1

Learning in and about Complex Systems

Experience is an expensive school.

—Benjamin Franklin

Experience is something you get just after you need it.

—Anonymous

1.1 Introduction

The greatest constant of modern times is change. Accelerating changes in technology, population, and economic activity are transforming our world, from the prosaic—the effect of information technology on the way we use the telephone—to the profound—the effect of greenhouse gases on the global climate. Some of the changes are wonderful; others defile the planet, impoverish the human spirit, and threaten our survival. All challenge traditional institutions, practices, and beliefs. Most important, most of the changes we now struggle to comprehend arise as consequences, intended and unintended, of humanity itself. All too often, well-intentioned efforts to solve pressing problems lead to *policy resistance,* where our policies are delayed, diluted, or defeated by the unforeseen reactions of other people or of nature. Many times our best efforts to solve a problem actually make it worse.

The dizzying effects of accelerating change are not new. Henry Adams, a perceptive observer of the great changes wrought by the industrial revolution, formulated the Law of Acceleration to describe the exponential growth of technology, production, and population that made the legacy of colonial America he inherited irrelevant:

> Since 1800, scores of new forces had been discovered; old forces had been raised to higher powers . . . Complexity had extended itself on immense horizons, and arithmetical ratios were useless for any attempt at accuracy.
>
> If science were to go on doubling or quadrupling its complexities every 10 years, even mathematics should soon succumb. An average mind had succumbed already in 1850; it could no longer understand the problem in 1900. (Adams 1918, pp. 490, 496)

Adams believed the radical changes in society induced by these forces "would require a new social mind." With uncharacteristic, and perhaps ironic, optimism, he concluded, "Thus far, since 5 or 10 thousand years, the mind had successfully reacted, and nothing yet proved that it would fail to react—but it would need to jump."

A steady stream of philosophers, scientists, and management gurus have since echoed Adams, lamenting the acceleration and calling for similar leaps to fundamental new ways of thinking and acting. Many advocate the development of *systems thinking*—the ability to see the world as a complex system, in which we understand that "you can't just do one thing" and that "everything is connected to everything else." If people had a holistic worldview, it is argued, they would then act in consonance with the long-term best interests of the system as a whole, identify the high leverage points in systems, and avoid policy resistance. Indeed, for some, the development of systems thinking is crucial for the survival of humanity.[1]

The challenge facing us all is how to move from generalizations about accelerating learning and systems thinking to tools and processes that help us understand complexity, design better operating policies, and guide change in systems from the smallest business to the planet as a whole. However, learning about complex systems when you also live in them is difficult. We are all passengers on an aircraft we must not only fly but redesign in flight.

System dynamics is a method to enhance learning in complex systems. Just as an airline uses flight simulators to help pilots learn, system dynamics is, partly, a method for developing management flight simulators, often computer simulation models, to help us learn about dynamic complexity, understand the sources of policy resistance, and design more effective policies.

But learning about complex dynamic systems requires more than technical tools to create mathematical models. System dynamics is fundamentally interdisciplinary. Because we are concerned with the behavior of complex systems, system

[1]There are many schools of systems thinking (for surveys, see Richardson 1991 and Lane 1994). Some emphasize qualitative methods; others stress formal modeling. As sources of method and metaphor they draw on fields as diverse as anthropology, biology, engineering, linguistics, psychology, physics, and Taoism and seek applications in fields still more diverse. All agree, however, that a systems view of the world is still rare. Jay Forrester developed system dynamics in the 1950s at MIT. Richardson (1991) traces the history of the field and relates system dynamics to other systems approaches.

dynamics is grounded in the theory of nonlinear dynamics and feedback control developed in mathematics, physics, and engineering. Because we apply these tools to the behavior of human as well as physical and technical systems, system dynamics draws on cognitive and social psychology, economics, and other social sciences. Because we build system dynamics models to solve important real world problems, we must learn how to work effectively with groups of busy policy makers and how to catalyze sustained change in organizations.

This chapter discusses the skills required to develop your systems thinking capabilities, how to create an effective learning process in dynamically complex systems, and how to use system dynamics in organizations to address important problems. I first review what we know about how people learn in and about complex dynamic systems. Such learning is difficult and rare because a variety of structural impediments thwart the feedback processes required for learning to occur. Successful approaches to learning about complex dynamic systems require (1) tools to elicit and represent the mental models we hold about the nature of difficult problems; (2) formal models and simulation methods to test and improve our mental models, design new policies, and practice new skills; and (3) methods to sharpen scientific reasoning skills, improve group processes, and overcome defensive routines for individuals and teams.

1.1.1 Policy Resistance, the Law of Unintended Consequences, and the Counterintuitive Behavior of Social Systems

And it will fall out as in a complication of diseases, that by applying a remedy to one sore, you will provoke another; and that which removes the one ill symptom produces others . . .

—Sir Thomas More

The best-laid schemes o' mice an' men/ Gang aft a-gley.

—Robert Burns

Anything that can go wrong will go wrong.

—"Murphy"

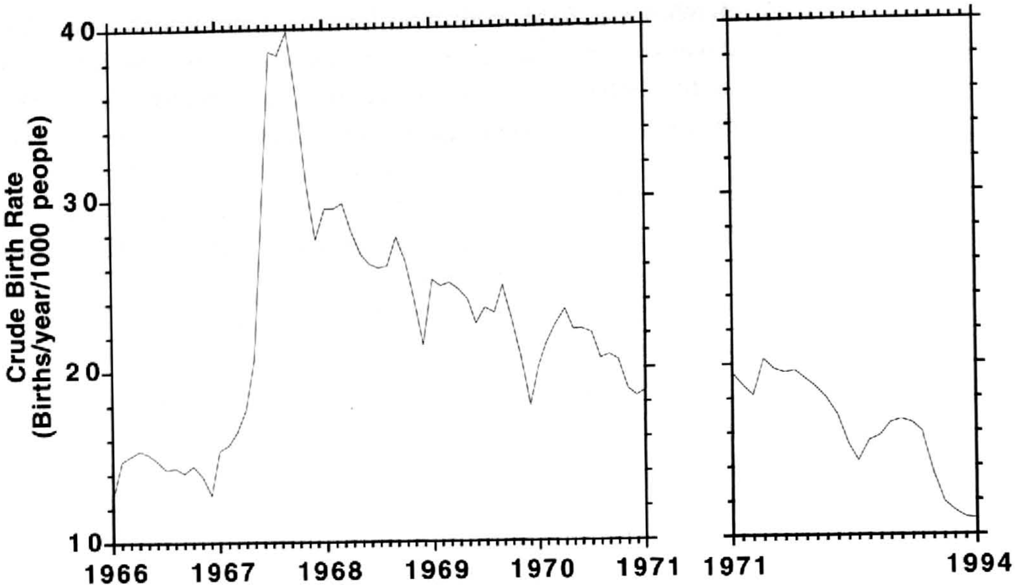
We have met the enemy and he is us.

—Pogo

From Thomas More in 1516 to Pogo in the mid 20th century it has long been acknowledged that people seeking to solve a problem often make it worse. Our policies may create unanticipated side effects. Our attempts to stabilize the system may destabilize it. Our decisions may provoke reactions by others seeking to restore the balance we upset. Forrester (1971a) calls such phenomena the "counterintuitive behavior of social systems." These unexpected dynamics often lead to policy resistance, the tendency for interventions to be delayed, diluted, or defeated by the response of the system to the intervention itself (Meadows 1982).

FIGURE 1-1
Policy resistance: Romanian birth rates

The crude birth rate in Romania showing the effect of restricting abortion beginning in 1966



Source: 1966–1971, David and Wright (1971); 1971–1994, *Romanian Statistical Yearbook 1995,* pp. 100–101. *Note:* 1971–1994 are annual averages.

As an example, consider the birth rate in Romania in the late 1960s. The crude birth rate (births per year per 1000 people) was extremely low—about 15 per thousand (Figure 1-1). For various reasons, including national pride and ethnic identity, the low birth rate was considered to be a grave problem by the government, including the dictator Nicolau Ceausesçu. The Ceausesçu regime responded by imposing policies designed to stimulate the birth rate. Importation of contraceptive devices was outlawed; propaganda campaigns extolling the virtues of large families and the patriotic (matriotic would be more accurate) duty to have more children were introduced, along with some modest tax incentives for larger families. Perhaps most important, abortion—freely available on demand since 1957 through the state health care system—was banned in October 1966 (David and Wright 1971).

The result was immediate and dramatic. The birth rate rose sharply to nearly 40 per 1000 per year, rivaling those of the fastest growing nations. The policy appeared to be a sensational success. However, within months the birth rate began to fall. By the end of 1970, only 4 years after the policy was implemented, the birth rate had dropped below 20 per thousand, close to the low levels seen prior to the intervention. Though the policy continued in force, the birth rate continued to fall, reaching 16 per thousand by 1989—about the same low rate that led to the imposition of the policy. What happened?

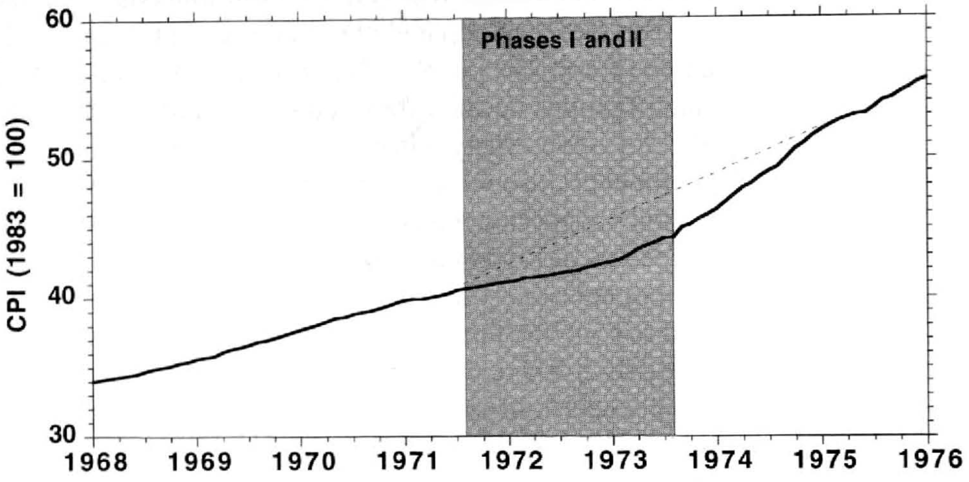
The system responded to the intervention in ways the regime did not anticipate. The people of Romania found ways around the policy. They practiced alternative methods of birth control. They smuggled contraceptive pills and devices in from other countries. Desperate women sought and found back-alley abortions. Many of these were unsanitary or botched, leading to a near tripling of deaths due to complications of abortion from 1965 to 1967. Most horribly, the number of neonatal deaths rose by more than 300% between 1966 and 1967, a 20% increase in the infant mortality rate (David and Wright 1971). The result: the policy was rendered completely ineffective almost immediately after implementation.

But the unanticipated consequences didn't end with the failure of the population policy. The people of Romania, among the poorest in Europe, were having small families because they couldn't afford larger ones. Child care was unavailable for some. Many others lived with their extended families in small, crowded apartments. Jobs were scarce; income was low. Many people gave children they couldn't support to state-run orphanages. The government's policy didn't prevent the people of Romania from controlling their own fertility, but it did breed intense resentment against the intrusive policies of the regime. In 1989, when the Berlin wall fell and the totalitarian regimes of Eastern Europe toppled, Romania was the only nation where the velvet revolution was violent. The hated Ceausesçu and his equally hated wife were summarily executed by firing squad. Their bloody bodies were left in the courtyard of the presidential palace while the scene was broadcast on national television. The law banning abortion was the first overturned by the new government. The birth rate, already low, fell further. By the mid 1990s, the population of Romania was actually declining as births dropped below deaths.

The children of Romania suffered the most from the population policy. During the years of the population policy thousands of children were placed in the care of state orphanages, where they were kept like animals in cribs (cages, really) without attention to basic needs, much less the love that all of us need and deserve. Food was so scarce that blood transfusions were routinely given as nutritional supplements. Because needles were used repeatedly, an epidemic of AIDS spread rapidly among the children. The side effects of the failed population policy cast a shadow on the health and happiness of an entire nation, a shadow stretching over generations.

Policy resistance is not limited to dictators. It doesn't respect national borders, political ideology, or historical epoch. Consider the US government's fight against inflation in the early 1970s. Figure 1-2 shows the Consumer Price Index (CPI) for the United States between 1968 and 1976. In the early 1970s inflation had accelerated and the Nixon administration felt action had to be taken. Though a Republican, Nixon chose to implement wage and price controls. The policy was expensive: A new federal bureaucracy, the Council on Wage and Price Stability, was created to oversee the controls and enforce compliance. Wage and price controls were viewed by many in Nixon's own party as verging on socialism, costing Nixon valuable political capital. At first, the policy seemed to work, although imperfectly. During so-called Phase I of the controls, the rate of inflation fell by about half. The administration decided the controls could be relaxed. In Phase II, President Ford (who inherited the program from Nixon) launched a jawboning campaign, complete with campaign-style buttons labeled "WIN!" for "Whip Inflation Now!". Few observers expected WIN! buttons to have any effect, and most felt inflation would return to its rate prior to the start of controls. Instead, inflation actually accelerated until, by 1975, the CPI had returned to the trajectory it was on prior to the imposition of the price controls. Less than 4 years after the intervention there was

FIGURE 1-2 Policy resistance in the fight against inflation
The US Consumer Price Index (CPI) showing the Nixon/Ford wage and price controls



no residue of benefit. Other examples of policy resistance can be found nearly every day in the newspaper. Table 1-1 lists a few.[2]

Machiavelli, a keen observer of human systems, discussed policy resistance at length, observing in the *Discourses* that

> When a problem arises either from within a republic or outside it, one brought about either by internal or external reasons, one that has become so great that it begins to make everyone afraid, the safest policy is to delay dealing with it rather than trying to do away with it, because those who try to do away with it almost always increase its strength and accelerate the harm which they feared might come from it. (Machiavelli 1979, pp. 240–241).

I find Machiavelli's view too cynical but can sympathize with his frustration in observing his client princes (the CEOs of Renaissance Italy) take actions that only made their problems worse. A more reflective view is offered by the late biologist and essayist Lewis Thomas (1974, p. 90):

> When you are confronted by any complex social system, such as an urban center or a hamster, with things about it that you're dissatisfied with and anxious to fix, you cannot just step in and set about fixing with much hope of helping. This realization is one of the sore discouragements of our century . . . You cannot meddle with one part of a complex system from the outside without the almost certain risk of setting off disastrous events that you hadn't counted on in other, remote parts. If you want to fix something you are first obliged to understand . . . the whole system . . . Intervening is a way of causing trouble.

[2]Further reading: John McPhee (1989) offers a wonderful description of policy resistance in the relationship of people with nature. McPhee brilliantly describes the unanticipated side effects and policy resistance arising from attempts to defeat three elemental forces of nature: volcanism, flood, and fire. Edward Tenner (1996) also identifies many examples of policy resistance.

TABLE 1-1
Examples of policy resistance

- "Use of Cheaper Drugs Pushes Costs Up, Not Down, Study Finds: Limiting what is prescribed, as managed-care systems do, has unintended effect of increasing costs, results show" (Headline in *LA Times*, 3/20/96, p. 1, reporting Univ. of Utah study of 13,000 patients in various HMOs).
- "Washington's biggest conservation program, which pays farmers to take soil out of cultivation for a decade to combat erosion and help the environment, is a waste of money, so says a new study of the 11-year-old program . . . For every eroding acre a farmer idles, another farmer—or sometimes the same one—simply plows up nearly as much additional erosion-prone land . . . In the Great Plains, for instance, farmers set aside 17 million acres, yet the total cultivated land dropped by only 2 million acres" (*Business Week*, 3/18/96, p. 6, reporting a Univ. of Minnesota study).
- Low tar and nicotine cigarettes actually increase intake of carcinogens, CO, etc. as smokers compensate for the low nicotine content by smoking more cigarettes per day, by taking longer, more frequent drags, and by holding the smoke in their lungs longer.
- Antilock brakes and other automotive safety devices cause some people to drive more aggressively, offsetting some of their benefits.
- Information technology has not enabled the "paperless office"—paper consumption per capita is up.
- Road building programs designed to reduce congestion have increased traffic, delays, and pollution.
- Despite widespread use of labor-saving appliances, Americans have less leisure today than 50 years ago.
- The US government's war on drugs, focusing on interdiction and supply disruption (particularly cocaine production in South America), with a cost in the billions, has had only a small impact on cocaine cultivation, production, or smuggling. Drug use in America and elsewhere remains high.
- The US policy of fire suppression has increased the size and severity of forest fires. Rather than frequent, small fires, fire suppression leads to the accumulation of dead wood and other fuels leading to larger, hotter, and more dangerous fires, often consuming the oldest and largest trees which previously survived smaller fires unharmed.
- Flood control efforts such as levee and dam construction have led to more severe floods by preventing the natural dissipation of excess water in flood plains. The cost of flood damage has increased as the flood plains were developed by people who believed they were safe.
- Imposing 200-mile territorial limits and quotas to protect fish stocks did not prevent the collapse of the Georges Bank fishery off the coast of North America. Once the world's richest, by the mid 1990s many species were commercially extinct, the fishery was shut down, the fleets were idled, and the local economies were in depression.
- Deregulation of the US Savings and Loan industry, designed to save the industry from financial problems, led to a wave of speculation followed by collapse, at a cost to taxpayers in the hundreds of billions of dollars.
- Antibiotics have stimulated the evolution of drug-resistant pathogens, including virulent strains of TB, strep, staph, and sexually transmitted diseases.
- Pesticides and herbicides have stimulated the evolution of resistant pests and weeds, killed off natural predators, and accumulated up the food chain to poison fish, birds, and possibly humans.

But how can one come to understand the whole system? How does policy resistance arise? How can we learn to avoid it, to find the high leverage policies that can produce sustainable benefit?

1.1.2 Causes of Policy Resistance

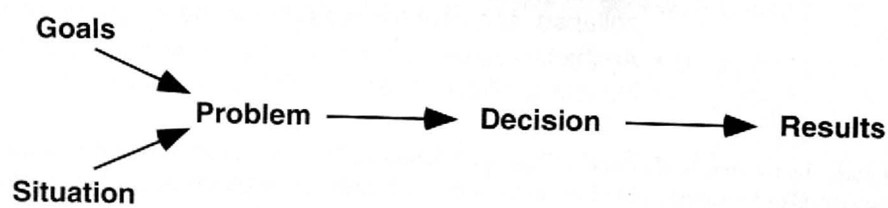
One cause of policy resistance is our tendency to interpret experience as a series of events, for example, "inventory is too high," or "sales fell this month." Accounts of who did what to whom are the most common mode of discourse, from the mailroom to the boardroom, from headlines to history books. We are taught from an early age that every event has a cause, which in turn is an effect of some still earlier cause: "Inventory is too high because sales unexpectedly fell. Sales fell because the competitors lowered their price. The competitors lowered their price because . . ." Such event-level explanations can be extended indefinitely, in an unbroken Aristotelian chain of causes and effects, until we arrive at some First Cause, or more likely, lose interest along the way.

The event-oriented worldview leads to an event-oriented approach to problem solving. Figure 1-3 shows how we often try to solve problems. We assess the state of affairs and compare it to our goals. The gap between the situation we desire and the situation we perceive defines our problem. For example, suppose sales of your organization were $80 million last quarter, but your sales goal was $100 million. The problem is that sales are 20% less than you desired. You then consider various options to correct the problem. You might cut prices to stimulate demand and increase market share, replace the vice president of sales with someone more aggressive, or take other actions. You select the option you deem best and implement it, leading (you hope) to a better result. You might observe your sales increase: problem solved. Or so it seems.

The system reacts to your solution: As your sales rise, competitors cut prices, and sales fall again. Yesterday's solution becomes today's problem. We are not puppet masters influencing a system *out there*—we are embedded in the system. The puppet master's movements respond to the position of the marionette on the strings. There is feedback: The results of our actions define the situation we face in the future. The new situation alters our assessment of the problem and the decisions we take tomorrow (see the top of Figure 1-4).

Policy resistance arises because we often do not understand the full range of feedbacks operating in the system (Figure 1-4). As our actions alter the state of the system, other people react to restore the balance we have upset. Our actions may also trigger side effects.

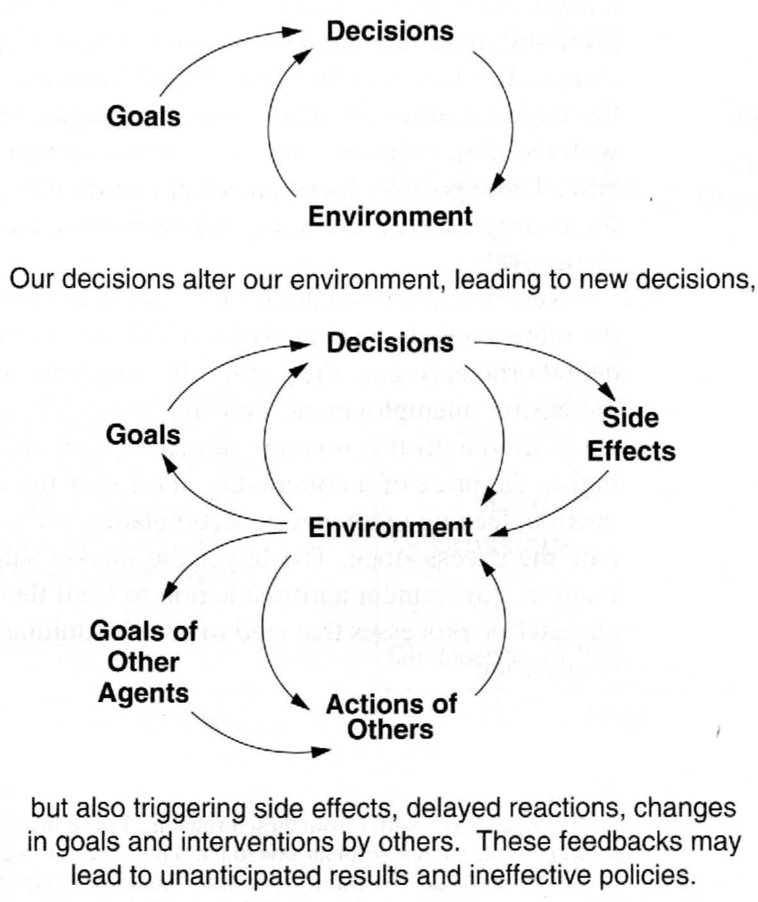
FIGURE 1-3 Event-oriented view of the world



We frequently talk about side effects as if they were a feature of reality. Not so. In reality, there are no side effects, there are just *effects*. When we take action, there are various effects. The effects we thought of in advance, or were beneficial, we call the main, or intended effects. The effects we didn't anticipate, the effects which fed back to undercut our policy, the effects which harmed the system—these are the ones we claim to be side effects. Side effects are not a feature of reality but a sign that our understanding of the system is narrow and flawed.

Unanticipated side effects arise because we too often act as if cause and effect were always closely linked in time and space. But in complex systems such as an urban center or a hamster (or a business, society, or ecosystem) cause and effect are often distant in time and space. Narrow model boundaries often lead to beliefs that violate the laws of physics: in the mid 1990s California and the automobile industry debated the introduction of so-called zero emission vehicles (ZEVs) to reduce air pollution. True, the ZEVs—electric cars—would have no tailpipe. But the power plants required to make the electricity to run them do generate pollution. In reality, California was promoting the adoption of DEVs—*displaced* emission vehicles—cars whose wastes would blow downwind to other states or accumulate in nuclear waste dumps outside its borders. Electric cars may turn out to be an environmental boon compared to internal combustion. The technology is improving rapidly, and air pollution is a major health problem in many cities. But no mode of

FIGURE 1-4
The feedback view



transport or energy conversion process is free of environmental impact, and no legislature can repeal the second law of thermodynamics.[3]

To avoid policy resistance and find high leverage policies requires us to expand the boundaries of our mental models so that we become aware of and understand the implications of the feedbacks created by the decisions we make. That is, we must learn about the structure and dynamics of the increasingly complex systems in which we are embedded.

1.1.3 Feedback

Much of the art of system dynamics modeling is discovering and representing the feedback processes, which, along with stock and flow structures, time delays, and nonlinearities, determine the dynamics of a system. You might imagine that there is an immense range of different feedback processes and other structures to be mastered before one can understand the dynamics of complex systems. In fact, the most complex behaviors usually arise from the interactions (feedbacks) among the components of the system, not from the complexity of the components themselves.

All dynamics arise from the interaction of just two types of feedback loops, positive (or self-reinforcing) and negative (or self-correcting) loops (Figure 1-5). Positive loops tend to reinforce or amplify whatever is happening in the system: The more nuclear weapons NATO deployed during the Cold War, the more the Soviet Union built, leading NATO to build still more. If a firm lowers its price to gain market share, its competitors may respond in kind, forcing the firm to lower its price still more. The larger the installed base of Microsoft software and Intel machines, the more attractive the "Wintel" architecture became as developers sought the largest market for their software and customers sought systems compatible with the most software; the more Wintel computers sold, the larger the installed base. These positive loops are all processes that generate their own growth, leading to arms races, price wars, and the phenomenal growth of Microsoft and Intel, respectively.

Negative loops counteract and oppose change. The less nicotine in a cigarette, the more smokers must consume to get the dose they need. The more attractive a neighborhood or city, the greater the inmigration from surrounding areas will be, increasing unemployment, housing prices, crowding in the schools, and traffic congestion until it is no more attractive than other places people might live. The higher the price of a commodity, the lower the demand and the greater the production, leading to inventory accumulation and pressure for lower prices to eliminate the excess stock. The larger the market share of dominant firms, the more likely is government antitrust action to limit their monopoly power. These loops all describe processes that tend to be self-limiting, processes that seek balance and equilibrium.

[3]Even scientists suffer from these problems. I once heard a distinguished physicist argue that the solution to the energy problem was to build hundreds of huge offshore nuclear power stations, to be cooled by seawater. The warm wastewater would be pumped back in the ocean where, he said, "The waste heat would disappear." Out of sight, out of mind.

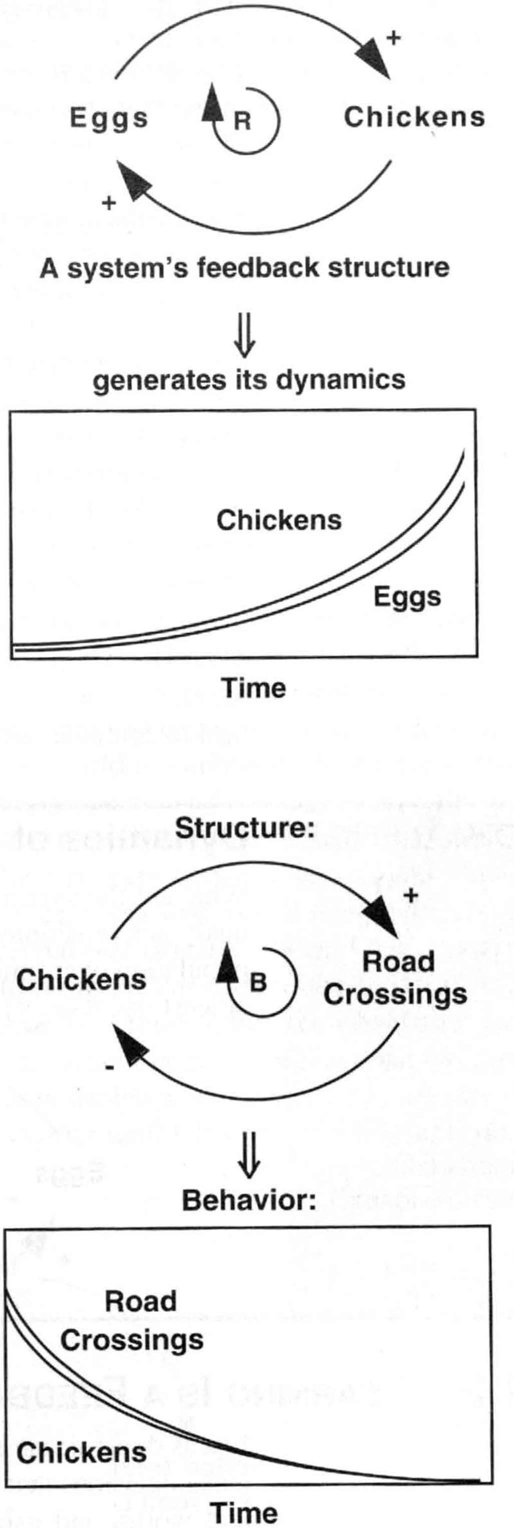
FIGURE 1-5
Positive and negative feedback loops

Positive feedback: Positive loops are self-reinforcing. In this case, more chickens lay more eggs, which hatch and add to the chicken population, leading to still more eggs, and so on. A Causal Loop Diagram or CLD (chapter 5) captures the feedback dependency of chickens and eggs. The arrows indicate the causal relationships. The + signs at the arrowheads indicate that the effect is positively related to the cause: an increase in the chicken population causes the number of eggs laid each day to rise above what it would have been (and vice versa: a decrease in the chicken population causes egg laying to fall below what it would have been). The loop is self-reinforcing, hence the loop polarity identifier **R.** If this loop were the only one operating, the chicken and egg population would both grow exponentially.

Of course, no real quantity can grow forever. There must be limits to growth. These limits are created by negative feedback.

Negative feedback: Negative loops are self-correcting. They counteract change. As the chicken population grows, various negative loops will act to balance the chicken population with its carrying capacity. One classic feedback is shown here: The more chickens, the more road crossings they will attempt. If there is any traffic, more road crossings will lead to fewer chickens (hence the negative – polarity for the link from road crossings to chickens). An increase in the chicken population causes more risky road crossings, which then bring the chicken population back down. The **B** in the center of a loop denotes a balancing feedback. If the road-crossing loop was the only one operating (say because the farmer sells all the eggs), the number of chickens would gradually decline until none remained.

All systems, no matter how complex, consist of networks of positive and negative feedbacks, and all dynamics arise from the interaction of these loops with one another.



1.1.4 Process Point: The Meaning of Feedback

In common parlance the term "feedback" has come to serve as a euphemism for criticizing others, as in "the boss gave me feedback on my presentation." This use of feedback is not what we mean in system dynamics. Further, "positive feedback" does not mean "praise" and "negative feedback" does not mean "criticism." Positive feedback denotes a self-reinforcing process, and negative feedback denotes a self-correcting one. Either type of loop can be good or bad, depending on which way it is operating and of course on your values. Reserve the terms positive and negative feedback for self-reinforcing and self-correcting processes, and avoid describing the criticism you give or receive to others as feedback. Telling someone your opinion does not constitute feedback unless they act on your suggestions and thus lead you to revise your view.

Though there are only two types of feedback loop, models may easily contain thousands of loops, of both types, coupled to one another with multiple time delays, nonlinearities, and accumulations. The dynamics of all systems arise from the interactions of these networks of feedbacks. Intuition may enable us to infer the dynamics of isolated loops such as those shown in Figure 1-5. But when multiple loops interact, it is not so easy to determine what the dynamics will be. Before continuing, try the challenge shown in Figure 1-6. When intuition fails, we usually turn to computer simulation to deduce the behavior of our models.

CHALLENGE

Dynamics of Multiple-Loop Systems

What are the dynamics of the chicken population when both loops are simultaneously active (Figure 1-6)? Sketch a graph showing the behavior of the chicken population over time. Assume the initial chicken population is small (but includes at least one rooster).

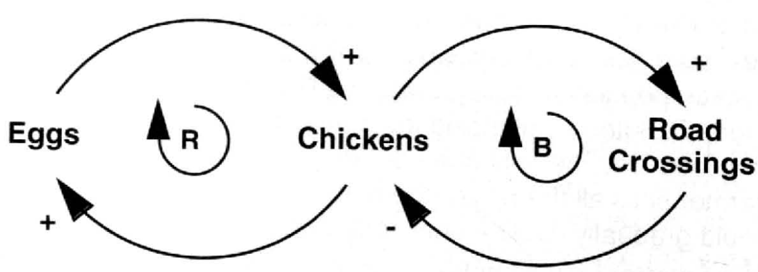


FIGURE 1-6 Dynamics arise from the interaction of multiple loops.

1.2 LEARNING IS A FEEDBACK PROCESS

Just as dynamics arise from feedback, so too all learning depends on feedback. We make decisions that alter the real world; we gather information feedback about the real world, and using the new information we revise our understanding of the world and the decisions we make to bring our perception of the state of the system closer to our goals (Figure 1-7).

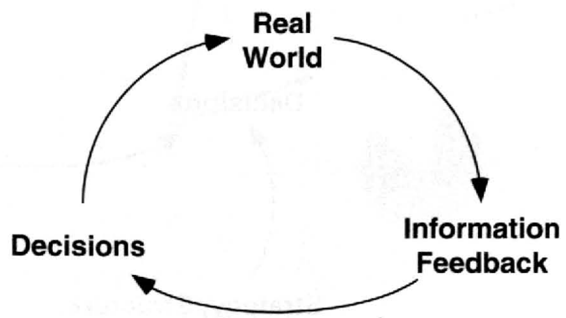
The feedback loop in Figure 1-7 appears in many guises throughout the social sciences. George Richardson (1991), in his history of feedback concepts in the social sciences, shows how beginning in the 1940s leading thinkers in economics, psychology, sociology, anthropology, and other fields recognized that the concept of feedback developed in physics and engineering applied not only to servomechanisms but to human decision making and social settings as well. By 1961, Forrester, in *Industrial Dynamics,* asserted that all decisions (including learning) take place in the context of feedback loops. Later, the psychologist Powers (1973, p. 351) wrote:

> Feedback is such an all-pervasive and fundamental aspect of behavior that it is as invisible as the air that we breathe. Quite literally it is behavior—we know nothing of our own behavior but the feedback effects of our own outputs.

These feedback thinkers followed in the footsteps of John Dewey, who recognized the feedback loop character of learning around the beginning of the 20th century when he described learning as an iterative cycle of invention, observation, reflection, and action (Schön 1992). Feedback accounts of behavior and learning have now permeated most of the social and management sciences. Learning as an explicit feedback process has even appeared in practical management tools such as Total Quality Management, where the so-called Shewhart–Deming PDCA cycle (Plan-Do-Check-Act) lies at the heart of the improvement process in the quality improvement literature (Shewhart 1939; Shiba, Graham, and Walden 1993).

The single feedback loop shown in Figure 1-7 describes the most basic type of learning. The loop is a classical negative feedback whereby decision makers compare information about the state of the real world to various goals, perceive discrepancies between desired and actual states, and take actions that (they believe) will cause the real world to move towards the desired state. Even if the initial choices of the decision makers do not close the gaps between desired and actual states, the system might eventually reach the desired state as subsequent decisions are revised in light of the information received (see Hogarth 1981). When driving, I may turn the steering wheel too little to bring the car back to the center of my lane, but as visual feedback reveals the error, I continue to turn the wheel until the car returns to the straight and narrow. If the current price for products of my firm is too low to balance orders with production, depleted inventories and long delivery delays may cause me to gradually raise price until I discover a price that clears the market.[4]

FIGURE 1-7
Learning is a feedback process.
Feedback from the real world to the decision maker includes all forms of information, both quantitative and qualitative.



[4]Depending on the time delays and other elements of dynamic complexity in the system, these examples may not converge. It takes but little ice, fog, fatigue, or alcohol to cause an accident, and equilibrium eludes many industries that experience chronic business cycles.

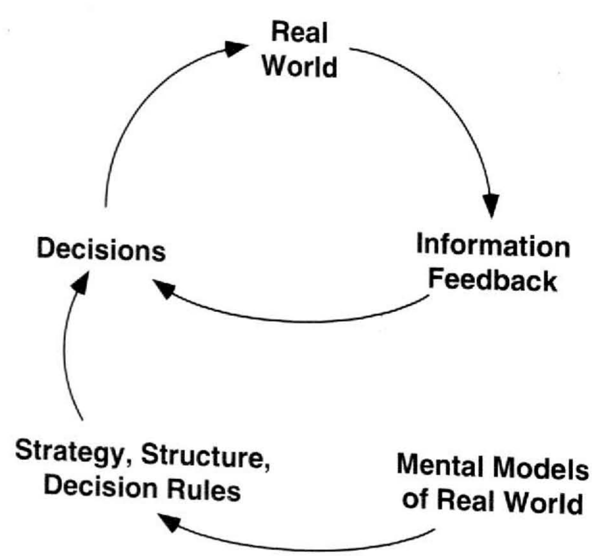
The feedback loop shown in Figure 1-7 obscures an important aspect of the learning process. Information feedback about the real world is not the only input to our decisions. Decisions are the result of applying a decision rule or policy to information about the world as we perceive it (see Forrester 1961, 1992). The policies are themselves conditioned by institutional structures, organizational strategies, and cultural norms. These, in turn, are governed by our mental models (Figure 1-8). As long as the mental models remain unchanged, the feedback loop shown in the figure represents what Argyris (1985) calls single-loop learning, a process whereby we learn to reach our current goals in the context of our existing mental models. Single-loop learning does not result in deep change to our mental models—our understanding of the causal structure of the system, the boundary we draw around the system, the time horizon we consider relevant—nor our goals and values. Single-loop learning does not alter our worldview.

Mental models are widely discussed in psychology and philosophy. Different theorists describe mental models as collections of routines or standard operating procedures, scripts for selecting possible actions, cognitive maps of a domain, typologies for categorizing experience, logical structures for the interpretation of language, or attributions about individuals we encounter in daily life (Axelrod 1976; Bower and Morrow 1990; Cheng and Nisbett 1985; Doyle and Ford 1998; Gentner and Stevens 1983; Halford 1993; Johnson-Laird 1983; Schank and Abelson 1977; Vennix 1990). The concept of the mental model has been central to system dynamics from the beginning of the field. Forrester (1961) stresses that all decisions are based on models, usually mental models. In system dynamics, the term "mental model" includes our beliefs about the networks of causes and effects that describe how a system operates, along with the boundary of the model (which variables are included and which are excluded) and the time horizon we consider relevant—our framing or articulation of a problem.

Most of us do not appreciate the ubiquity and invisibility of mental models, instead believing naively that our senses reveal the world as it is. On the contrary,

FIGURE 1-8
Single-loop learning: information feedback is interpreted by existing mental models.

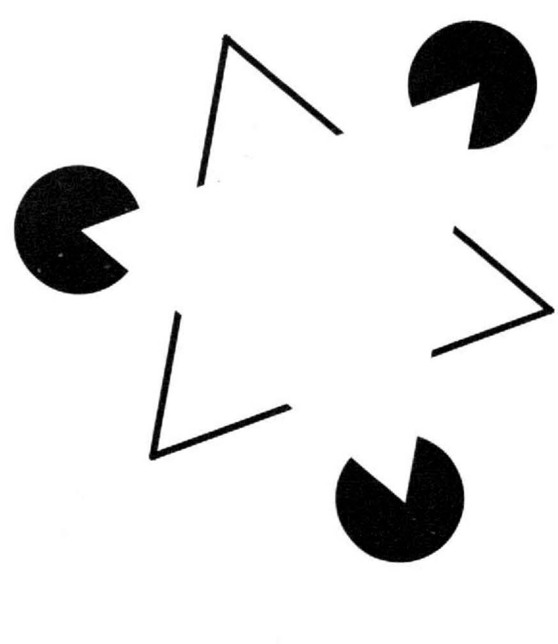
The learning feedback operates in the context of existing decision rules, strategies, culture, and institutions which in turn are derived from our mental models.



our world is actively constructed (modeled) by our senses and brain. Figure 1-9 shows an image developed by psychologist Gaetano Kanizsa. The vast majority of people see a bright white triangle resting on top of three circles and a second triangle with black edges. The illusion is extremely powerful (try to look at the figure and "not see" the two triangles!). Research shows that the neural structures responsible for the ability to see illusory contours such as the white triangle exist between the optic nerve and the areas of the brain responsible for processing visual information.[5] Active modeling occurs well before sensory information reaches the areas of the brain responsible for conscious thought.[6] Powerful evolutionary pressures are responsible: Our survival depends so completely on the ability to rapidly interpret our environment that we (and other species) long ago evolved structures to build these models automatically. Usually we are completely unaware these mental models even exist. It is only when a construction such as the Kanizsa triangle reveals the illusion that we become aware of our mental models.

The Kanizsa triangle illustrates the necessity of active and unconscious mental modeling or construction of "reality" at the level of visual perception. Modeling of higher-level knowledge is likewise unavoidable and often equally unconscious. Figure 1-10 shows a mental model elicited during a meeting between my colleague Fred Kofman and a team from a large global corporation. The company worked with the Organizational Learning Center at MIT in the early 1990s to reduce the total cycle time for their supply chain. At that time the cycle time was 182 days and they sought to cut it in half. The company viewed reductions in cycle time as essential for continued competitiveness and even corporate survival. With the

FIGURE 1-9
Kanizsa triangle
Do you see the bright white triangle lying on top of the three dark circles and a second triangle?



[5]See *Science*, 256, (12 June 1992), pp. 1520–1521.

[6]Even more obviously, our ability to see a three-dimensional world is the result of extensive modeling by the visual processing system, since the retina images a planar projection of the visual field.

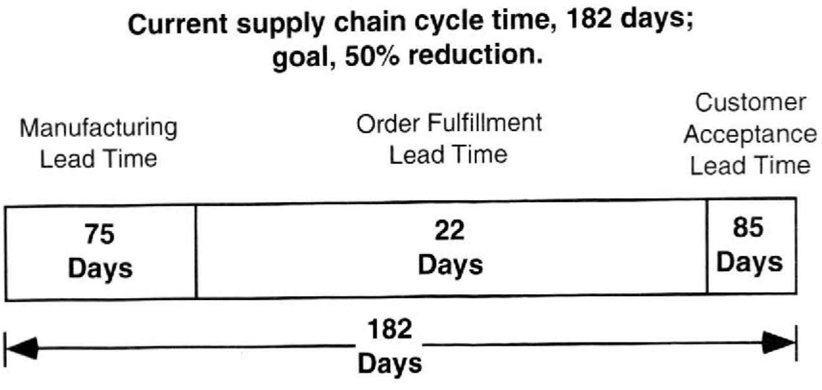


FIGURE 1-10 Mental model revealed by a diagram of a company's supply chain

The figure has been simplified compared to the actual chart to protect company-confidential information but is drawn to scale.

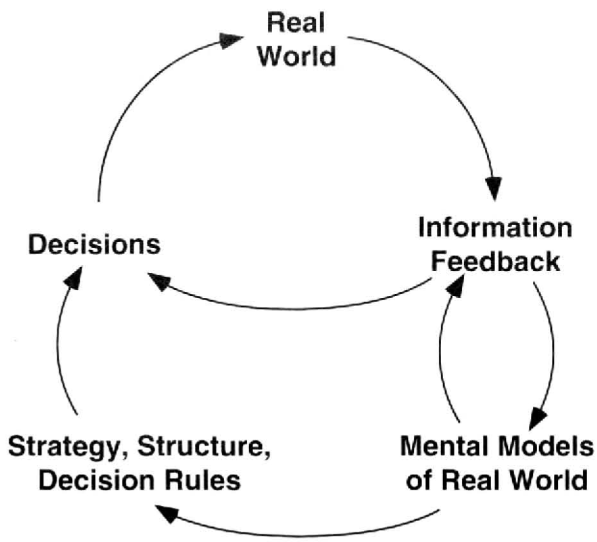
support of senior management, they assembled a team to address these issues. At the first meeting the team presented background information, including Figure 1-10.

The figure shows the current cycle time divided into three intervals along a line: manufacturing lead time, order fulfillment lead time, and customer acceptance lead time. Order fulfillment, which then required 22 days, occupies more than half of the total length of the line, while the manufacturing lead time, then requiring 75 days (70 days due to suppliers), receives about one-fourth of the length. Customer acceptance, then requiring 85 days, occupies only about one-eighth of the total length. What the figure reveals is the prominence of order fulfillment operations in the mental models of the people on the team and the insignificance in their minds of suppliers and customers. It will come as no surprise that the members of the team all worked in functions contributing to order fulfillment. There was not a single person at the meeting representing procurement, nor a single supplier representative, nor anyone from accounting, nor a single customer. Until Fred pointed out this distortion, the members of the group were as unaware of the illusory character of their image of the supply line as we normally are of the illusory contours our brains project onto the data transmitted by our optic nerves. The distorted mental model of the supply chain significantly constrained the company's ability to reduce cycle time: Even if order fulfillment could be accomplished instantly the organization would fall well short of its goal.

The type of reframing stimulated by Fred's intervention, denoted *double-loop learning* by Argyris (1985), is illustrated in Figure 1-11. Here information feedback about the real world not only alters our decisions within the context of existing frames and decision rules but also feeds back to alter our mental models. As our mental models change we change the structure of our systems, creating different decision rules and new strategies. The same information, processed and interpreted by a different decision rule, now yields a different decision. Altering the structure of our systems then alters their patterns of behavior. The development of systems thinking is a double-loop learning process in which we replace a reductionist, narrow, short-run, static view of the world with a holistic, broad, long-term, dynamic view and then redesign our policies and institutions accordingly.

FIGURE 1-11
Double-loop learning

Feedback from the real world can also stimulate changes in mental models. Such learning involves new understanding or reframing of a situation and leads to new goals and new decision rules, not just new decisions.



1.3 BARRIERS TO LEARNING

For learning to occur each link in the two feedback loops shown in Figure 1-11 must work effectively and we must be able to cycle around the loops quickly relative to the rate at which changes in the real world render existing knowledge obsolete. Yet in the real world, particularly the world of social action, these feedbacks often do not operate well. More than two and a half centuries elapsed from the first experiments showing that lemon juice could prevent and cure scurvy until citrus use was mandated in the British merchant marine (Table 1-2). Learning in this case was terribly slow, despite the enormous importance of the problem and

TABLE 1-2
Teaching scurvy dogs new tricks

Total delay in learning: 264 years.

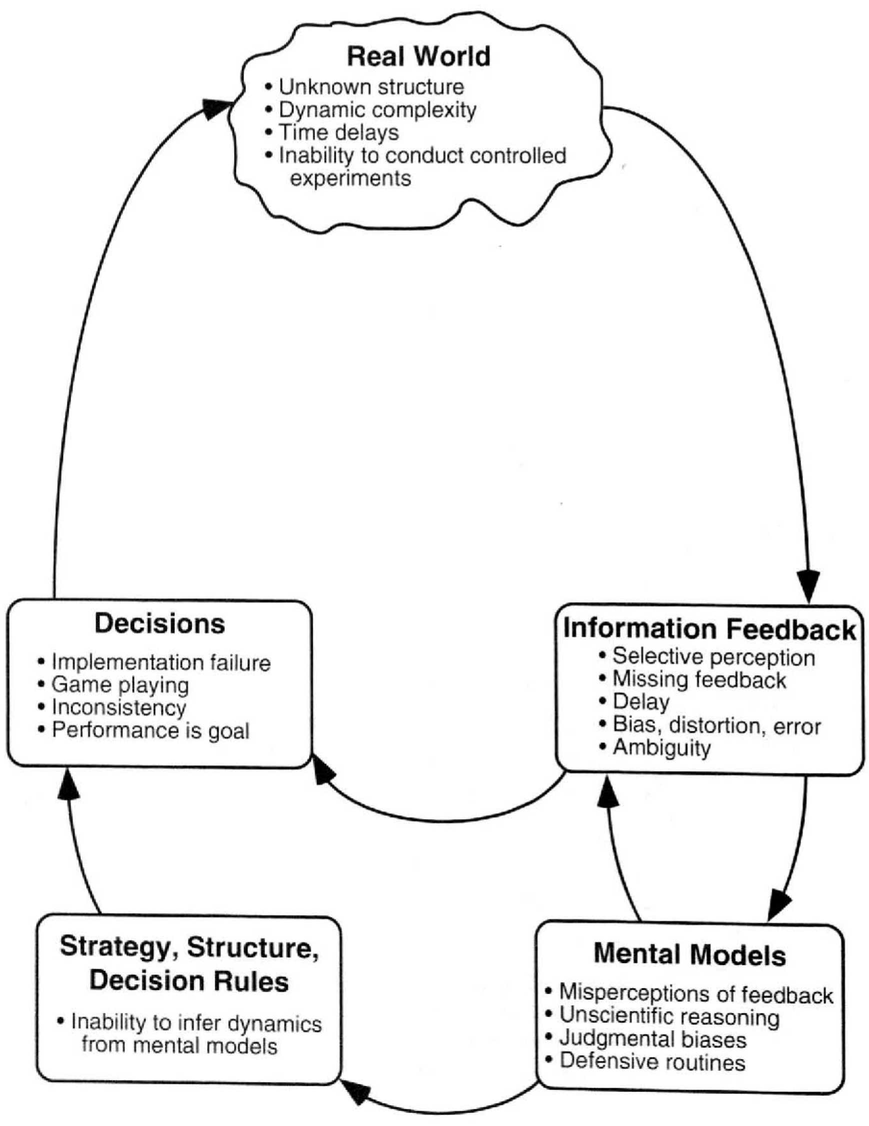
• Prior to the 1600s, scurvy (vitamin C deficiency) was the greatest killer of seafarers—more than battle deaths, storms, accidents, and all others *combined.*
• 1601: Lancaster conducts a controlled experiment during an East India Company voyage: The crew on one ship received 3 tsp. of lemon juice daily; the crew on three other ships did not. Results: At the Cape of Good Hope 110 out of 278 sailors had died, most from scurvy. The crew receiving lemon juice remained largely healthy.
• 1747: Dr. James Lind conducts a controlled experiment in which scurvy patients were treated with a variety of elixirs. Those receiving citrus were cured in a few days; none of the other treatments worked.
• 1795: The British Royal Navy begins using citrus on a regular basis. Scurvy wiped out.
• 1865: The British Board of Trade mandates citrus use. Scurvy wiped out in the merchant marine.

Source: Mosteller (1981).

the decisive evidence supplied by controlled experiments throughout the years. You may reply that today we are much smarter and learn faster. Perhaps. Yet the rate of corporate and organizational failure remains high (for example, over one-third of the Fortune 500 largest industrial firms in 1970 had disappeared by 1983 [de Geus 1997]). Today the rate of change in our systems is much faster, and their complexity is much greater. The delays in learning for many pressing problems remain woefully long. In most settings we lack the ability to run experiments, and the delays between interventions and outcomes are much longer. As the rate of change accelerates throughout society, learning remains slow, uneven, and inadequate.

Figure 1-12 shows the main ways in which each link in the learning feedbacks can fail. These include dynamic complexity, imperfect information about the state of the real world, confounding and ambiguous variables, poor scientific reasoning skills, defensive routines, and other barriers to effective group processes, implementation failure, and the misperceptions of feedback that hinder our ability to understand the structure and dynamics of complex systems.

FIGURE 1-12 Impediments to learning



1.3.1 Dynamic Complexity

Much of the literature in psychology, economics, and other fields suggests learning proceeds via the simple negative feedback loops described in Figure 1-11. Implicitly, the loops are seen as swift, linear, negative feedbacks that produce stable convergence to an equilibrium or optimal outcome, just as immediate visual feedback allows you to fill a glass of water without spilling. The real world is not so simple. From the beginning, system dynamics emphasized the multiloop, multistate, nonlinear character of the feedback systems in which we live (Forrester 1961). The decisions of any one agent form but one of many feedback loops that operate in any given system. These loops react to the decision maker's actions in ways both anticipated and unanticipated; there may be positive as well as negative feedback loops, and these loops will contain many stocks (state variables) and many nonlinearities. Natural and human systems have high levels of *dynamic complexity*. Table 1-3 shows some of the characteristics of systems that give rise to dynamic complexity.

Most people think of complexity in terms of the number of components in a system or the number of combinations one must consider in making a decision. The problem of optimally scheduling an airline's flights and crews is highly complex, but the complexity lies in finding the best solution out of an astronomical number of possibilities. Such needle-in-a-haystack problems have high levels of *combinatorial* complexity (also known as *detail* complexity). *Dynamic* complexity, in contrast, can arise even in simple systems with low combinatorial complexity. The Beer Distribution Game (Sterman 1989b, chap. 17.4) provides an example: Complex and dysfunctional behavior arises from a very simple system whose rules can be explained in 15 minutes. Dynamic complexity arises from the interactions among the agents over time.

Time delays between taking a decision and its effects on the state of the system are common and particularly troublesome. Most obviously, delays reduce the number of times one can cycle around the learning loop, slowing the ability to accumulate experience, test hypotheses, and improve. Schneiderman (1988) estimated the improvement half life—the time required to cut defects in half—in a wide range of manufacturing firms. He found improvement half lives as short as a few months for processes with short delays, for example reducing operator error in a job shop, while complex processes with long time delays such as product development had improvement half lives of several years or more.[7]

Dynamic complexity not only slows the learning loop; it also reduces the learning gained on each cycle. In many cases controlled experiments are prohibitively costly or unethical. More often, it is simply impossible to conduct controlled experiments. Complex systems are in disequilibrium and evolve. Many actions yield irreversible consequences. The past cannot be compared well to current circumstance. The existence of multiple interacting feedbacks means it is difficult to hold other aspects of the system constant to isolate the effect of the variable of interest. Many variables change simultaneously, confounding the interpretation

[7]Sterman, Repenning, and Kofman (1997) show how these differential improvement rates led to difficulty at a leading semiconductor manufacturer.

TABLE 1-3 Dynamic complexity

Dynamic complexity arises because systems are

- **Dynamic:** Heraclitus said, "All is change." What appears to be unchanging is, over a longer time horizon, seen to vary. Change in systems occurs at many time scales, and these different scales sometimes interact. A star evolves over billions of years as it burns its hydrogen fuel, then can explode as a supernova in seconds. Bull markets can go on for years, then crash in a matter of hours.
- **Tightly coupled:** The actors in the system interact strongly with one another and with the natural world. Everything is connected to everything else. As a famous bumper sticker from the 1960s proclaimed, "You can't do just one thing."
- **Governed by feedback:** Because of the tight couplings among actors, our actions feed back on themselves. Our decisions alter the state of the world, causing changes in nature and triggering others to act, thus giving rise to a new situation which then influences our next decisions. Dynamics arise from these feedbacks.
- **Nonlinear:** Effect is rarely proportional to cause, and what happens locally in a system (near the current operating point) often does not apply in distant regions (other states of the system). Nonlinearity often arises from the basic physics of systems: Insufficient inventory may cause you to boost production, but production can never fall below zero no matter how much excess inventory you have. Nonlinearity also arises as multiple factors interact in decision making: Pressure from the boss for greater achievement increases your motivation and effort—up to the point where you perceive the goal to be impossible. Frustration then dominates motivation and you give up or get a new boss.
- **History-dependent:** Taking one road often precludes taking others and determines where you end up (path dependence). Many actions are irreversible: You can't unscramble an egg (the second law of thermodynamics). Stocks and flows (accumulations) and long time delays often mean doing and undoing have fundamentally different time constants: During the 50 years of the Cold War arms race the nuclear nations generated more than 250 tons of weapons-grade plutonium (^{239}Pu). The half life of ^{239}Pu is about 24,000 years.
- **Self-organizing:** The dynamics of systems arise spontaneously from their internal structure. Often, small, random perturbations are amplified and molded by the feedback structure, generating patterns in space and time and creating path dependence. The pattern of stripes on a zebra, the rhythmic contraction of your heart, the persistent cycles in the real estate market, and structures such as sea shells and markets all emerge spontaneously from the feedbacks among the agents and elements of the system.
- **Adaptive:** The capabilities and decision rules of the agents in complex systems change over time. Evolution leads to selection and proliferation of some agents while others become extinct. Adaptation also occurs as people learn from experience, especially as they learn new ways to achieve their goals in the face of obstacles. Learning is not always beneficial, however.
- **Counterintuitive:** In complex systems cause and effect are distant in time and space while we tend to look for causes near the events we seek to explain. Our attention is drawn to the symptoms of difficulty rather than the underlying cause. High leverage policies are often not obvious.
- **Policy resistant:** The complexity of the systems in which we are embedded overwhelms our ability to understand them. The result: Many seemingly obvious solutions to problems fail or actually worsen the situation.
- **Characterized by trade-offs:** Time delays in feedback channels mean the long-run response of a system to an intervention is often different from its short-run response. High leverage policies often cause worse-before-better behavior, while low leverage policies often generate transitory improvement before the problem grows worse.

of system behavior and reducing the effectiveness of each cycle around the learning loop.

Delays also create instability in dynamic systems. Adding time delays to negative feedback loops increases the tendency for the system to oscillate.[8] Systems from driving a car, to drinking alcohol, to raising hogs, to construction of office buildings all involve time delays between the initiation of a control action (accelerating/braking, deciding to "have another," choosing to breed more hogs, developing a new building) and its effects on the state of the system. As a result, decision makers often continue to intervene to correct apparent discrepancies between the desired and actual state of the system even after sufficient corrective actions have been taken to restore the system to equilibrium. The result is overshoot and oscillation: stop-and-go traffic, drunkenness, commodity cycles, and real estate boom-and-bust cycles (see chapter 17.4). Oscillation and instability reduce our ability to control for confounding variables and discern cause and effect, further slowing the rate of learning.

1.3.2 Limited Information

We experience the real world through filters. No one knows the current sales rate of their company, the current rate of production, or the true value of the order backlog at any given time. Instead we receive estimates of these data based on sampled, averaged, and delayed measurements. The act of measurement introduces distortions, delays, biases, errors, and other imperfections, some known, others unknown and unknowable.

Above all, measurement is an act of selection. Our senses and information systems select but a tiny fraction of possible experience. Some of the selection is hardwired (we cannot see in the infrared or hear ultrasound). Some results from our own decisions. We define gross domestic product (GDP) so that extraction of nonrenewable resources counts as production rather than depletion of natural capital stocks and so that medical care and funeral expenses caused by pollution-induced disease add to the GDP while the production of the pollution itself does not reduce it. Because the prices of most goods in our economic system do not include the costs of resource depletion or environmental degradation, these externalities receive little weight in decision making (see Cobb and Daly 1989 for thoughtful discussion of alternative measures of economic welfare).

Of course, the information systems governing the feedback we receive can change as we learn. They are part of the feedback structure of our systems. Through our mental models we define constructs such as GDP or scientific research, create metrics for these ideas, and design information systems to evaluate and report them. These then condition the perceptions we form. Changes in our mental models are constrained by what we previously chose to define, measure,

[8] Technically, negative loops with no time delays are first-order; the eigenvalue of the linearized system can only be real and oscillation is impossible. Adding delays (state variables) allows the eigenvalues to become complex conjugates, yielding oscillatory solutions. Whether the oscillations of the linearized system are damped or expanding depends on the parameters. All else equal, the more phase lag in a control loop, the less stable the system will be.

and attend to. Seeing is believing *and* believing is seeing. They feed back on one another.

In a famous experiment, Bruner and Postman (1949) showed playing cards to people using a tachistoscope to control exposure time to the stimuli. Most could identify the cards rapidly and accurately. They also included some anomalous cards, such as a black three of hearts or a red ten of spades. People took on average four times as long to judge the anomalous cards. Many misidentified them (e.g., they said three of spades or three of hearts when shown a black three of hearts). Some could not identify the card at all, even with very long exposure times, and grew anxious and confused. Only a small minority correctly identified the cards. Bruner and Postman concluded, "Perceptual organization is powerfully determined by expectations built upon past commerce with the environment." Henri Bergson put it more succinctly: "The eye sees only what the mind is prepared to comprehend."

The self-reinforcing feedback between expectations and perceptions has been repeatedly demonstrated in a wide variety of experimental studies (see Plous 1993 for excellent discussion). Sometimes the positive feedback assists learning by sharpening our ability to perceive features of the environment, as when an experienced naturalist identifies a bird in a distant bush where the novice birder sees only a tangled thicket. Often, however, the mutual feedback of expectations and perception limits learning by blinding us to the anomalies that might challenge our mental models. Thomas Kuhn (1970) cited the Bruner–Postman study to argue that a scientific paradigm suppresses the perception of data inconsistent with the paradigm, making it hard for scientists to perceive anomalies that might lead to scientific revolution.[9]

As one of many examples, the history of ozone depletion by chlorofluorocarbons (CFCs) shows the mutual dependence of expectation and perception is no laboratory artifact but a phenomenon with potentially grave consequences for humanity.

The first scientific papers describing the ability of CFCs to destroy atmospheric ozone were published in 1974 (Molina and Rowland 1974; Stolarski and Cicerone 1974). Yet much of the scientific community remained skeptical, and despite a ban on CFCs as aerosol propellants, global production of CFCs remained near its all time high. It was not until 1985 that evidence of a deep ozone hole in the Antarctic was published (Farman, Gardiner, and Shanklin 1985). As described by Meadows, Meadows, and Randers (1992, pp. 151–152):

> The news reverberated around the scientific world. Scientists at [NASA] . . . scrambled to check readings on atmospheric ozone made by the Nimbus 7 satellite, measurements that had been taken routinely since 1978. Nimbus 7 had never indicated an ozone hole.

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[9]Sterman (1985a) developed a formal model of Kuhn's theory, which showed that the positive feedback between expectations and perceptions suppressed the recognition of anomalies and the emergence of new paradigms. Sterman and Wittenberg (1999) extended the model to simulate the competition among rival theories.

> Checking back, NASA scientists found that their computers had been programmed to reject very low ozone readings on the assumption that such low readings must indicate instrument error.

The NASA scientists' belief that low ozone readings must be erroneous led them to design a measurement system that made it impossible to detect low readings that might have shown their belief to be wrong. Fortunately, NASA had saved the original, unfiltered data and later confirmed that ozone concentrations had indeed been falling since the launch of Nimbus 7. Because NASA created a measurement system immune to disconfirmation the discovery of the ozone hole and resulting global agreements to cease CFC production were delayed by as much as 7 years. Those 7 years could be significant: ozone levels in Antarctica dropped to less than one-third of normal in 1993, and current models show that even with full compliance with the ban (there is a thriving black market in CFCs), atmospheric chlorine will not begin to fall until the first decade of the 21st century, and then only slowly. Data collected near Toronto in the early 1990s showed a 5% increase in cancer-causing UV-B ultraviolet radiation at ground level, indicating that ozone depletion already affects the heavily populated and agriculturally vital northern hemisphere (Culotta and Koshland 1993). The thinning of the ozone layer is a global phenomenon, not just a problem for penguins.

1.3.3 Confounding Variables and Ambiguity

To learn we must use the limited and imperfect information available to us to understand the effects of our own decisions, so we can adjust our decisions to align the state of the system with our goals (single-loop learning) and so we can revise our mental models and redesign the system itself (double-loop learning). Yet much of the information we receive is ambiguous. Ambiguity arises because changes in the state of the system resulting from our own decisions are confounded with simultaneous changes in a host of other variables. The number of variables that might affect the system vastly overwhelms the data available to rule out alternative theories and competing interpretations. This identification problem plagues both qualitative and quantitative approaches. In the qualitative realm, ambiguity arises from the ability of language to support multiple meanings. In the opening soliloquy of *Richard III,* the hump-backed Richard laments his deformity:

> And therefore, since I cannot prove a lover
> To entertain these fair well-spoken days,
> I am determinèd to prove a villain
> And hate the idle pleasures of these days.
> (I, i, 28–31)

Does Richard celebrate his free choice to be evil or resign himself to a predestined fate? Did Shakespeare intend the double meaning? Rich, ambiguous texts, with multiple layers of meaning often make for beautiful and profound art, along with employment for literary critics, but also make it hard to know the minds of others, rule out competing hypotheses, and evaluate the impact of our past actions so we can decide how to act in the future.

In the quantitative realm, engineers and econometricians have long struggled with the problem of uniquely identifying the structure and parameters of a system from its observed behavior. Elegant and sophisticated theory exists to delimit the conditions in which one can identify a system from its behavior alone. In practice the data are too scarce and the plausible alternative specifications are too numerous for statistical methods to discriminate among competing theories. The same data often support wildly divergent models equally well, and conclusions based on such models are not robust. As Leamer (1983) put it in an article entitled "Let's Take the 'Con' Out of Econometrics":

> In order to draw inferences from data as described by econometric texts, it is necessary to make whimsical assumptions . . . The haphazard way we individually and collectively study the fragility of inferences leaves most of us unconvinced that any inference is believable.[10]

1.3.4 Bounded Rationality and the Misperceptions of Feedback

Dynamic complexity and limited information reduce the potential for learning and performance by limiting our knowledge of the real world. But how wisely do we use the knowledge we do have? Do we process the information we do get in the best way and make the best decisions we can? Unfortunately, the answer is no.

Humans are not only rational beings, coolly weighing the possibilities and judging the probabilities. Emotions, reflex, unconscious motivations, and other nonrational or irrational factors all play a large role in our judgments and behavior. But even when we find the time to reflect and deliberate we cannot behave in a fully rational manner (that is, make the best decisions possible given the information available to us). As marvelous as the human mind is, the complexity of the real world dwarfs our cognitive capabilities. Herbert Simon has best articulated the limits on human decision-making ability in his famous "principle of bounded rationality," for which he won the Nobel Memorial Prize in economics in 1979:

> The capacity of the human mind for formulating and solving complex problems is very small compared with the size of the problem whose solution is required for objectively rational behavior in the real world or even for a reasonable approximation to such objective rationality. (Simon 1957, p. 198)

Faced with the overwhelming complexity of the real world, time pressure, and limited cognitive capabilities, we are forced to fall back on rote procedures, habits, rules of thumb, and simple mental models to make decisions. Though we sometimes strive to make the best decisions we can, bounded rationality means we often systematically fall short, limiting our ability to learn from experience.

While bounded rationality affects all decision contexts, it is particularly acute in dynamic systems. Indeed, experimental studies show that people do quite poorly

[10] I am not arguing that econometrics should be abandoned, despite its difficulties. On the contrary, wise use of numerical data and statistical estimation is central to good system dynamics practice, and more effort should be devoted to the use of these tools in simulation model development and testing. See chap. 21.

in systems with even modest levels of dynamic complexity (Table 1-4). These studies led me to suggest that the observed dysfunction in dynamically complex settings arises from *misperceptions of feedback*. The mental models people use to guide their decisions are dynamically deficient. As discussed above, people generally adopt an event-based, open-loop view of causality, ignore feedback processes, fail to appreciate time delays between action and response and in the reporting of information, do not understand stocks and flows and are insensitive to nonlinearities that may alter the strengths of different feedback loops as a system evolves.

Subsequent experiments show that the greater the dynamic complexity of the environment the worse people do *relative to potential*. Further, the experiments show the misperceptions of feedback are robust to experience, financial incentives, experience, and the presence of market institutions (see, e.g., Diehl and Sterman 1993; Paich and Sterman 1993; Kampmann and Sterman 1998).

The robustness of the misperceptions of feedback and the poor performance they cause are due to two basic and related deficiencies in our mental model. First, our cognitive maps of the causal structure of systems are vastly simplified compared to the complexity of the systems themselves. Second, we are unable to infer correctly the dynamics of all but the simplest causal maps. Both are direct consequences of bounded rationality, that is, the many limitations of attention, memory, recall, information processing capability, and time that constrain human decision making.

TABLE 1-4 Misperceptions of feedback have been documented in many experimental studies.

- In a simple production–distribution system (the Beer Distribution Game), people, from high school students to CEOs, generate costly fluctuations (business cycles). Average costs were more than 10 times greater than optimal (Sterman 1989b).
- Subjects responsible for capital investment in a simple multiplier-accelerator model of the economy generate large amplitude cycles even though consumer demand is constant. Average costs were more than 30 times greater than optimal (Sterman 1989a).
- Subjects managing a firm in a simulated consumer product market generate the boom and bust, price war, and shake-out characteristic of industries from video games to chain saws (Paich and Sterman 1993).
- Participants in experimental asset markets repeatedly bid prices well above fundamental value, only to see them plummet when a "greater fool" can no longer be found to buy. These speculative bubbles do not disappear when the participants are investment professionals, when monetary incentives are provided, or when short-selling is allowed (Smith, Suchanek, and Williams 1988).
- In a forest fire simulation, many people allow their headquarters to burn down despite their best efforts to put out the fire (Brehmer 1989).
- In a medical setting, subjects playing the role of doctors order more tests while the (simulated) patients sicken and die (Kleinmuntz and Thomas 1987).

1.3.5 Flawed Cognitive Maps

Causal attributions are a central feature of mental models. We all create and update cognitive maps of causal connections among entities and actors, from the prosaic—if I touch a flame I will be burned—to the grand—the larger the government deficit, the higher interest rates will be. Studies of cognitive maps show that few incorporate any feedback loops. Axelrod (1976) found virtually no feedback processes in studies of the cognitive maps of political leaders; rather, people tended to formulate intuitive decision trees relating possible actions to probable consequences—an event-level representation. Hall (1976) reports similar open-loop mental maps in a study of the publishing industry. Dörner (1980, 1996) found that people tend to think in single strand causal series and had difficulty in systems with side effects and multiple causal pathways (much less feedback loops). Similarly, experiments in causal attribution show people tend to assume each effect has a single cause and often cease their search for explanations when the first sufficient cause is found (see the discussion in Plous 1993).

The heuristics we use to judge causal relations lead systematically to cognitive maps that ignore feedbacks, multiple interconnections, nonlinearities, time delays, and the other elements of dynamic complexity. The causal field or mental model of the stage on which the action occurs is crucial in framing people's judgments of causation (Einhorn and Hogarth 1986). Within a causal field, people use various cues to causality including temporal and spatial proximity of cause and effect, temporal precedence of causes, covariation, and similarity of cause and effect. These heuristics lead to difficulty in complex systems where cause and effect are often distant in time and space, where actions have multiple effects, and where the delayed and distant consequences are different from and less salient than proximate effects (or simply unknown). The multiple feedbacks in complex systems cause many variables to be correlated with one another, confounding the task of judging cause. However, people are poor judges of correlation. Experiments show people can generally detect linear, positive correlations among variables if they are given enough trials and if the outcome feedback is accurate enough. However, we have great difficulty in the presence of random error, nonlinearity, and negative correlations, often never discovering the true relationship (Brehmer 1980).

A fundamental principle of system dynamics states that the structure of the system gives rise to its behavior. However, people have a strong tendency to attribute the behavior of others to dispositional rather than situational factors, that is, to character and especially character flaws rather than the system in which these people are acting. The tendency to blame the person rather than the system is so strong psychologists call it the "fundamental attribution error" (Ross 1977). In complex systems different people placed in the same structure tend to behave in similar ways. When we attribute behavior to personality we lose sight of how the structure of the system shaped our choices. The attribution of behavior to individuals and special circumstances rather than system structure diverts our attention from the high leverage points where redesigning the system or governing policy can have significant, sustained, beneficial effects on performance (Forrester 1969, chap. 6; Meadows 1982). When we attribute behavior to people rather than system structure the focus of management becomes scapegoating and blame rather than the design of organizations in which ordinary people can achieve extraordinary results.[11]

1.3.6 Erroneous Inferences about Dynamics

Even if our cognitive maps of causal structure were perfect, learning, especially double-loop learning, would still be difficult. To use a mental model to design a new strategy or organization we must make inferences about the consequences of decision rules that have never been tried and for which we have no data. To do so requires intuitive solution of high-order nonlinear differential equations, a task far exceeding human cognitive capabilities in all but the simplest systems (Forrester 1971a; Simon 1982). In many experimental studies, including Diehl and Sterman (1995) and Sterman (1989a), the participants were given complete knowledge of all structural relationships and parameters, along with perfect, comprehensive, and immediate knowledge of all variables. Further, the systems were simple enough that the number of variables to consider was small. Yet performance was poor and learning was slow. Poor performance in these tasks is due to our inability to make reasonable inferences about the dynamics of the system despite perfect and complete knowledge of the system structure.

People cannot simulate mentally even the simplest possible feedback system, the first-order linear positive feedback loop.[12] Such positive feedback processes are commonplace, from the compounding of interest to the growth of populations. Wagenaar and Sagaria (1975) and Wagenaar and Timmers (1978, 1979) showed that people significantly underestimate exponential growth, tending to extrapolate linearly rather than exponentially. Using more data points or graphing the data did not help, and mathematical training did not improve performance.

Bounded rationality simultaneously constrains the complexity of our cognitive maps and our ability to use them to anticipate the system dynamics. Mental models in which the world is seen as a sequence of events and in which feedback, nonlinearity, time delays, and multiple consequences are lacking lead to poor performance when these elements of dynamic complexity are present. Dysfunction in complex systems can arise from the misperception of the feedback *structure* of the environment. But rich mental models that capture these sources of complexity cannot be used reliably to understand the dynamics. Dysfunction in complex systems can arise from faulty mental simulation—the misperception of feedback *dynamics*. These two different bounds on rationality must both be overcome for effective learning to occur. Perfect mental models without a simulation capability yield little insight; a calculus for reliable inferences about dynamics yields systematically erroneous results when applied to simplistic models.

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[11] Repenning and Sterman (1999) show how the fundamental attribution error arose in a major manufacturing organization, thwarting their efforts to improve operations and product development.

[12] The first-order linear positive loop is represented by the differential equation $dx/dt = gx$ and yields pure exponential growth, $x = x_0\exp(gt)$; see chap. 8.

1.3.7 Unscientific Reasoning: Judgmental Errors and Biases

To learn effectively in a world of dynamic complexity and imperfect information people must develop what Davis and Hogarth (1992) call "insight skills"—the skills that help people learn when feedback is ambiguous:

> [T]he interpretation of feedback . . . needs to be an *active* and *disciplined* task governed by the rigorous rules of scientific inference. Beliefs must be actively challenged by seeking possible disconfirming evidence and asking whether alternative beliefs could not account for the facts (emphasis in original).

Unfortunately, people are poor intuitive scientists, generally failing to reason in accordance with the principles of scientific method. For example, people do not generate sufficient alternative explanations or consider enough rival hypotheses. People generally do not adequately control for confounding variables when they explore a novel environment. People's judgments are strongly affected by the frame in which the information is presented, even when the objective information is unchanged. People suffer from overconfidence in their judgments (underestimating uncertainty), wishful thinking (assessing desired outcomes as more likely than undesired outcomes), and the illusion of control (believing one can predict or influence the outcome of random events). People violate basic rules of probability, do not understand basic statistical concepts such as regression to the mean, and do not update beliefs according to Bayes' rule. Memory is distorted by hindsight, the availability and salience of examples, and the desirability of outcomes. And so on. Hogarth (1987) discusses 30 different biases and errors documented in decision-making research and provides a good guide to the literature (see also Kahneman, Slovic, and Tversky 1982). The research convincingly shows that scientists and professionals, not only "ordinary" people, suffer from many of these judgmental biases.

Among the failures of scientific reasoning most inimical to learning is the tendency to seek evidence consistent with current beliefs rather than potential disconfirmation (Einhorn and Hogarth 1978; Klayman and Ha 1987). In a famous series of experiments, Wason and colleagues presented people tasks of the sort shown in Figure 1-13.[13] Before continuing, try the challenge shown in the figure.

CHALLENGE

Hypothesis Testing

You are shown these four cards. Each card has a letter on one side and a number on the other. What is the smallest number of cards you should turn over to test the rule that cards with vowels on one side have even numbers on the reverse? Which are they?

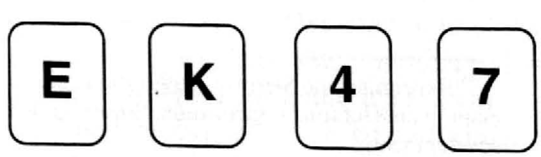


FIGURE 1-13 Wason card puzzle

[13] The summary of the Wason test is drawn from Plous (1993, chap. 20).

In one version you are shown one side of four cards, each with a letter on one side and a number on the other, say E, K, 4, and 7. You are told that if a card has a vowel on it, then it has an even number on the other side. You must then identify the smallest set of cards to turn over to see if the proposed rule is correct.

Wason and Johnson-Laird (1972) found that the vast majority of subjects selected E or E and 4 as the answers. Less than 4% gave the correct answer: E and 7. The rule has the logical form *if p, then q*. Falsification requires observation of *p and not-q*. The only card showing *p* is the E card, so it must be examined (the back of the E card must be an even number for the rule to hold). The only card showing *not-q* is the 7, so it too must be examined. The K and 4 cards are irrelevant. Yet people consistently choose the card showing *q*, a choice that can only provide data consistent with the theory, but cannot test it; if the back of the 4 is a consonant, you have learned nothing, since the rule is silent about the numbers associated with consonants. Experiments show the tendency to seek confirmation is robust in the face of training in logic, mathematics, and statistics. Search strategies that focus only on confirmation of current beliefs slow the generation and recognition of anomalies that might lead to learning, particularly double-loop learning.

Some argue that while people err in applying the principles of logic, at least people are rational in the sense that they appreciate the desirability of scientific explanation. Unfortunately, the situation is far worse. The rational, scientific worldview is a recent development in human history and remains rare. Many people place their faith in what Dostoyevsky's Grand Inquisitor called "miracle, mystery, and authority," for example, astrology, ESP, UFOs, creationism, conspiracy theories of history, channeling of past lives, cult leaders promising Armageddon, and Elvis sightings. The persistence of such superstitious beliefs depends partly on the bias towards confirming evidence. Wade Boggs, former Boston Red Sox batting champion, ate chicken every day for years because he once had a particularly good day at the plate after a dinner of lemon chicken (Shaughnessy 1987). During this time Boggs won five batting championships, proving the wisdom of the "chicken theory." Consider the continued popularity of astrology, psychics, and economic forecasters, who publicize their successes and suppress their (more numerous) failures. Remember that the 40th president of the United States and first lady managed affairs of state on the basis of astrology (Robinson 1988). And it worked: He was reelected in a landslide.

Such lunacy aside, there are deeper and more disturbing reasons for the prevalence of these learning failures and the superstitions they engender. Human beings are more than cognitive information processors. We have a deep need for emotional and spiritual sustenance. But from Copernican heliocentrism through evolution, relativity, quantum mechanics, and Gödelian uncertainty, science has stripped away ancient and comforting beliefs placing humanity at the center of a rational universe designed for us by a supreme authority. For many people scientific thought leads not to enlightenment and empowerment but to existential angst and the absurdity of human insignificance in an incomprehensibly vast universe. Others believe science and technology were the shock troops for the triumph of materialism and instrumentalism over the sacred and spiritual. These antiscientific reactions are powerful forces. In many ways they are important truths. They have led to many of the most profound works of art and literature. But they can also lead to mindless new-age psychobabble.

The reader should not conclude from this discussion that I am a naive defender of science as it is practiced nor an apologist for the real and continuing damage done to the environment and to our cultural, moral, and spiritual lives in the name of rationality and progress. On the contrary, I have stressed the research showing that scientists are often as prone to the judgmental errors and biases discussed above as laypeople. It is precisely because scientists are subject to the same cognitive limitations and moral failures as others that we experience abominations such as the US government funded research in which plutonium was injected into seriously ill patients, and in which radioactive calcium was fed to retarded children, all without their knowledge or consent (Mann 1994). A central principle of system dynamics is to examine issues from multiple perspectives; to expand the boundaries of our mental models to consider the long-term consequences and "side effects" of our actions, including their environmental, cultural, and moral implications (Meadows, Richardson, and Bruckmann 1982).

1.3.8 Defensive Routines and Interpersonal Impediments to Learning

Learning by groups, whether system dynamics is used or not, can be thwarted even if participants receive excellent information feedback and reason well as individuals. We rely on our mental models to interpret the language and acts of others, construct meaning, and infer motives. However, as Forrester (1971) argues,

> The mental model is fuzzy. It is incomplete. It is imprecisely stated. Furthermore, within one individual, a mental model changes with time and even during the flow of a single conversation. The human mind assembles a few relationships to fit the context of a discussion. As the subject shifts so does the model . . . [E]ach participant in a conversation employs a different mental model to interpret the subject. Fundamental assumptions differ but are never brought into the open.

Argyris (1985), Argyris and Schön (1978), Janis (1982), Schein (1969, 1985, 1987), and others document the defensive routines and cultural assumptions people rely on, often unknowingly, to interact with and interpret their experience of others. We use defensive routines to save face, assert dominance over others, make untested inferences seem like facts, and advocate our positions while appearing to be neutral. We make conflicting, unstated attributions about the data we receive. We fail to distinguish between the sense-data of experience and the attributions and generalizations we readily form from them. We avoid publicly testing our hypotheses and beliefs and avoid threatening issues. Above all, defensive behavior involves covering up the defensiveness and making these issues undiscussable, even when all parties are aware they exist.

Defensive routines are subtle. They often arrive cloaked in apparent concern and respect for others. Consider the strategy called "easing-in:"

> If you are about to criticize someone who might become defensive and you want him to see the point without undue resistance, do not state the criticism openly; instead, ask questions such that if he answers them correctly, he will figure out what you are not saying (Argyris, Putnam, and Smith 1985, p. 83).

But easing-in often

> Creates the very defensiveness that it is intended to avoid, because the recipient typically understands that the actor is easing-in. Indeed, easing-in can be successful only if the recipient understands that he is supposed to answer the questions in a particular way, and this entails the understanding that the actor is negatively evaluating the recipient and acting as if this were not the case (Argyris, Putnam, and Smith 1985, p. 85).

Defensive behavior, in which the espoused theories we offer to others differ from our theories in use, prevents learning by hiding important information from others, avoiding public testing of important hypotheses, and tacitly communicating that we are not open to having our mental models challenged. Defensive routines often yield groupthink (Janis 1982), where members of a group mutually reinforce their current beliefs, suppress dissent, and seal themselves off from those with different views or possible disconfirming evidence. Defensive routines ensure that the mental models of team members remain ill formed, ambiguous, and hidden. Thus learning by groups can suffer even beyond the impediments to individual learning.

1.3.9 Implementation Failure

In the real world decisions are often implemented imperfectly, further hindering learning. Even if a team agreed on the proper course of action, the implementation of these decisions can be delayed and distorted as the actual organization responds. Local incentives, asymmetric information, and private agendas can lead to game playing by agents throughout a system. Obviously implementation failures can hurt the organization. Imperfect implementation can defeat the learning process as well, because the management team evaluating the outcomes of their decisions may not know the ways in which the decisions they thought they were implementing were distorted.

Finally, in the real world of irreversible actions and high stakes the need to maintain performance often overrides the need to learn by suppressing new strategies for fear they would cause present harm even though they might yield great insight and prevent future harm.

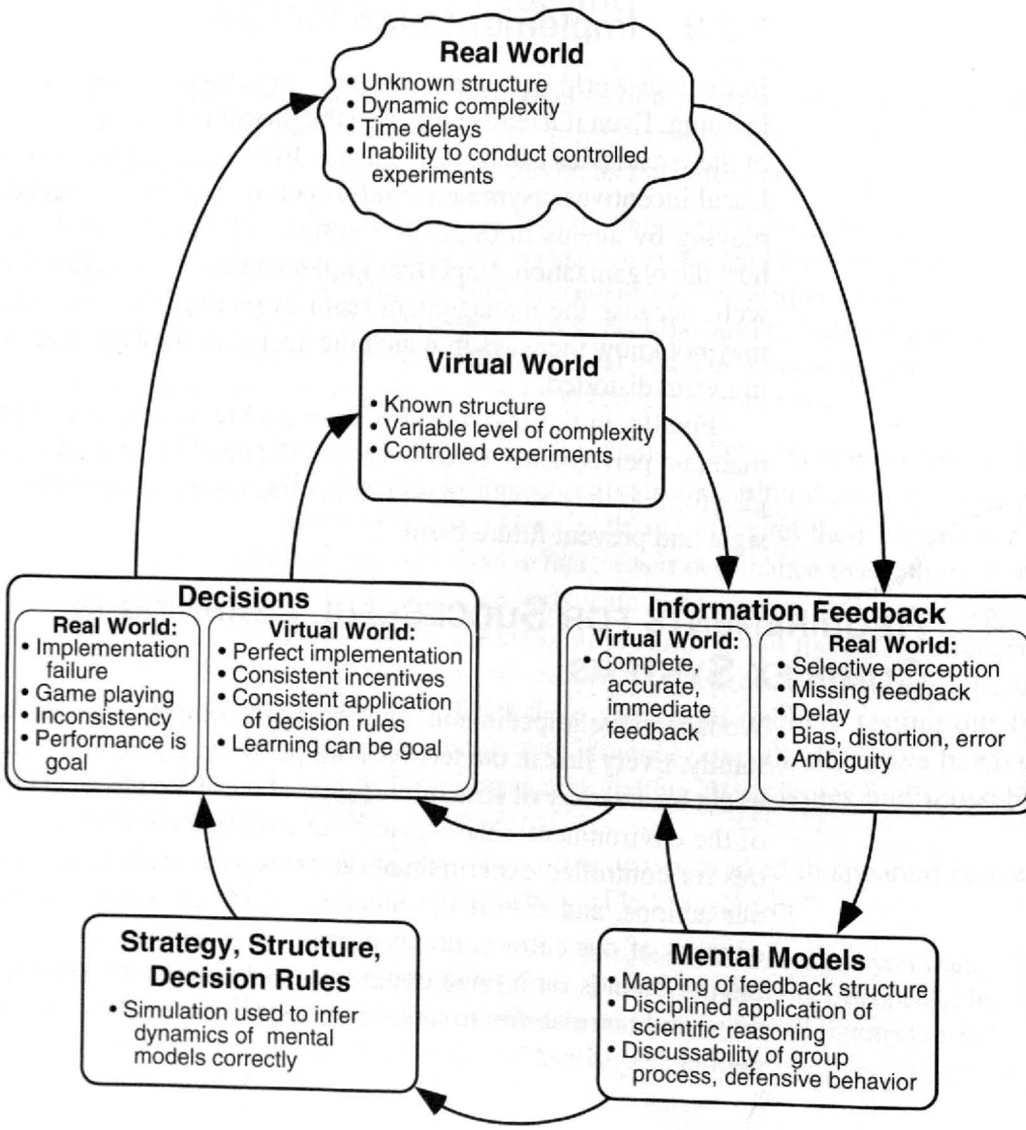
1.4 Requirements for Successful Learning in Complex Systems

We face grave impediments to learning in complex systems like a nation, firm, or family. Every link in the feedback loops by which we might learn can be weakened or cut by a variety of structures. Some of these are physical or institutional features of the environment—the elements of dynamic complexity that reduce opportunities for controlled experimentation, prevent us from learning the consequences of our actions, and distort the outcome feedback we do receive. Some are consequences of our culture, group process, and inquiry skills. Still others are fundamental bounds on human cognition, particularly the poor quality of our mental maps and our inability to make correct inferences about the dynamics of complex nonlinear systems.

1.4.1 Improving the Learning Process: Virtues of Virtual Worlds

What then are the requirements for successful learning in complex systems? If we are to create useful protocols and tools for learning effectively in a world of dynamic complexity we must attend to all of the impediments to learning. Figure 1-14 shows how the learning feedbacks would operate when all the impediments to learning are addressed. The diagram features a new feedback loop created by the use of *virtual worlds.* Virtual worlds (the term is Schön's [1983]) are formal models, simulations, or "microworlds" (Papert 1980), in which decision makers can refresh decision-making skills, conduct experiments, and play. They can be physical models, role plays, or computer simulations. In systems with significant dynamic complexity, computer simulation will typically be needed (though there are notable exceptions, such as the Beer Distribution Game (Sterman 1989b) and the Maintenance Game described in section 2.4, along with role-play/computer hybrids such

FIGURE 1-14
Idealized learning process
Effective learning involves continuous experimentation in both the virtual world and real world. Feedback from both informs the development of mental models, formal models, and the design of experiments for the next iteration.



as Fish Banks, Ltd. (Meadows, Fiddaman, and Shannon 1993). Many of the tools of system dynamics are designed to help you develop useful, reliable, and effective models to serve as virtual worlds to aid learning and policy design.

Virtual worlds have several virtues. First, they provide low-cost laboratories for learning. The virtual world allows time and space to be compressed or dilated. Actions can be repeated under the same or different conditions. One can stop the action to reflect. Decisions that are dangerous, infeasible, or unethical in the real system can be taken in the virtual world. Thus controlled experimentation becomes possible, and the time delays in the learning loop through the real world are dramatically reduced. In the real world the irreversibility of many actions and the need to maintain high performance often override the goal of learning by preventing experiments with untried possibilities ("If it ain't broke, don't fix it"). In the virtual world you can try strategies that you suspect will lead to poor performance or even (simulated) catastrophe. Often pushing a system into extreme conditions reveals more about its structure and dynamics than incremental adjustments to successful strategies. Virtual worlds are the only practical way to experience catastrophe in advance of the real thing. Thus a great deal of the time pilots spend in flight simulators is devoted to extreme conditions such as engine failure or explosive decompression.

Virtual worlds provide high-quality outcome feedback. In the *People Express Management Flight Simulator* (Sterman 1988a), for example, and similar system dynamics simulations, players receive perfect, immediate, undistorted, and complete outcome feedback. In an afternoon one can gain years of simulated experience. The degree of random variation in the virtual world can be controlled. Virtual worlds offer the learner greater control over strategy, lead to more consistent decision making, and deter implementation failure and game playing. In contrast to the real world, which, like a black box, has a poorly resolved structure, virtual worlds can be open boxes whose assumptions are fully known and can even be modified by the learner.

Virtual worlds for learning and training are commonplace in the military, in pilot training, in power plant operations, and in many other real time tasks where human operators interact with complex technical systems. Virtual worlds are also common in professions such as architecture and engineering that lend themselves to the use of physical models (Schön 1983). The use of virtual worlds in managerial tasks, where the simulation compresses into minutes or hours dynamics extending over years or decades, is more recent and less widely adopted. Yet these are precisely the settings where dynamic complexity is most problematic, where the learning feedbacks described above are least effective, and where the stakes are highest.

1.4.2 Pitfalls of Virtual Worlds

Virtual worlds are effective when they engage people in what Dewey called "reflective thought" and what Schön (1992) calls "reflective conversation with the situation." Though simulation models and virtual worlds may be necessary for effective learning in dynamically complex systems, they are not sufficient to overcome the flaws in our mental models, scientific reasoning skills, and group processes.

Obviously, while the virtual world enables controlled experimentation, it does not require the learner to apply the principles of scientific method. Many participants in system dynamics projects lack training in scientific method and awareness of the pitfalls in the design and interpretation of experiments. A commonly observed behavior among modelers and in workshops using management flight simulators is the video game syndrome in which people play too much and think too little. People often do not take time to reflect on the outcome of a simulation, identify discrepancies between the outcomes and their expectations, formulate hypotheses to explain the discrepancies, and then devise experiments to discriminate among the competing alternatives. Effective learning using system dynamics will often require training for participants in scientific method. Protocols for the use of simulations should be structured to encourage proper procedure, such as keeping laboratory notebooks, explicitly formulating hypotheses and presenting them to the group, and so on.

Defensive routines and groupthink can operate in the learning laboratory just as in the real organization. Indeed, protocols for effective learning in virtual worlds such as public testing of hypotheses, accountability, and comparison of different strategies can be highly threatening, inducing defensive reactions that prevent learning (Isaacs and Senge 1992). The use of system dynamics to stimulate learning in organizations often requires members of the client team to spend time addressing their own defensive behavior. Managers unaccustomed to disciplined scientific reasoning and an open, trusting environment with learning as its goal will have to build these basic skills before a system dynamics model—or indeed, any model—can prove useful. Developing these skills takes effort and practice.

Still, settings with high dynamic complexity can garble the reflective conversation between the learner and the situation. Long time delays, causes and effects that are distant in time and space, and the confounding effects of multiple nonlinear feedbacks can slow learning even for people with good insight and group process skills. Learning in virtual worlds can be accelerated when the modeling process also helps people learn how to represent complex feedback structures and understand their implications rather than simply presenting the results of an analysis. To learn in dynamically complex systems participants must have confidence that the model is an appropriate representation of the problem they care about. They must believe it mimics the relevant parts of the real world well enough that the lessons emerging from the virtual world apply to the real one. To develop such confidence the virtual world must be an open box whose assumptions can be inspected, criticized, and changed. To learn, participants must become modelers, not merely players in a simulation game.

In practice, effective learning from models occurs best, and perhaps only, when the decision makers participate actively in the development of the model. Modeling here includes the elicitation of the participants' existing mental models, including articulating the issues (problem structuring), selecting the model boundary and time horizon, and mapping the causal structure of the relevant system. Along with techniques developed in system dynamics, many tools and protocols for group model-building are now available, including causal loop diagrams, policy structure diagrams, interactive computer mapping, and various problem structuring and soft systems methods (see, e.g., Checkland 1981; Eden, Jones and

Sims 1983; Lane 1994; Morecroft 1982; Morecroft and Sterman 1994; Reagan-Cirincione et al. 1991; Richmond 1987, 1993; Rosenhead 1989; Senge and Sterman 1992; and Wolstenholme 1990).

1.4.3 Why Simulation Is Essential

Eliciting and mapping the participants' mental models, while necessary, is far from sufficient. As discussed above, the temporal and spatial boundaries of our mental models tend to be too narrow. They are dynamically deficient, omitting feedbacks, time delays, accumulations, and nonlinearities. The great virtue of many protocols and tools for elicitation is their ability to improve our models by encouraging people to identify the elements of dynamic complexity normally absent from mental models. However, most problem structuring methods yield qualitative models showing causal relationships but omitting the parameters, functional forms, external inputs, and initial conditions needed to fully specify and test the model. Regardless of the form of the model or technique used, the result of the elicitation and mapping process is never more than a set of causal attributions, initial hypotheses about the structure of a system, which must then be tested.

Simulation is the only practical way to test these models. The complexity of our mental models vastly exceeds our capacity to understand their implications. Typical conceptual models such as the type of causal diagram shown in Figure 1-6 are too large and complex to simulate mentally. Without simulation, even the best conceptual models can only be tested and improved by relying on the learning feedback through the real world. As we have seen, this feedback is very slow and often rendered ineffective by dynamic complexity, time delays, inadequate and ambiguous feedback, poor reasoning skills, defensive reactions, and the costs of experimentation. In these circumstances simulation becomes the only reliable way to test hypotheses and evaluate the likely effects of policies.

Some scholars argue that formal modeling can at best provide quantitative precision within preexisting problem definitions but cannot lead to fundamentally new conceptions (for various views see Dreyfus and Dreyfus 1986 and the discussion in Lane 1994). On the contrary, formalizing qualitative models and testing them via simulation often leads to radical changes in the way we understand reality. Simulation speeds and strengthens the learning feedbacks. Discrepancies between formal and mental models stimulate improvements in both, including changes in basic assumptions such as model boundary, time horizon, and dynamic hypotheses (see Forrester 1985 and Homer 1996 for philosophy and examples). Without the discipline and constraint imposed by the rigorous testing enabled by simulation, it becomes all too easy for mental models to be driven by ideology or unconscious bias.

Some argue that formalization forces the modeler to omit important aspects of the problem to preserve tractability and enable theorems to be proved or to omit soft variables for which no numerical data exist. These are indeed dangers. The literature of the social sciences is replete with models in which elegant theorems are derived from questionable axioms, where simplicity dominates utility, and where variables known to be important are ignored because data to estimate parameters are unavailable. System dynamics was designed specifically to overcome these limitations and from the beginning stressed the development of useful models; models unconstrained by the demands of analytic tractability, based on realistic assumptions about human behavior, grounded in field study of decision making, and utilizing the full range of available data, not only numerical data, to specify and estimate relationships (see Forrester 1961, 1987).

Some people don't believe that models of human behavior can be developed. Simulations of natural and technical systems such as the climate or an oil refinery are based on well-understood laws of physics, but, it is argued, there are no comparably reliable laws of human behavior. This view overestimates our understanding of nature and underestimates the regularities in human decision making. As Kenneth Boulding points out, "Anything that exists is possible." You will see many examples of models of human systems throughout this book (see also the models in Levine and Fitzgerald 1992; Roberts 1978; Langley et al. 1987; Sterman 1985a; Homer 1985; and many of the models cited in Sastry and Sterman 1993).

Is it possible to learn effectively in complex settings without simulation? Can the use of problem structuring methods, elicitation techniques, and other qualitative systems methods overcome the impediments to learning? If intuition is developed highly enough, if systems thinking is incorporated in precollege education early enough, or if we are taught how to recognize a set of "system archetypes" (Senge 1990), will we be able to improve our intuition about complex dynamics enough to render simulation unnecessary?

The answer is clearly no. It is true that systems thinking techniques, including system dynamics and qualitative methods such as soft systems analysis, can enhance our intuition about complex situations, just as studying physics can improve our intuition about the natural world.[14] As Wolstenholme (1990) argues, qualitative systems tools should be made widely available so that those with limited mathematical background can benefit from them. I am a strong advocate for the introduction of system dynamics and related methods at all levels of the educational system. Yet even if we all began serious study of physics in kindergarten and continued it through a Ph.D., it is ludicrous to suggest that we could predict the track of a hurricane or understand by intuition alone what happens when two galaxies collide. Many human systems are at least as complex. Even if children learn to think in systems terms—a goal I believe is vitally important—it will still be necessary to develop formal models, solved by simulation, to learn about such systems.

Most important, when experimentation in real systems is infeasible, simulation becomes the main, and perhaps the only, way you can discover for yourself how complex systems work. The alternative is rote learning based on the authority of the teacher and textbook, a method that dulls creativity and stunts the development of the scientific reasoning skills needed to learn about complexity.

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[14]Such knowledge of basic physics is desperately needed. When asked the question "If a pen is dropped on the moon, will it (a) float away; (b) float where it is; (c) fall to the surface of the moon?" 48 out of 168 students in physics courses at Iowa State University gave incorrect answers. Typical student explanations were "The gravity of the moon can be said to be negligible" and "The moon's a vacuum, there is no external force on the pen. Therefore it will float where it is." (Partee, personal communication, 1992).

The implications for this book are clear. System dynamics is not a spectator sport: Throughout the book I have tried to encourage the active participation of you, the reader. You will find Challenges in each chapter—examples for you to consider and work through yourself, such as the chicken and egg causal loop diagram in Figure 1-6 and the Wason card puzzle in Figure 1-13. Some of these are followed by a suggested response. Others are not. As you work through the book, extend the examples. Build the models. Experiment with them. Apply your skills to new problems and new issues. And, most of all, have fun.[15]

1.5 Summary

Complex dynamic systems present multiple barriers to learning. The challenge of bettering the way we learn about these systems is itself a classic systems problem. System dynamics is a powerful method to gain useful insight into situations of dynamic complexity and policy resistance. It is increasingly used to design more successful policies in companies and public policy settings. However, no one method is a panacea. Overcoming the barriers to learning requires a synthesis of many methods and disciplines, from mathematics and computer science to psychology and organizational theory. Theoretical studies must be integrated with field work. Interventions in real organizations must be subjected to rigorous follow-up research.

The field of system dynamics is itself dynamic. Recent advances in interactive modeling, tools for representation of feedback structure, and simulation software make it possible for anyone to engage in the modeling process. Corporations, universities, and schools are experimenting vigorously. The library of successful interventions and insightful research is growing. Much further work is needed to test the utility of the tools and protocols, evaluate their impact on individual and organizational learning, and develop effective ways to train others to use them. Never before have the challenges of our increasingly dynamic world been more daunting. Never before have the opportunities been greater. It's an exciting time to be learning in and about complex systems.

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[15]The accompanying CD-ROM and website (http://www.mhhe.com/sterman) include the models developed in the text and simulation software you can use to run and extend them.