previous period influences the behavior of the premium rate limit agency in the next period. All decision-making agents have a memory of past events that can affect their future behavior.
- **There is no central controller.** There is no central controller managing the evolution of the health system being simulated. For example, no one dictates who buys insurance.
- **Multiple simultaneous processes.** The health system cannot be expressed as one linear process. If this were possible, then another modeling approach, such as traditional discrete simulation, might be more appropriate. Rather, the system's agents engage in many independent behaviors simultaneously.
- **Aggregate functions do not apply.** The simulation does not lend itself to mathematical formulation. That is, the complexity of agent interactions cannot be captured by traditional aggregate mathematical functions. If this were possible, then another modeling approach, such as system dynamics, might be more appropriate.
- **Spatial factors are important.** Because people can base their health insurance purchase decisions on the corresponding behavior of their neighbors, the spatial location of people in the population is important.

D. ADVERSE SELECTION MODEL continued

3. Agents and their behaviors

The model includes the following agents and behaviors:

- **Person:** An individual inhabitant of the state providing the Exchange. The Person agent decides whether to purchase a health insurance plan from the Exchange. If a Person purchases insurance, the Person requests treatment from a Provider Network if the Person becomes ill. If a Person does not purchase insurance, the Person pays a penalty tax to the Penalty Tax Agency and does not request treatment when ill. Person agents can be influenced in their insurance purchase decisions by the intensity of Exchange advertising, as well as several other factors. There can be many Person agents.
- **Health Insurance Company:** A health insurance company that sets premium rates for its plans on the Exchange, negotiates fee levels with its Provider Network, pays claims submitted by its Provider Network, submits its profit experience to the Premium Rate Limit Agency, and submits its risk experience results to the Risk Adjustment Agency. There are two companies, Company A and Company B. Each offers two insurance plans: one that has no member co-payment and is therefore “richer” (Plans “A1” and “B1”), and one that has a co-payment (Plans “A2” and “B2”).
- **Exchange:** A Health Insurance Exchange that offers individual health plans for Person agents to purchase. The Exchange offers four insurance plans (A1, A2 and B1, B2), two from each Health Insurance Company. The Exchange also advertises its services to encourage Person agents to purchase health insurance, and sets the order in which plans are offered on its website. In the model, there is one Exchange.
- **Penalty Tax Agency:** A federal agency that sets the level of penalty tax for Person agents who do not purchase insurance. There is one Penalty Tax Agency.
- **Provider Network:** A group of healthcare providers that provides medical treatment for Person agents who request treatment, that submits claims to its associated Health Insurance Company, and that negotiates fee levels with its Health Insurance Company. There are two Provider Networks (one for each Health Insurance Company): Provider Network A and Provider Network B.

D. ADVERSE SELECTION MODEL continued

3. Agents and their behaviors continued

- **Premium Rate Limit Agency:** A state agency that sets a limit on the premium rates that a Health Insurance Company can charge for each of its insurance plans.
- **Risk Adjustment Agency:** A state agency that reallocates premium income among the Health Insurance Companies in order to maintain health risk equity among them.
- **Environment:** The container for the model's agents. It creates the simulation's agents and maintains lists of them. It also obtains and validates user-provided parameters, and schedules agent behaviors.

Appendix C provides details about these agents and their behaviors, as well as the model's simplifying assumptions.

4. Running the model

As with the Physician Network Model and the Workplace Wellness Model, to run the Adverse Selection Model, you enter parameters in the user interface, set run controls, initialize the run, and then start the simulation.¹

In contrast to the two earlier models, in the Adverse Selection Model, the parameters to determine the characteristics of the agents and their behaviors are available in two places. High-level parameters are available on the “parameter pane”, and more detailed parameters are in the “user panel” area. The user panel has five tabs: “Simulation”, “Person”, “Person goals”, “Health Insurance Company”, and “Provider Network”.

Most of the model's variables can be changed during the course of a simulation. To do this, the user pauses the simulation, changes the parameter, and then resumes running the simulation.²

If a user does not enter a parameter, the model will supply a default value.

¹ For more detailed information about running the model, see Subsection 4 (Running the model) of the Physician Network Model description earlier in this chapter.

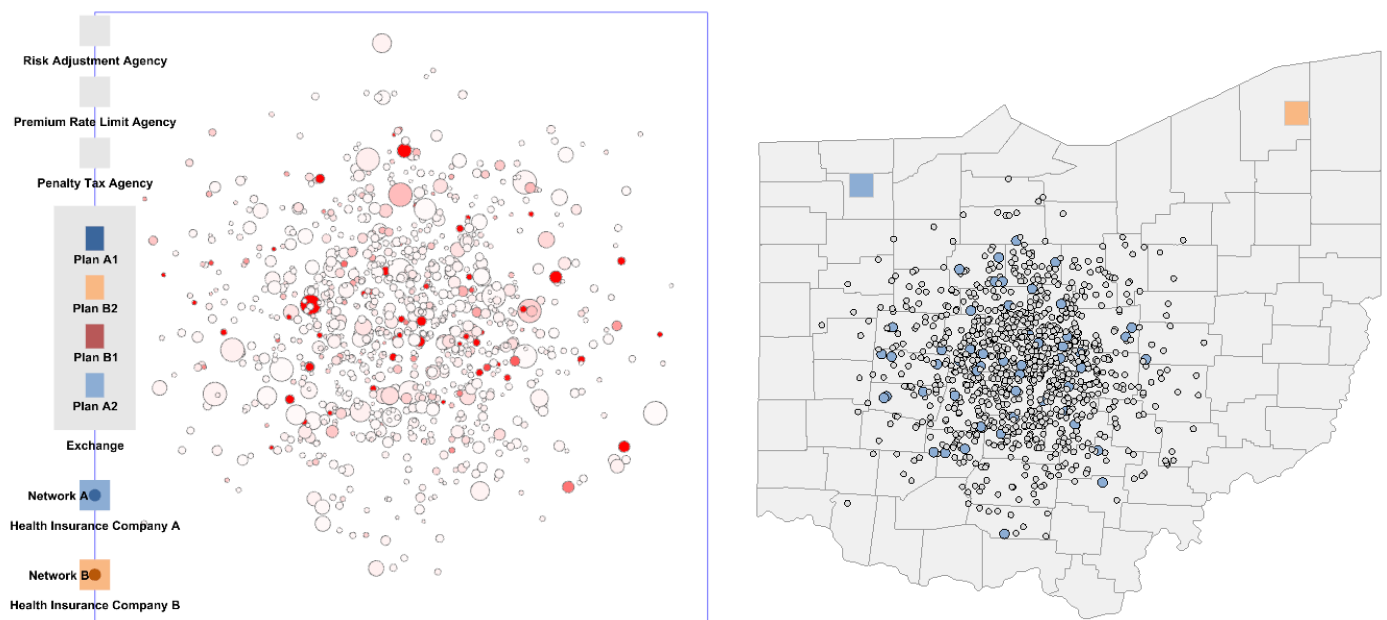
² It would not make sense to change some variables—such as the number of Person agents—during a simulation.

D. ADVERSE SELECTION MODEL continued

5. Default scenario

The model’s default scenario is based on a scenario that, under health reform, may play out in several states.

The default model starts with 500 Person agents geographically dispersed across the state according to a random normal distribution.¹ The distribution of Person agents over both a hypothetical 2D environment and an actual state are shown below.²



The display on the left (called the “community” display in the model) shows the community where Person agents live. Person agents are represented by disks. The disease status of a Person is shown by the disk’s color. Person agents colored white have perfect health, whereas disks with increasingly bright hues of red indicate increasingly serious disease. Person agents who die are removed.

¹ To try different scenarios, these—and all other—model parameters can be changed.

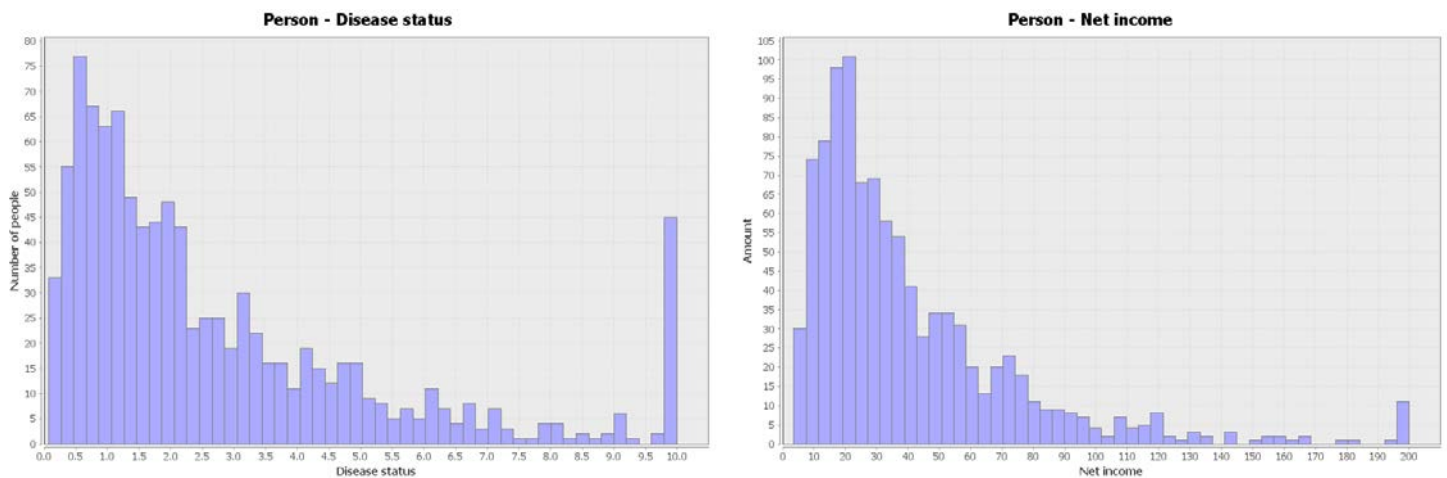
² The hypothetical 2D distribution is found on the Environment: Community tab, and the state distribution is found on the Environment: State tab. I included the State tab in the model to demonstrate that realistic GIS backgrounds with real latitude and longitude locations can be used in agent-based models. Of course, instead of 1,000 Person agents distributed according to a hypothetical random distribution, actual people could be distributed on a GIS background, placed according to their actual geographic location. On the state map, Person agents who adversely select are shown in the color of the Health Insurance Company that covers them.

D. ADVERSE SELECTION MODEL continued

5. Default scenario continued

The size of a disk corresponds to the Person agent's net income. Person agents with smaller disks have small income levels.

In the default scenario, the initial disease status and net incomes of Person agents are distributed according to the log normal distribution. The following histograms show these distributions at time 0.



As the charts show, initial disease status is continuous and distributed between 0.0 and 10.0. The distribution's mean is 3.0. The mean of the initial net income distribution is 40.0. This distribution roughly corresponds to the distribution of family income in the U.S., in thousands.¹

The model's governmental entities—the Risk Adjustment Agency, the Premium Rate Limit Agency, the Penalty Tax Agency, and the Exchange—are represented by gray rectangles.

Health Insurance Company A is represented by a blue square, and its Provider Network A by a blue disk. Similarly, Health Insurance Company B is represented by an orange square, and its Provider Network B by an orange disk.

¹ Somewhat surprisingly, Repast Symphony does not provide a log normal distribution function. Therefore, I derived the log normal distribution for this model from the normal distribution.

D. ADVERSE SELECTION MODEL continued

5. Default scenario continued

Insurance plans offered by the Exchange are represented by rectangles with colors corresponding to the Health Insurance Company that provides them. Thus, Plans A1 and A2 are blue (with Plan A1, the “richer” plan darker blue. Similarly, Plans B1 and B2 are orange.

In the “State” display, Person agents who adversely select health insurance are represented by disks the color of the Health Insurance Company that covers them. All other Person agents are represented by gray disks.

In the default scenario, Health Insurance Company A has different characteristics from Health Insurance Company B. Company A wants to maximize its market share, whereas Company B wants to increase its profit. Therefore, Company A is more generous with its Provider Network (its initial treatment cost alpha—a key determinant of reimbursement amounts—is higher), its initial premiums are lower, and its behavior is different.¹ Because like often attracts like, Provider Network B is more focused on profit than Provider Network A. This difference is reflected in the difference between their negotiation increase percentages for treatment cost alpha.

Key parameters for the default scenario are given in the sidebar.

Let’s now take a brief tour through the default scenario’s results. The four charts on the next page address the four questions.

Default scenario

The model’s default scenario has the following key parameters:

Person agents

- **Number of Person agents:** 1,000
- **First priority goal distribution:**
 - **Maximize income:** 0.40
 - **Increase health:** 0.20
 - **Conform:** 0.20
 - **Follow policy:** 0.10
 - **Follow advertising:** 0.10

Health Insurance Company A

- **Primary goal:** Maximize market share
- **Initial treatment cost alpha:** 0.6
- **Initial premium – Plan A1:** 7.0
- **Initial premium – Plan A2:** 4.5

Health Insurance Company B

- **Primary goal:** Maximize profit
- **Initial treatment cost alpha:** 0.5
- **Initial premium – Plan B1:** 8.0
- **Initial premium – Plan B2:** 5.0

Exchange

- **Plan presentation order:** Random
- **Initial advertising intensity:** 3
- **Advertising expense percentage:** 0.01
- **Uninsured decrease target:** 0.7

Penalty Tax Agency

- **Initial penalty tax rate:** 0.03
- **Maximum penalty tax rate:** 0.05
- **Uninsured decrease target:** 0.7

Premium Rate Limit Agency

- **Profit percentage maximum:** 0.03

Random number seed: 10

For definitions of these parameters, and a list of all parameters, see Appendix C. Appendix C also describes how these parameters are used to determine agent behaviors.

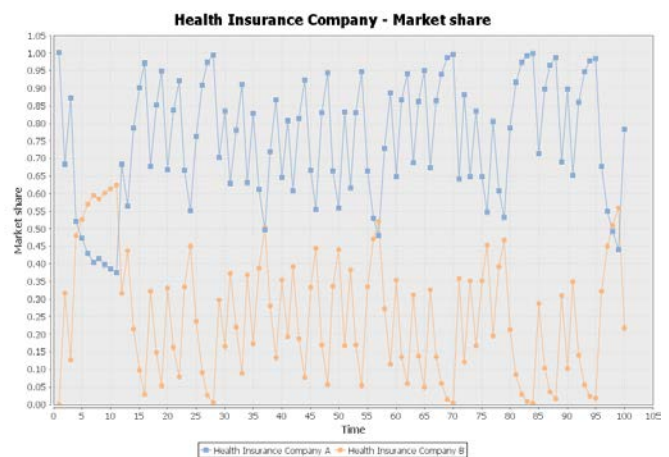
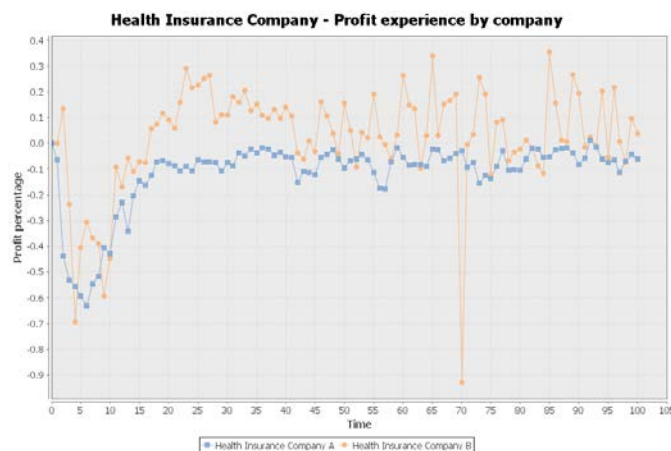
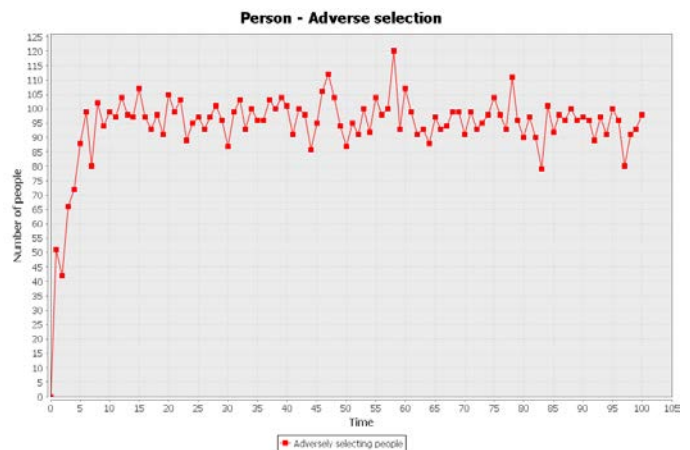
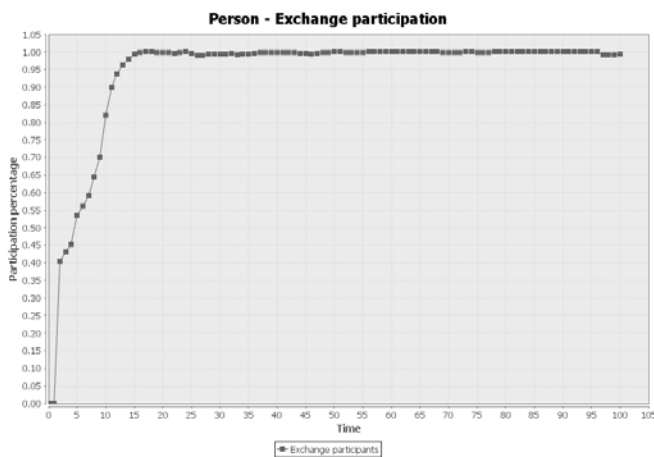
¹ For more information about these parameters and the implications of these differences, see the model’s detailed description in Appendix C. The detailed parameters associated with the two Health Insurance Company agents (found on the Health Insurance Company user panel) are also different.

D. ADVERSE SELECTION MODEL continued

5. Default scenario continued

As the first chart (Person–Exchange participation) shows, under the default scenario, over 15 time periods Exchange participation grows from zero to 100 percent. The second chart (Person – Adverse selection) shows that after 10 time periods the number of adversely selecting people stays level at about 100 people, out of the original population of 1,000.

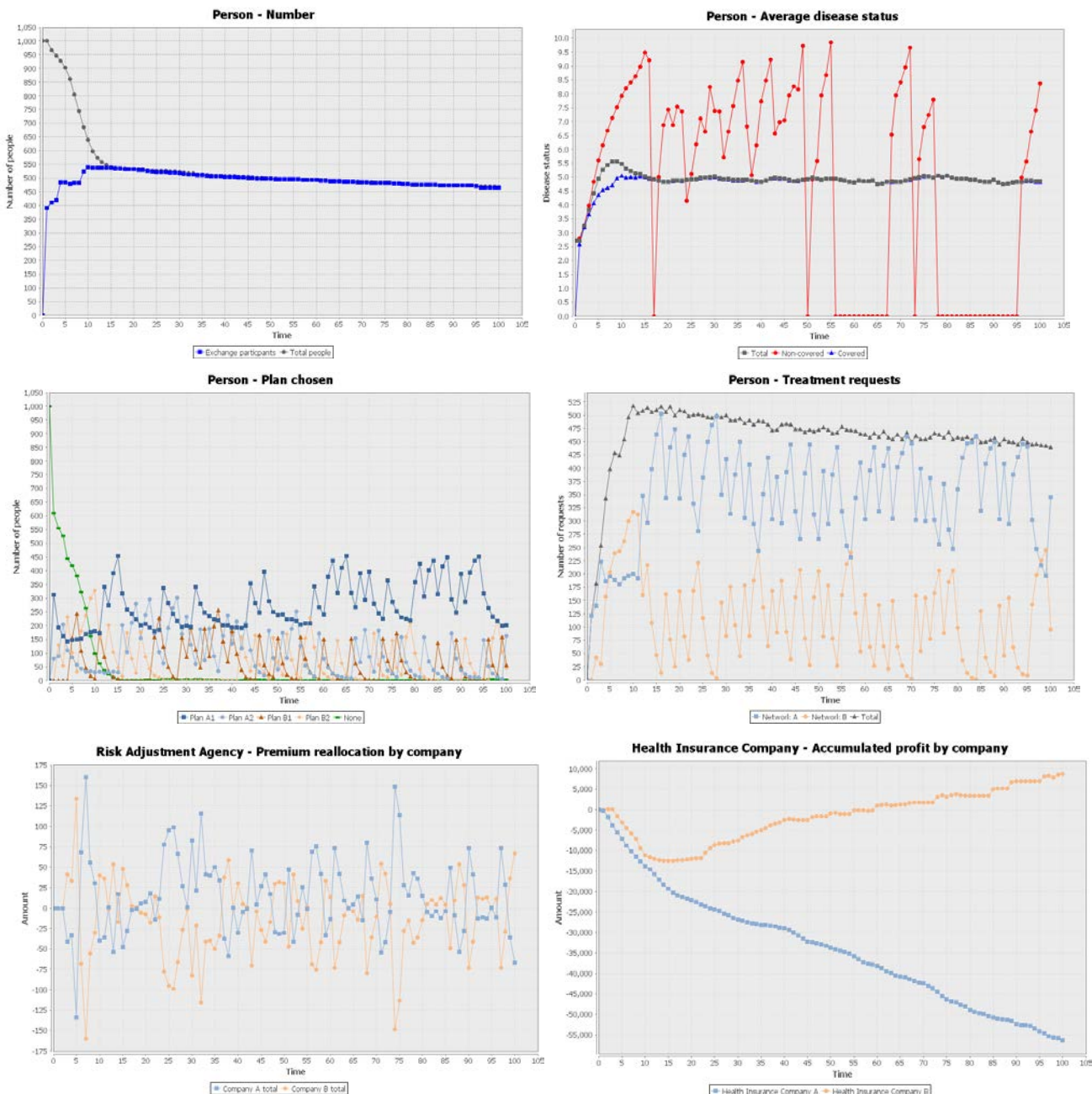
The third chart (Health Insurance Company–Profit experience by company) shows that after a rocky start, Health Insurance Company B (the one with the primary goal of maximizing profit) has positive profit rates, whereas Company A (with a primary goal of maximizing market share) has slightly negative rates. The fourth chart shows that Company A keeps the lion’s share of the market.



D. ADVERSE SELECTION MODEL continued

5. Default scenario continued

In a nutshell, under this scenario, everyone becomes insured, adverse selection will hover at about 100 people (out of an original population of 1,000), and one insurance company will experience slightly negative profit rates but maintain high market share. Although Health Insurance Company A would want to tweak its premiums to increase profit rates, from an aggregate bird's eye view the scenario appears generally rosy. But, as the following set of charts shows, a closer look reveals an underlying story that is more bleak.



D. ADVERSE SELECTION MODEL continued

5. Default scenario continued

The charts on the previous page show that the community is on the verge of collapse: The first chart (Person–Number) shows that in the next 15 time periods, more than half of the population will die, because—as the second chart (Person–Average disease status) shows—people who elect to remain uninsured sicken quickly and die.¹ The third chart (Person–Plan chosen) shows that there will be considerable volatility in the health insurance market. The number of people who choose an insurance plan (and an insurance company) will vary considerably from period to period. This volatility is also reflected in the wide swings in market share from period to period that we saw earlier.

The fourth chart (Person–Treatment requests) shows that the number of treatment requests from the provider networks will vary widely from period to period, and that the surge in treatment requests from Network A may overwhelm its capacity.

The fifth chart (Risk Adjustment Agency–Premium reallocation by company) shows that the specter of adverse selection is a red herring. Even with 20 percent of the population (100 out of 500 total people) adversely selecting, the total amounts of premium transferred to maintain insurer risk equity (at least according to the model's formula) are small (at most 150 units out of about 5,000 units of total premiums paid).

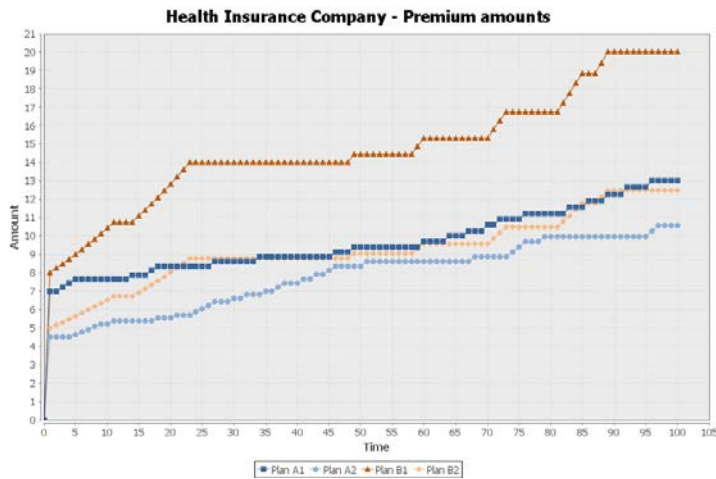
The last chart (Health Insurance Company–Accumulated profit by company) shows that Health Insurance Company A will lose a lot of money and may go out of business.

¹ Of course, it is unrealistic to think that so many people will die so quickly merely because they elected not to purchase health insurance. However, it is not unrealistic to think that in the new health environment of ACA, Provider Networks will be less willing to offer optimal care to those without insurance. For more about this, see the exercises.

D. ADVERSE SELECTION MODEL continued


5. Default scenario continued

That’s not all. As the chart below shows, the periodic premium for even the lowest-cost plan will rise to about 25 percent of the average Person’s income ($10/40 = 0.25$), a level that is surely intolerable.



Thus, under the default scenario, the community is an unpleasant place to live: A large proportion of the population will quickly sicken and die, the health insurance market will be extremely volatile, providers will be strained beyond capacity and subject to extreme volatility, one of the two insurance companies may go out of business, and the disposable income of many people will disappear.

Thus, again, our agent-based model shows us that our original questions were too narrow. We should also be concerned about the population’s health and income levels, about market volatility, and about provider capacity. The model also shows us that our worries about adverse selection may have been unfounded.



Pause to reflect

Before continuing, take a moment to ask yourself what the Exchange, the Health Insurance Companies, the Provider Networks, the Penalty Tax Agency, or the Premium Rate Limit Agency might do to make the community a better place to live.

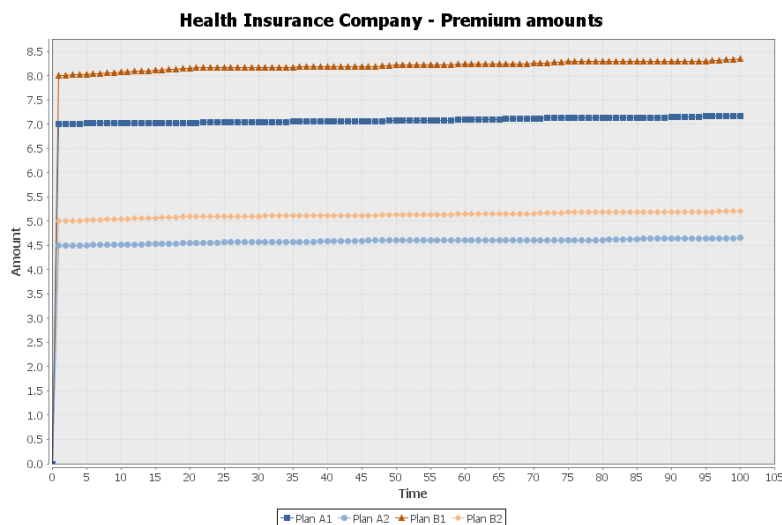
D. ADVERSE SELECTION MODEL *continued*

6. Other scenarios

To improve conditions in the community, there are infinitely many alternative scenarios to consider.

Let's start by considering how to decrease the number of uninsured people. One possible way would be for the Exchange to increase its advertising intensity to the maximum (10) from the start. However, this option has negligible impact on the number of uninsured people, and dramatically increases Exchange expenses (thus reducing premiums transferred to Health Insurance Companies). It is not a good option. A more powerful option is to increase the initial penalty tax rate. An increase from 3 percent to 30 percent decreases the number of uninsured people by about 350.

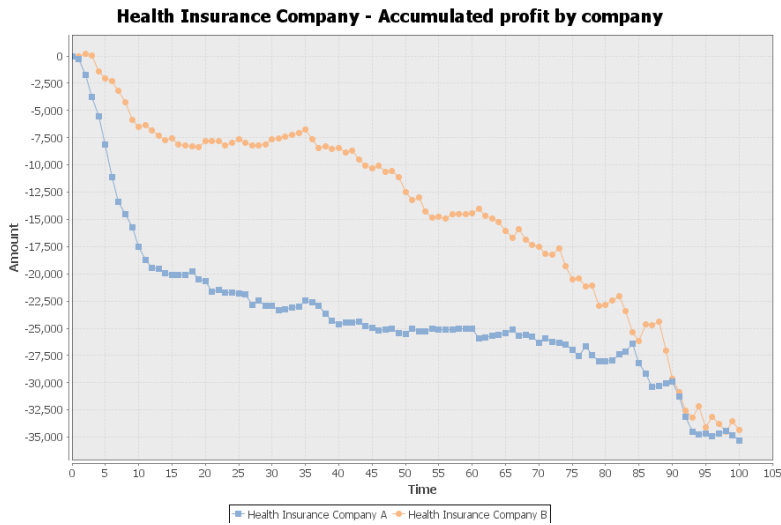
To decrease the adverse impact of rapidly escalating premiums, the Premium Rate Limit Agency can reduce the profit percentage maximum. Reducing this parameter from 3 percent to 0.1 percent results in the premiums shown in the following chart—a simple change that produces a dramatic difference that will improve disposable incomes of the population.



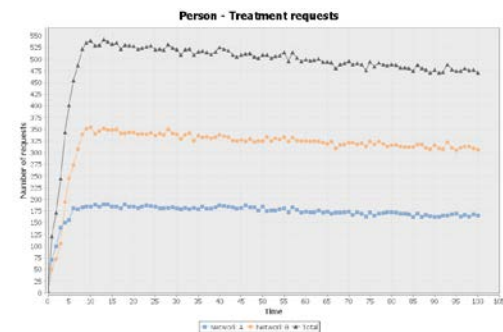
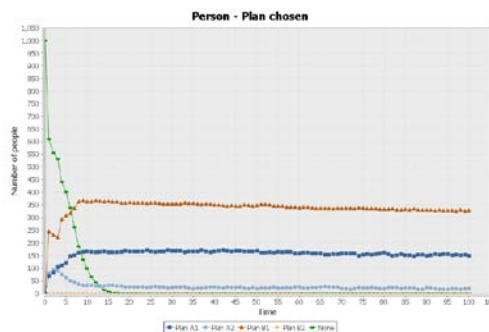
D. ADVERSE SELECTION MODEL continued

6. Other scenarios continued

Based on the parameters on the “Parameters” panel, the best that Health Insurance Company A can do to improve its relative profit position is to change its primary goal from “Maximize market share” to “Maximize profit”. This change produces the results in the chart below, a relative improvement for Company A.



To ameliorate market volatility and some of the strain on Provider Networks, the Exchange can make one simple, no-cost, change: merely change the plan presentation order from “Random” to a “High to low premium” order. The charts below show the effects of this change.



E. ISSUES AND FUTURE DIRECTIONS

The models presented in this chapter are simple hypothetical models; they do not solve real problems. The next step is to use these models as a starting point from which you develop real models that help to solve real health system problems.

F. TO LEARN MORE

A good way to learn more about these models is to work with them.

For starters, play a health system simulation game: Take one of the three sample models, change one or more of its parameters, and guess what the result will be. If your guess is correct, you win a point. If not, you lose a point. You may be surprised how often your guess is wrong. Play with a colleague.

As you play the game, you will probably find parts of a model that you want to change. That is your opportunity to learn even more about agent-based modeling. Tinker with the model's computer code to create a new and better model. Then play the simulation game with your new model. Challenge your colleagues to create a better model that is truer to reality.

G. REVIEW AND A LOOK AHEAD

This chapter ends Part V. In it, we explored three sample agent-based simulation models and analyzed their results.

In the next part, I will propose a program for improving the simulation and analysis of health systems.

(Don't forget to take a look at the exercises for this chapter. They start on the next page.)

EXERCISES

1. With a random number seed of 10 and the default parameters of the Physician Network Model, what is the number of untreated patients at time 100? And what is the number of people with Disease 2?¹
2. With a random number seed of 10 and the default parameters of the Physician Network Model, what is the number of untreated patients at time 100 if you increase the Disease 2 probability to 0.05? And what is the number of people with Disease 2?
3. With a random number seed of 10 and the default parameters of the Physician Network Model, what is the number of untreated patients at time 100 if you increase the Disease 2 probability to 0.05 and increase the number of Specialists to 10? And what is the number of people with Disease 2? Did increasing the number of Specialists help?
4. With the same parameters as in Exercise 3, now also increase the number of PCPs to 20. What is the number of untreated patients at time 100? And what is the number of people with Disease 2? Did increasing the number of PCPs help?
5. For the Run 93 program design of the Workplace Wellness Model, determine the ten-period average of the employer's total medical expenditures from time 91 through time 100, for each of the ten integral number seeds from 1 to 10 (inclusive). Graph the ten results, and take *their* average. What does the result tell you?
6. For the Run 93 program design of the Workplace Wellness Model, how do average medical expenditure results, program costs, and average career length vary as the incidence and remission rates of diabetes vary? (Hint: Vary the diabetes incidence and remission adjustment factors—parameters L2b and L4b—from 0.80 to 1.20 and produce a 3D or topographical chart.) What do your results say about the robustness of the Run 93 program design?
7. Improve the Workplace Wellness Model by including a section in the “i1_getInputParameters” method of the Environment class to validate the parameters that the user inputs. (For an example of parameter validation, see the Environment class of the Physician Network Model.)

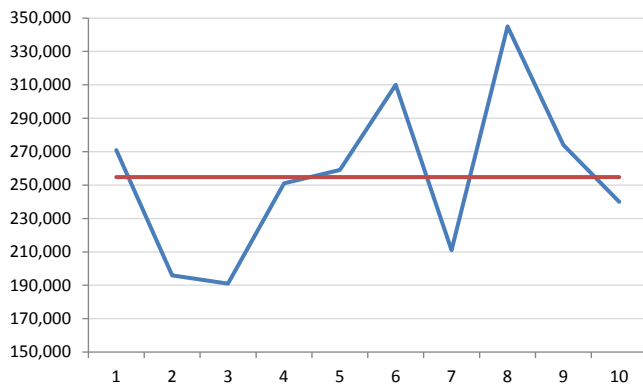
¹ If the environment is not centered in the middle pane of your Repast Symphony user interface, and you are using a Windows PC, click and hold your right mouse button on the environment and move the mouse. The environment will then move to where you want it.

EXERCISES continued

8. Using the data from the charts showing the results of implementing the Run 93 program design for the Workplace Wellness Model at time 50, show how an employer can determine the net cost of the program for its first ten years.
9. For the Adverse Selection Model, how would you include a feature to vary Person behavior by age?
10. For the Adverse Selection Model, how would you include a feature to reflect the treatment quality of Provider Networks in the Person agent's plan purchasing behavior?
11. How could you modify the Adverse Selection Model to turn it into a "serious game", with two human players representing the two Health Insurance Companies?
12. How would you modify the Adverse Selection Model to add a feature that more realistically captures how uninsured people will seek and pay for medical care? Why is this important?
13. The Adverse Selection Model includes a "health gravity threshold" that serves two purposes. It is the point beyond which a Person considers his or her disease status to be grave. When the Person's disease status is more than the threshold, and thus worse than the threshold, the Person may (depending on the Person's goals) purchase health insurance, and will (if insured) request treatment. However, in real life, a person's threshold for purchasing insurance might be lower than the threshold for seeking treatment (or conversely). How would you modify the model to include two such thresholds?
14. Javadoc was purposefully left out of the Adverse Selection Model. How would Javadoc be useful to the model's users? Add Javadoc to the model's Environment class.

SOLUTIONS

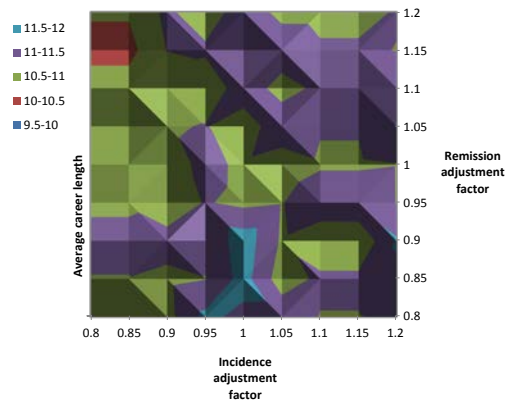
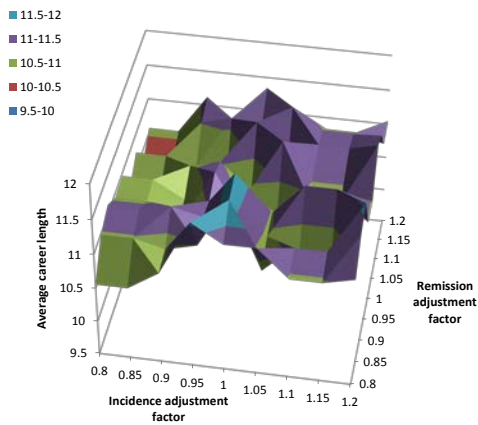
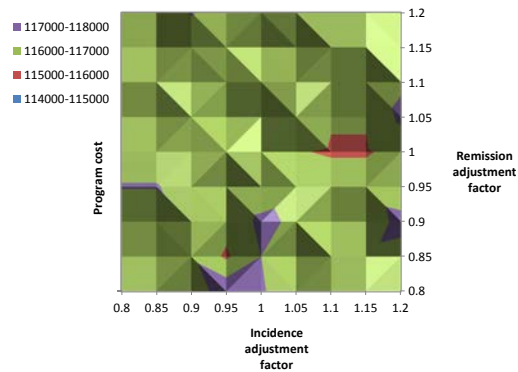
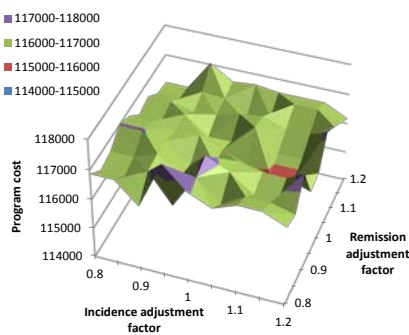
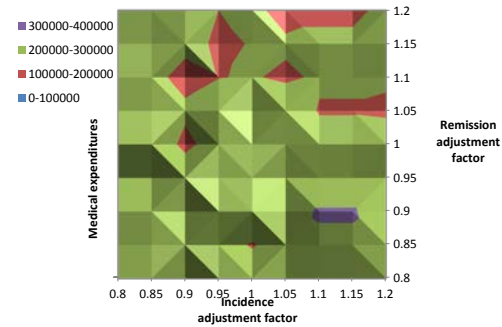
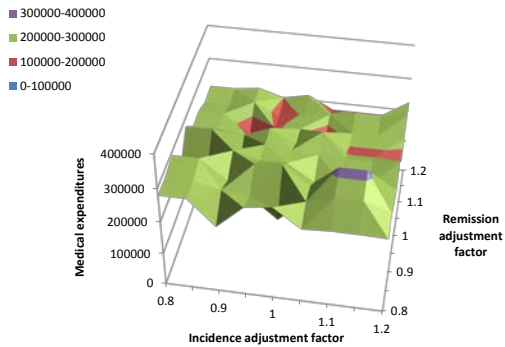
1. Untreated patients: 109 (from inspecting the “Patient type” chart)
 Number of people with Disease 2: 90 (from the “Disease prevalence chart”).
2. The simulation doesn’t make it to time 100, because the number of Specialists is overwhelmed, Specialist errors increase, and Specialists are dropped from the network. At time 92 there are no more Specialists in the network, and the simulation stops. At time 93 there are about 530 untreated patients, and about 625 people with Disease 2.
3. Untreated patients: about 520
 Number of people with Disease 2: about 650
 Increasing the number of Specialists did not help.
4. Untreated patients: about 310
 Number of people with Disease 2: about 360
 Increasing the number of PCPs helped.
5. The averages are shown in the chart below:



They vary from 191,000 to 345,000. The average of these averages (the red line) is 254,800. Thus the net savings we derived for Run 93 (about 100,000) could be wiped out by statistical variation. In other words, the confidence interval appears to be wide. Of course, this tentative result needs further investigation.

6. Following are the desired charts. They demonstrate that, for Run 93, the medical expenditures and program costs are relatively robust to changes in diabetes incidence and remission parameters. However, the average career length is more sensitive to changes in these parameters.

SOLUTIONS continued



7. Be sure to carefully test your result by entering inaccurate parameters.
8. Assess the net cost of the program for its first ten years by estimating the present value of program costs and expenditure savings for the ten years, using an appropriate interest discount rate.

SOLUTIONS continued

9. You might assign Person ages according to a random normal or other distribution, or read in a custom distribution from an Excel file. Then in the Person's behavior processes P1 (Purchase plan), P3 (Request treatment) or P5 (Update disease status), include branches that vary by age. For example, in process P5 (Update disease status) without treatment an older Person agent's disease status might deteriorate more rapidly.
10. You might vary the treatment quality measure of a Provider Network by the alpha level it negotiates relative to the alpha level the other Network Provider negotiates. You might assume that a higher alpha level results in greater quality. Then you might incorporate the quality measure in the Person agent's process P1 (Purchase plan), perhaps by developing a rule that compares premium and quality levels.
11. Develop a separate User Panel tab for each player. Then at the start of each period, allow each player to change any parameters on the player's tab.
12. Many low-income uninsured people will not be able to pay for medical care, and the Provider Networks will have to absorb these costs. This will place additional strain on the Networks. As a result, the Networks may provide sub-optimal care, and the disease status of the uninsured may advance more rapidly than similarly situated insured people. To reflect this dynamic in the model, you might have uninsured people seek treatment, but instead of paying a copayment to Provider Networks, they would pay a negative amount, representing the cost of their care. For such people, the Health Improvement Percentage might be less than for insured people.
13. Simply add another threshold to the model's Person tab on the User Panel.
14. On YouTube, there are excellent Javadoc tutorials. Search "Javadoc Eclipse".

PART VI: FILLING THE GAPS

The practical value of increasing knowledge and understanding of health behavior through rigorous research is implicit in the grave concern with health status in many contemporary societies.

David Gochman, 1997¹

Over the past few decades, we've enriched the labs, drug companies, medical device makers, hospital administrators and purveyors of CT scans, MRIs, canes and wheelchairs. Meanwhile, we've squeezed the doctors who don't own their own clinics, don't work as drug or device consultants or don't otherwise game a system that is so gameable. And of course, we've squeezed everyone outside the system who gets stuck with the bills. We've created a secure, prosperous island in an economy that is suffering under the weight of the riches those on the island extract. And we've allowed those on the island and their lobbyists and allies to control the debate. ...

Steven Brill²

Faced with what is right, to leave it undone shows a lack of courage.

Confucius³

¹ Gochman (1997), Volume 1, Preface.

² Steven Brill is an influential journalist and entrepreneur. This quote is from his *Time* magazine cover article "Bitter pill: Why medical bills are killing us". Brill (2013).

³ The Analects 2:24

INTRODUCTION

With this part we end our journey, one I hope you have enjoyed.

We began by reviewing the unintended consequences that MaineCare experienced when it implemented a formulary to reduce its drug expenditures. We learned that such unintended consequences are common when policymakers try to improve health systems, because health systems are complex systems. Such systems have many heterogeneous agents and many intricately interwoven health behaviors that often cannot be understood from a top-down perspective. We observed that if we are to implement decisions for health systems that are likely to have the results we intend, we must understand the behavior of their agents from the bottom up. Understanding health behavior is the key to good health system decisions.

In Part I (Health behavior) we explored how behavior in general can be described, and learned about the major academic fields that study health behavior.

In Part II (Classification of agents and behavior) we developed a way to classify health system agents and health behavior, and proposed an ontology structure to facilitate communications about health systems.

Based on results from the *International compendium of health behavior*, in Part III (Health behavior facts), we surveyed what researchers have discovered about health behavior. We also learned about results from behavioral economics, and how they might apply to health behavior.

In Part IV (Health behavior theory) we reviewed what it takes to be a scientific theory, and asked if there are any such theories that apply to health behavior. We then covered five hypotheses that are useful for describing and modeling health behavior.

In Part V (Methods and tools) we learned about tools that can be used to develop agent-based models for simulating health systems from the bottom up. We also proposed best-practice guidelines and a method for developing such models for health systems. Then we explored three sample agent-based models in detail, and saw that such models can be useful for informing health system decisions.

INTRODUCTION continued

During our journey, we marveled at magnificent work, such as the health behavior research compilation by David Gochman, the behavioral economics research of Kahneman and Tversky, as well as the agent-based modeling work of the Argonne Repast Symphony team and Joshua Epstein. But—perhaps prejudiced by well-established fields like physics and medicine—a few times we felt disappointed.

This part is about what we expected to find, but did not, what I will call “gaps”. In the first chapter I will point out seven important gaps, and in the second I will propose a way to start filling them.

This part is more than a mere exercise. For unless we learn how to effectively craft health systems in the light of how people and institutions will behave in them, unless we can challenge ignorance and greed with knowledge, skill, organization, and resolve, our health systems will be ineffective and expensive; our health and wealth—perhaps even our freedom—will wane.

CHAPTER SEVENTEEN: SEVEN HEALTH BEHAVIOR GAPS

If you don't know where you are going, any road will get you there.

George Harrison¹

A. SEVEN GAPS

Following are seven important gaps in the field of health behavior. They hamper our ability to model health behavior from the bottom up, and so impede good health system decision making.

1. No accepted description of health behavior

There is no consensus about how we should describe any behavior, much less health behavior.

To make progress in clearly communicating about and modeling health behavior, it would be helpful to agree on a basic approach for describing behavior. Such agreement could also help unite the fragmented fields related to health behavior.

We explored this gap in Chapter one (Dimensions of behavior).

2. No classification of health behavior

Although there have been attempts to organize and classify subsets of health system agents (such as healthcare practitioners), it appears that no one has yet attempted to classify the *behaviors* of health system agents. For certain, no one has developed a health systems ontology.

The relatively immature state of health behavior research and health system policymaking appears to stem, at least in part, from this lack of a language about health systems. Until we have a coherent and widely accepted way to name and discuss the agents and behaviors of health systems, researchers and policymakers will continue to have trouble merely trying to talk about issues clearly.

We explored this gap throughout Part II (Classification of agents and behavior).

¹ From “Any road”, the last song George Harrison performed in public that was filmed. It is a paraphrase of the exchange between Alice and the Cheshire Cat in Chapter six of Lewis Carroll’s book “Alice in wonderland”.

A. SEVEN GAPS continued**3. No catalog of health behavior facts**

There is no easy way to find what is known about a particular health behavior. Research about it may be scattered across dozens of journals, without any central resource pointing to the relevant work. There is no comprehensive catalog of health behavior facts.¹

One might argue that we should not expect to find such a catalog, because such catalogs don't even exist for established fields such as physics and medicine. I would counter by pointing out that, at least in summary form, such catalogs do exist for physics and medicine. They are commonly called textbooks.

This gap makes it difficult to find the health behavior facts needed to build health behavior models. It also obscures the research that is missing, and inhibits further research. Chapter seven (Overview of health behavior facts) addresses this gap.

4. Inadequate health behavior facts

Our stock of useful health behavior facts is meager. In spite of much effort, researchers have not produced the rigorous knowledge about health behavior that we need in order to build agent-based models to simulate health behavior. For many of the behavior components, little research has been performed. In particular, the "Produce output" component has been neglected, a gap that is especially important, because this component ties together all the others.

Where work has been done, researchers mainly based their research on correlation analyses and surveys; approaches notoriously deficient in rigor. People and organizations often do not behave in the way their survey responses indicate, and correlation analysis is a poor indicator of causation. In the main, researchers do not base their research on scientific experiments. Of the hundreds of research studies I reviewed for the Compendium, only a few (fewer than ten) were based on rigorous experiment. When one considers that experiments are the mainstay of medical research, and that behavioral economics researchers have had spectacular success using experiments to unravel mysteries of behavior, such neglect is puzzling.

¹ Although the four-volume work of David Gochman, Gochman (1997), is a great compilation of wellness behavior facts, it does not pretend to cover health behavior in general.

A. SEVEN GAPS continued**4. Inadequate health behavior facts** continued

Research about the behavior of organizations is especially sparse, perhaps because organizations are harder to study with correlation studies and surveys. And even though behavioral economics researchers have produced interesting and useful results about behavior in general, they have not yet focused on health behavior.

We need rigorous knowledge about all the components of health behaviors, in order to accurately prepare models of health behavior to inform policy decision making. Further, because scientific experiment is the best way we know to accumulate knowledge, the lack of experiments in health behavior research diminishes the rigor and usefulness of its results.

We explored this gap in Part III (Health behavior facts).

5. No health behavior theory

Although there are many hypotheses about health behavior, no one has yet developed a health behavior hypothesis that satisfies the criteria for a scientific theory. In particular, no hypothesis is consistent with all experimental results, partly because health behavior researchers have generally not tested hypotheses with experiments.

Until we have scientifically validated health behavior theories, we cannot be confident in our models for health system decision making. Until we have adequate facts and theories about health behavior, the plans of policymakers to improve health systems are mere guesses.

Chapter ten (Overview of health behavior theories) addresses this gap.

6. No complete modeling method or standards for simulating health behavior

Complete standards for simulating health systems do not exist. Neither does a complete method for developing agent-based models for simulating health behavior.

Without widely accepted standards and a method, health behavior simulation models will continue to be ad hoc creations, and modeling results will continue to be unreliable and impossible to replicate. We explored this gap in Chapters thirteen (Agent-based modeling method) and fourteen (Simulation modeling guidelines).

A. SEVEN GAPS continued

7. Inadequate use of agent-based simulation modeling for informing health system decisions

Despite the proven power of agent-based modeling and simulation in other fields, health behavior researchers generally have not used this method to help health system stakeholders make decisions. The use of this tool has been restricted mainly to the field of Epidemiology, where it has been used with great success.

The lack of agent-based simulation modeling in health behavior research and policymaking is a major impediment for good health system decision making.

Chapters two (Health behavior fields) and seven (Overview of health behavior facts) address this gap.

B. ISSUES AND FUTURE DIRECTIONS

The main issue about these gaps is that they need to be filled. As we fill these gaps, we will likely find others.

C. TO LEARN MORE

To learn more about the gaps, see the report sections referenced above.

D. REVIEW AND A LOOK AHEAD

In this chapter, I presented seven major gaps that keep us from understanding how people and institutions behave in health systems.

In the next chapter, we will look at a way to fill these gaps.

(Don't forget to take a look at the exercises for this chapter. They start on the next page.)

EXERCISES

1. In organizational management literature, “gap analysis” is a method that determines the gap between an organization’s actual performance with its potential performance, and the identification of factors that contribute to the gap. How would you apply gap analysis to the performance of a modern health system? Do you think any of the seven gaps in this chapter would end up among the factors that you identify as contributing to the health system’s performance gap?

SOLUTIONS

1. To apply gap analysis to a health system, first determine the system’s goals. A goal of most is to increase population health with a sustainable level of expenditures. Now see if the system’s performance accords with its goals. If not, determine the factors that prevent it from performing as it should. Because a lack of good decision making is a frequent cause of performance gaps, it is likely that at least some of the seven gaps in the chapter are among the gaps you will find in your analysis, for the seven gaps are common obstacles to good decision making for health systems.

CHAPTER EIGHTEEN: EIGHT HEALTH BEHAVIOR CHALLENGES

La santé est la première des libertés ... (Health is the first of all liberties ...)
 Henri-Frédéric Amiel¹

A. EIGHT CHALLENGES

On August 8, 1900, at the International Congress of Mathematicians in Paris, the eminent mathematician David Hilbert presented a set of mathematical challenges, in the form of problems to resolve, that profoundly influenced the direction of mathematics for the next hundred years (see the sidebar). The challenges varied in clarity, scope, and precision. Some were easy to understand and others were difficult to interpret; some had one precise answer and others admitted many answers. But all were hard, and several are still unmet.

In a similar spirit, here I offer eight health behavior challenges, seven to fill the gaps presented in the last chapter, and one more.

The table below lists the challenges, and provides my assessment of the impact that the resolution of each could have on simulating health behavior, as well as my estimate of the length of time it will take to meet the challenge. Some of the challenges—such as developing an ontology (challenge number 2)—are strategic; they will help build the foundations for effectively simulating health behavior. Others—such as employing agent-based simulation to help solve one problem—are more tactical; they will incrementally move the field forward. Similarly, in my opinion some challenges will take a relatively long time to resolve, while others could be resolved readily. In the rest of this chapter, we will explore each challenge.

Hilbert's problems

The problems that Hilbert presented became famous as “Hilbert’s problems”. Initially there were 10 problems, but the number quickly expanded to 23.

An example of the problems is number 3: “Given any two polyhedra of equal volumes, is it always possible to cut the first into finitely many polyhedral pieces which can be reassembled to yield the second.” This one was resolved quickly, in 1900. The answer is no.

One of the problems, number 18 (“What shape contains the densest arrangement of non-overlapping equally-sized spheres?”) was not resolved until 1998. The answer is that the most space-efficient way is to pack spheres in a pyramid shape. The density is about 74 percent.

Several of the problems have been resolved in ways that may have been disturbing to Hilbert. For example, problem 18 was resolved with a computer algorithm. And Kurt Gödel showed that problem 2 (“Prove that the axioms of arithmetic are consistent.”) is not finitely provable.

Challenge	Impact	Completion time
1. Describe health behavior	Strategic	Short-term
2. Develop a health systems ontology	Strategic	Long-term
3. Catalog health behavior research results	Strategic	Long-term
4. Discover one new health behavior fact	Tactical	Short-term
5. Develop one good health behavior theory	Tactical	Long-term
6. Develop a complete set of simulation modeling standards for health behavior	Strategic	Short-term
7. Employ an agent-based simulation model to help solve one health system problem	Tactical	Short-term
8. Establish an international health behavior institute	Tactical	Short-term

¹ From Amiel (1908) for the entry of April 3, 1865. Henri-Frédéric Amiel, 1821-1881, was a Swiss professor of aesthetics and moral philosophy, and a poet.

A. EIGHT CHALLENGES continued**1. Describe health behavior**

The first challenge is to describe health behavior in a way that can be used in a computer model to simulate the behavior of any health system agent. The result must be published in a peer-reviewed journal.

Resolving this strategic challenge will clarify what we mean by health behavior, and thus help health system stakeholders discuss and model it. This solution should not take much time. The parameterized approach that I proposed in Chapter one (Dimensions of behavior) may be a place to start. On the other hand, the challenge might be met by proving that such a description is impossible.

2. Develop a health systems ontology

Develop a freely available, international, and complete ontology that describes health system agents, health behaviors, and relationships among agents and behaviors. A summary of the result must be published in a peer-reviewed journal.

Resolving this strategic challenge is essential to provide health system researchers and other stakeholders with a common vocabulary and syntax to clearly discuss health behavior and, thus, the problems of health systems.

The solution may take time. Remember that to develop the first draft of the HL7 RIM ontology for exchange of medical record information, it took a team of experts about ten years.

The health systems ontology that I proposed in Chapters five (Classification of behavior) and six (Using the health systems ontology) may be a place to start.

3. Catalog health behavior research results

Compile a freely available, publicly maintained, international, and complete catalog of health behavior research results. The catalog should bring together in one place all we know about health behavior, in an easily searchable format. A summary of the result should be published in a peer-reviewed journal.

A. EIGHT CHALLENGES *continued*

3. Catalog health behavior research results *continued*

Meeting this strategic challenge would greatly facilitate health behavior research, but may take considerable time to accomplish. The *International compendium of health behavior* that I prepared for this project may be a place to start.

4. Discover one new health behavior fact

This challenge has three parts. First, using a scientifically valid experimental method—perhaps a method used in behavioral economics (see Chapter eight) that incorporates randomization (see the sidebar)—discover one new health behavior fact. The fact must be sufficiently definite and robust to be included in an agent-based model to help solve an important health system problem. The fact must be unrelated to epidemiology and must be published in a peer-reviewed journal. Second, establish and publish standards for health behavior experimental research. And third, develop and publish a method to determine a desired priority order for such research.¹

Meeting this challenge would be a first step to extricate health behavior research from its rut of correlation-based analyses and surveys applied to too few behavior components, and should not take long to complete.

5. Develop one good health behavior theory

This challenge has two parts. First, develop one scientifically valid health behavior theory that explains a large body of known health behavior facts and is based on experiment, or prove that such theory cannot be developed. The result must be published in a peer-reviewed journal. Second, develop and publish an appropriate scientific paradigm for health behavior research that encompasses the theory.

Meeting these challenges would be a first step to develop rigorous theories on which to base health system simulations. Because good theories depend on good facts, meeting the challenges may take time. An approach to both challenges is discussed in Chapter twelve (One good theory).

Randomization

Paul Meier, who died in 2011 at age 87, was a statistician and an early proponent of experimental “randomization”. He inspired U.S. drug regulatory agencies--and hence clinical researchers throughout the U.S. and other countries--to insist that scientific evidence should be based on randomized experiments.

Consider a simple health behavior question, such as whether a default health insurance option for individuals to purchase affects their purchase decision. There are a few ways to investigate this question. One is to simply survey a group of people to find out whether the default would alter their purchase decision. To isolate the specific effect of the default, though, the survey would need to ask many additional questions, such as whether the respondent currently has insurance, as well as the respondent’s age, gender, educational level, income level, type of work, and so on. This would allow the researcher to “control” for factors that might influence the purchase decision other than the default option. But with this approach there are problems. It is well known that survey answers often do not correspond to how people actually behave. And, even after controlling for many factors, how could the researcher be certain that there is not another unidentified but important factor?

Another way to investigate the question would be to perform a randomized experiment. By randomly assigning people to groups making a real purchase decision with and without the default, the potential confounding factors are balanced out. There is no need to statistically (and artificially) “control” for them.

Randomization is such a simple technique, but it is a powerful way to help us understand health behavior.

¹ Experimental standards might be similar to the standards used for experimental economics. The method for determining the priority of research might be similar to the Grannemann matrix, found in National Research Council (U.S.) Panel to Evaluate Microsimulation Models for Social Welfare Programs, Citro, & Hanushek (1991).

A. EIGHT CHALLENGES *continued***6. Develop a complete set of simulation modeling standards for health behavior**

This challenge has two parts. First, develop and promulgate a complete set of standards for models that simulate health behavior. The set must include standards for the management, development, evaluation, implementation, operation, and maintenance of simulation models. The standards must be promulgated and maintained by a recognized standards organization such as the International Standards Organization or a large professional association. The second part is to develop a complete method for building, using, and maintaining agent-based models for simulating health systems. The method must be published in a peer-reviewed journal.

Meeting this challenge is an essential part of the foundation for developing rigorous health system simulation models. Chapter thirteen (Agent-based modeling method) proposes a complete method for agent-based models, and Chapter fourteen (Simulation modeling guidelines) proposes a set of simulation modeling guidelines. For this challenge, these may provide a starting place.

7. Employ an agent-based simulation model to help solve one health system problem

This challenge has two parts. The first is to develop a generalized platform for developing agent-based models. The platform must be able to incorporate agents developed separately by various independent international development teams. Thus, as part of the platform, there must be standards for agent software development, standard protocols for inter-agent communications, and standards for simulation timing. The resulting platform must be freely available, supported by complete user documentation, and described in a peer-reviewed journal. Such a platform would enable the development of sophisticated and rigorous health system simulations.

The second part is to use the platform developed in the first part to develop an agent-based simulation model, using agents developed by at least two independent teams, to help solve a significant health system problem. The simulation results and their impact on the problem must be published in a peer-reviewed journal.

The sample agent-based models presented in Chapter sixteen (Sample agent-based models) may be a place to start.

A. EIGHT CHALLENGES *continued*

8. Establish an international health behavior institute

As we saw in Chapter two (Health behavior fields) there is no organized academic field, scientific discipline, profession, or other group that focuses either on researching health behavior, or on solving health system problems by modeling health behavior from the bottom up. The current fields related to health behavior—such as health economics, health psychology, and public health—are fragmented and entrenched in traditional approaches.

The eighth—and most important—challenge is to break away from the entrenched fields and establish a new health behavior institute that will carry forward a program of health behavior research and simulation modeling, with a mission to use such knowledge and skills to help solve international health system problems. The institute should be non-profit and independent.

The institute should establish a new peer-reviewed online journal devoted to health behavior research and applications. It should also engage international corporate and governmental sponsors for health behavior research to resolve this chapter’s challenges, and then provide public recognition when they have been resolved. Similar to the Medicis of fifteenth-century Italy (see the sidebar) and the Santa Fe Institute of today,² the institute should host cross-discipline meetings to generate new ideas about health behavior and help solve knotty international health system problems. It should also host workshops to teach agent-based simulation of health systems.

The institute might also maintain the health systems ontology, the catalog of health behavior facts, and the simulation platform developed in response to challenges 2, 3, and 7.

With such an organization leading the way to meet these challenges, we may avoid the unintended consequences that have haunted health system policymakers. Effective, affordable, and sustainable health systems may then take root and flourish.

The Medici effect

The Medicis were a prosperous banking family in fifteenth-century Florence who brought together creators from many disciplines and cultures.

Sculptors, scientists, poets, philosophers, financiers, painters, and architects met in Florence, learning from one another, breaking down barriers between disciplines and cultures. Together they created new ideas that would bring about a new world, the world of the Renaissance. They provided the ideas for one of the most creative periods in history.

For a stunning look at the impact of the Medicis and how their approach can be harnessed to solve today’s most intractable problems, see the fascinating book by Frans Johansson, titled “The Medici effect”.¹

Johansson writes, “We can ignite this explosion of extraordinary ideas and take advantage of it ... We can do it by bringing together different disciplines and cultures and searching for the places where they connect.”

¹ Johansson (2006)

² To learn about the Santa Fe Institute, see Chapter one (Complexity science) of my report titled “Complexity science: an introduction (and invitation) for actuaries”, at: “www.soa.org/research/research-projects/health/research-complexity-science.aspx”.

B. ISSUES AND FUTURE DIRECTIONS

The main issue about these challenges is that they need to be met. Many more related challenges are likely to follow. For example, the new agent-based simulation models will require new optimization techniques to explore the vast spaces of model results.

C. TO LEARN MORE

To learn more about these challenges, see the report sections referenced above.

D. REVIEW AND A LOOK AHEAD

In this chapter, I presented eight challenges that, once resolved, will help us better understand how people and institutions behave in health systems.

Will you help resolve any of them? I hope so.

(Don't forget to take a look at the exercises for this chapter. They start on the next page.)

EXERCISES

1. If the challenges in this chapter had been resolved before 2001, how might the MaineCare advisory committee we met in the Preface have approached MaineCare's drug expenditure problem?

SOLUTIONS

1. Instead of jumping to an intuitively appealing solution, the committee might have requested an agent-based simulation model of the problem, so that they could test the potential impacts of many potential solutions. The agent-based model would have been built based on widely accepted simulation standards, using a standard development method. It would have been developed using a standard agent-based modeling platform, using relevant agents that had been developed and tested by an international team of experts. The behavior of the model's agents would conform to the health behavior facts in the *International compendium of health behavior*, and to scientifically validated theories about health behavior.

GLOSSARY

agent: A self-directed (able to take actions on its own to attain a goal) and adaptive (able to change its behavior to fit in with a new environment) individual entity. Agents are a system's actors.

computation: A transformation of input into output, based on rules underlying the transformation.

computationally irreducible: For a process, the impossibility of finding a shortcut, mathematical or otherwise.

construct: Concepts that are the building blocks of a scientific theory, and that are sometimes only understandable in relation to the theory.

controlled vocabulary: A classification system that is a listing of terms (usually called "entry terms"), sometimes in a certain order. It is called "controlled" because for the domain covered, only the entry terms may be used.

genetic algorithm: A method inspired by the mechanics of biological evolution to search for optimal solutions in large solution spaces.

health: A person's robustness, the ability of the person's body and mind to operate effectively within a usually wide (but always limited) range of conditions, but to fail outside that range.

health behavior: Any behavior of any health system agent.

health system: The set of agents that affect the health of a specific group of people, together with their relevant behaviors.

health system problem: The conflict that arises when a health system agent, or a group of agents, cannot achieve one of their goals.

heuristics: A simple procedure, like a rule of thumb, that helps us make adequate, but often imperfect, responses to hard questions.

hypothesis: A proposed explanation of phenomena that is testable (falsifiable).

integrated development environment (IDE): An environment for developing computer code, that typically provides a computer programmer with an editor for writing computer code, a way to run the code, and a debugger for finding and repairing code defects.

law: The same as a scientific theory, except that it is typically expressed in more formal, often mathematical, language.

GLOSSARY continued

model: A logical framework, often incorporating several theories, that represents or explains a set of phenomena, or that helps to solve a particular problem.

ontology: A classification scheme that fully describes a domain of knowledge, including both the domain's agents as well as relevant agent relationships and behaviors.

paradigm: The set of practices that define a scientific discipline during a historical period, including its theory, what is to be observed, how experiments should be conducted, and how results should be interpreted.

role: A set of functions (health behaviors) within a health system.

scientific theory: A well-substantiated explanation of some aspect of the natural world, based on a body of facts that have been repeatedly confirmed through observation and experiment.

validation: To ensure that a computer model is an accurate reflection of the real world, and that experts assess the model as reasonable, practicable, and relevant.

verification: To ensure that a computer model is an accurate reflection of stakeholder needs, that design accurately follows requirements, and that construction accurately follows design. Internally, it ensures that the model is internally consistent and without defects.

taxonomy: A type of classification system that is a hierarchy of entry terms, an upside-down tree.

thesaurus: A classification scheme that shows simple relationships among terms, such as whether they are synonymous.

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NOTES

^A The sociologist Robert K. Merton popularized the concept of the “law of unintended consequences”. In his 1936 paper titled “The unanticipated consequences of purposive social action”, he listed five possible causes of unanticipated consequences: ignorance, error, immediate interest (which may override long-term interests), basic values that force certain actions that may be unfavorable, and self-defeating prophecy.

When we change one part of a complex system with many interacting parts that we do not fully understand, we will also make changes in other parts of the system, changes that may be impossible to predict. It should not be surprising that intervention in a complex system that is insufficiently understood will produce unintended consequences.

^B In “Everybody’s business: Strengthening health systems to improve health outcomes” (2007) the World Health Organization (WHO) defines “health system” as “All organizations, people and actions whose primary intent is to promote, restore or maintain health. This includes efforts to influence determinants of health as well as more direct health-improving activities. A health system is therefore more than the pyramid of publicly owned facilities that deliver personal health services. It includes, for example, a mother caring for a sick child at home; private providers; behavior change programs; vector-control campaigns; health insurance organizations; occupational health and safety legislation. It includes inter-sectoral action by health staff, for example, encouraging the ministry of education to promote female education, a well known determinant of better health.”

The WHO’s definition is in the same spirit as that of the definition we are using for this work. Thus, our concept of “health system” is much broader than merely the components of a medical care system focused mainly on the clinical or treatment aspects of care.

^C In addition to being autonomous, adaptive, and hierarchical, agents are:

- **Local.** They generally act locally, only interacting with other agents within a defined neighborhood.
- **Heterogeneous.** Agents can be quite different from one another and follow different behavior rules.
- **Proactive.** Agents persistently pursue their goals.
- **Flexible.** They have multiple ways of achieving their goals.
- **Social.** They interact with other agents.
- **Boundedly rational.** Their behavior is based on real-world behavior, which is far from perfectly rational. Real people and organizations generally act based on limited information and simple, often illogical, heuristics; they are what behavioral economics researchers call ‘boundedly rational’.

As we build agent-based models, you will encounter agents that exhibit each of these characteristics.

^D Health is one of the more difficult concepts to define. In 1970, Dr. Charles Wylie wrote, “Any attempt to define what health means lays the definer open to attack by critics armed with heavy reference books. Fortunately, this phenomenon has not prevented many groups and individuals from suggesting definitions...” (Wylie (1970) page

100). In their book about health promotion, Dines and Cribb state, “health is an abstract idea that is constantly alluded to in our conversations, but once we try to capture and define it, it melts to nothing like candyfloss on our tongue.” (Dines & Cribb (1993) page 3)

One widely quoted, but problematic, definition is from the World Health Organization (WHO): “Health is a state of complete physical, mental and social well-being and not merely the absence of disease or infirmity”. One problem with this definition is that it is circular and nearly vacuous. For it to have meaning, we would have to understand “well-being”, a term just as difficult to define as health. About the WHO definition, Huber et al. (2011) write, “Although the definition has been criticised over the past 60 years, it has never been adapted. Criticism is now intensifying, and as populations age and the pattern of illnesses changes the definition may even be counterproductive.” Current criticisms include the unrealistic scope of the word “complete” in the definition, and the difficulty of applying it (for example, the definition does not indicate a way to measure health).

Others have offered alternative definitions. For example, in 1986 the Ottawa Charter (an international health promotion agreement) suggested extending the WHO definition by adding, “To reach a state of complete physical, mental and social well-being, an individual or group must be able to identify and to realize aspirations, to satisfy needs, and to change or cope with the environment. Health is, therefore, seen as a resource for everyday life, not the objective of living. Health is a positive concept emphasizing social and personal resources, as well as physical capacities.” But the WHO has not adopted the suggested extension.

Then, in 2009, the two leading Dutch governmental organizations providing scientific advice about health convened international health experts to develop a more useful definition. The title of the conference was “Is health a state or an ability?” The experts concluded that “Health should not be considered a state, but should be seen in relation to dynamic factors like the balance or equilibrium of different aspects, homeostasis, allostasis, resilience, and it should also be related to age. Further characteristics of health include: an inner resource, a capacity, an ability, a potentiality to cope with or adapt to internal and external challenges, to perform (relative to potential, aspirations and values), to achieve individual fulfillment, to live, function and participate in a social environment, to reach a high level of well-being, even without nutritional abundance or physical comfort.” (See Huber (2010).) Thus, even though Stephen Hawking cannot move more than his eyes, he can be very healthy.

Although not recognized by the conference participants, such an ability-based approach to health corresponds to the notion of robustness in complex systems. Therefore, because the human body/mind is a quintessential complex system, I suggest that we define health simply as each person’s “robustness”, in the complex systems sense. With such a definition, we can apply to the measurement and maintenance of health what we know about the measurement and maintenance of robustness in complex systems. For example, we know that one of the hallmarks of a robust complex system is an ability to cope with the unpredictable, and that such an ability is fostered by system diversity (heterogeneous components linked by disperse networks). Thus, as measures of a person’s health we might assess the diversity of the person’s skills and social networks, and the response of the person’s body and mind to a variety of atypical conditions.

Such a definition is far removed from the concept of statistically average bodily “health” common in medicine today: We know that healthy people deviate widely from statistical averages.

For an in-depth treatment of the definition of health, see Gochman (1997), Volume I pages 8-18. (I extracted the quotes above about the difficulties of defining health from this discussion.) Dr. Gochman concludes that exploring, and continually improving, the definitions of health should be on the health behavior research agenda.

^E Dr. Ossorio wrote about his description of behavior in Ossorio (1966), pages 44-55. Following is the correspondence between my parameters and his:

My parameters	Corresponding Ossorio parameters
Goals	Want: “This is the ‘motivation’ aspect of behavior. Behavior is in part distinguished by (and oriented toward) a wanted state of affairs, and the Want parameter provides a place to specify what that state of affairs is.”
Attributes	Identity: “Every behavior is someone’s behavior, and this parameter of behavior provides a place to specify that.” Person characteristics: “Every behavior reflects some of the characteristics of the person whose behavior it is. This parameter codifies that aspect of behavior.”
Get input	Know: “This is the ‘cognitive’ aspect of behavior. Here, we specify which distinctions (concepts) are being acted on in the given behavior.”
Produce output	Performance: “This parameter represents the process, or procedural, aspect of behavior.”
Output messages	Achievement: “This parameter represents the outcome aspect of behavior. It refers to whatever is different in the world by virtue of the occurrence of the behavior in question. Although some outcomes may be quite trivial, a behavior, being historically unique, always makes some kind of difference.”
Experience	Know How: “This parameter represents the ‘competence’ aspect of the behavior in question, which in turn reflects the learning history of the person whose behavior is in question.”
Rules	Know How: “This parameter represents the ‘competence’ aspect of the behavior in question, which in turn reflects the learning history of the person whose behavior is in question.”

Dr. Ossorio did not provide parameters corresponding to my “Input messages”, “Send output”, or “Context” parameters, and I do not have a parameter corresponding to his “Significance” parameter. He describes the “Significance” parameter as “This parameter codifies the ‘meaningful’ and/or ‘ulterior’ aspects of behavior. ... In cases where the person does X by doing Y, doing Y is the implementation of doing X and doing X is the significance of doing Y.” For agent-based simulation modeling, I do not see a need for a separate “Significance” parameter. Lastly, because his Know How parameter appears to be compound, I represent it by two parameters: “Experience” and “Rules”.

^F In a 1996 book titled “Explaining culture”, Dan Sperber, a social and cognitive scientist, described culture as a giant network of ideas that are internalized, modified, expressed, and spread to others within the culture. The more nodes of the network that maintain the idea, the stronger the idea’s hold on the culture. We might expand this notion and explain the “culture” of a system as the network of behaviors within the system, with the impact of

a particular behavior on the system's culture at any time being commensurate with the frequency of the behavior's repetition among the network's nodes.

^G The seminal taxonomy of individual health behavior was in Kasl & Cobb (1966b) and Kasl & Cobb (1966a). It remained, with relatively minor modification, the primary taxonomy for four decades. It is based on the division of behavior into three categories:

- **Health behavior:** Medically recommended actions that healthy people take to detect and prevent disease.
- **Illness behavior:** Actions that people take who are uncertain if they are well, who are troubled by sensations they believe are signs or symptoms of illness, who want to clarify the meaning of these experiences and determine if they are well, and who want to know what to do if they are not well.
- **Sick role behavior:** Actions that sick people take.

In Gochman (1997), Volume IV, pages 416-422, David Gochman extended the Kasl & Cobb taxonomy to include the following categories:

- **Health cognitions:** Thought processes that serve as frames of reference for organizing and evaluating health, illness, disease, and sickness.
- **Care seeking:** Actions to involve some other person in health-related issues; can be for preventive reasons or response to illness.
- **Nonaddictive risk behaviors:** Initiation/maintenance of actions amenable to conscious control that increase likelihood of negative health outcome; nonengagement in actions that reduce such likelihoods.
- **Addictive risk behaviors:** Actions that are beyond conscious control that increase likelihood of negative health outcomes.
- **Lifestyle:** Actions to avoid general risk, or directed toward health/fitness; not undertaken in response to illness in relation to specific diseases.
- **Responses to illness/adherence:** Actions undertaken to restore or maintain health in the face of a diagnosis.
- **Preventive, protective safety:** Specific actions undertaken to avoid identifiable negative health outcomes; early detection of disease.

These taxonomies were for behaviors of individual people and patients. Even less has been done to classify the behaviors of healthcare practitioners. And almost nothing has been done regarding the behavior of organizations. In 1997, Robert Daugherty wrote, "The field of management in health care has been little researched within a health behavior framework. Research has primarily focused upon the organizational aspects vis-à-vis provider and consumer behavior and has paid little attention to the managerial functions, behavior, or perspective." Daugherty (1997)

^H Fifty years ago, questioning the assumption of rationality, Herbert Simon developed a concept he called "bounded rationality". Bounded rationality is the idea that in decision making, people are limited by the information they have, their cognitive limitations, and the amount of time available. He pointed out that most people are only partly rational; in general, they are emotional and irrational. The reason we are boundedly rational is because the

information space in which we live is vast compared to our limited computational power and our limited capacity to control our behavior.

^J The concept of System 1 and System 2 corresponds to what we know about the physiology of the brain. Some parts of the brain are fast, automatic, below the surface of consciousness. Others are slow, logical, and conscious. And there may be other areas that have characteristics somewhere between those of System 1 and System 2, corresponding to Systems 3, 4, etc.

Our brains, and hence our behavior processes, appear to solve problems with overlapping and competing programs, an approach that is quite different from that of our present-day computers. This is the hypothesis of the “modular mind”, that the human mind is composed of many specialized components (modules) that operate independently. Each module independently collects input, processes it, and sends output. These modules correspond roughly to instances of the “Rules” behavior component proposed in this report.

^J A scientific hypothesis can never be proven to be universally true, because some day a fact may be discovered that contradicts it, just as discoveries about the behavior of small-scale reality contradicted Newton’s laws. A hypothesis can only be disproved, or falsified, and must therefore be constantly tested.

^K As Newton’s theories demonstrate, a scientific theory need not be true everywhere. It is vitally important to carefully describe the boundaries within which a scientific theory is considered true. In developing theories of health behavior, this is especially true, for the boundaries of a scientific health behavior theory may be quite small.

^L The relationship between theory and practice is much deeper. In his letter of September 18, 1861 to Henry Fawcett, Charles Darwin wrote “How odd it is that anyone should not see that all observation must be for or against some view if it is to be of any service.” Thus, according to Darwin and many others, practical observation is not even possible without some view, hypothesis, or theory underlying it.

^M Not all social scientists would agree with these statements. For example, in describing what “theory” in the health behavior context means, Karen Glanz, a prominent health behavior researcher, writes, “A theory presents a systematic way of understanding events, behaviors, and/or situations. A theory is a set of interrelated concepts, definitions, and propositions that explain or predict events or situations by specifying relations among variables. The notion of generality, or broad application, is important. Thus, theories are, by their nature, abstract and not content- or topic-specific. Even though various theoretical models of health behavior may reflect the same general ideas, each theory employs a unique vocabulary to articulate the specific factors considered to be important. Theories vary in the extent to which they have been conceptually developed and empirically tested; however, testability is an important feature of a theory.” (Glanz, K and Bishop DB; The role of behavioral science theory in development and implementation of public health interventions; Annual Review of Public Health; 2010, 31:399-418)

For researchers to make progress in developing scientific health behavior theory, the word “hypothesis” should replace every instance of the word “theory”, and “hypothetical” should replace “theoretical” in the above quote.

- ^N How can both players in the prisoner's dilemma commit themselves to cooperating? Thomas Schelling suggested several ways. For example, in his 1985 commencement address to the Rand Graduate Institute, he described a strategy the clientele of a Denver rehabilitation clinic used to curb their cocaine addiction: self-blackmail. Schelling said, "The patient is offered an opportunity to write a self-incriminating letter that will be delivered if and only if the patient, who is tested on a random schedule, is found to have used cocaine. A physician, for example, writes to the State Board of Medical Examiners confessing that he has violated state law and professional ethics in administering cocaine to himself and deserves to lose his license. That is a powerful deterrent." The physician was committed to cooperating.
- ^O Adam Smith's "invisible hand" is usually considered in a positive light, as a societal force that produces the miracle of markets and economies, increasing the common good. However, the invisible hand also includes the effects of society's many prisoner's dilemmas working in a contrary direction, to undermine the common good.
- ^P To be fair, I should point out that game theory was not developed to predict what real people do. Rather, it was developed to be more normative than predictive; it describes how a perfectly rational agent would play a game.
- ^Q For example, the search space may be as wide as all human behavior, for health behavior intersects with other behaviors ("I would have visited the doctor today, but my boss gave me an urgent assignment.").
- ^R It is common knowledge that bugs and defects are ubiquitous in computer programs. One might ask why. Frederick Brooks, in his famous collection of essays about software engineering titled "The mythical man-month", offered one good answer: "In many creative activities the medium of execution is intractable. Lumber splits; paints smear; electrical circuits ring. These physical limitations of the medium constrain the ideas that may be expressed, and they also create unexpected difficulties in the implementation. ... Computer programming, however, creates with an exceedingly tractable medium. The programmer builds from pure thought-stuff: concepts and very flexible representations thereof. Because the medium is tractable, we expect few difficulties in implementation; hence our pervasive optimism. Because our ideas are faulty, we have bugs; hence our optimism is unjustified." Thus, in computer programming as in behavioral economics, our frailty is manifest.
- ^S But we are hardly starting from scratch. Consider, for example, the "fitness landscapes" of Sewall Wright. In 1932, he suggested the landscape as a way to visualize and explain how biological agents search through a space of possible solutions to avoid disadvantageous low hills and steep downhill inclines, and instead find a relatively advantageous peak. Since Sewall, such landscapes have become well-developed ways to visualize a space of possibilities and how agents might find paths to reach an optimal solution.

Following is a detailed description of the “Physician Network Model”, in the following sections:

- A. Model overview:** A brief overview of the model.
- B. Agent overview diagram:** A diagram, with accompanying discussion, showing the communication relationships among the model’s agents.
- C. Behavior summary:** A summary of when agent behaviors are scheduled.
- D. Detailed agent descriptions:** For each agent, a detailed description of its attributes, goals, memory, rules, and output processes.
- E. Message passing feature:** A description of the simulation’s message passing feature.
- F. Model testing:** A description of how the model can be tested.

Additional documentation about the model is found in the model’s computer source code, and “Javadoc” documentation.

A. MODEL OVERVIEW

- | | |
|----------------------------|--|
| 1. Description | The model simulates how a physician network serves a community of people. Here, a “physician network” is a group of primary care and specialist physicians who serve the community. As inhabitants become sick and are treated by physicians in the network, the model traces the interactions among the inhabitants, the physicians, and an insurance company that provides health insurance for the community. |
| 2. Question addressed | The model is designed to address the following question: How can the characteristics of a physician network of primary care physicians (PCPs) and specialists be modified to optimize: <ul style="list-style-type: none">▪ its “carrying capacity” (the number of patients it serves),▪ healthcare expenditures associated with its services, and▪ the population health of its community? |
| 3. Interested stakeholders | It is likely that the following health system stakeholders would find the model interesting: <ul style="list-style-type: none">1. Physician network management2. Health insurance company management3. State and federal government policymakers |
-

A. MODEL OVERVIEW CONTINUED

4. Agents and their behaviors

The model includes the following agents:

Person. An individual inhabitant of the community. A Person assesses the quality of physician performance, chooses a primary care physician, requests treatment from a physician, and complies with treatment recommendations.

Primary care physician (PCP). A physician in the network who provides the first line of health care. The PCP recommends treatment for a Person, refers a Person to a Specialist, and submits claims to the Health Insurance Company. For the simulation, there must be at least one PCP.

Specialist. A physician in the network who focuses on a specialized area of medicine. A Specialist recommends treatment for a Person, and submits claims to the Health Insurance Company. There is only one type of Specialist. For the simulation, there must be at least one Specialist.

Health Insurance Company. A Health Insurance Company that pays claims to PCPs and Specialists, assesses the performance quality of PCPs and Specialists, and determines which PCPs and Specialists will remain in the network. There is one Health Insurance Company. All people in the community have health insurance through the Health Insurance Company.

Environment. The container for the model's agents. It creates the simulation's agents, and maintains a list of Person agents, a list of Physician agents, and a list of Health Insurance Company agents (there is only one). It also schedules agent behaviors, and manages the passing of messages among agents. There is one Environment.

5. Output

For each simulation period, the model provides the following results:

- **Disease prevalence.** The number of Person agents with each disease.
- **Disease status.** The average population disease status.
- **Expenditures.** Total community healthcare expenditures, by physician type.
- **Network members.** The number of physicians in the network, by physician type.
- **Patient load—PCPs:** The number of annual patients for each PCP.
- **Patient load—Specialists.** The number of annual patients for each Specialist.
- **Patient visits.** The number of patient visits, by physician type (PCP or Specialist)
- **Patient types.** The number of each type of patient (for a description of patient types, see the Person detailed description below).
- **Physician income.** The average physician income, by physician type.
- **Referrals.** The number of referrals that PCPs make to Specialists.

A. MODEL OVERVIEW CONTINUED

6. Simplifying assumptions
1. In the model, each Person is single. There are no families.
 2. Except for geographic location all inhabitants have the same demographic characteristics. For example, there is no distinction by age, gender, or income.
 3. There are two types of one disease, low intensity (D_1) and high intensity (D_2). The high-intensity disease costs more to treat. In order to disappear, each disease requires treatment. The low-intensity disease can progress to the high-intensity level if a Person with the low-intensity disease receives no treatment or the wrong treatment. The low-intensity disease never requires referral, and the high-intensity disease should always be referred to a Specialist. There are two treatment options for each disease type, one that is low cost (T_1) and one that is high cost (T_2). The low-cost option is just as effective as the high-cost option. However, when a specialist prescribes a low-cost treatment, it costs more than when a PCP prescribes it. The treatments for D_1 are labels T_1D_1 and T_2D_1 , and similarly for D_2 . There is an additional treatment option, T_z , that is not appropriate for either D_1 or D_2 . Physicians sometimes prescribe T_z in error. When treated correctly, a disease entirely disappears.
 4. Each Person recognizes the signs and symptoms of a disease when it arises.
 5. PCPs and Specialists correctly diagnose each Person's disease. (But they may not correctly treat each disease.)
 6. Each Person contracts at most one disease per period.
 7. A Person cannot self-refer to a Specialist.
 8. From the perspective of the Health Insurance Company, physicians have two performance quality levels: "high-quality" PCPs who prescribe low-cost correct treatments and refer patients to specialists appropriately, and "high-quality" Specialists who prescribe low-cost correct treatments. The Health Insurance Company considers other PCPs and specialists to be "low quality".
 9. Everyone is covered by the same individual health insurance policy from the Health Insurance Company.
 10. Health insurance premiums and co-payments are omitted from the model.
 11. Claims submitted to the Health Insurance Company are paid immediately in full.
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A. MODEL OVERVIEW CONTINUED

7. User-defined parameters

Following are the parameters the user can set before the simulation starts. If a user does not enter a parameter, the model will supply a default value.

- A1. Agent label.** Whether identification labels are shown for agents on the display. Labels are especially helpful when testing the model, or trying to figure out an unusual pattern. Choices: “yes”, “no”. Default value: “no”.
 - A2. Maximum number of simulation periods.** The maximum number of simulation periods. Choices: any integer. Default value: 100.
 - B. Random number seed.** The “seed” number used for the simulation’s random number generators. To vary the generation of random numbers for simulation runs, the seed can be varied. Choices: any integer. Default value: automatic.
 - C1. Number of Persons.** The number of Person agents for the simulation. Choices: any integer. (It is best to choose an integer between 1 and 10,000.) Default value: 1,000.
 - C2. Number of PCPs.** The number of PCP agents for the simulation. Choices: any integer. (It is best to choose an integer greater than 1.) Default value: 15.
 - C3. Number of Specialists.** The number of Specialists for the simulation. Choices: any integer. (It is best to choose an integer greater than 1.) Default value: 5.
 - D1. Person distribution type.** How Persons are geographically distributed on the Environment. Choices: “Random normal distribution” and “Random uniform distribution”. Default: Random normal distribution.
 - D2. Standard deviation (normal distribution).** If the user selects “Random normal distribution” for parameter D1, this parameter gives the normal distribution’s standard deviation. Choices: any number. (It is best to limit the standard deviation to a positive number less than half the width of the Environment. Otherwise, many Persons will end up at the Environment’s boundaries. The Environment’s width is 100.) Default: 15.0.
 - E1. Physician distribution type.** How physicians are geographically distributed on the Environment. Choices: “Random normal distribution” and “Random uniform distribution”. Default: Random normal distribution.
 - E2. Standard deviation (normal distribution).** If the user selects “Random normal distribution” for parameter E1, this parameter gives the normal distribution’s standard deviation. Choices: any number. (It is best to limit the standard deviation to a positive number less than half the width of the Environment. Otherwise, many physicians will end up at the Environment’s boundaries. The Environment’s width is 100.) Default: 15.0.
-

A. MODEL OVERVIEW CONTINUED

7. User-defined parameters continued

- F1. Disease 1 probability.** The annual probability that a Person will contract D_1 . Choices: 0.0, 0.01, 0.02, 0.03, 0.04, 0.05, 0.06, 0.07, 0.08, 0.09, 0.10. Default: 0.03.
 - F2. Disease 2 probability.** The annual probability that a Person will contract D_2 . Choices: 0.0, 0.01, 0.02, 0.03, 0.04, 0.05, 0.06, 0.07, 0.08, 0.09, 0.10. Default: 0.01.
 - G. Initial PCP assignment.** How PCPs are initially assigned to Persons. Choices: “Random”, “Nearest PCP”. Default: “Nearest PCP”.
 - H. Person 1st goal.** With this parameter the user indicates the percentage of the population that has each of the three Person goals as a top priority. Choices: any number between 0.00 and 100.00. (The percentages for the three goals should add to 100 percent.) Default: 33.33 percent for each goal.
 - I. PCP 1st goal.** With this parameter the user indicates the percentage of the population that has each of the three PCP goals as a top priority. Choices: any number between 0.00 and 100.00. (The percentages for the three goals should add to 100 percent.) Default: 33.33 percent for each goal.
 - J. Specialist 1st goal.** With this parameter the user indicates the percentage of the population that has each of the three Specialist goals as a top priority. Choices: any number between 0.00 and 100.00. (The percentages for the three goals should add to 100 percent.) Default: 33.33 percent for each goal.
 - K. Health Insurance Company 1st goal.** With this parameter the user indicates the likelihood of each of the three Health Insurance Company goals being a top priority. Choices: any number between 0.00 and 100.00. (The percentages for the three goals should add to 100 percent.) Default: 33.33 percent for each.
 - L1. Person neighborhood radius.** The geographic radius for a Person to use in determining the most frequent PCP selection among the Person’s neighbors. Choices: any number. (It is best to choose a positive number.) Default: 10.0.
 - L2. Physician neighborhood radius.** The geographic radius for a physician to use in determining treatment and referral norms (i.e., the most frequent treatment and referral practices). Choices: any number between 0.00 and 100.00. (It is best to choose a positive number.) Default: 10.0.
 - L3. Physician convenience radius.** The geographic radius outside of which Persons will consider it inconvenient to visit a PCP or Specialist. Choices: any number. (It is best to choose a positive number.) Default: 20.0.
-

A. MODEL OVERVIEW CONTINUED

7. User-defined parameters continued

- M. Treatment cost.** The claim cost for each treatment T_1D_1 , T_2D_1 , T_1D_2 , T_2D_2 , T_z , and for a referral, separately for the PCP and the Specialist. Generally, for the same treatment, the claim cost is higher if prescribed by a Specialist. Choices: Any number. (It is best to choose positive numbers.) Defaults: PCP: Treatment 1 = 100, Treatment 2 = 150, Treatment z = 100, Referral = 50; Specialist: Treatment 1 = 200; Treatment 2 = 300, Treatment z = 200.
- N. Physician quality thresholds.** The number of mistakes (wrong treatments, inappropriate referrals, or high-cost treatments) a PCP or Specialist has to make before the Health Insurance Company will remove the physician from the network. Choices: Any integer. Default: 10 for PCPs and 5 for Specialists.
- O. Treatment pain threshold.** The threshold beyond which a Person considers a treatment painful (and thus will be less likely to comply with the treatment). Choices: 1, 2, 3, 4, 5, 6, 7, 8, 9, 10. Default: 5.
- P. Physician error rate.** The probability that a physician will recommend an erroneous treatment (separately for PCPs and Specialists). Choices: 0.0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0. Default: 0.3 for PCPs and 0.2 for Specialists.
- Q1,2. Minimum patient load.** The minimum number of patients that a PCP or Specialist (separately) should treat in a period. Choices: Any integers. Default: 5 for PCPs, 5 for Specialists.
- Q3,4. Maximum patient load.** The maximum number of patients that a PCP or Specialist (separately) can treat in a period. Choices: Any integers. Default: 15 for PCPs, 15 for Specialists.
- R. Referral specialist selection criterion.** The criterion that a PCP uses to select a specialist for referral. Choices: “random”, “nearest to patient”, or “nearest to PCP”. Default: “nearest to PCP”.
- S1. Override parameters.** Whether the model program can override parameters provided through the user interface. Choices: “Yes”, “No”. Default: “No”.
- S2. Write output file.** Whether an output file can be written from inside the model program (as opposed to writing output files through the user interface). Choices: “Yes”, “No”. Default: “No”.
- S3. Output file name.** The name of the output file to be written from inside the model program. The file will be written to the model’s “output” folder. Choices: any valid file name. Default: “None”.
-

A. MODEL OVERVIEW CONTINUED

8. Displays

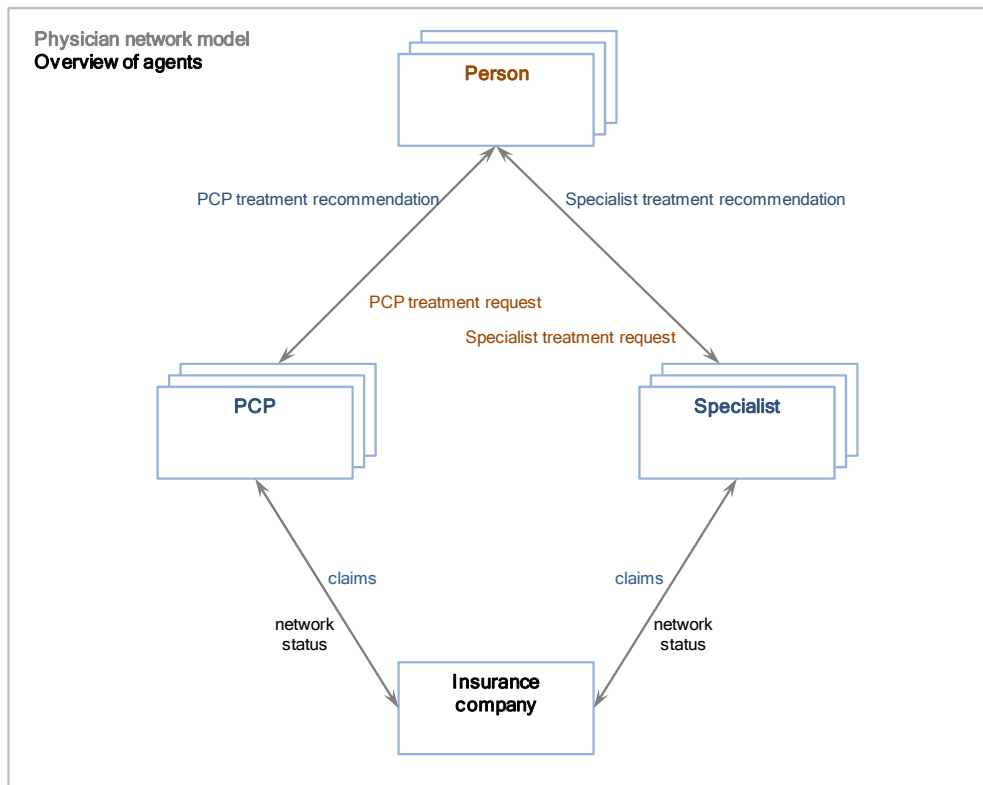
There are three Environment displays:

- 1 General.** This display shows the simulation agents. Person agents are represented by round disks. Those with Disease 1 are colored light red, those with Disease 2 are dark red, and those without disease are grey. Physician agents are squares. PCPs are colored green, and Specialists blue. The Health Insurance Company is shown as a blue cross at position (0,0).
 - 2 Patient-PCP network.** The networks of patient-PCP relationships.
 - 3 Patient-Specialist network.** The networks of patient-Specialist relationships.
-

B. AGENT OVERVIEW DIAGRAM

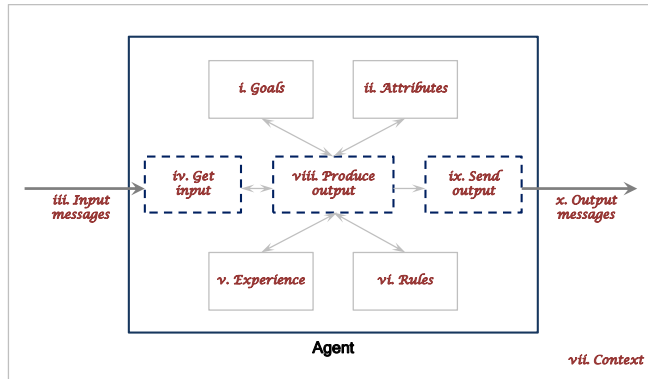
The diagram below shows the model’s main agents and the flow of messages among them. (The messages are color coded; a data item of a certain color is from the agent name of the same color. For example, the data item “PCP treatment request” is brick colored, and flows from “Person”, which is brick-colored.)

In the following sections, each data item is explained in more detail.



C. BEHAVIOR SUMMARY

As discussed in Chapter One (Dimensions of behavior) of the health behavior project report, there are ten dimensions of behavior:



The chart below shows the agent behaviors for the Physician Network Model and the order in which they occur. In the chart, each behavior is represented by its core “produce-output” process. For example, the Person’s behavior “Select PCP” is represented by the process “P1: Select PCP”. This one-to-one relationship between a behavior and its core “produce output” process is possible because the core process is connected to all behavior components.

As the chart shows, some behaviors take place at the beginning of each simulation period, some take place at the end of each period, and some happen mid-period.¹ The order of behavior (indicated by the number in parentheses after the behavior name) is important. For example, in the middle of a period, a Person cannot “Comply with PCP treatment (3)” until the PCP “Provide PCP treatment recommendation (2)” behavior.

Agent	Behavior for each simulation period		
	Beginning of period	Middle of period	End of period
1. Person	P1: Select PCP (1)	P2: Request PCP treatment (1) P4: Comply with PCP treatment (3) P3: Request Specialist treatment (4) P5: Comply with Specialist treatment (6) P6: Update disease status (7)	P7: Contract new disease (1)
2. PCP		P1: Provide PCP treatment recommendation (2) P2: Submit claim (8)	
3. Specialist		P1: Provide Specialist treatment recommendation (5) P2: Submit claim (9)	
4. Insurance company			P1: Update network status (2)
5. Environment			

¹ Technical note: Agent behaviors for the simulation are scheduled in the model’s “Schedule” class, which is called by the Environment. In the Schedule class, there are many clock ticks in a simulation period. Each behavior is scheduled during one of these clock ticks, in an order indicated by the decimal part of each clock tick. For example, Behavior1 might take place at time “1.1”, followed by Behavior2 at time “1.2”.

D. DETAILED AGENT DESCRIPTIONS

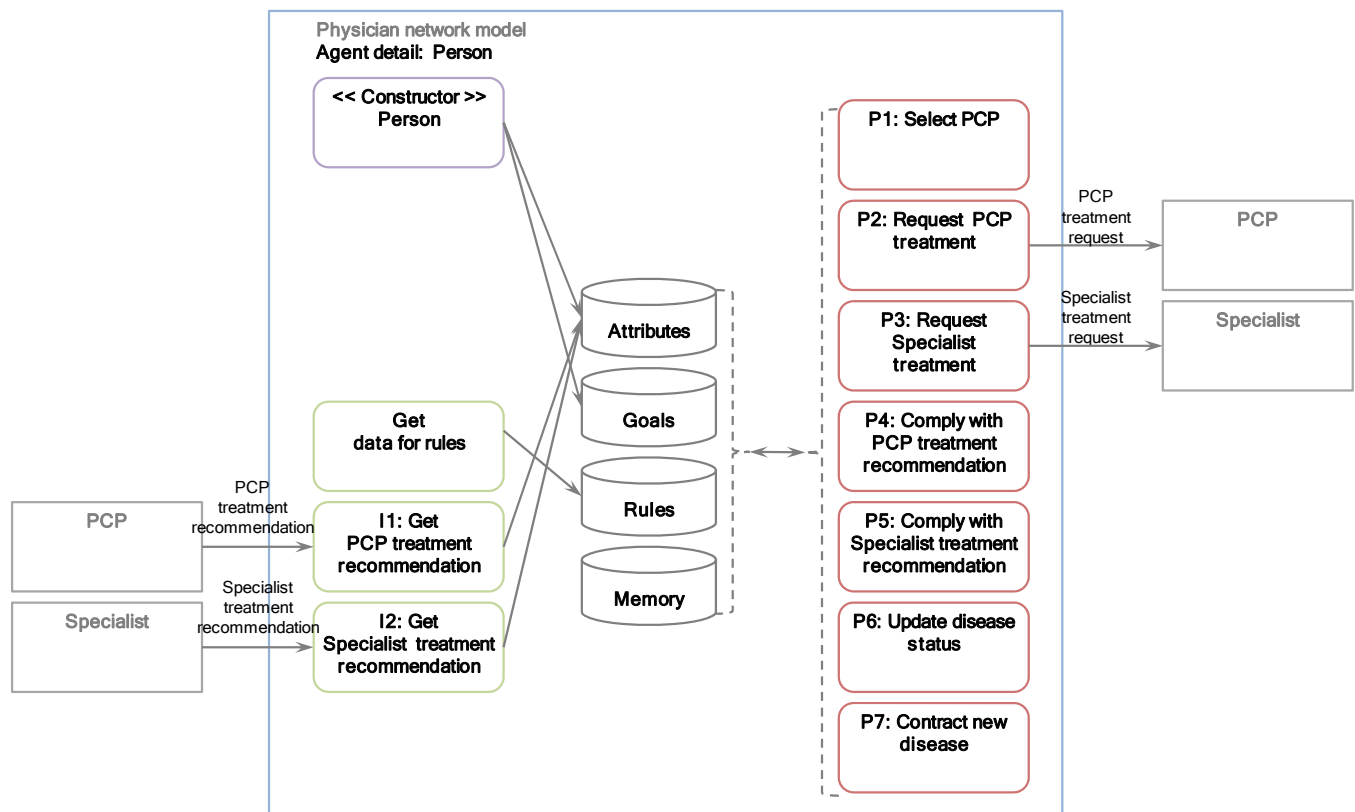
1. Person

This section describes the “Person” agent in detail.¹

a. Behavior overview

The diagram below shows the components of Person behaviors, including:

- **Produce output and send output.** Seven “produce output” processes (represented by rose-colored rounded boxes) that produce the agent’s output messages. These correspond to the Person’s seven behaviors. For two of the processes (shown with arrows pointing to other agents) the process result is a message sent to another agent. The other five processes update the Person’s internal attributes
- **Get input.** Three “get input” processes (in green) get data to support the behaviors. For two of these (shown with arrows coming from other agents) the input is in the form of messages from other agents.²
- **Attributes, goals, rules, memory.** Data stores for the person’s attributes, goals, rules, and memory.



For completeness, the diagram also shows a “constructor” process (in mauve) that creates each instance of a Person for the simulation, and initializes the Person’s attributes and goals.³

¹ Technical note: In the model, the Person class is an extension of the Agent class.
² Technical note: The “Get data for rules” process employs “getter” methods in the classes of other agents.
³ Technical note: The constructor process is the “constructor” for the Person class.

D. DETAILED AGENT DESCRIPTIONS CONTINUED

1. Person continued

b. Attributes

The person has the following primary attributes:

- **Identifier.** An integer uniquely identifying each person.
- **Location.** Where the person lives (x and y coordinates on the two-dimensional grid).
- **Disease status.** The Person’s disease status (D_1 , D_2 , or none).
- **Treating Specialist.** The Specialist to whom the Person is referred
- **Goals.** The Person’s goals.

c. Memory

In memory, the person stores the following primary information:

- **Disease status history.** For each simulation period, the Person’s disease status at the start of the period (before treatment) and after the middle of the period (after treatment, if any), as well as the physicians involved in treatment.
- **Patient type.** If the Person contracted a disease during the simulation, the type of patient that the Person was, according to the following chart (each patient is exactly one of these types):

Patient type	Treatment requested	Treatment received	Compliant	Treatment effective
1. Properly treated	Yes	Yes	Yes	Yes
2. Improperly treated	Yes	Yes	Yes	No
3. Non-compliant	Yes	Yes	No	NA
4. Untreated	Yes	No	NA	NA
5. Non-requesting	No	NA	NA	NA

d. Goals

A person has the following major goals:

- **Treatment.** The Person wants to engage in behaviors that treat disease.
- **Convenience.** The Person wants to engage in behaviors that maximize the Person’s convenience.
- **Conformance.** The Person wants to conform to the behavior of the majority of the Person’s neighbors.

The model user enters parameters to indicate the probability distribution for the highest priority of these goals. Each of the remaining two goals then has a 50 percent chance of being the second-priority goal.

e. Input processes

Following are the Person’s primary input processes:

- I1: **Get PCP treatment recommendation.** Get a PCP’s treatment recommendation message.
- I2: **Get Specialist treatment recommendation.** Get a Specialist’s treatment recommendation message.

D. DETAILED AGENT DESCRIPTIONS CONTINUED

1. Person continued

f. Rules

Following is the Person's repertoire of rules:

- R1: Determine first goal.** Determine the Person's goal with the highest priority. This rule returns the highest-priority goal.
- R2: Determine second goal.** Determine the Person's goal with the second highest priority. This rule returns the second highest-priority goal.
- R3: Assess PCP treatment quality.** Determine the treatment quality of the Person's PCP. If the Person did not have a disease in the previous simulation period, or had a disease in the previous period and it was cured, assess treatment quality as "1". Otherwise, assess the treatment quality as "0". If the Person's PCP is no longer in the network, this rule's result is "0".
- R4: Determine nearest PCP.** Determine the nearest PCP in the network.
- R5: Determine favored PCP.** Determine the PCP in the network whom most of the Person's neighbors selected in the previous simulation period.
- R6: Check for disease:** If the Person has a disease, the result is "TRUE". Otherwise, it is "FALSE".
- R7: Compare goal priorities.** If the priority of the "Treatment" goal is higher than the priority of the "Convenience" goal, the result is "Treatment". Otherwise, it is "Convenience".
- R8: Check physician convenience.** If the location of the physician is within the "Physician convenience radius" (entered by the user as a parameter) the result is "TRUE". Otherwise it is "FALSE".
- R9: Determine treatment pain level.** Randomly determine a number from 0.00 to 10.00 (exclusive). If the number is greater than the "treatment compliance pain threshold" that the user entered as a parameter, and if "Treatment" is not the Person's first goal, then the result is "TRUE". Otherwise, it is "FALSE".
- R10: Check for appropriate treatment.** If the Person had a disease, but did not obtain an appropriate treatment, set the patient type to "improperly treated" and return "FALSE". Otherwise, set the patient type to "properly treated" and return "TRUE". If the person had a disease, but received a PCP or Specialist treatment recommendation of "Overload" (the physician exceeded the maximum patient capacity), set the patient type to "untreated".
- R11: Check for referral.** If the Person has received a referral from a PCP in the current simulation period, the result is "TRUE". Otherwise, the result is "FALSE".
- R12: Check network participation.** Check if a physician is in the network. If so, the result is "TRUE". Otherwise, the result is "FALSE".

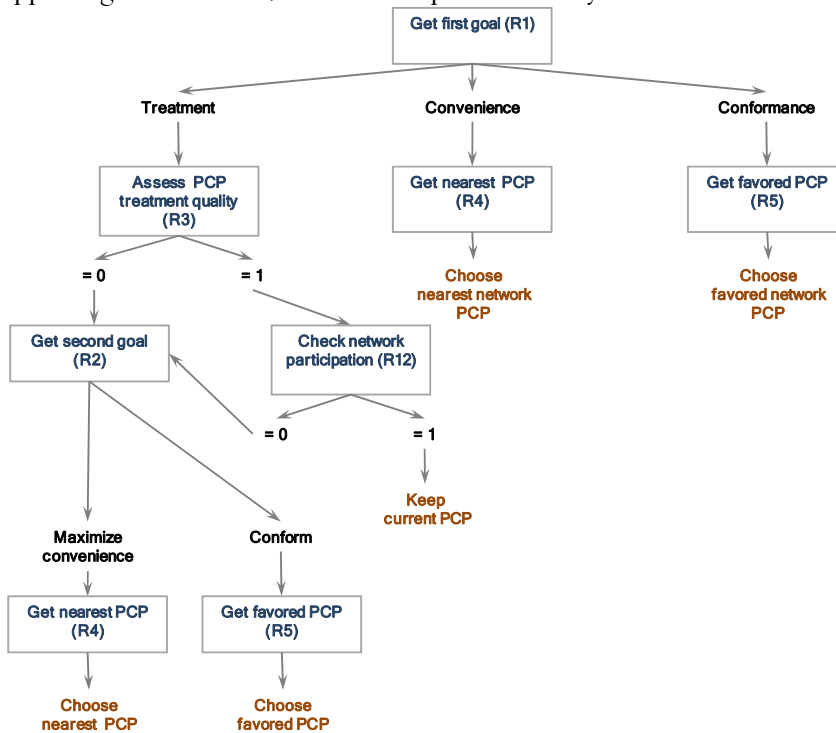
D. DETAILED AGENT DESCRIPTIONS CONTINUED

1. Person continued

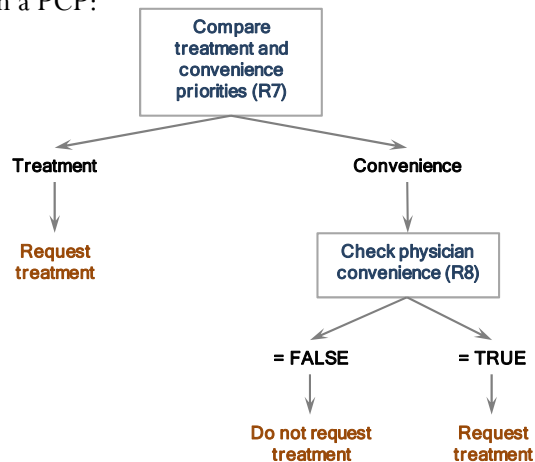
g. Output processes

Following are the Person’s output processes:

P1: Select PCP¹. The Person employs the following process to select the Person’s PCP. The items in boxes are rules supporting this behavior, identified in parentheses by a rule number.



P2: Request PCP treatment². If the result of Rule 6 (Check for disease) is “TRUE”, the Person employs the following process to request treatment from a PCP:



If the Person does not request a treatment, set the patient type to “non-requesting”.

¹ Behavior A1.1.01:G1.1:B001.001 – Select a primary care physician (US), and behavior A1.1.01:G1.1:B002.001 – Switch primary care physicians (US) in the *International compendium of health behavior*.

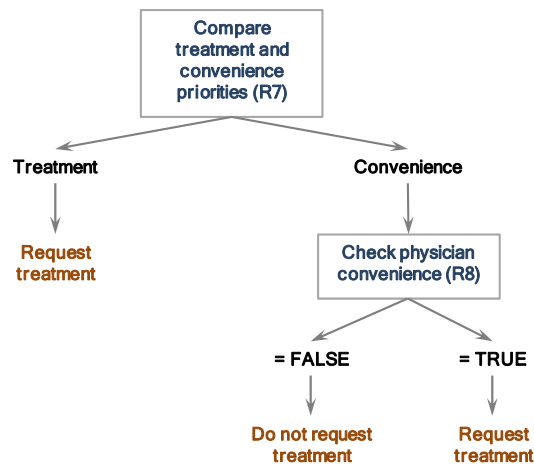
² Behavior A1.1.01:G1.3:B001.001 – Request treatment from a primary care physician (US) in the *International compendium of health behavior*.

D. DETAILED AGENT DESCRIPTIONS CONTINUED

1. Person *continued*

g. Output processes *continued*

P3: Request Specialist treatment. If the result of Rule 11 (Check for referral) is TRUE, the Person employs the following process to request treatment from a Specialist:



If the Person does not request a treatment, set the patient type to “non-requesting”.

- P4: Comply with PCP treatment recommendation.** If the Person receives a PCP treatment recommendation, and if the result of Rule 9 (Determine treatment pain level) is “FALSE”, then the Person complies with the treatment. Otherwise, the Person does not comply with the treatment, and the patient type is set to “non-compliant”.
- P5: Comply with Specialist treatment recommendation.** If the Person receives a Specialist treatment recommendation, and if the result of Rule 9 (Determine treatment pain level) is “FALSE”, then the Person complies with the treatment. Otherwise, the Person does not comply with the treatment, and the patient type is set to “non-compliant”.
- P6: Update disease status.** If the result of Rule 10 (Check for appropriate treatment) is “TRUE”, then set the Person’s disease status to “None”. Otherwise, leave the disease status alone.
- P7: Contract new disease.** The Person contracts a new disease according to the disease incidence probabilities the user enters as parameters. If the Person already has disease D_1 , it can progress to disease D_2 . If the Person already has disease D_2 , there is no change.

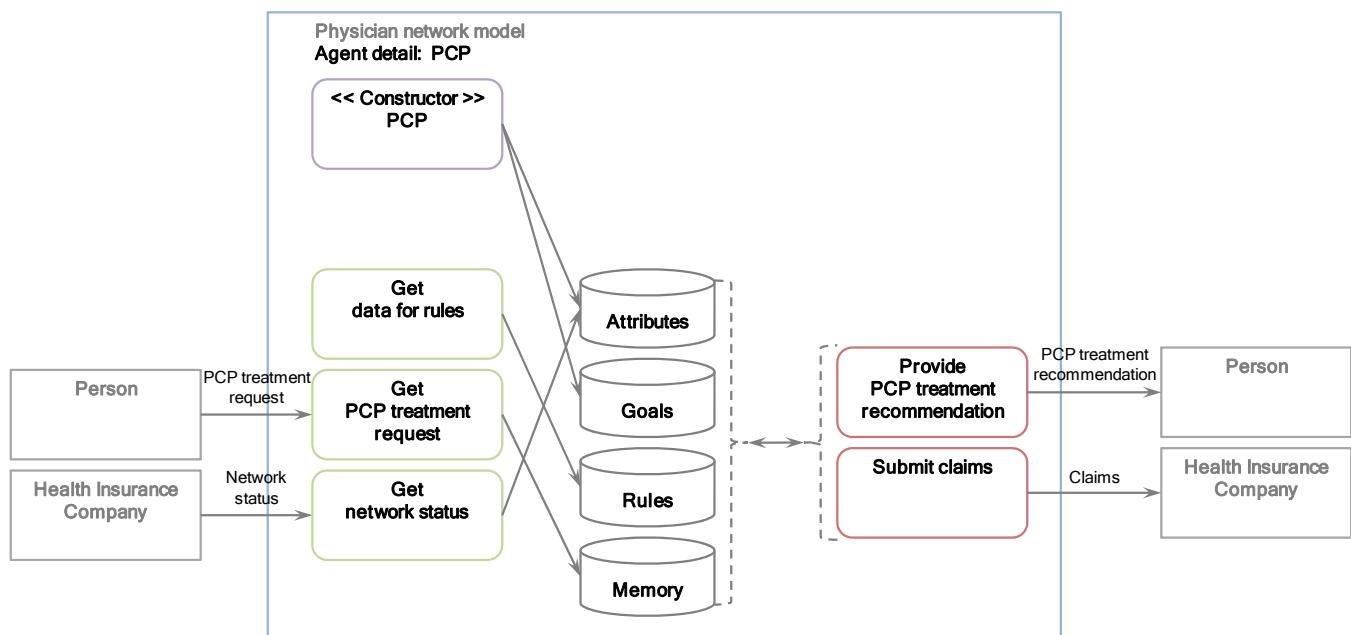
D. DETAILED AGENT DESCRIPTIONS CONTINUED

2. PCP

This section describes the “PCP” agent in detail.

a. Behavior overview

The diagram shows the components of PCP behaviors. For a general discussion of the diagram, see the behavior overview for “Person” (Section D.1.a above). As the diagram shows, the PCP agent includes two processes that result in sending a message to another agent, and two processes that get messages from other agents.¹



b. Attributes

The PCP has the following primary attributes:

- **Identifier.** An integer uniquely identifying the PCP.
- **Current income.** The PCP’s current income for the simulation period, equal to the total claims submitted.
- **Network status.** Whether the PCP is in (“TRUE”) or out (“FALSE”) of the network.
- **Goals.** The PCP’s goals.

c. Memory

In memory, the PCP does not need to store any information.

¹ Technical note: In the model, the PCP class is an extension of the “Physician” class, which is in turn an extension of the “Agent” class.

D. DETAILED AGENT DESCRIPTIONS CONTINUED

2. PCP continued

d. Goals

Each PCP has the following major goals:

- **Care.** The PCP wants to treat patients with correct and least-expensive treatments, and to refer patients only when necessary.
- **Income.** The PCP wants to maximize the amount of claim payments received from the Health Insurance Company.
- **Conformance.** The PCP wants to conform to the most common treatment and referral patterns of neighboring PCPs.

The model user enters parameters to indicate the probability distribution for the highest priority of these goals. Each of the remaining two goals then has a 50 percent chance of being the second-priority goal.

e. Input processes

Following are the PCP's input processes:

- I1: **Get PCP treatment request.** Get a Person's treatment request message.¹
- I2: **Get network status.** Get the PCP's network status from the Health Insurance Company.²

f. Rules

Following are the PCP's rules:

- R1: **Determine first goal.** Determine the PCP's goal with the highest priority.
- R2: **Determine error.** Determine if the PCP will erroneously recommend treatment T_z , based on the error probability rate the user entered as a parameter ("PCP error rate"). Result is "TRUE" if an error, and "FALSE" otherwise.
- R3: **Determine most effective care.** Determine the appropriate, lowest-cost, treatment or referral for the patient's disease.
- R4: **Determine highest-cost care.** Determine the treatment that would result in the highest claim payment.
- R5: **Determine PCP care norm.** Determine the treatment corresponding to the most common first-priority goal among neighboring PCPs. Neighboring PCPs are those within the physician neighborhood radius entered as a parameter. If there are no other PCPs within the neighborhood, revert to the treatment corresponding to the PCP's own first-priority goal.
- R6: **Select referral specialist.** Based on the selection criterion entered as a parameter ("random", "nearest to patient", or "nearest to PCP") the PCP selects a specialist for referral.

¹ Technical note: In the model, this input process is imbedded within the method "p2_ProvideTreatmentRecommendation()".

² Technical note: In the model, this is a method of the "Physician" class, which the PCP inherits.

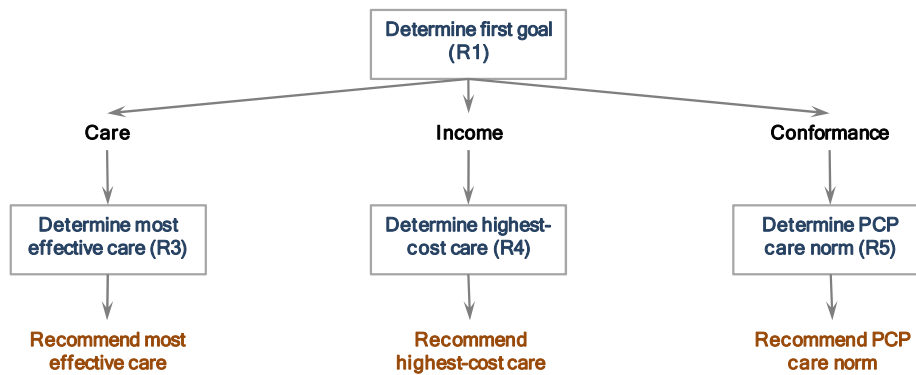
D. DETAILED AGENT DESCRIPTIONS CONTINUED

2. PCP continued

g. Output processes

Following are the PCP’s output processes:

P1: Provide care. If in the current period the PCP has received a number of treatment requests that is greater than the PCP maximum patient load, the PCP replies to remaining requests with the recommended treatment “None”. If the result of R2 (Determine error) is “TRUE”, the PCP recommends the treatment T_z . Otherwise, the PCP recommends a treatment or referral according to the following process. If the recommended treatment is “referral”, then the PCP selects a Specialist for referral whose location is nearest to the patient.



P2: Submit claims. Submit claims for the PCP’s treatments during the simulation period, and increase the PCP’s income by the amount of the claims (it is assumed that the Health Insurance Company pays all claims).

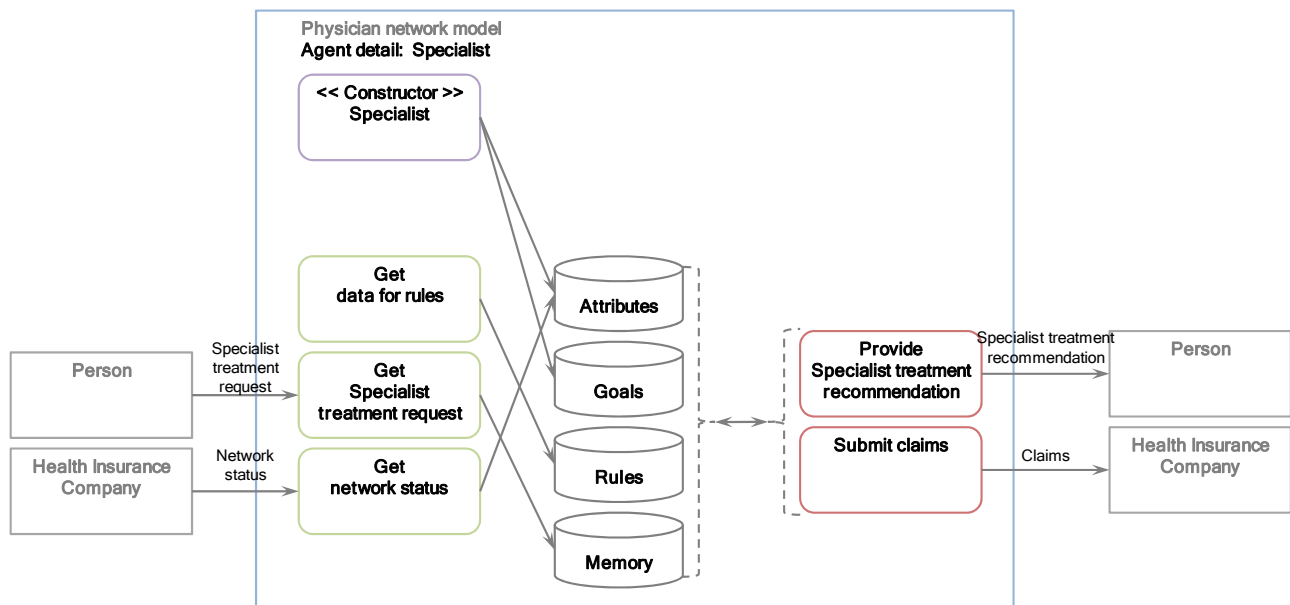
D. DETAILED AGENT DESCRIPTIONS CONTINUED

3. Specialist

This section describes the “Specialist” agent in detail.

a. Behavior overview

The diagram shows the components of Specialist behaviors. For a general discussion of the diagram, see the behavior overview for “Person” (Section D.1.a above). As the diagram shows, the Specialist agent includes two processes that result in sending a message to another agent, and two processes that get messages from other agents.



b. Attributes

The Specialist has the following attributes:

- **Identifier.** An integer uniquely identifying the Specialist.
- **Current income.** The Specialist’s current income for the simulation period, equal to the total claims submitted.
- **Network status.** Whether the Specialist is in (“TRUE”) or out (“FALSE”) of the network.
- **Goals.** The Specialist’s goals.

c. Memory

In memory, the Specialist does not need to store any information.

D. DETAILED AGENT DESCRIPTIONS CONTINUED

3. Specialist *continued*

c. Goals

Each Specialist has the following major goals:

- **Care.** The Specialist wants to treat patients with correct and least-expensive treatments, and to refer patients only when necessary.
- **Income.** The Specialist wants to maximize the amount of claim payments received from the Health Insurance Company.
- **Conformance.** The Specialist wants to conform to the most common treatment pattern of neighboring Specialists.

The model user enters parameters to indicate the probability distribution for the highest priority of these goals. Each of the remaining two goals then has a 50 percent chance of being the second-priority goal.

e. Input processes

Following are the Specialist's input processes:

- I1: **Get Specialist treatment request.** Get a Person's treatment request message.¹
- I2: **Get network status.** Get the Specialist's network status from the Health Insurance Company.²

f. Rules

Following are the Specialist's rules:

- R1: **Determine first goal.** Determine the Specialist's goal with the highest priority.
- R2: **Determine error.** Determine if the Specialist will erroneously recommend treatment T_z , based on the error probability rate the user entered as a parameter ("Specialist error rate"). Result is "TRUE" if an error, and "FALSE" otherwise.
- R3: **Determine most effective care.** Determine the appropriate, lowest-cost, treatment or referral for the patient's disease.
- R4: **Determine highest-cost care.** Determine the appropriate treatment or referral that would result in the highest claim payment.
- R5: **Determine Specialist care norm.** Determine the treatment corresponding to the most common first-priority goal among neighboring Specialists. Neighboring Specialists are those within the Specialists neighborhood radius entered as a parameter. If there are no other Specialists within the neighborhood, revert to the treatment corresponding to the Specialists' second-priority goal.

¹ Technical note: In the model, this input process is imbedded within the method "p2_ProvideTreatmentRecommendation()".

² Technical note: In the model, this is a method of the "Physician" class, which the Specialist inherits.

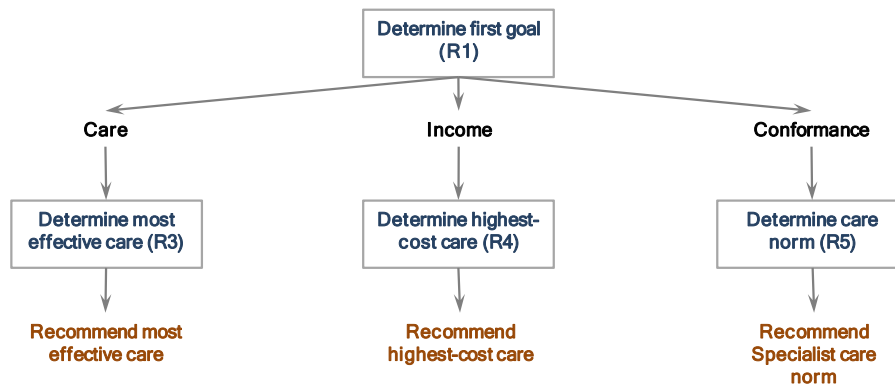
D. DETAILED AGENT DESCRIPTIONS CONTINUED

3. Specialist *continued*

g. Output processes

Following are the Specialist's processes to produce output messages:

P1: Provide specialist treatment. If in the current period the Specialist has received a number of treatment requests that is greater than the Specialist maximum patient load, the Specialist replies to remaining requests with the recommended treatment "None". If the result of R2 (Determine error) is "TRUE", the Specialist recommends the treatment T_z . Otherwise, the Specialist recommends a treatment according to the following process.



P2: Submit claims. Submit claims for the Specialist's treatments during the simulation period, and increase the Specialist's income by the amount of the claims (it is assumed that the Health Insurance Company pays all claims).

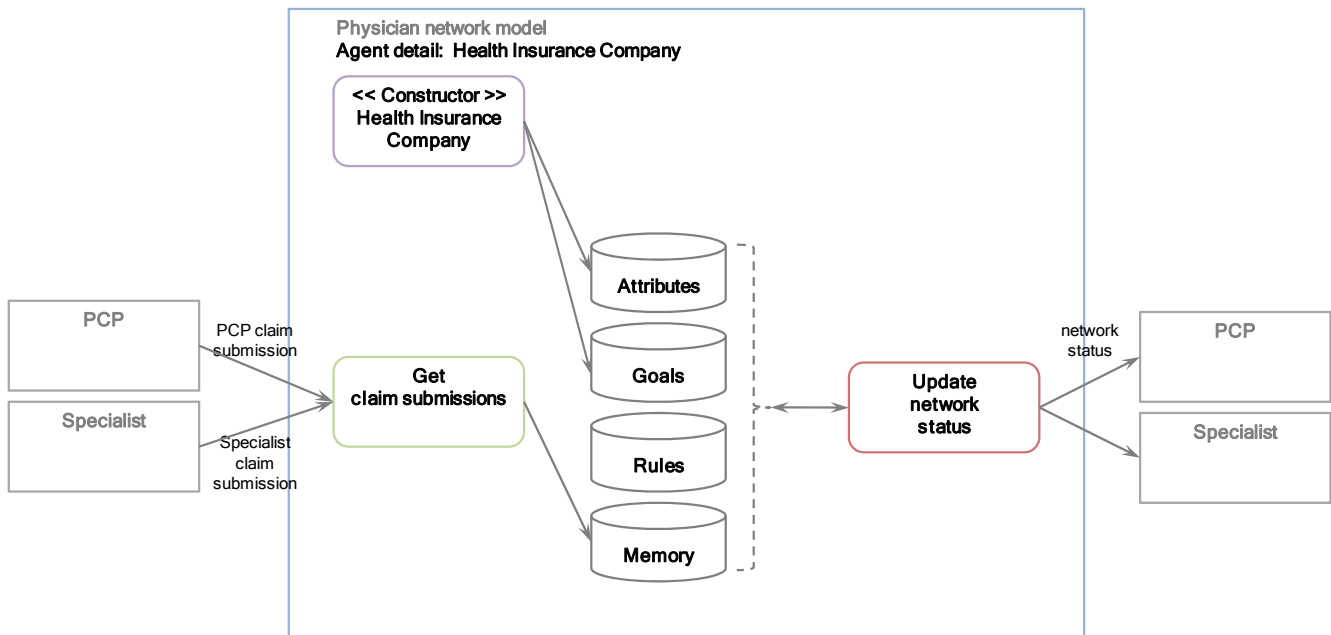
D. DETAILED AGENT DESCRIPTIONS CONTINUED

4. Health Insurance Company

This section describes the “Health Insurance Company” agent in detail.

a. Behavior overview

The diagram shows the components of the Health Insurance Company’s behaviors. For a general discussion of the diagram, see the behavior overview for “Person” (Section D.1.a above). As the diagram shows, the Health Insurance Company agent includes one process that produces output messages.



b. Attributes

The Health Insurance Company has the following attributes:

- **Identifier.** An integer uniquely identifying the company.
- **Goals.** The Health Insurance Company’s goals.

c. Memory

In memory, the Health Insurance Company stores the following information as of the start of the simulation, and for each simulation period thereafter:

- **Claim payments.** The annual amount of claims submitted by PCPs and Specialists.

D. DETAILED AGENT DESCRIPTIONS CONTINUED

4. Health Insurance Company continued

d. Goals

The Health Insurance Company has the following major goals:

- **Income.** The company wants to minimize its claim payments.
- **Network stability.** It wants to keep the physician network stable, so that patient-physician relationships will be minimally affected.
- **Network size.** It wants to keep the physician network as small as possible, to minimize administrative costs.

The model user enters parameters to indicate the probability distribution for the highest priority of these goals. Each of the remaining two goals then has a 50 percent chance of being the second-priority goal.

e. Input processes

Following are the Specialist's input processes:

- I1: Get claims submissions.** Get claims submissions from PCPs and Specialists.

f. Rules

Following are the company's rules:

- R1: Determine first goal.** Determine the company's goal with the highest priority.
- R2: Determine ineffective physicians.** Determine the PCPs and Specialists who in prior periods recommended above a threshold number of inappropriate treatments, inappropriate referrals, or high-cost treatments. The threshold number is entered as a parameter.
- R3: Determine under-utilized physicians.** Determine physicians who did not have the minimum patient load in the prior simulation period. The minimum patient load is entered by the user as a parameter ("minimum patient load").

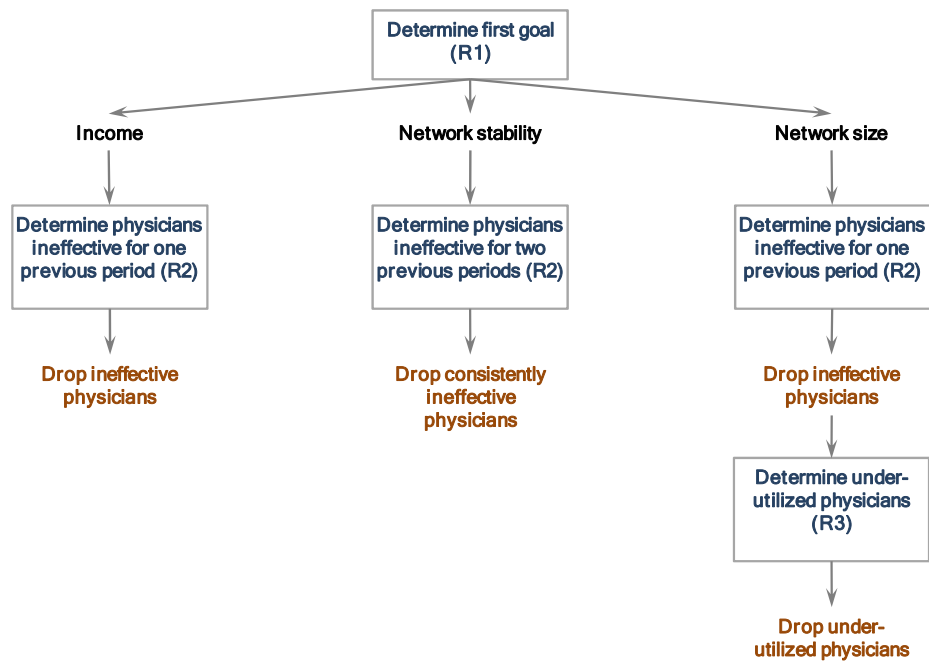
D. DETAILED AGENT DESCRIPTIONS CONTINUED

4. Health Insurance Company *continued*

g. Output processes

Following are the company's processes to produce output messages:

P1 Update network status. The company employs the following process to determine each physician's network status:



D. DETAILED AGENT DESCRIPTIONS CONTINUED

5. Environment

This section describes the “Environment” agent in detail.

a. Behavior overview

The Environment is container for the model’s agents. It creates the simulation’s agents, schedules agent behaviors, and manages the passing of messages among agents. There is one Environment.

The Environment does not have attributes, goals, input processes, rules, or output processes. It does maintain a list of Person agents, a list of Physician agents, and a list of Health Insurance Company agents (there is only one).

To manage messages among agents, it provides the following “management” methods:

- M1: Send message.** Adds a message to the Environment’s message list.
- M2: Get messages.** Returns all the messages of a requested type in the message list for the agent calling the method. After the messages are returned, the Environment removes them from the message list.

E. MESSAGE PASSING FEATURE

For agent-based simulation models, it is critical to establish a robust infrastructure and protocol for agents to communicate with one another, a so-called “message passing mechanism”. In order to set up an agent-based modeling framework for health care decision making, to which others can add custom agents, a standardized message-passing mechanism is particularly important, for it allows agents to communicate with one another and with the framework’s Environment.

Messages

The result—or “output”—from every agent behavior is either a change in one of the agent’s attributes or a “message” that the agent sends to another agent via the Environment. Each message has the following attributes:

- **messageID.** A unique identifier for the message (a string). It consists of the sending agent’s identifier, the simulation’s clock tick when the message is sent, and an ordinal number (1, 2, 3, ...) for the message’s order among all the messages being sent at the clock tick, all separated by dashes. For example, if the message is the fourth message that agent “123” sent at clock tick 97, the messageID would be “123-97-4”.
- **sentTime.** The simulation’s clock tick when the message is posted to the Environment (an integer).
- **messageType.** The type of message being sent (a string). Possible types are:
 - PCP treatment request: A request from a Person agent for a PCP treatment recommendation.
 - Specialist treatment request: A request from a Person agent for a Specialist treatment recommendation.
 - PCP treatment recommendation: A treatment recommendation from a PCP.
 - Specialist treatment recommendation: A treatment recommendation from a Specialist.
 - Claim submission: A claim submission from a PCP or a Specialist.
 - Network membership: A message from the Health Insurance Company giving the results of its network membership decision for a particular PCP or Specialist.
- **fromAgent.** The identifier of the agent sending the message (an integer).
- **toAgent.** The identifier of the agent to which the message is ultimately directed (an integer).
- **message content.** The content of the message. The possible message contents are standardized according to an “ontology” that describes possible agent roles, behaviors, and messages. For the Physician Network Model there are four types of message content: treatment (the treatment recommended by a physician), specialistReferred (the specialist recommended by a PCP), claim (the claim amount submitted by a physician), and networkStatus (the network status decision of the Health Insurance Company).

The message template is a Java class named “Message”, with a getter and setter method for each of its attributes.

Message list

The Environment agent maintains a “Message List” of all the messages that agents in the simulation send. The Message List is an array list of Message objects, “ArrayList<Message>”.

E. MESSAGE PASSING FEATURE CONTINUED

Message passing

The Environment agent has two methods that enable communication—or “message passing”—between two agents:

- **sendMessage()**. An agent calls this method when the agent wants to send a message to another agent. Its signature is “public void sendMessage(MessageID messageID, double sentTime, MessageType messageType, AgentID fromAgent, AgentID toAgent, Treatment treatment, AgentID SpecialistReferred, Claim claim, boolean networkStatus)”. When this method is called, the Environment agent adds the message to the Message List.
- **getMessages()**. An agent calls this method when the agent wants to check if it has received any messages of a particular type. The method returns an array list with all the messages of the requested type that are available for the agent to receive since the last time the agent checked for messages. This list of messages is a subset of the entire message list maintained by the Environment agent. The method’s signature is “public ArrayList<Message> getMessages(AgentID idAgent, MessageType messageType)”, where idAgent is the identifier of the agent checking for messages. When this method is called, the Environment agent removes the returned messages from the Message List.

Examples

Following is an example of how the message passing mechanism would work for the Physician Network Model.

In this example, Person123 sends a message at clock tick 1.10 to PCP3, asking for treatment. PCP3 responds by sending a message to Person123 at clock tick 1.11 with treatment T₁D₁.

Message component	PCP treatment request	PCP treatment recommendation
messageID	Person123-7-1	PCP3-10-21
sentTime	1.10	1.11
messageType	Request PCP treatment	Inform
fromAgent	Person123	PCP3
toAgent	PCP3	Person123
treatment	None	T1D1

E. MESSAGE PASSING FEATURE CONTINUED

Comparison to FIPA-ACL

The most commonly used communication standard for agent-based modeling is the Foundation for Intelligent Physical Agents—Agent Communication Language (FIPA-ACL). This standard is maintained by the IEEE Computer Society, and information about it—including its standards documentation—is found at “www.fipa.org”. The key FIPA agent communication standards are:

- **Specification SC000061 (Message structure specification).** This standard provides that each message between agents should contain the following information:
 - *type*: The message’s type of communication (called the “performative” in the standard). The most common types of communication are “inform”, “request”, “agree”, “not understood”, and “refuse”. All the performatives are described in standard SC000037 (FIPA Communicative Act Library Specification).
 - *sender*: Identity of the sender of the message.
 - *receiver*: Identity of the intended recipients of the message.
 - *reply-to*: Within a conversation thread, the identity of the agent to which reply messages should be directed.
 - *content*: Content of the message.
 - *language*: Language in which the message content is expressed.
 - *encoding*: How the message content is expressed in computer terms, or “encoded”.
 - *ontology*: The ontology underlying the symbols and semantics of the content.
 - *protocol*: Agent interaction protocol in which the message is generated.
 - *conversation-id*: Unique identity of a conversation thread.
 - *reply-with*: An expression to be used by the responding agent to identify the message.
 - *in-reply-to*: Reference to an earlier action to which the message is a reply.
 - *reply-by*: A time/date indicating by when a reply should be received.
- **Specification SC000070 (Message representation string specification).** This standard describes the syntax for the components of the message to be represented by strings of characters.
- **Specification SC000081 (SL content language specification).** This standard describes a recommended syntax for composing the message content.
- **Specification SC000067 (Agent message transport service specification).** This standard describes the “envelope” surrounding a message that the agent-based simulation platform uses to manage the message, as well as how the platform should manage the message. An important aspect of message management is that the platform should deliver all messages to intended recipient agents, rather than wait for the agents to request messages from the platform. After the platform delivers a message, it no longer keeps a record of it. Following are the FIPA message envelope parameters:
 - *to*: Names of the primary recipients of the message.
 - *from*: Name of the agent that sent the message.
 - *comments*: Text comments regarding the message.
 - *payload-length*: Length in bytes of the message “payload”.
 - *payload-encoding*: Language encoding of the message payload.
 - *date*: Creation date and time of the message envelope.
 - *intended-receiver*: Name of the agents to whom the message is to be delivered.
 - *received*: A stamp indicating receipt of a message by the platform.
 - *transport-behavior*: Transport requirements of the message.

E. MESSAGE PASSING FEATURE CONTINUED

The proposed message passing mechanism for the Physician Network Model is different from the FIPA-ACL standard in the following respects:

- It includes only the following FIPA-ACL message information: *reply-with*, *type*, *sender*, *receiver*, and *content*.
- It does not include a message envelope. However, it does include *date* (the time the message was sent).
- It uses very simple syntax.
- The Environment waits for agents to ask for their messages, rather than delivering all messages upon receipt.

Nevertheless, because the proposed message passing mechanism is very similar to the FIPA-ACL standard, it could be easily modified to be fully FIPA-ACL compliant.

F. MODEL TESTING

To test the model, there are several alternatives:

1. Inspection

By running the model under various parameter scenarios, one can assess the model's face validity. The model's many graphs and display options provide details about simulation results. And it is possible to "probe" key agent variables by double-clicking on an agent's icon in a display.

For testing, it is also helpful to use the "A. Agent labels" switch on the parameters screen to turn on the agent identifier labels.

2. Console testing

Throughout the computer code are test sections that send critical variables to the console. These test sections are set off from other code with a special header. Following is an example:

```
//+++++  
//+++++  
// Test  
// This outputs data to the console, to test this method.  
// To run the test, remove comments from the code below.  
// It is best to run the test with a small number of agents.  
//+++++  
//     System.out.println("PCP p2_SubmitClaim() at " +  
//         RunEnvironment.getInstance().getCurrentSchedule().getTickCount());  
//     System.out.println("PCP ID: " + getAgentID().getAgentIDString());  
//     System.out.println("Claim message: " + claimMessage.toString());  
//     System.out.println("Current income: " + currentIncome);  
//     System.out.println("New income: " + newIncome);  
//     System.out.println("-----");  
//+++++  
//+++++
```

To run the test, remove comments from each line of the test code (the lines that begin with "System.out.println").

3. Debugging

Eclipse has a powerful debugging feature. The Web page "eclipsetutorial.sourceforge.net/introduction.html" provides an excellent introduction to the Eclipse debugger.

4. JUnit

Eclipse includes a feature to automate model testing, called JUnit. The Physician Network Model provides examples for using JUnit.

Following is a detailed description of the Workplace Wellness Model, in four sections:

- A. Model overview.** A brief overview of the model.
- B. Agent overview diagram.** A diagram, with accompanying discussion, showing the model's agents.
- C. Behavior schedule.** A summary of when agent behaviors are scheduled.
- D. Detailed agent descriptions.** For each agent, a detailed description of its attributes, goals, memory, rules, and output processes.

Additional documentation about the model is found in the model's computer source code, and associated "Javadoc" documentation.

A. MODEL OVERVIEW

- | | |
|----------------------------------|---|
| 1. General description | <p>The Workplace Wellness Model simulates the behavior of employees working for an employer that provides a workplace wellness program. The program promotes employee exercise, with a goal of reducing the number of overweight and obese employees, thereby reducing the incidence of Type 2 diabetes among employees, reducing the employer's medical expenditures for diabetes care, reducing the number of days of absenteeism and presenteeism (staying at work while sick and unproductive), and lengthening the number of years that employees work before terminating or retiring.</p> <p>The model traces the number of employees who participate in the program, the number of employees who are overweight and obese, the prevalence of diabetes, program costs, medical expenditures, the number of absenteeism and presenteeism days, and the number of years that employees work before terminating or retiring.</p> |
| 2. Questions the model addresses | <p>The model addresses the following questions:</p> <ol style="list-style-type: none">1. What is the impact of various wellness program designs on:<ul style="list-style-type: none">▪ the employer's medical expenditures for diabetes care,▪ employee absenteeism and presenteeism,▪ the number of years employees work until termination or retirement, and▪ employee health (measured by average body weight and diabetes prevalence)?And how do such impacts evolve over time?2. What wellness program design optimizes the combination of (a) the difference between reductions in employer medical expenditures for diabetes care and employer program costs, (b) improvements in absenteeism and presenteeism, (c) improvements in the number of years that employees work, and (d) improvements in employee health? |
-

A. MODEL OVERVIEW CONTINUED

3. Stakeholders interested in the model	<p>It is likely that the following health system stakeholders would find the model useful:</p> <ul style="list-style-type: none">▪ Employer management▪ Health insurance company management▪ State and federal government policymakers
4. Agents	<p>Included in the model are the following agents:</p> <p>Employee. An individual employee of the Employer. An Employee decides whether to participate in the wellness program, decides whether to comply with the program’s exercise recommendations, progresses along three “stages of change” (Ignorance, Awareness, Implementation) for maintaining an exercise regimen¹, decides whether to terminate employment in order to work elsewhere, and decides when to retire. The Employee also changes body weight, may develop diabetes, may incur medical expenses for diabetes, has days of absence from work, and has days of presenteeism.</p> <p>Employer. The model’s user plays the role of the Employer. The Employer decides the type of wellness program to implement. As part of the wellness program, the Employer decides:</p> <ul style="list-style-type: none">▪ the employee body weight categories to target with the program▪ the intensity of the program design▪ whether to reflect in the program’s design and marketing what we have learned about human decision making from behavioral economics▪ the level of program incentives to reward employees who comply with program requirements <p>There are three levels of wellness program design intensity: “None”, “Level 1”, and “Level 2”. The Level 2 program is more effective than the Level 1 program in getting employees to join the program and exercise, but it is more costly. For example, a Level 1 program might supply employees with written information about ways to prevent or reduce obesity, while a Level 2 program might provide such information in a video format, together with a weight screening program and an online health risk assessment.</p>

¹ The model implements a hypothetical three-stage model of behavior change for maintaining an exercise regimen. According to this model, an Employee progresses from Stage 1 (Ignorance) to Stage 2 (Awareness) to Stage 3 (Implementation) in discrete steps, with different factors influencing the Employee’s progression from stage to stage. This model is a simplification of “stage of change” models in the research literature, such as the “transtheoretical model”, the “caution adoption process model”, and the “health action process” model. For more information about “stage of change” health behavior models, see Chapter 6 of the book “Predicting health behavior” by Mark Conner and Paul Norman (published in 2005 by Open University Press).

A. MODEL OVERVIEW CONTINUED

4. Agents continued

There are three levels of reflecting results from behavioral economics (that we will call the “choice architecture intensity”): “None”, “Level 1”, and “Level 2”. Level 2 is more effective than Level 1 in getting employees to join the program and comply with its recommendations, but is more costly. For example, Level 1 might involve presenting program choices (such as whether or not to join) in an order and with defaults that encourage participation. Level 2 might also incorporate results about focusing, ordering, anchoring, etc. throughout the program’s marketing and educational materials. Similarly, there are three levels of incentives: “None”, “Level 1”, and “Level 2”. Level 2 incentives are more effective than the Level 1 incentives in getting employees to join the program and exercise, but are more costly.

Program intensity levels, choice architecture intensity, and program incentive levels are independent: For each program intensity level, the Employer can choose any incentive level and any level of choice architecture intensity.

Environment. The container for the model’s agents. It creates the simulation’s initial Employee agents and maintains a list of Employees. It also reads data from external files, obtains and validates user-provided parameters, and schedules agent behaviors.

5. Output

For each year of the simulation, the model provides the following results, each broken down by program participants and non-participants:

- **Medical expenditures.** The Employer’s medical expenditures for diabetes care.
- **Average medical expenditures.** Per employee average of the Employer’s medical expenditures for diabetes care.
- **Absence.** The number of days of absenteeism and presenteeism.
- **Diabetes prevalence.** The number of Employees with diabetes.
- **Weight prevalence.** The number of Employees who are normal weight, overweight, and obese.¹
- **Average career length.** The average number of employee career years.
- **Average age.** The average age of Employees.
- **Employee turnover.** The number of Employees who terminate employment or retire.
- **Program participants.** The number of participating Employees.
- **Total program costs.** The Employer’s costs for program administration, choice architecture, and incentives.

¹ The model employs three weight categories: Normal (18.5 to 25.0 BMI), Overweight (25.0 to 30.0 BMI), and Obese (30 BMI and above). BMI stands for “Body Mass Index” and is equal to weight (in pounds) divided by height (in inches) squared, times the constant 703.

A. MODEL OVERVIEW CONTINUED

6. Simplifying assumptions
1. Except for age, disease status, stage of change, weight category, and workplace location, all Employees have the same demographic characteristics. There is no distinction by gender, family status, job title, or income level.
 2. An Employee's exercise level is directly dependent on the Employee's stage of change: An Employee at Stage 3 (Implementation) is maintaining a full exercise regimen, and an Employee at other stages of change is not exercising. Thus, there are two levels of exercise: none and full compliance with an exercise regimen.
 3. In the absence of a wellness program, an Employee will not progress along the stages of change.
 4. An Employee will not retrogress along the stages of changes. For example, an Employee will not go from Stage 3 (Implementation) to Stage 2 (Awareness).¹
 5. Only an Employee's level of exercise affects the employee's weight. The model ignores other factors that influence weight, such as diet.
 6. Only an Employee's weight affects the risk of contracting diabetes. For example, the model ignores the effects of diet on contracting diabetes.
 7. Only exercising (Stage 3) Employees can drop weight, and only non-exercising (Stage 1 or 2) Employees can gain weight.
 8. The model does not measure other wellness impacts of exercise, such as cholesterol and mental health.
 9. In the simulation, the Employer establishes a new workplace wellness program at time 0.00.
-
7. Parameters
- Following are parameters the user can set before the simulation starts. If a user does not enter a parameter, the model will supply a default value.
- A1. Employee labels.** Whether identification labels are shown for Employees on the display. Labels are especially helpful when testing the model, or trying to figure out an unusual pattern. Choices: "Yes", "No". Default value: "No".
- A2. Maximum number of simulation periods.** The maximum number of simulation periods. Choices: any integer. Default value: 100.
- B. Random number seed.** The "seed" number used for the simulation's random number generators. To vary the generation of random numbers for simulation runs, the seed can be varied. Using a constant random number seed enables the model user to reproduce simulation runs. Choices: any integer. Default value: automatically generated based on the computer system's clock.
-

¹ This assumption is contrary to what we know about stages of behavior change. According to research, people commonly retrogress.

A. MODEL OVERVIEW CONTINUED

-
7. Parameters continued
- C1. Program design - Target group.** The weight category that the Employer targets with the wellness program. Choices: Normal, Overweight, Obese, Normal and Overweight, Overweight and Obese, All, None. Default: All.
 - C2a. Program design - Type.** The type of wellness program the Employer establishes. Choices: None, Level 1, Level 2. Default: Level 1.
 - C2b. Program design - Type Level 1 annual cost (per participant).** The annual per-Participant cost of administering a Level 1 wellness program. Choices: Any positive number. Default: 150.00.¹
 - C2c. Program design - Type Level 2 annual cost (per participant).** The annual per-Participant cost of administering a Level 2 wellness program. Choices: Any positive number. Default: 250.00.
 - C3a. Program design - Choice architecture intensity.** The intensity level of implementing behavioral economics choice architecture. Choices: None, Level 1, Level 2. Default: None.
 - C3b. Program design - Choice architecture Level 1 annual cost (per participant).** The annual per-Participant cost of implementing a Level 1 choice architecture. Choices: Any positive number. Default: 50.00.
 - C3c. Program design - Choice architecture Level 2 annual cost (per participant).** The annual per-Participant cost of implementing a Level 2 choice architecture. Choices: Any positive number. Default: 100.00.
 - C4a. Program design - Incentive intensity.** The type of wellness program incentive that the Employer employs. Choices: None, Level 1, Level 2. Default: Level 1.
 - C4b. Program design - Incentive Level 1 annual cost (per participant).** The annual per-participant cost of offering a Level 1 incentive. Choices: Any positive number. Default: 500.00.²
 - C4c. Program design - Incentive Level 2 annual cost (per participant).** The annual per-participant cost of offering a Level 2 incentive. Choices: Any positive number. Default: 750.00.
 - D. Average annual diabetes medical expenditure (per participant).** The Employer's average per person annual medical expenditures for diabetes care. Choices: Any positive number. Default: 10,000.00.
-

¹ Fidelity Investments and the National Business Group on Health

² Fidelity Investments and the National Business Group on Health

A. MODEL OVERVIEW CONTINUED

7. Parameters continued
- E1. Number of Employees.** The number of Employee agents for the simulation. Choices: any integer. (It is best to choose a positive integer between 1 and 10,000.) Default value: 500.
 - E2. Employee age distribution type.** How Employee ages are distributed. Ages are integers from 25 to 64, inclusive. Choices: “Random normal distribution” and “Random uniform distribution”. Default: Random normal distribution.
 - E3. Employee average age (normal distribution).** If the user selects “Random normal distribution” for parameter E2, this parameter gives the average age for the distribution. Choices: any number from 25 to 64, inclusive. Default: 45.
 - E4. Employee age standard deviation (normal distribution).** If the user selects “Random normal distribution” for parameter E2, this parameter gives the normal distribution’s standard deviation. Choices: any number. (It is best to limit the standard deviation to a positive number less than half the span of possible ages. Otherwise, many Employees will end up at the age boundaries. The age span is 40 years.) Default: 10.0.
 - E5. Employee workplace location distribution type.** How Employees are located in their workplace Environment. Choices: “Random normal distribution” and “Random uniform distribution”. Default: Random normal distribution.
 - E6. Employee workplace location standard deviation (normal distribution).** If the user selects “Random normal distribution” for parameter E5, this parameter gives the normal distribution’s standard deviation. Choices: any number. (It is best to limit the standard deviation to a positive number less than half the width of the workforce Environment. Otherwise, many Employees will end up at the Environment’s boundaries. The Environment’s width is 100.) Default: 15.0.
 - F. Employee workplace neighborhood radius.** The radius to determine Employees in an Employee’s workplace neighborhood.¹ Choices: any number. (It is best to choose a positive number.) Default: 10.0.
-

¹ For an Employee with “Conformance” as a top priority, the Employee’s neighborhood is used to help determine the Employee’s decisions with respect to participation in the wellness program, and compliance with program exercise recommendations. The model assumes that such Employees will conform to the most common decision of the Employees who are within the Employee’s neighborhood.

A. MODEL OVERVIEW CONTINUED

-
7. Parameters continued
- G1. Employee first goal percent - Health.** With this parameter the user indicates the percentage of Employees who have the goal “Health” as a top priority.¹ Choices: any number between 0.00 and 100.00. (G1, G2, and G3 should add to 100.00.) Default: 33.33.
 - G2. Employee first goal percent - Conformance.** With this parameter the user indicates the percentage of Employees who have the goal “Conformance” as a top priority. Choices: any number between 0.00 and 100.00. (G1, G2, and G3 should add to 100.00.) Default: 33.33.
 - G3. Employee first goal percent - Income.** With this parameter the user indicates the percentage of Employees who have the goal “Income” as a top priority. Choices: any number between 0.00 and 100.00. (G1, G2, and G3 should add to 100.00.) Default: 33.33.
 - H1. Employees normal weight percent.** The percentage of Employees initially in the normal weight category. Choices: any number between 0.00 and 100.00 (H1, H2, and H3 should add to 100.00). Default: 40.00.
 - H2. Employees overweight percent.** The percentage of Employees initially in the overweight category. Choices: any number between 0.00 and 100.00 (H1, H2, and H3 should add to 100.00). Default: 45.00.
 - H3. Employees obese percent.** The percentage of Employees initially in the obese category. Choices: any number between 0.00 and 100.00 (H1, H2, and H3 should add to 100.00). Default: 15.00.
-

¹ The three Employee goals are Health, Conformance, and Income. For more information about these goals, see the detailed Employee agent description below.

A. MODEL OVERVIEW CONTINUED

-
7. Parameters continued
- I1a. Employee stage of change - Normal weight - Stage 1 percent.** The percentage of normal-weight Employees initially at Stage 1 (Ignorance). Choices: Any number between 0.00 and 100.00. (I1a, I1b, and I1c should add to 100.00.) Default: 33.33.
 - I1b. Employee stage of change - Normal weight - Stage 2 percent.** The percentage of normal-weight Employees initially at Stage 2 (Awareness). Choices: Any number between 0.00 and 100.00. (I1a, I1b, and I1c should add to 100.00.) Default: 33.33.
 - I1c. Employee stage of change - Normal weight - Stage 3 percent.** The percentage of normal-weight Employees initially at Stage 3 (Implementation). Choices: Any number between 0.00 and 100.00. (I1a, I1b, and I1c should add to 100.00.) Default: 33.33.
 - I2a. Employee stage of change - Overweight - Stage 1 percent.** The percentage of overweight Employees initially at Stage 1 (Ignorance). Choices: Any number between 0.00 and 100.00. (I2a, I2b, and I2c should add to 100.00.) Default: 33.33.
 - I2b. Employee stage of change - Overweight - Stage 2 percent.** The percentage of overweight Employees initially at Stage 2 (Awareness). Choices: Any number between 0.00 and 100.00. (I2a, I2b, and I2c should add to 100.00.) Default: 33.33.
 - I2c. Employee stage of change - Overweight - Stage 3 percent.** The percentage of overweight Employees initially at Stage 3 (Implementation). Choices: Any number between 0.00 and 100.00. (I2a, I2b, and I2c should add to 100.00.) Default: 33.33.
 - I3a. Employee stage of change - Obese - Stage 1 percent.** The percentage of obese Employees initially at Stage 1 (Ignorance). Choices: Any number between 0.00 and 100.00. (I3a, I3b, and I3c should add to 100.00.) Default: 33.33.
 - I3b. Employee stage of change - Obese - Stage 2 percent.** The percentage of obese Employees initially at Stage 2 (Awareness). Choices: Any number between 0.00 and 100.00. (I3a, I3b, and I3c should add to 100.00.) Default: 33.33.
 - I3c. Employee stage of change - Obese - Stage 3 percent.** The percentage of obese Employees initially at Stage 3 (Implementation). Choices: Any number between 0.00 and 100.00. (I3a, I3b, and I3c should add to 100.00.) Default: 33.33.
-

A. MODEL OVERVIEW CONTINUED

-
7. Parameters continued
- J1. Turnover - Base probability.** Annual base probability that an Employee terminates. Choices: any number between 0.00 and 1.00. Default: 0.05.
 - J2. Turnover - Additional probability.** The additional annual probability that an Employee with a 1st goal of “Health” will terminate if there is no wellness program. Choices: any number between 0.00 and 1.00. Default: 0.03.
 - J3. Retirement age.** The Employer’s earliest retirement age. There is no mandatory retirement age. Choices: any integer greater than 25. Default: 65.
 - K1. Absenteeism days.** Number of days per year that an Employee with diabetes is absent from work. Choices: any number. Default: 10.00 days.
 - K2. Presenteeism days.** Number of days per year that an Employee with diabetes is at work but unproductive. Choices: any number. Default: 20.00 days.
 - L1. Data workbook file name:** The name of the Excel workbook with data for this model. The file should be in the model’s “data” folder. Choices: any valid file name. Default: “WorkplaceWellnessModelData_v1.xls”.
 - L2a. Diabetes incidence worksheet name.** The name of the Excel worksheet with diabetes incidence factors. Choices: any valid worksheet name. Default: “Diabetes incidence”.
 - L2b. Diabetes incidence adjustment factor.** A multiplicative factor to adjust the diabetes incidence factors. Choices: any number. Default: “1.00”.
 - L3a. Diabetes prevalence worksheet name.** The name of the Excel worksheet with diabetes prevalence factors. Choices: any valid worksheet name. Default: “Diabetes prevalence”.
 - L3b. Diabetes prevalence adjustment factor.** A multiplicative factor to adjust the diabetes prevalence factors. Choices: any number. Default: “1.00”.
 - L4a. Diabetes remission worksheet name.** The name of the Excel worksheet with diabetes remission factors. Choices: any valid worksheet name. Default: “Diabetes remission”.
 - L4b. Diabetes remission adjustment factor.** A multiplicative factor to adjust the diabetes remission factors. Choices: any number. Default: “1.00”.
 - L5a. Weight progression worksheet name.** The name of the Excel worksheet with weight progression factors for Employees who do not exercise. Choices: any valid worksheet name. Default: “Weight progression”.
 - L5b. Weight progression adjustment factor.** A multiplicative factor to adjust the weight progression factors. Choices: any number. Default: “1.00”.
-

A. MODEL OVERVIEW CONTINUED

-
7. Parameters continued
- L6a. Weight regression worksheet name.** The name of the Excel worksheet with weight regression factors for Employees who exercise. Choices: any valid worksheet name. Default: “Weight regression”.
 - L6b. Weight regression adjustment factor.** A multiplicative factor to adjust the weight regression factors. Choices: any number. Default: “1.00”.
 - M1. Override parameters.** Whether the model program can override parameters provided through the user interface or from the data file. Choices: “Yes”, “No”. Default: “No”.
 - M2. Write output file.** Whether the model’s program can write an output file (as opposed to writing output files through the user interface). Choices: “Yes”, “No”. Default: “No”.
 - M3. Output file name.** The name of the output file that the model’s program will write out. The file will be written to the model’s “output” folder. Choices: any valid file name. (It is a good idea to end the file name with “.csv”, to make it easy to open in Excel.) Default: “None”.

8. Data files

The following data is found in an Excel workbook in the model’s “data” folder, in separate worksheets:

- **Diabetes incidence.** Annual probabilities that an Employee will develop diabetes. These incidence rates are given by age from 25 through 75, separately by weight (normal weight, overweight, and obese) and exercise regimen (with exercise, without exercise) categories. A source for this data is Melton LF, Palumbo PJ, Chu CP: Incidence of diabetes mellitus by clinical type. *Diabetes Care* 6:75-86, 1983.
 - **Diabetes remission.** Annual probabilities that an exercising Employee with diabetes will remit. These remission rates are given by age from 25 through 75, separately by weight category (normal weight, overweight, and obese).
 - **Weight progression.** Annual probabilities that a non-exercising Employee will progress to the next weight category. These progression rates are given by age from 25 through 75, separately by weight category (normal weight and overweight).
 - **Weight regression.** Annual probabilities that an exercising Employee will regress to the previous weight category. These regression rates are given by age from 25 through 75, separately by weight category (overweight and obese).
-

A. MODEL OVERVIEW CONTINUED

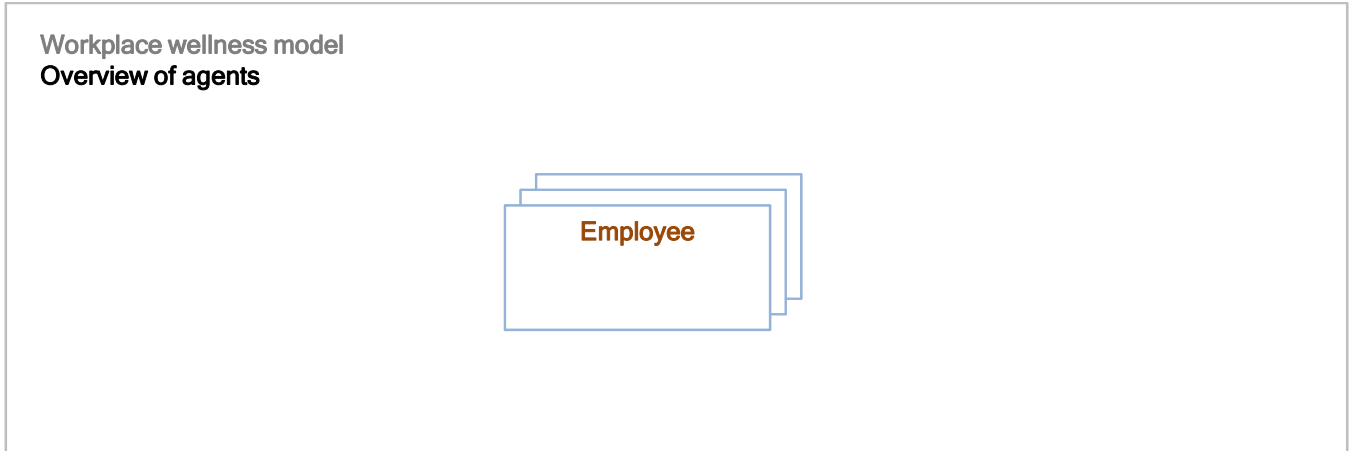
9. Environment displays 1. **Workplace.** This display shows where the Employees work. Employees are represented by disks.

Employees with diabetes are colored red, and those without diabetes are grey. The size of the disk corresponds to the Employee's weight category. Employees with small disks have normal weight, those with larger disks are overweight, and those with the largest disks are obese.

Disks with a blue border represent Employees in the wellness program; and those with a black border are not in the program. Disks of Employees who terminate or retire are first colored white, and are then removed from the workplace environment.

B. AGENT OVERVIEW DIAGRAM

The diagram below shows the model’s main agents. As the diagram shows, the model includes only Employee agents.



C. BEHAVIOR SCHEDULE

The chart below shows the agent behaviors and the order in which they occur. In the chart, each behavior is represented by its core “produce output” process. For example, the Employee’s behavior “Make participation decision” is represented by the process “P1: Make participation decision”. This one-to-one relationship between a behavior and its core “produce output” process is possible because the core process is connected to all behavior components.¹

As the chart shows, some behaviors take place at the beginning of each year, some take place at the end of each year, and some happen mid-year.² The order of behavior is indicated by the number in parentheses after the behavior name.

Agent	Behavior for each year of the simulation		
	Beginning of year	Middle of year	End of year
1. Employee	P1: Make participation decision(1)	P2: Make compliance decision (1)	P3: Determine weight category (1) P4: Determine disease status (2) P5: Terminate employment (3) P6: Retire (4)

¹ For more information about behavior components, see Chapter One (Dimensions of behavior).

² Technical note: Agent behaviors for the simulation are scheduled in the model’s “Schedule” class, which is called by the Environment. In the Schedule class, there are many clock ticks in a year. Each behavior is scheduled during one of these clock ticks, in an order indicated by the decimal part of each clock tick. For example, Behavior1 might take place at time “1.1”, followed by Behavior2 at time “1.2”.

D. DETAILED AGENT DESCRIPTIONS

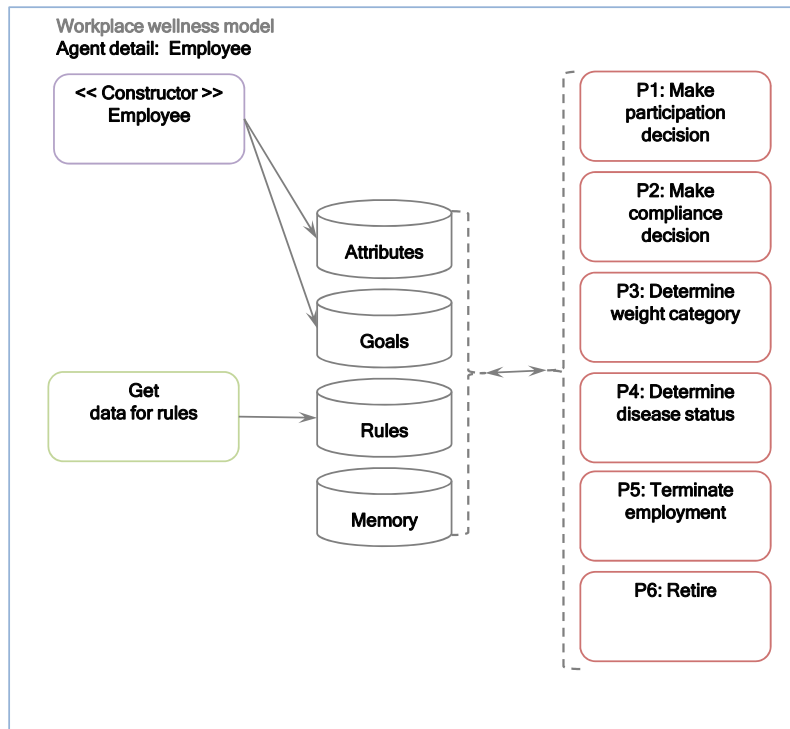
1. EMPLOYEE

This section describes the “Employee” agent in detail.¹

a. Behavior overview

The diagram below shows the components of Employee behaviors, including:

- **Produce output and send output.** Six “produce output” processes (represented by rose-colored rounded boxes) that produce the agent’s behaviors. These correspond to the Employee’s six behaviors.
- **Get input.** One “get input” process (in green) to get data to support the behaviors.²
- **Attributes, goals, rules, memory.** Data stores for the Employee’s attributes, goals, rules, and memory (in grey).



For completeness, the diagram also shows a “constructor” process (in mauve) that creates each instance of an Employee for the simulation, and initializes the Employee’s attributes and goals.³

¹ Technical note: In the model, the Employee class is an extension of the Agent class.
² Technical note: The “Get data for rules” process employs “getter” methods in the classes of other agents.
³ Technical note: The constructor process is the “constructor” for the Employee class.

D. DETAILED AGENT DESCRIPTIONS CONTINUED

1. Employee continued

b. Attributes

Each Employee has the following primary attributes:

- **Identifier.** An integer uniquely identifying the Employee.
- **Location.** Where the Employee is located in the workplace environment (x and y coordinates on the two-dimensional grid).
- **Goals.** The Employee's goals.
- **Current age.** The Employee's age.
- **Current weight category.** The Employee's weight category ("Normal", "Overweight", "Obese").
- **Current disease status.** The Employee's current disease status ("Diabetes" or "None").
- **Current stage of change.** The Employee's current stage of change ("Stage 1", "Stage 2", or "Stage 3").
- **Current program participation.** Whether the Employee is currently participating in the wellness program ("true" or "false").
- **Current employment status.** Whether the Employee is currently employed with the Employer ("true" or "false").
- **Current retirement status.** Whether the employee is currently retired ("true" or "false").

c. Memory

In memory, the Employee stores the following historical information:

- **Previous stage of change.** The Employee's previous stage of change ("Stage 1", "Stage 2", or "Stage 3").
- **Previous program participation.** Whether the Employee participated in the wellness program in the previous year ("true" or "false").

d. Goals

An Employee has the following major goals:

- **Health.** The Employee wants to engage in behaviors that increase health.
- **Conformance.** The Employee wants to conform to the behavior of the majority of the Employee's workplace neighbors.
- **Income.** The Employee wants to engage in behavior that maximizes the Employee's income.

The model user enters parameters to indicate the probability distribution for the highest priority of these goals. Each of the remaining two goals then has a 50 percent chance of being the second-priority goal.

D. DETAILED AGENT DESCRIPTIONS CONTINUED

1. Employee continued

e. Input processes

The Employee uses the following processes to obtain data:

- I1: **Get incentive level.** Get the level of incentives that the Employer established as part of the wellness program. Possible values are “None”, “Level 1”, or “Level 2”.
- I2: **Get program level.** Get the level of wellness program design that the Employer established. Possible values are “None”, “Level 1”, or “Level 2”.
- I3: **Get choice architecture level.** Get the level of choice architecture that the Employer employs. Possible values are “None”, “Level 1”, or “Level 2”.

f. Rules

Following is the Employee’s repertoire of rules:

- R1: **Determine first goal.** Determine the Employee’s goal with the highest priority. This rule returns the highest-priority goal.
- R2: **Determine favored participation decision.** Determine the participation decision that most of the Employee’s workplace neighbors selected in the previous year.
- R3: **Get disease status.** If the Employee has diabetes, the result is “Diabetes”. Otherwise, it is “None”.
- R4: **Get neighbor’s most common stage of change.** Determine the stage of change that most of the Employee’s workplace neighbors had in the previous year. Note that in the previous year these neighbors may not have been program participants.

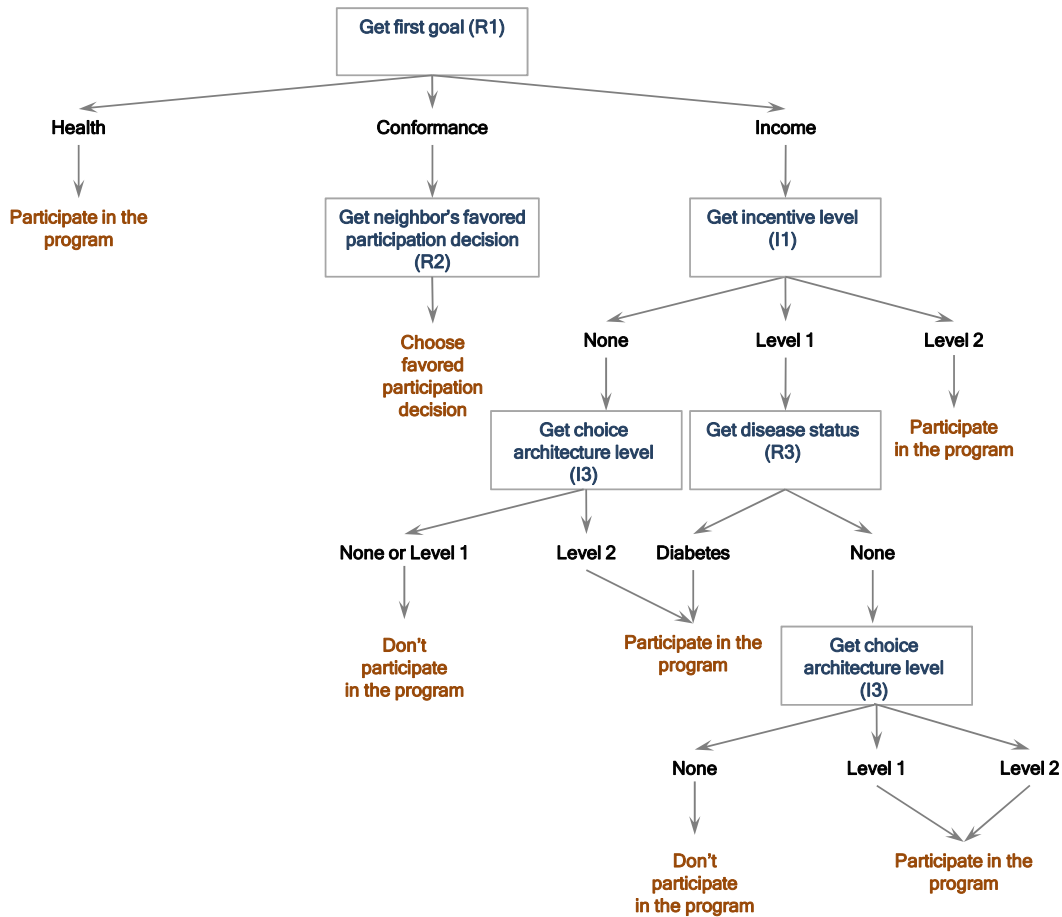
D. DETAILED AGENT DESCRIPTIONS CONTINUED

1. Employee continued

g. Output processes

Following are the Employee’s output processes:

P1: Make participation decision. If the Employer offers a wellness program and the Employee is eligible for it, the Employee employs the following process to decide whether to participate in the program. The items in boxes are rules or input methods supporting this behavior, identified in parentheses by a rule (preceded by “R”) or input (preceded by “I”) method number. This decision is repeated each year of the simulation.

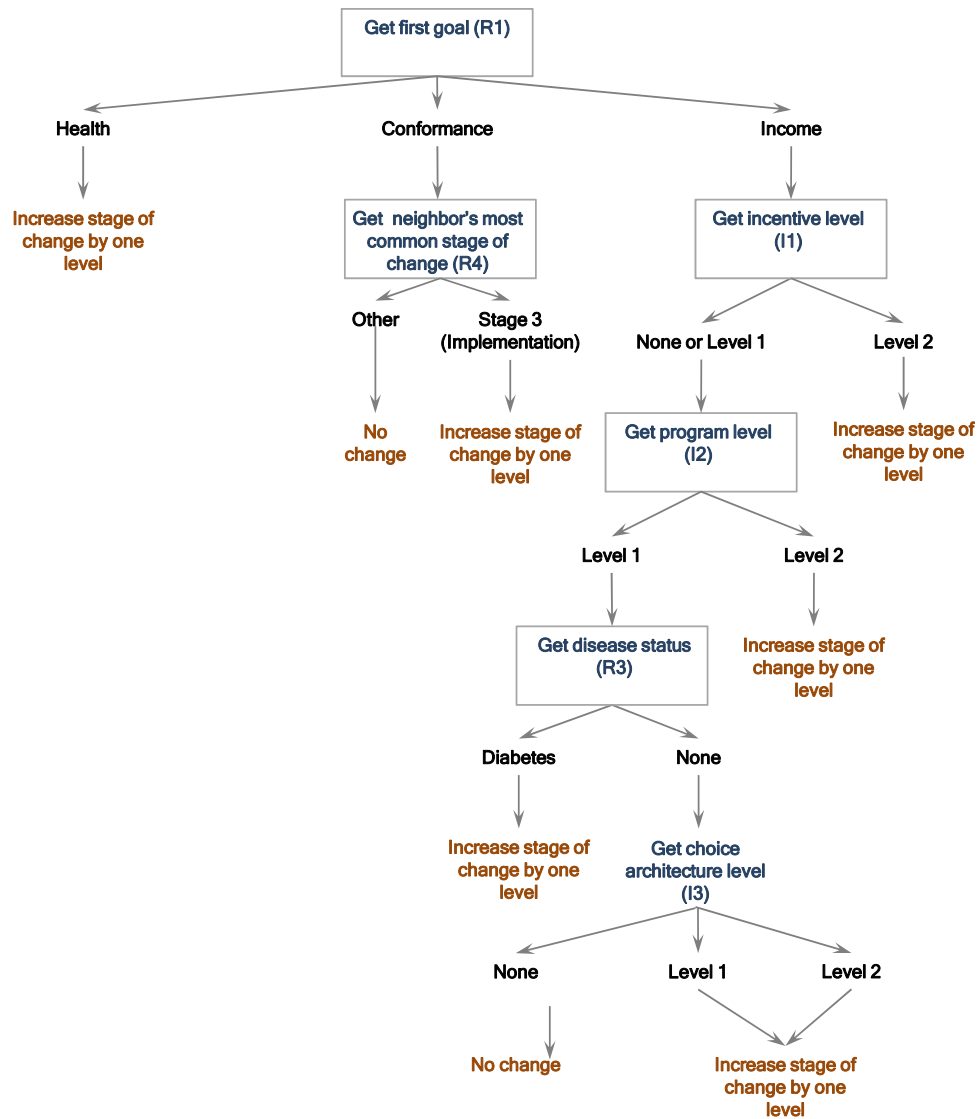


D. DETAILED AGENT DESCRIPTIONS CONTINUED

1. Employee continued

g. Output processes continued

P2: Make compliance decision. If the Employee is participating in the wellness program, and the Employee is not already at stage of change 3 (Implementation), the Employee employs the following process to determine whether to follow the wellness program’s recommendations to exercise (and thereby increase the stage of change by one level). After employing this process, if the Employee is at stage of change 3 (Implementation), the Employee is maintaining an exercise regimen and is thus compliant with the program.



D. DETAILED AGENT DESCRIPTIONS CONTINUED

1. Employee continued

g. Output processes continued

P3: Determine weight category. If the Employee's stage of change is Stage 3 (Implementation) and the Employee's current weight category is either Overweight or Obese, the Employee's weight category regression is determined according to weight **regression** probability parameters (from the Excel data file).

If the Employee's stage of change is not Stage 3 and the Employee's weight category is either Normal or Overweight, the Employee's weight category progression is determined according to the weight **progression** probability parameters (from the Excel data file).

Otherwise there is no change in the weight category.

P4: Determine disease status. If the Employee does not currently have Diabetes, the Employee's disease status is determined based on the Employee's stage of change and weight category and the diabetes incidence parameters (from the Excel data file).¹

If the Employee currently has Diabetes, and the Employee is exercising (Stage of Change 3), the disease status is determined based on the Employee's weight category and the diabetes remission probabilities (from the Excel data file).

P5: Terminate employment. Based on the Employee's goals and the level of the Employer's wellness program, the probability of the Employee's termination is determined according to the parameters J (Turnover – Base probability, and Turnover – Additional probability). If the Employee terminates, another Employee is hired with characteristics determined as for the simulation's initial employees.

P6: Retire. If the Employee is at the retirement age (parameter J3) or older, and the Employee has diabetes or is obese, the employee retires. Also, if the Employee reaches the maximum age of the data tables, the Employee retires. Otherwise the Employee continues to work. If the Employee retires, another Employee is hired with characteristics determined as for the simulation's initial employees.

2. ENVIRONMENT

This section describes the "Environment" agent.

a. Behavior overview

The Environment is the container for the model's agents. It creates the simulation's agents, maintains a list of Employee agents, schedules agent behaviors, obtains parameters that the user enters, and obtains data from data files.

The Environment does not have attributes, goals, input processes, rules, or output processes.

¹ The diabetes incidence and remission factors vary by weight category and stage of change (exercising or not exercising).

Following is a detailed description of the “adverse selection” sample model. The description is in several sections:

A. Model overview. A brief overview of the model.

B. Agent overview diagram. A diagram, with accompanying discussion, showing the communication relationships among the model’s agents.

C. Behavior schedule. A summary of when agent behaviors are scheduled.

D. Detailed agent descriptions. For each agent, a detailed description of its attributes, goals, experience, rules, and output processes.

Additional documentation about the model is found in the model’s computer source code documentation.

A. MODEL OVERVIEW

1. Description	The model simulates how uninsured people purchase individual health insurance from a Health Insurance Exchange (“Exchange”). ¹ For each time period of the simulation, it simulates the interrelated behaviors of the following agents: uninsured inhabitants of a community, two competing health insurance companies, a state-run Exchange, a state insurance commissioner (called a “premium rate limit agency” in the model), a state risk adjustment agency (which reallocates premium income among insurance companies to maintain health risk expenditure equity among them), a federal government penalty tax agency, and two networks of healthcare providers (one for each health insurance company).
2. Questions addressed	The model is designed to address the following questions: <ol style="list-style-type: none">1. How can state agencies and the federal government work together to minimize the number of uninsured people?2. In an Exchange environment, how can a health insurance company:<ul style="list-style-type: none">▪ minimize adverse selection?▪ maximize its profit for health insurance offered through an Exchange?▪ maximize its market share for health insurance offered through an Exchange, while maintaining profitability?
3. Interested stakeholders	It is likely that the following stakeholders would find the model interesting: <ol style="list-style-type: none">1. Health insurance company management2. Provider network management3. State and federal government policymakers

¹ As a result of recent healthcare reform in the US, each state must establish such an Exchange as of January 1, 2014. An Exchange provides individuals and small companies a central place to purchase health insurance.

A. MODEL OVERVIEW CONTINUED

4. Agents and their behaviors

The model includes the following agents:

Person. An individual inhabitant of the state providing the Exchange. The Person agent decides whether to purchase a health insurance plan from the Exchange. If a Person purchases insurance, the Person requests treatment from a Provider Network if the Person becomes ill. If a Person does not purchase insurance, the Person pays a penalty tax to the Penalty Tax Agency and does not request treatment when ill. There can be many Person agents.

Health Insurance Company. A health insurance company that sets premium rates for its plans on the Exchange, negotiates fee levels with its Provider Network, pays claims submitted by its Provider Network, submits its profit experience to the Premium Rate Limit Agency, and submits its risk experience results to the Risk Adjustment Agency. There are two companies, Company A and Company B. Each offers two insurance plans: one that has no member co-payment and is therefore “richer” (Plans “A1” and “B1”), and one that has a co-payment (Plans “A2” and “B2”).

Exchange. A Health Insurance Exchange that offers individual health plans for Person agents to purchase. The Exchange offers four insurance plans (A1, A2 and B1, B2), two from each Health Insurance Company. The Exchange also advertises its services to encourage Person agents to purchase health insurance, and sets the order in which plans are offered on its website. In the model, there is one Exchange.

Penalty Tax Agency. A federal agency that sets the level of penalty tax for Person agents who do not purchase insurance. There is one Penalty Tax Agency.

Provider Network. A group of healthcare providers that provides medical treatment for Person agents who request treatment, that submits claims to its associated Health Insurance Company, and that negotiates fee levels with its Health Insurance Company. There are two Provider Networks (one for each Health Insurance Company), Provider Network A and Provider Network B.

Premium Rate Limit Agency. A state agency that sets a limit on the premium rates that a Health Insurance Company can charge for each of its insurance plans.

Risk Adjustment Agency. A state agency that reallocates premium income among the Health Insurance Companies in order to maintain health risk equity among them.

Environment. The container for the model’s agents. It creates the simulation’s agents and maintains lists of them. It also obtains and validates user-provided parameters, and schedules agent behaviors.

A. MODEL OVERVIEW CONTINUED

5. Output

For each time period of the simulation, the model provides the following results:

- **Percentage insured.** The percentage of Person agents who purchase insurance.
 - **Disease status distribution.** The distribution of disease status among Person agents (histogram).
 - **Income distribution.** The distribution of net income (gross income minus premiums, copayments, and penalties) among Person agents (histogram).
 - **Insured Person agents.** The number of Person agents who purchase insurance, broken down by the plan purchased.
 - **Adverse selection.** The number of Person agents who adversely select a health plan. For the purpose of this model, a Person adversely selects a health insurance plan when the Person determines that the Person's health is grave and chooses a "rich" plan (one without co-payment), rather than a lower-cost plan.
 - **Lapsing Person agents.** The number of Person agents who drop (lapse) an insurance plan in order to choose another plan.
 - **Income.** The average income of Person agents, broken down by those who are insured and those who are uninsured
 - **Expenditures.** The average health-related expenditures of Person agents, broken down by premiums, penalty taxes, and co-payments.
 - **Disease status.** The population's average disease status, by insurance plan.
 - **Treatments.** The number of treatments that Person agents request, broken down by insurance plan.
 - **Insurer financial results.** Each Health Insurance Company's net premium income (after Exchange expenses and risk reallocation), claim expenditures, and profit.
 - **Insurer accumulated profit.** Each Health Insurance Company's accumulated profits.
 - **Insurer market share.** Each Health Insurance Company's market share (the number of Person agents it covers divided by total covered Person agents).
 - **Premium rates.** The premium rate for each insurance plan.
 - **Premiums reallocated.** The amount of premiums that the Risk Adjustment Agency reallocates to each Health Insurance Company.
 - **Maximum premium rate increases.** The maximum premium rate increases set by the Premium Rate Limit Agency, for each plan.
 - **Exchange advertising intensity.** The intensity of Exchange advertising.
 - **Penalty tax level.** The level of penalty tax.
-

A. MODEL OVERVIEW CONTINUED

6. Simplifying assumptions
1. In the model, there are only single Person agents. There are no families. Thus, Person agents only purchase individual health insurance.
 2. Except for geographic location, income level, and disease status, all Person agents have the same characteristics.
 3. A Person's income does not change from period to period, except for decreases due to premiums for purchasing health insurance, decreases due to paying penalty taxes, and decreases due to co-payments for medical care.
 4. Because medical expenses for uninsured Person agents are not needed to answer the questions that the model addresses, they are not included in the model.
 5. On the simulation's start date, all Person agents are uninsured.
 6. Person agents are not eligible for public health insurance (such as Medicaid), nor are they eligible for government subsidies.
 7. For each Person agent, there is at most one health incident per time period that requires treatment.
 8. As of the start of the simulation, the Health Insurance Company agents are equal in size and resources.
 9. All health insurance plans provide the same benefits, except that for each Health Insurance Company, the "richer" plan (plan "A1" or "B1") does not require member co-payments, whereas the other plan (plan "A2" or "B2") does.
 10. The Health Insurance Company agents have no administrative expenses and do not maintain reserves.
 11. Premium rates do not vary by geographic area, disease status, or income level.
 12. Each Health Insurance Company offers only two plans for the Exchange.
 13. Each Health Insurance Company pays all claims that its Provider Network submits.
 14. Each Provider Network provides all treatments that Person agents request.
-

A. MODEL OVERVIEW CONTINUED

7. Parameters on the parameter pane

Following are the parameters on the model's "parameter pane" that the user can set before the simulation starts. If a user does not enter a parameter, the model will supply a default value.

- A1. Initial treatment cost alpha - Health Insurance Company A.** For a Person with disease status DS , the cost of a treatment is equal to $\alpha (DS)^2$. The user can set the initial value of alpha (α) for Health Insurance Company A. Choices: any positive number. Default: 0.6.
 - A2. Initial treatment cost alpha - Health Insurance Company B.** The initial value of alpha (α) for Health Insurance Company B. Choices: any positive number. Default: 0.5.
 - B1. Initial premium - Plan A1.** The initial annual premium amount for plan A1. Choices: any positive number. Default: 7.0.
 - B2. Initial premium - Plan A2.** The initial annual premium amount for plan A2. Choices: any positive number. Default: 4.5.
 - B3. Co-payment percentage - Plan A2.** The co-payment percentage for plan A2. Choices: any number between 0.00 and 1.00. Default: 0.20.
 - B4. Initial premium - Plan B1.** The initial annual premium amount for plan B1. Choices: any positive number. Default: 7.0.
 - B5. Initial premium - Plan B2.** The initial annual premium amount for plan B2. Choices: any positive number. Default: 5.0.
 - B6. Co-payment percentage - Plan B2.** The co-payment percentage for plan B2. Choices: any number between 0.00 and 1.00. Default: 0.20.
 - C1. Primary goal - Health Insurance Company A.** The primary goal for Health Insurance Company A. Options: "Maximize profit", "Maximize market share". Default: "Maximize market share".
 - C2. Primary goal - Health Insurance Company B.** The primary goal for Health Insurance Company B. Options: "Maximize profit", "Maximize market share". Default: "Maximize profit".
-

A. MODEL OVERVIEW CONTINUED

7. Parameters on the parameter pane continued

- D1. Exchange - Plan presentation order.** The ordering of plans that the Exchange offers on its website. Choices: “Random”, “Low to high premium”, “High to low premium” Default: “Random”.
- D2. Exchange - Initial advertising intensity.** The initial advertising intensity for the Exchange. Choices: any integer between 1 (low intensity) to 10 (high intensity). The higher the advertising intensity the higher the Exchange’s expenses for advertising, and the lower the amount of premiums the Exchange can transfer to Health Insurance Companies. Default: 3.
- D3. Exchange - Advertising expense percentage.** The percentage of total Exchange premiums that, when multiplied by the Exchange’s advertising intensity, determines the Exchange’s advertising expenses. Choices: any number between 0.00 and 0.10 (so that $D2 \times D3$ doesn’t exceed 1.00). Default: 0.01.
- D4. Exchange - Uninsured decrease target.** The percentage by which the Exchange wants to decrease the number of uninsured Person agents. Choices: any number between 0.00 and 1.00. Default: 0.70.
- E1. Penalty Tax Agency - Initial penalty tax level.** The initial penalty tax percentage. Choices: any number between 0.00 and 0.10. Default: 0.03.
- E2. Penalty Tax Agency - Maximum penalty tax level.** The maximum penalty tax percentage that the Penalty Tax Agency will levy. Choices: any number between 0.00 and 0.10. Default: 0.05.
- E3. Penalty Tax Agency - Uninsured decrease target.** The percentage by which the Penalty Tax Agency wants to decrease the number of uninsured Person agents. Choices: any number between 0.00 and 1.00. Default: 0.70.
- F1. Premium Rate Limit Agency - Profit percentage maximum.** The maximum profit (as a percentage of total income) that the Premium Rate Limit Agency allows a Health Insurance Company to make. Choices: any number between 0.00 and 0.20. Default: 0.03.
- G1. Random number seed.** The “seed” number used for the simulation’s random number generators. To vary the generation of random numbers for simulation runs, the seed can be varied. Using a constant random number seed enables the model user to reproduce simulation runs. Choices: any integer. Default value: automatically generated based on the computer system’s clock.
-

A. MODEL OVERVIEW CONTINUED

8. Parameters on the user panel

Following are the parameters on the model's "user panel" that the user can set before the simulation starts. The user panel has five tabs: "Simulation", "Person", "Person goals", "Health Insurance Company", and "Provider Network". If a user does not enter a parameter, the model will supply a default value.

"Simulation" tab

- A1. Maximum simulation periods.** The maximum number of simulation periods. Choices: any integer. Default value: 100.
- B1. Override parameters.** Whether the input parameters can be overridden by custom code in the simulation program. Choices: "On", "Off". Default: "Off".
- C1. Output file.** Whether an output file will be written. Choices: "On", "Off". Default: "Off".
- C2. Output file name.** If item C1 is "Yes", the name of the output file. Choices: any valid output file name. Default: "None".

"Person" tab

- A1. Labels.** Whether identification labels are shown for Person agents on the display. Labels are especially helpful when testing the model, or trying to figure out an unusual pattern. Choices: "On", "Off". Default value: "Off".
 - B1. Number.** The number of Person agents at the simulation's start. Choices: any positive integer less than 1,000. Default: 1,000.
 - C1. Geographic location distribution type.** Where Person agents are located in their community. Choices: "Normal distribution" (such as for states that are predominantly urban) and "Uniform distribution" (such as for states that are predominantly rural). Default: Normal distribution.
 - C2. Normal distribution mean.** If the user selects "Normal distribution" for parameter C1, this parameter gives the distribution's mean. Choices: any positive real number. Default: 50.0.
-

A. MODEL OVERVIEW CONTINUED

8. Parameters on the user panel <small>continued</small>	<p>“Person” tab <small>continued</small></p> <p>C3. Normal distribution standard deviation. If the user selects “Normal distribution” for parameter C1, this parameter gives the normal distribution’s standard deviation. Choices: any number. (It is best to limit the standard deviation to a positive number less than half the width of the community. Otherwise, many Person agents will end up at the community’s boundaries. The community’s width is 100.) Default: 15.0.</p> <p>C4. Neighborhood radius. The radius to determine which Person agents are in a Person’s neighborhood.¹ Choices: any positive number. Default: 10.0.</p> <p>D1. Maximum income. A Person agent’s maximum income for a period. Choices: any positive number. Default: 200.00.</p> <p>D2. Income distribution type. How the Person agent incomes are distributed from 1.00 to the maximum income (parameter D1). Choices: “Random uniform distribution”, “Random log normal distribution”. Default: “Random log normal distribution”.</p> <p>D3. Log normal distribution mean. If the user selects “Random log normal distribution” for parameter D2, this parameter gives the mean income for the distribution. Choices: any positive real number. Default: 40.0.</p> <p>D4. Log normal distribution standard deviation. If the user selects “Random log normal distribution” for parameter D2, this parameter gives the distribution’s standard deviation. Choices: any positive number. Default: 35.0.</p> <p>E1. Initial disease status distribution type. The type of distribution for the initial disease status of Person agents. Disease status is a continuous variable from 0.0 (perfect health) to 10.0 (dead). Choices: “Random uniform distribution”, “Random log normal distribution”. Default: “Random log normal distribution”.</p> <p>E2. Log normal distribution mean. If the user selects “Random log normal distribution” for parameter E1, this parameter gives the mean for the distribution. Choices: any positive real number. Default: 3.0.</p>
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¹ For a Person with “Conform” as a top priority, the Person’s neighborhood is used to help determine the Person’s decisions about purchasing a health insurance plan. The model assumes that such Person agents will conform to the most common decision of the Person agents who are within the Person’s neighborhood. A “neighborhood” can refer to a Person’s geographic neighborhood, as well as a friend or peer neighborhood.

A. MODEL OVERVIEW CONTINUED

8. Parameters on
the user panel
continued

“Person” tab continued

- E3. Log normal distribution standard deviation.** If the user selects “Random log normal distribution” for parameter E1, this parameter gives the distribution’s standard deviation. Choices: any positive number. Default: 4.0.
 - F1. Disease status random increment maximum.** The maximum disease status random increment for a period. Choices: 0.0 to 10.0. Default: 3.0.
 - F2. Disease status increment distribution type.** The type of distribution for incrementing the disease status of Person agents each period. The disease status increment is a continuous variable from 0.0 to the “Disease status random increment maximum” (parameter F1). Choices: “Random uniform distribution”, “Random log normal distribution”. Default: “Random log normal distribution”.
 - F3. Log normal distribution mean.** Mean for the log normal distribution. Choices: any positive real number. Default: 1.0.
 - F4. Log normal distribution standard deviation.** Standard deviation for the log normal distribution. Choices: any positive number. Default: 2.0.
 - G1. Health improvement percentage.** The percentage by which a Person’s disease status decreases when the Person is treated by a Provider Network. Choices: any number between 0.00 and 1.00. Default: 0.20.
 - G2. Health deterioration percentage.** The percentage by which a Person’s disease status increases in one period when the Person is not treated by a Provider Network. Choices: any number between 0.00 and 1.00. Default: 0.05.
-

A. MODEL OVERVIEW CONTINUED

8. Parameters on the user panel continued

“Person” tab continued

- H1. Decision inertia percentage.** The percentage of Person agents who will make the same health insurance purchase decision that they made in the prior period, regardless of all other factors. Choices: any number between 0.00 and 1.00. Default: 0.40.
- H2. Health gravity threshold.** The threshold beyond which a Person views his or her disease status as grave. When the Person’s disease status is more than the threshold, and thus worse than the threshold, the Person may (depending on the Person’s goals) purchase health insurance, and will (if insured) request treatment. Choices: Any number between 0.0 and 10.0. Default: 3.0.
- H3. Advertising impact threshold.** The threshold beyond which Exchange advertising can affect a Person agent’s health insurance purchasing behavior. Choices: Any number between 0.0 and 10.0. Default: 5.0.

“Person goals” tab

A1. Person goal priority distribution. The distribution of Person agent goal priorities. Choices: for each goal and priority, any number between 0.00 and 1.00. Defaults:

Goal	Priority order				
	1st	2nd	3rd	4th	5th
Maximize income	0.20	0.20	0.20	0.20	0.20
Increase health	0.40	0.20	0.20	0.10	0.10
Conform	0.20	0.20	0.20	0.20	0.20
Follow policy	0.10	0.20	0.20	0.20	0.30
Follow advertising	0.10	0.20	0.20	0.30	0.20

A. MODEL OVERVIEW CONTINUED

8. Parameters on the user panel continued

“Health Insurance Company” tab

- A1. Health Insurance Company A lapse threshold.** The percentage of Person agents to drop (lapse) a plan in the prior period in order for Health Insurance Company A to consider the lapse rate problematic. Options: any number between 0.00 and 1.00. Default: 0.20.
- A2. Health Insurance Company B lapse threshold.** The percentage of Person agents to drop (lapse) a plan in the prior period in order for Health Insurance Company B to consider the lapse rate problematic. Options: any number between 0.00 and 1.00. Default: 0.15.
- B1. Health Insurance Company A premium discount factor.** A discount factor to adjust competitor premiums to determine the level of premiums that Company A believes would be competitive in the marketplace. Options: any number between 0.00 and 2.00. Default: 1.05.
- B2. Health Insurance Company B premium discount factor.** A discount factor to adjust competitor premiums to determine the level of premiums that Company B believes would be competitive in the marketplace. Options: any number between 0.00 and 2.00. Default: 1.10.
- C1. Health Insurance Company A maximum offer increase percent.** During negotiations with the Provider Network, the maximum percentage by which Health Insurance Company A will try (during negotiations) to increase the prior period’s treatment cost alpha. Options: any number between 0.00 and 1.00. Default: 0.03.
- C2. Health Insurance Company B maximum offer increase percent.** During negotiations with the Provider Network, the maximum percentage by which Health Insurance Company B will try (during negotiations) to increase the prior period’s treatment cost alpha. Options: any number between 0.00 and 1.00. Default: 0.02.
-

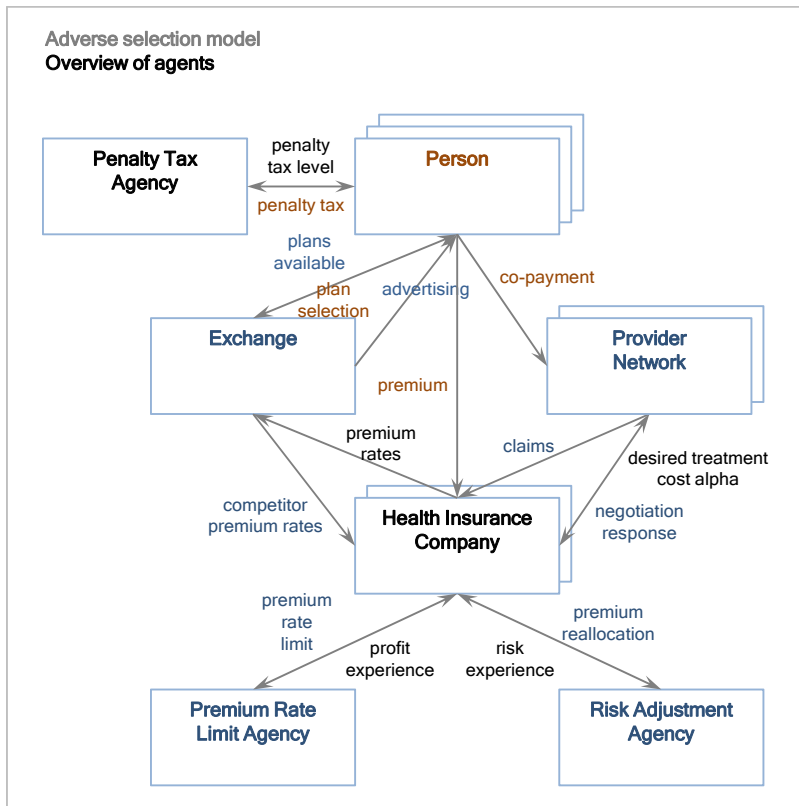
A. MODEL OVERVIEW CONTINUED

8. Parameters on the user panel continued	“Provider Network” tab A1. Provider Network A minimum alpha increase percent. The minimum percentage by which Provider Network A will increase the treatment cost alpha. Choices: any number between 0.00 and 1.00. Default: 0.10. A2. Provider Network B minimum alpha increase percent. The minimum percentage by which Provider Network B will increase the treatment cost alpha. Choices: any number between 0.00 and 1.00. Default: 0.10.
9. Displays	Following are the displays shown in the model’s user interface: 1. Community. This display shows the community where Person agents live. Person agents are represented by disks. <p>The disease status of a Person is shown by the disk’s color. Person agents colored white have perfect health, whereas disks with increasingly bright hues of red indicate increasingly serious disease. Person agents who die are removed from the community.</p> <p>Disks with a blue border represent Person agents who are covered by insurance. Dark blue represents insurance with no co-payment (a “richer” plan), and light blue represents Person agents with a co-payment.</p> <p>The size of the disk corresponds to the Person agent’s income level. Person agents with smaller disks have smaller income levels.</p> <p>The model’s governmental entities—the Risk Adjustment Agency, the Premium Rate Limit Agency, the Penalty Tax Agency, and the Exchange—are represented by gray rectangles.</p> <p>Health Insurance Company A is represented by a blue square, and its Provider Network A by a blue disk. Similarly, Health Insurance Company B is represented by an orange square, and its Provider Network B by an orange disk.</p> <p>Insurance plans offered by the Exchange are represented by rectangles with colors corresponding to the insurance company that provides them.</p> 2. State. This display shows the network of relationships between Person agents who are adversely selecting health insurance and the two Health Insurance Company agents. Adversely selecting Person agents are red.

B. AGENT OVERVIEW DIAGRAM

The diagram below shows the model’s agents and the flow of data among them. (Because there are many data items, they are color coded; a data item of a certain color is from the agent name of the same color. For example, the data item “penalty tax” is brick colored, and flows from “Person”, which is brick colored.).

In the following sections, each data item is explained in more detail.



C. BEHAVIOR SCHEDULE

The chart below shows the agent behaviors and the order in which the behaviors occur. In the chart, each behavior is represented by its core “produce output” process. For example, the Person’s behavior “Purchase plan” is represented by the process “P1. Purchase plan”. This one-to-one relationship between a behavior and its core “produce output” process is possible because the core process is connected to all behavior components.¹

As the chart shows, some behaviors take place at the beginning of each simulation period, some take place at the end of each period, and some happen mid-period.²

The order of behavior is important. For example, the Premium Rate Limit Agency cannot set premium rate increase limits until it knows the profit experience of Health Insurance Companies. Thus, at the end of the period, the Premium Rate Limit Agency’s behavior “P2. Set premium increase limit (10)” is the 10th behavior to take place (the order is indicated in parentheses after the behavior name.) It happens after the Health Insurance Company behavior “P3. Provide profit experience (3)”.

Agent	Behavior for each simulation period		
	Beginning of period	Middle of period	End of period
1. Person	P1. Purchase plan (5) P2. Pay penalty tax (6)	P3. Request treatment (1) P4. Pay co-payment (2)	P5. Update disease status (1)
2. Health Insurance Company	P1. Set premium rates (1)		P2. Provide risk experience (2) P3. Provide profit experience (3) P4. Negotiate treatment cost alpha (4, 6, 8)
3. Provider Network		P1. Submit claims (3)	P2. Provide negotiation response (5, 7)
4. Exchange	P1. Offer plans (2) P2. Advertise plans (3) P3. Transfer premiums (7)		
5. Risk Adjustment Agency			P1. Reallocate premiums (9)
6. Premium Rate Limit Agency			P1. Set premium increase limit (10)
7. Penalty Tax Agency	P1. Set penalty tax rate (4)		

¹ For more information about behavior components, see Chapter One (Dimensions of behavior).

² Technical notes:

A. Agent behaviors for the simulation are scheduled in the model’s “Schedule” class, which is called by the Environment. In the Schedule class, there are many clock ticks in a period. Each behavior is scheduled during one of these clock ticks, in an order indicated by the decimal part of each clock tick. For example, Behavior1 might take place at time “1.1”, followed by Behavior2 at time “1.2”.

B. System events (updating data stores, charts, displays, etc.) occur on integral clock ticks (1.0, 2.0, 3.0, etc.). The initialization of variables happens immediately after system events (at time 1.001). This is when “prior” variables are updated from “current” variables, and when “current” variables are initialized. Thus, for example, when system events happen at time 3.0, “current” refers to the period from 2.001 to 3.0, inclusive. At time 3.001, “current” refers to the period from 3.001 to 4.0, inclusive.

D. DETAILED AGENT DESCRIPTIONS

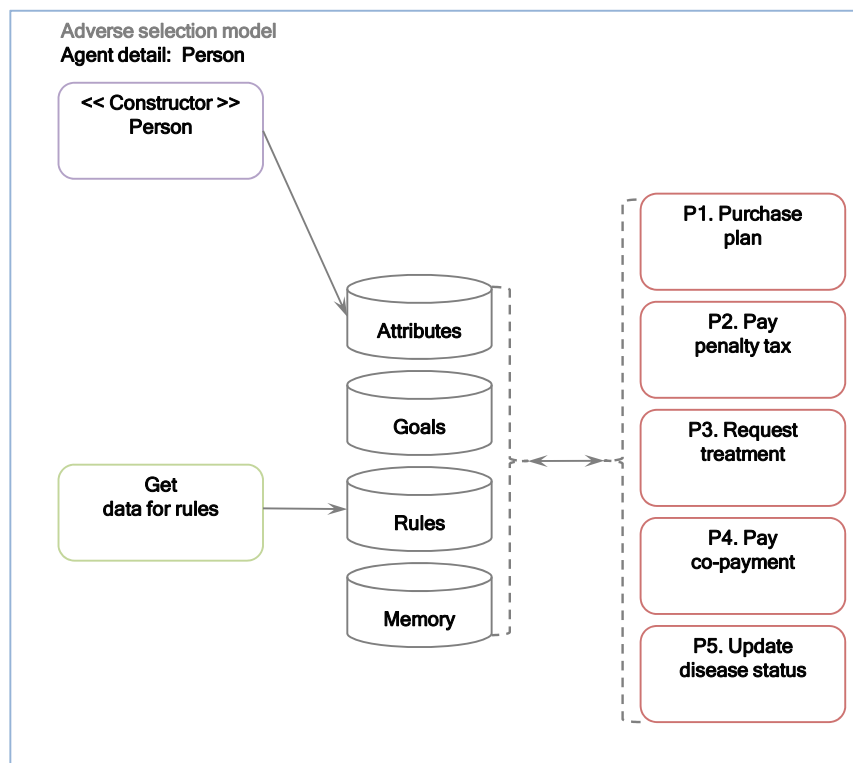
1. Person

This section describes the Person agent in detail.¹

a. Behavior overview

The diagram shows the Person’s behaviors. Included in the behaviors are:

- **Produce output.** Five output processes (represented by rose-colored rounded boxes). These processes update the Person’s attributes and memory.
- **Get input.** Processes (in green) that get data from other agents, to support the Person’s rules.²
- **Attributes, goals, rules, memory.** Data stores for the Person’s attributes, goals, rules, and memory.



For completeness, the diagram also shows a “constructor” process (in mauve) that creates each instance of a Person for the simulation.³ The remainder of this detailed description discusses each component of these behaviors.

The Person behavior overview diagram above corresponds to the approach we established to describe behavior as a combination of parameters, as discussed in Chapter One (Dimensions of behavior) of the project report.

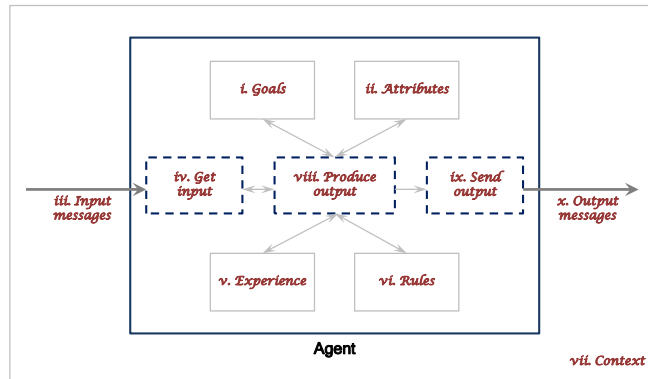
¹ Technical note: In the model, the Person class is an extension of the Agent class.
² Technical note: The “Get data for rules” process employs “getter” methods in the classes of other agents.
³ Technical note: The constructor process is the “constructor” for the Person class.

D. DETAILED AGENT DESCRIPTIONS CONTINUED

1. Person continued

a. Behavior overview continued

As a reminder, below is the diagram representing our parameterized approach to behavior.



b. Attributes

The Person has the following attributes:

- **Identifier.** An integer uniquely identifying each Person.
- **Location.** Where the Person lives (x and y coordinates on the two-dimensional grid representing the community).
- **Goals.** The Person's goals and their priority order (see Section c below).
- **Current gross income.** The Person's gross annual income amount for the current period. During the course of the simulation, a Person's gross income does not change. The Person's gross income level is set by the Person's "constructor", based on parameters D1 – D4 on the Person tab of the user panel.
- **Current disease status.** A continuous variable from 0.0 (perfect health) to 10.0 (dead). The initial disease status is set by the "constructor", based on parameters E1 – E3 on the Person tab of the user panel. Thereafter, disease status fluctuates based on disease deterioration (percentage increments to the Person's disease status) and treatments received (expressed as percentage decrements to the Person's disease status).

c. Goals

A Person has the following goals, in an order determined by parameter A1 on the "Person goals" tab.

- **Increase health.** The Person wants to engage in behaviors that decrease the Person's disease status.
- **Maximize income.** The Person wants to engage in behaviors that maximize the Person's income.
- **Conform.** The Person wants to conform to the behavior of the majority of the Person's neighbors.
- **Follow advertising.** The Person follows the suggestions of Exchange's advertising, if it is convincing (see below).
- **Follow policy.** The Person wants to follow government policy requiring people to purchase health insurance.

D. DETAILED AGENT DESCRIPTIONS CONTINUED

1. Person continued

d. Experience

In memory, the Person stores the following information as of the start of the simulation, and for each simulation period thereafter.

- **Current net income.** The Person's annual net income amount for the current period. A Person's annual net income is equal to the Person's gross income, less penalty tax payments, premium payments for purchasing health insurance, and co-payments for medical care.
- **Current favored plan.** The most frequently chosen insurance plan among the Person's neighbors in the prior period. The Person gets this information by querying the Person's neighbors. If the most frequent neighbor selection is to forgo health insurance, the value is "0".
- **Current exchange advertising intensity.** The Exchange's advertising intensity in the current period.
- **Advertising impact threshold.** The threshold beyond which Exchange advertising has an impact on the Person. This is a parameter the user can enter.
- **Health gravity threshold.** The threshold beyond which the Person's disease is considered grave. This is a parameter the user can enter.
- **Current plan selection.** The insurance plan the Person purchases from the Exchange in the current period.
- **Current premium amount.** The premium amount that the Person pays in the current period.
- **Current co-payment percentage.** The co-payment percentage for the plan the Person selects.
- **Current co-payment.** The co-payment amount the Person pays in the current period.
- **Current penalty tax level.** The penalty tax level for the current period.
- **Current penalty tax.** The penalty tax amount the Person pays to the Penalty Tax Agency in the current period.
- **Current treatment cost alpha.** The current treatment cost alpha (α) for the Health Insurance Company for which the Person is a member, which, except for the first period, is established through negotiations between the Health Insurance Company and its Provider Network (in the first period it is set by parameter pane parameters A1 and A2).
- **Current treatment request.** "TRUE" if the Person requested treatment in the current period. "FALSE" otherwise.
- **Current adverse selection results.** "TRUE" if the Person adversely selects a health insurance plan to purchase. For the purpose of this model, a Person adversely selects a health insurance plan when the Person determines that the Person's health is grave and chooses a "rich" plan (one without a co-payment), rather than a lower-cost plan. Otherwise the result is "FALSE".

D. DETAILED AGENT DESCRIPTIONS CONTINUED

1. Person continued

d. Experience continued

- **Health improvement percentage.** The percentage by which a Person's disease status decreases when the Person is treated.
- **Health deterioration percentage.** The percentage by which a Person's disease status increases when the Person is not treated.

e. Rules

Following are the Person's rules:

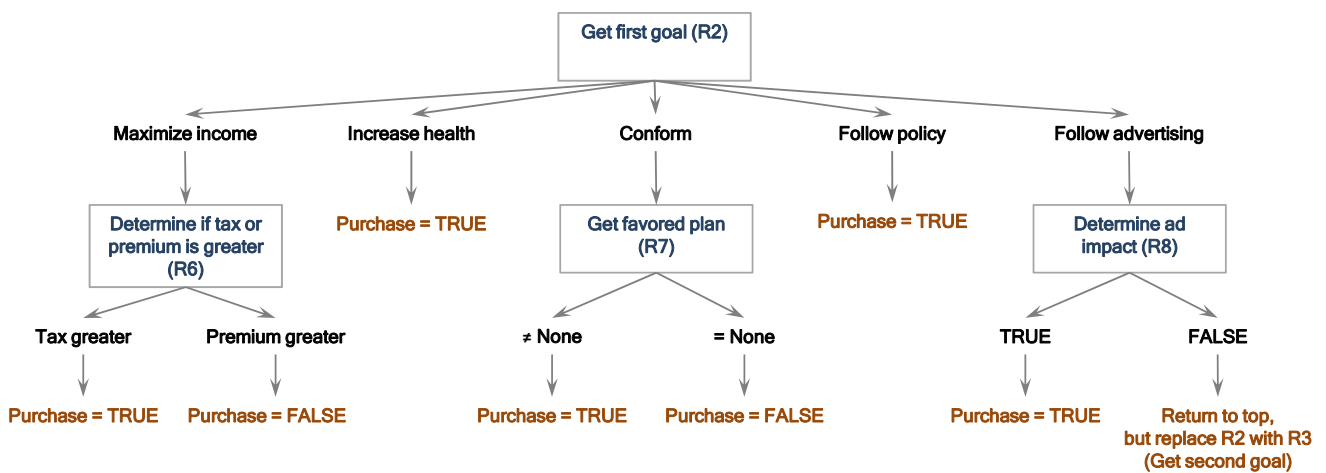
- R1: Determine inertia effect.** If a random number between 0 and 1 is less than the "Decision inertia percentage" (a parameter), return "TRUE". Otherwise return "FALSE". A result of "TRUE" means that the Person is under the influence of inertia, and will select the same health plan that the Person selected in the prior period.
- R2: Get first goal.** Determine the Person's highest-priority goal.
- R3: Get second goal.** Determine the Person's second-priority goal.
- R4: Get last goal.** Determine the Person's last-priority goal.
- R5: Calculate penalty tax amount.** Calculate the potential current penalty tax amount by multiplying the "Penalty tax level" (obtained from the Penalty Tax Agency agent) times the Person's "Current gross income" (an attribute).
- R6: Determine if tax or premium is greater.** Determine which is greater, the penalty tax amount or the premium for the lowest-cost health plan. If the tax is greater, the result is "Tax". If the premium is greater, the result is "Premium".
- R7: Get favored plan.** Get the most frequent plan choice among all Person agents within a certain geographic radius of the Person making the request. The "neighborhood radius" is parameter C4 on the user panel. If most Person agent neighbors choose to remain uninsured, the result is "None". In the first simulation period, the result is "None".
- R8: Determine ad impact.** Determine if the Exchange advertising intensity is greater than the "advertising impact threshold" (parameter H3 on the Person tab of the user panel). If so, then the advertising has an impact ("TRUE") Otherwise: "FALSE".
- R9: Determine health gravity.** If the Person's disease status is more than the "health gravity threshold" (parameter H2 on the user panel), it is grave ("TRUE"). Otherwise the result is "FALSE".
- R10: Select first offered plan.** Select the first plan offered on the Exchange's list of plans.
- R11: Select lowest cost plan.** Select the plan on the Exchange with the lowest premium.
- R12: Select richest plan.** Select the lowest-cost plan on the Exchange that has no co-payment.
- R13: Calculate co-payment.** For plans that require a co-payment, calculate the amount of a Person's co-payment, equal to the plan's co-payment percentage times $\alpha (DS)^2$, where DS is a Person's disease status and α is the "treatment cost alpha" that for the simulation's first period is entered by the user (parameters A1 and A2 on the parameter pane), and that thereafter is negotiated between each Health Insurance Company and its Provider Network.

D. DETAILED AGENT DESCRIPTIONS CONTINUED

f. Output processes

Following are the Person’s Produce Output processes:

P1: Purchase plan. For simulation periods after the first period, if the rule “R1. Determine inertia effect” is TRUE and the Person selected a plan in the prior period, the Person selects the same health plan that the Person selected in the prior period. Otherwise: The Person employs two sub-processes to determine the plan to purchase. The first sub-process (P1a. Make plan purchase decision) is to determine whether to purchase a plan at all, as shown in the following diagram. The items in boxes are rules, identified in parentheses by a rule number.

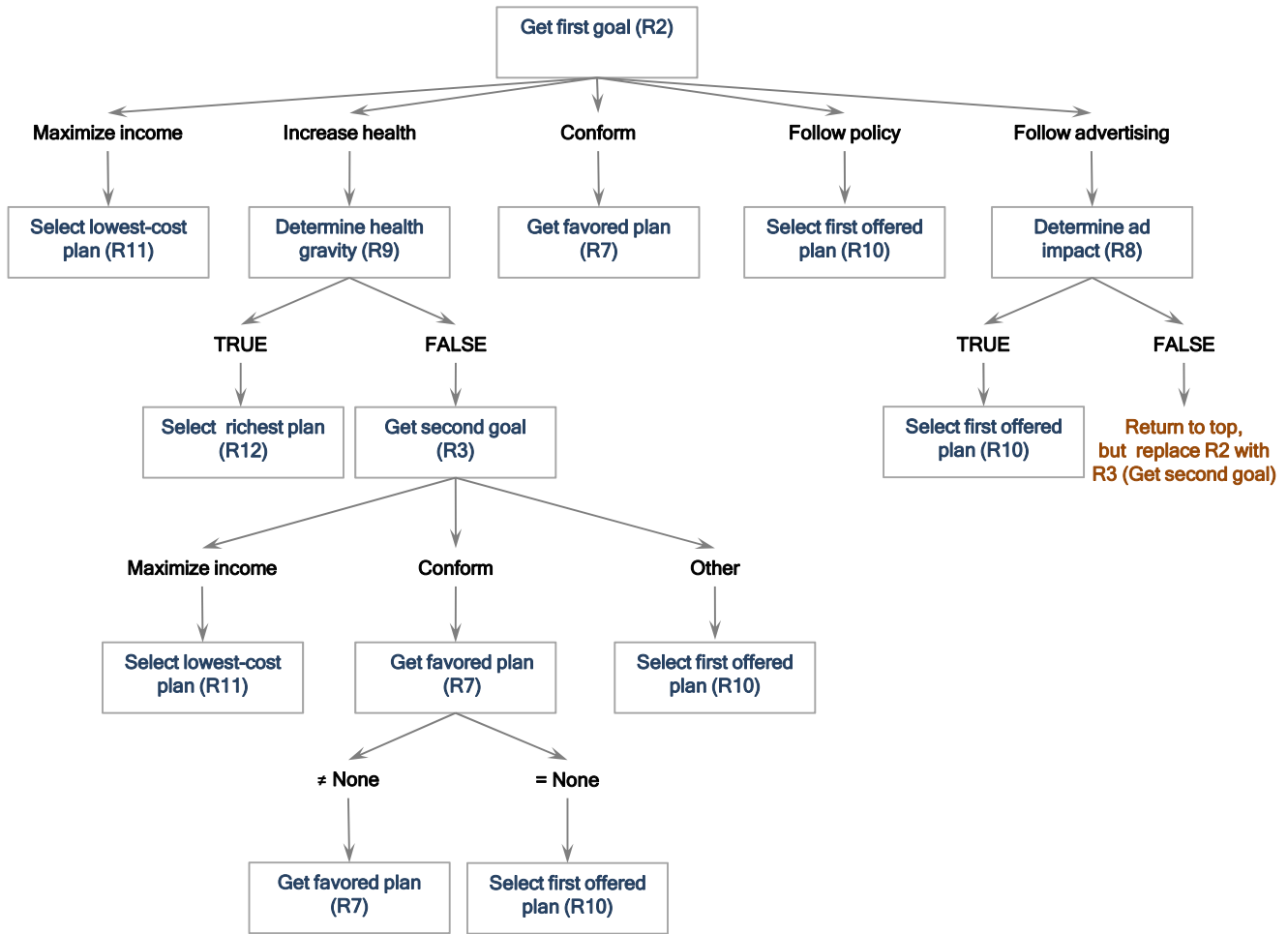


D. DETAILED AGENT DESCRIPTIONS CONTINUED

1. Person continued

f. Output processes continued

The second sub-process determines the plan to purchase, and is shown in the following diagram.



D. DETAILED AGENT DESCRIPTIONS CONTINUED

1. Person continued

f. Output processes continued

- P2: Pay penalty tax.** If a Person does not purchase health insurance, the Person pays a penalty tax amount obtained by rule “R5. Calculate penalty tax amount”.
- P3: Request treatment.** If the Person has purchased health insurance, and the Person’s disease status is grave (as determined by the rule “R9. Determine health gravity”) the person requests (and receives) treatment from the Provider Network. If the Person requests treatment, set “Current treatment request” to “TRUE”. Otherwise the result is “FALSE”.
- P4: Pay co-payment.** If the Person requests treatment and has a health insurance plan that requires co-payment, pay the co-payment amount (determined by rule “R13. Calculate co-payment”).
- P5: Update disease status.** If the Person was not treated in the current period, increase the Person’s disease status by the “Health deterioration percentage” (parameter F2 on the user panel). If the Person was treated in the current period, decrease the Person’s disease status by the “Health improvement percentage” (parameter F1 on the user panel). The Person’s disease status is also increased by the “Disease status random increment” (parameters F on the Person tab of the user panel). If the Person’s resulting disease status is greater than or equal to 10, remove the Person from the simulation (because the Person has died).

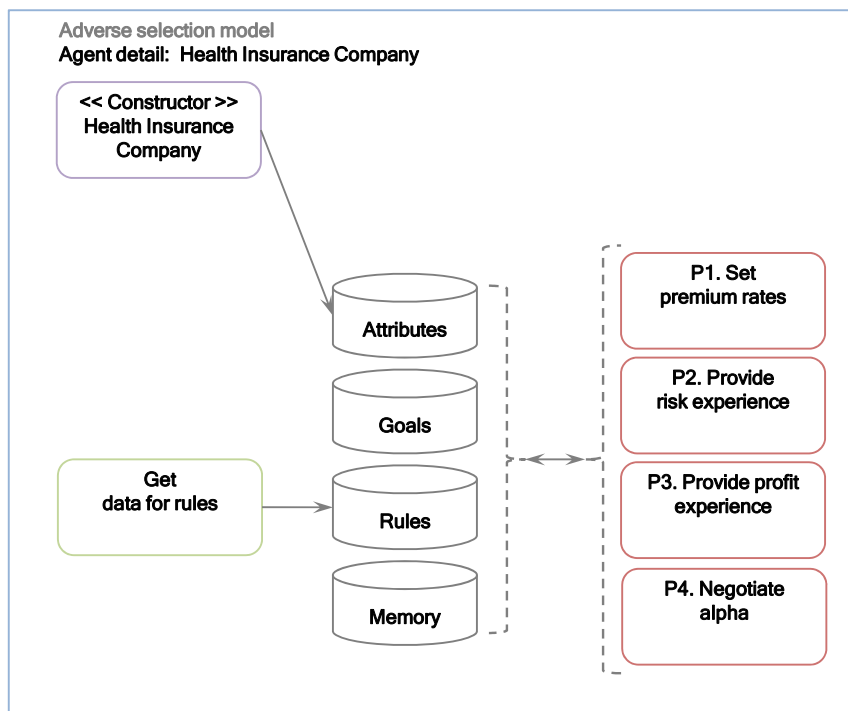
D. DETAILED AGENT DESCRIPTIONS CONTINUED

2. Health Insurance Company

This section describes the Health Insurance Company agent in detail.

a. Behavior overview

The diagram shows the Health Insurance Company’s behaviors. For a general discussion of the diagram, see the behavior overview for “Person” (Section D.1.a above). As the diagram shows, each Health Insurance Company includes four output processes, and processes that get data from other agents in order to support the company’s rules.



b. Attributes

The Health Insurance Company has the following attributes:

- **Identifier.** An integer uniquely identifying each company.
- **Goal.** The company’s first-priority goal.
- **Current premium income.** The net amount of premiums received from policyholders in the current period. This amount is after the Exchange withholds advertising expenses, and after premium reallocation by the Risk Adjustment Agency.

D. DETAILED AGENT DESCRIPTIONS CONTINUED

2. Health Insurance Company *continued*

c. Goals

The Health Insurance Company has the following goals, in a priority order determined by parameters C1 and C2 on the parameter pane:

- **Maximize profit.** The company wants to maximize the difference between premiums received and claims paid.
- **Maximize market share.** It also wants to maximize the number of Person agents who purchase its plans.

d. Experience

In memory, the Health Insurance Company stores the following information as of the start of the simulation, and for each simulation period thereafter.

- **Current premiums.** The premiums for each of the Health Insurance Company's plans, for the current period, including the premium rate and co-payment percentage, if applicable.
- **Current claims paid.** The amount of claims paid in the current period.
- **Current treatment cost alpha.** The treatment cost alpha (α) that the company and its Provider Network negotiate. The cost for treating a Person is expressed by the formula:

$$fee = \alpha(DS)^2$$

where DS is a Person's disease status, and α is the "treatment cost alpha" that the Health Insurance Company and the Provider Network negotiate. Thus, the treatment cost for treating a Person with disease status "9.0" is "81.0 α ", while the cost for treating a Person with disease status "1.0" is " α ".

- **Current premium reallocation amount.** The annual premium reallocation amount that the Risk Adjustment Agency provides the company.
- **Current premium rate increase limit.** The premium rate increase limit for the company's plans that the Premium Rate Limit Agency set.
- **Prior competitor premium rates.** The premium rate for each of the two plans of the Company's competitor, for the prior period.
- **Prior risk experience.** The average disease status of Person agents for whom the Health Insurance Company paid claims in the previous period, for each of the company's plans.

D. DETAILED AGENT DESCRIPTIONS CONTINUED

2. Health Insurance Company *continued*

e. Rules

Following are the company’s rules:

- R1: Get first goal.** Determine the Health Insurance Company’s first-priority goal.
- R2: Compute profit maximizing premiums.** For each of the company’s plans, set the premium equal to the premium in the prior period times the premium rate increase limit for the period, provided by the Premium Rate Limit Agency.
- R3: Identify lapse rate problem.** Determine if the lapse rate for each plan (the percentage of Person agents who dropped the plan in the prior period) is greater than the company’s “lapse threshold” (a parameter). If it is, or if nobody chooses the plan, return “TRUE”. Otherwise, return “FALSE”. Because of inadequate experience, for the first two simulation periods, the rule returns “FALSE”.
- R4: Compute competitive premium.** For the relevant competitor’s plan, calculate the competitive premium as the competitor’s premium for the plan in the previous period, divided by the “premium discount factor” (a parameter), but not more than the profit maximizing premium for the company’s plan (the result of Rule 2). This is the premium that the Company believes would be competitive in the marketplace.
- R5: Compute average disease status.** Calculate the average disease status of Person agents for whom the Health Insurance Company paid claims in the previous period, for each of the company’s plans.
- R6: Compute profit percentage.** For each plan, calculate the period’s profit, equal to total net premiums (gross premiums less Exchange advertising expenses) minus total claims paid, divided by total net premiums. Note that risk allocation amounts are not part of this calculation.
- R7: Compute maximum alpha.** Calculate the maximum treatment cost alpha as:

$$\alpha_{max} = \alpha_{previous} \frac{\textit{previous period net premiums}}{\textit{previous period total claims}}$$

- R8: Compute treatment cost alpha offer.** Calculate the treatment cost alpha to initially offer the Provider Network as:

$$\alpha_{offer} = \frac{\alpha_{previous} + \alpha_{max}}{2} \textit{ but } \not\geq \alpha_{max} \textit{ and } \not\geq (\alpha_{previous} \times \textit{Max offer increase percent})$$

where “maximum offer increase percent” is parameter C1 under the Health Insurance Company tab on the user panel.

- R9: Compute negotiation response.** Calculate the treatment cost alpha to offer the Provider Network as a response to its negotiation response:

$$\alpha_{response} = \frac{\alpha_{network\ response} + \alpha_{max}}{2} \not\geq \alpha_{max} \textit{ and } \not\geq \alpha_{previous} \times \textit{Max offer increase percent}$$

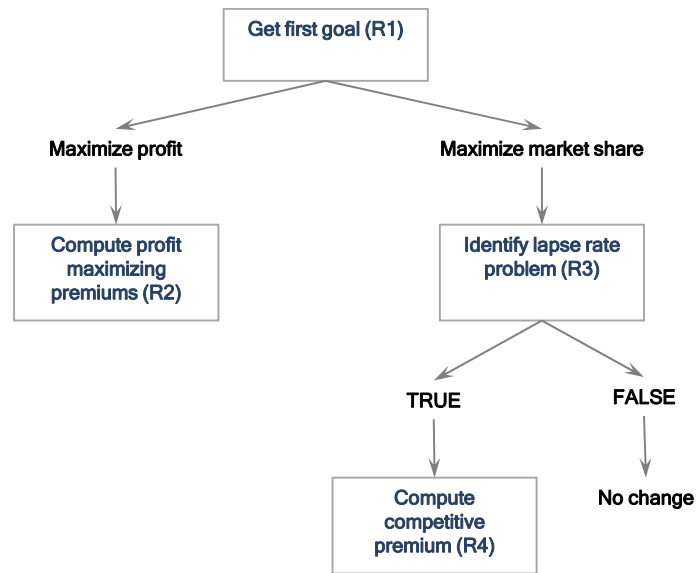
D. DETAILED AGENT DESCRIPTIONS CONTINUED

2. Health Insurance Company *continued*

f. Output processes

Following are the Health Insurance Company's output processes:

P1: Set premium rates. The premium rates for the first period are set by initialization parameters B1 – B6 on the parameter pane. In later periods, the Health Insurance Company employs the following process to set premium rates for each of its plans:



P2: Provide risk experience. The Health Insurance Company provides the Risk Adjustment Agency the results of Rule 5 (Compute average disease status).

P3: Provide profit experience. The company provides the Premium Rate Limit Agency the results of Rule 6 (Compute profit percentage).

P4: Negotiate treatment cost alpha. The treatment cost alpha for the first period is set by the initialization parameters A1 and A2 on the parameter pane. Thereafter, to negotiate alpha, the Health Insurance Company first offers the result of Rule 8 (Compute treatment cost alpha level offer). It then responds to the Provider Network response with Rule 9 (Compute negotiation response). Lastly, it accepts the Provider Network's second response.

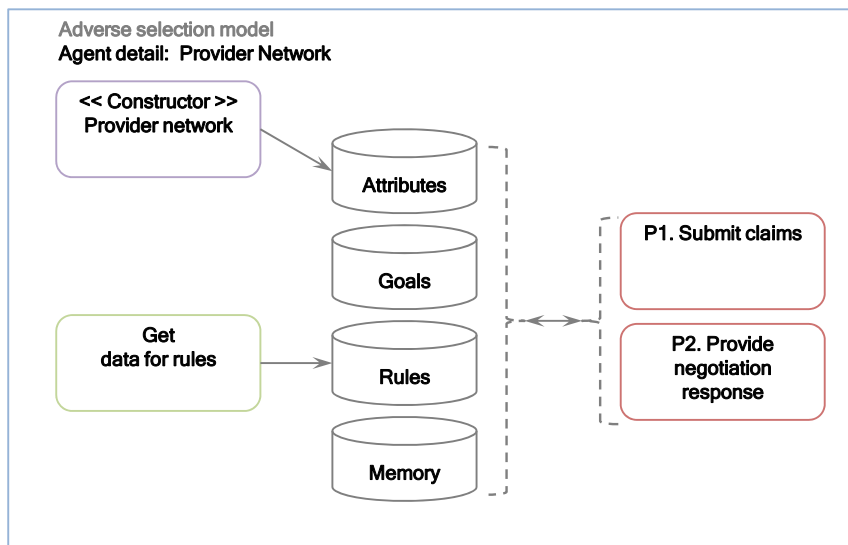
D. DETAILED AGENT DESCRIPTIONS CONTINUED

3. Provider Network

This section describes the Provider Network agent in detail.

a. Behavior overview

The diagram shows the behaviors of the Provider Network. For a general discussion of the diagram, see the behavior overview for “Person” (Section D.1.a above). As the diagram shows, the Provider Network includes two output processes, and processes that get data from other agents in order to support the Provider Network’s rules.



b. Attributes

Each Provider Network has the following attribute:

- **Identifier.** An integer uniquely identifying the Provider Network.

c. Goals

Each Provider Network has the following major goal:

- **Maximize income.** Over the course of the simulation, the Provider Network wants to maximize its income.

D. DETAILED AGENT DESCRIPTIONS CONTINUED

3. Provider Network continued

d. Experience

In memory, each Provider Network stores the following information as of the start of the simulation, and for each simulation period thereafter.

- **Current first desired alpha.** The first treatment cost alpha received from the Health Insurance Company as part of alpha negotiations for the current period.
- **Current second desired alpha.** The second treatment cost alpha received from the Health Insurance Company as part of alpha negotiations for the current period.
- **Current first fee negotiation response.** The Provider Network's negotiation response to the Health Insurance Company's first desired treatment cost alpha.
- **Current second fee negotiation response.** The Provider Network's negotiation response to the Health Insurance Company's second desired treatment cost alpha.
- **Current claims.** Claim amounts for the current period that are submitted to the Health Insurance Company.

e. Rules

Following are the rules of a Provider Network:

R1: Compute negotiation response. Calculate the fee level to offer the Health Insurance Company in response to its desired fee level. The response for the first negotiation round is:

$$\alpha_{response} = \alpha_{previous} \times \text{Minimum alpha increase percent}$$

R2: Compute claims. Calculate the amount of claims to submit to the Health Insurance Company. This is equal to the sum of $\alpha (DS)^2$ times $(1 - \text{the "co-payment percentage"})$ for all Person agents treated.

R3: Compute co-payments. Calculate the amount of co-payments received from Person agents covered under plans with co-payments, equal to the sum of $\alpha (DS)^2$ times the "co-payment percentage" (parameters B3 and B6 of the parameter pane) for all Person agents treated under such plans.

R4: Compute total income. Calculate the amount of claims (Rule R2) plus the amount of co-payments (Rule R3) for the current period, for each plan.

f. Output processes

Following are the Provider Network's output processes:

P1: Submit claims. Calculate the amount of claims submitted from the Provider Network for each plan for the period, using Rule 2 (Compute claims). This process also calculates co-payments received (Rule 3) and total income (Rule 3).

P2: Provide negotiation response. In response to the Health Insurance Company's desired treatment cost alpha, if the desired alpha is less than $(\alpha_{previous} \times \text{"minimum alpha increase percent"}) - \text{a parameter}$, for the first negotiation round the Provider Network sends the response calculated according to Rule 1 (Compute negotiation response). Otherwise, the network accepts the offer. The response for the second round is the average of the Provider Network's first response and the Health Insurance Company's response. The network iterates this process no more than twice.

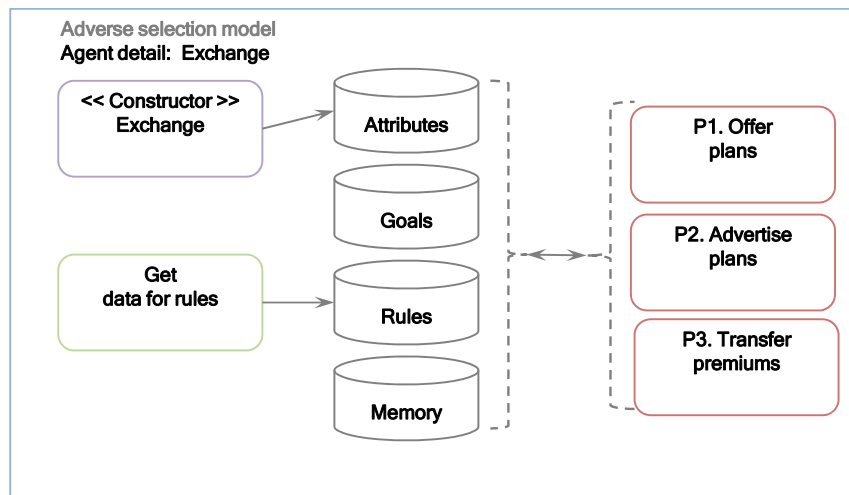
D. DETAILED AGENT DESCRIPTIONS CONTINUED

4. Exchange

This section describes the Exchange agent in detail.

a. Behavior overview

The diagram shows the behaviors of the Exchange. For a general discussion of the diagram, see the behavior overview for “Person” (Section D.1.a above). As the diagram shows, the Exchange includes three output processes as well as processes that get data from other agents in order to support the rules of the Exchange.



b. Attributes

The Exchange has the following attribute:

- **Identifier.** An integer uniquely identifying the Exchange.

c. Goals

The Exchange has the following major goal:

- **Minimize the number of uninsured person agents.** Over the course of the simulation, the Exchange wants to decrease the number of uninsured Person agents by the “uninsured decrease target”, a percentage that the user can enter as parameter D4 on the parameter pane.

D. DETAILED AGENT DESCRIPTIONS CONTINUED

4. Exchange continued

d. Experience

In memory, the Exchange stores the following information as of the start of the simulation, and for each simulation period thereafter.

- **Current plans offered.** The plans that the Exchange offers on its website, in order, including each plan's premium and co-payment percentage.
- **Current premiums received.** The total premiums that the Exchange receives from Person agents as they purchase a plan, by plan.
- **Current advertising intensity.** The intensity of the Exchange's advertising for the period.
- **Current advertising expenses.** The amount of advertising expenses for the current period.
- **Current premiums transferred.** The amount of premiums transferred to Health Insurance Companies, by company.

e. Rules

Following are the Exchange's rules:

- R1: Arrange plan order.** Based on the parameter D1 on the parameter pane, the Exchange determines the order in which it will offer plans on the Exchange website.
- R2: Determine advertising intensity.** If the Exchange has not reached its goal, it increases its advertising intensity each period by 1, up to the maximum advertising intensity of 10. If the Exchange has attained its goal, it does not change its advertising intensity.
- R3: Determine advertising expenses.** The amount of advertising expenses for the Exchange is equal to the amount of premiums received in the current period times the current advertising intensity (from Rule 2) times the "advertising expense percentage", parameter D3 of the parameter pane.

f. Output processes

Following are the Exchange's output processes:

- P1: Offer plans.** The Exchange offers plans on its website according to the order determined by Rule 1 (Arrange plan order).
- P2: Advertise plans.** The Exchange produces advertising, with an advertising intensity equal to the result of Rule 2 (Determine advertising intensity).
- P3: Transfer premiums.** The Exchange transfers an amount to each Health Insurance Company, equal to the amount of premiums received for the company's plans, minus the Exchange's advertising expenses for the year, calculated by Rule 3 (Determine advertising expenses). The amount of premiums transferred is not less than 0.0.

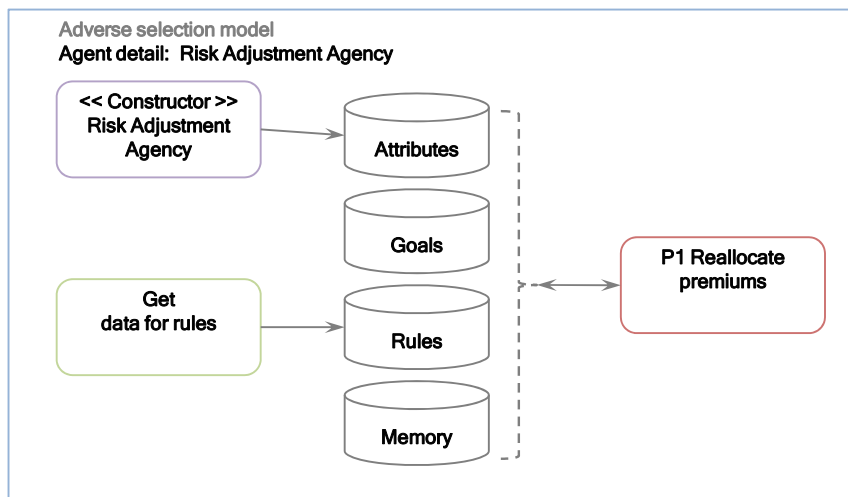
D. DETAILED AGENT DESCRIPTIONS CONTINUED

5. Risk Adjustment Agency

This section describes the Risk Adjustment Agency agent in detail.

a. Behavior overview

The diagram shows the behaviors of the Risk Adjustment Agency. For a general discussion of the diagram, see the behavior overview for “Person” (Section D.1.a above). As the diagram shows, the Risk Adjustment Agency includes one output process as well as processes that get data from other agents in order to support the Agency’s rules.



b. Attributes

The Risk Adjustment Agency has the following attribute:

- **Identifier.** An integer uniquely identifying the agency.

c. Goals

The Risk Adjustment Agency has the following major goal:

- **Maintain health risk equity.** Over the course of the simulation, the Agency wants to help Health Insurance Companies maintain health risk equity. That is, the Agency will strive to make sure that one Health Insurance Company is not saddled with a disproportionate number of sick Person agents, so that the ratio of medical expenditures to premiums is unfair relative to the other Company.

d. Experience

In memory, the Risk Adjustment Agency stores the following information for each simulation period.

- **Current risk experience.** The disease status averages that Health Insurance Companies submit, by company and plan.
- **Current premium reallocation.** The amount of premiums reallocated, by Health Insurance Company.

D. DETAILED AGENT DESCRIPTIONS CONTINUED

5. Risk Adjustment Agency *continued*

e. Rules

Following are the rules of the Risk Adjustment Agency:

R1: Compute premium reallocation. For each plan type (that is, with or without co-payment), the amount of additional premium to be allocated to Health Insurance Company A and taken away from Health Insurance Company B is:

$$\frac{(DS_A)^2 - (DS_B)^2}{\frac{(DS_B)^2}{C_A} + \frac{(DS_A)^2}{C_B}}$$

Where DS_A is the average disease status for Person agents who generated claims covered by Health Insurance Company A's plan, and C_A are Health Insurance Company A's actual claims for the plan during the prior period.

As we would hope, this formula has the following properties:

- when $DS_A = DS_B$, nothing is reallocated
- when $DS_A > DS_B$ (i.e., Company A's disease status is worse than Company B's), a positive amount is reallocated to Company A.
- for the same ratio (DS_A / DS_B), more is reallocated to company A when C_A is larger.

The reallocation amount is obtained by solving for R in the following equation¹:

$$\frac{C_A + R}{C_B - R} = \frac{(DS_A)^2 C_A}{(DS_B)^2 C_B}$$

f. Output processes

Following are the Risk Adjustment Agency's output processes:

P1: Reallocate premiums. The Agency provides each Health Insurance Company with reallocated premiums, calculated according to Rule 1 (Compute premium reallocation) for each plan.

¹ This formula is merely one of an infinite number of possible reallocation formulas. It provides that the ratio of claims after reallocation is equal to the ratio of claims before reallocation, adjusted by the ratio of disease statuses squared.

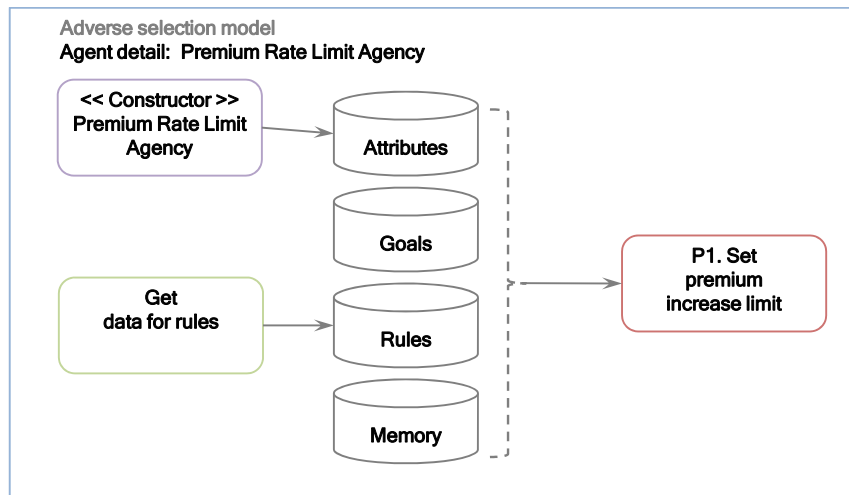
D. DETAILED AGENT DESCRIPTIONS CONTINUED

6. Premium Rate Limit Agency

This section describes the Premium Rate Limit Agency agent in detail.

a. Behavior overview

The diagram shows the behaviors of the Premium Rate Limit Agency. For a general discussion of the diagram, see the behavior overview for “Person” (Section D.1.a above). As the diagram shows, the Premium Rate Limit Agency includes one output process, and one process that gets data from other agents to support the Agency’s rules.



b. Attributes

The Premium Rate Limit Agency has the following attribute:

- **Identifier.** An integer uniquely identifying the agency.

c. Goals

The Premium Rate Limit Agency has the following major goal:

- **Moderate profits.** Over the period of the simulation, the Agency wants to maintain Health Insurance Company profits at the “Profit percentage maximum” (parameter F1 on the parameter pane) or less.

d. Experience

In memory, the Premium Rate Limit Agency stores the following information for each simulation period.

- **Current profit experience.** The annual profit percentages, by plan, that the Health Insurance Company agents submit.
- **Current premium rate increase limit.** The current premium rate increase limit for each Health Insurance Company and plan.

D. DETAILED AGENT DESCRIPTIONS CONTINUED

6. Premium Rate Limit Agency continued

e. Rules

Following are the Premium Rate Limit Agency's rules:

R1: Determine premium increase limit. If a Health Insurance Company's profit percentage for a plan exceeds the "Profit percentage maximum" (parameter F1 on the parameter pane), the Agency sets the "Premium rate increase limit" for the next simulation period to 0.0. If the Health Insurance Company's profit was less than or equal to the "Profit maximum percentage", for the next simulation period the agency sets the "Premium rate increase limit" to the "Profit percentage maximum".

f. Output processes

Following are the Premium Rate Limit Agency's output processes:

P1: Set premium increase limit. To all Health Insurance Companies, the agency sends the "Premium increase limit" determined according to Rule 1 (Determine premium increase limit).

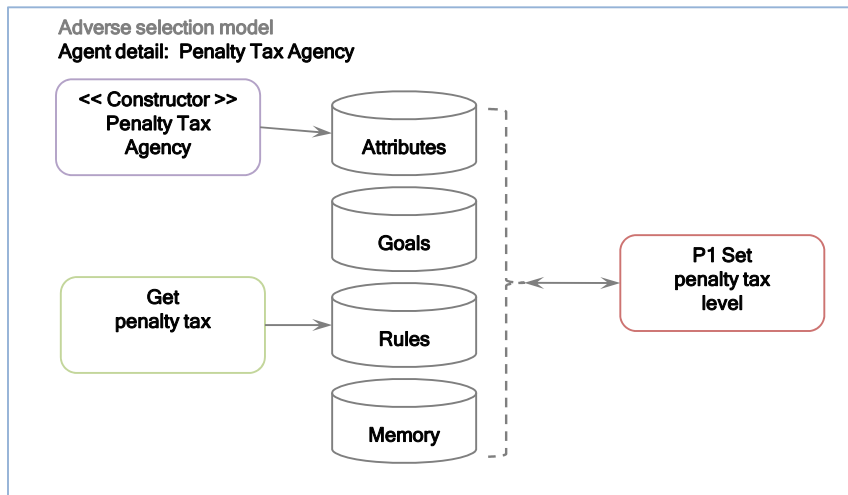
D. DETAILED AGENT DESCRIPTIONS CONTINUED

7. Penalty Tax Agency

This section describes the Penalty Tax Agency agent in detail.

a. Behavior overview

The diagram shows the behaviors of the Penalty Tax Agency. For a general discussion of the diagram, see the behavior overview for “Person” (Section D.1.a above). As the diagram shows, the Penalty Tax Agency includes one output process, and one process that gets data from other agents to support the Agency’s rules.



b. Attributes

The Penalty Tax Agency has the following attribute:

- **Identifier.** An integer uniquely identifying the Agency.

c. Goals

The Penalty Tax Agency has the following major goal:

- **Maximize coverage.** The Agency wants to decrease the percentage of Person agents who are uninsured to below the “Uninsured percentage target” (parameter E2 on the parameter pane).

d. Experience

In memory, the Penalty Tax Agency stores the following information for each simulation period.

- **Current penalty tax level.** The penalty tax level determined by the Agency for the current simulation period.
- **Current penalty tax amount.** The penalty tax amount paid by Person agents during the simulation period.

D. DETAILED AGENT DESCRIPTIONS CONTINUED

7. Penalty Tax Agency continued

e. Rules

Following are the Penalty Tax Agency's rules:

R1: Determine penalty tax rate. If the Agency has not reached its goal, it increases the penalty tax rate by 1.0 percent each simulation period, up to the maximum level of "Maximum penalty tax rate" (parameter E2 on the parameter pane). If the Agency has attained its goal, it does not change the penalty tax rate.

f. Output processes

Following are the Penalty Tax Agency's output processes:

P1: Set penalty tax rate. The Penalty Tax Agency sets the penalty tax rate according to Rule 1 (Determine penalty tax rate).

8. Environment

The Environment is the container for the model's agents. It creates the simulation's agents, maintains a list of agents, schedules agent behaviors, and obtains parameters that the user enters.