6 Modelling

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A picture is a model of reality.

Ludwig Wittgenstein

6.1 Introduction

Tacitly we all use models all the time to help us understand and operate in the world around us. Modelling is a *formal* approach to understanding the *real world* through a *simplified external and explicit representation of a mental model* which can be manipulated and tested, before being implemented back into the real world. Mikulecky described the underlying *mental processes* as summarised in Fig. 6.1 [1].

The form and details of a model depend on its purpose.[1] Pidd [2] defines a model as *an external and explicit representation of part of reality as seen by the people who wish to use that model to understand, to change, to manage and to control that part of reality* (p. 10). They are the product of human thought and ingenuity and can consist of a simple diagram or map or a complex mathematical formulation.

Models are an important part of modern science and have helped to understand and investigate important aspects of scientific and social phenomena. Examples include the billiard ball model of a gas, the Bohr model of the atom, the MIT bag model of the nucleon, the Gaussian-chain model of a polymer, the Lorenz model of the atmosphere, the Lotka–Volterra model of predator–prey interaction, the double helix model of DNA, agent-based and evolutionary models in the social sciences, or general equilibrium models of markets [3, 4].

In this chapter we firstly demonstrate that in practice we all "model" in our daily work, modelling is a natural way of thinking and acting. We then provide an outline of the principle of modelling, before describing different modelling techniques and examples of their application, covering clustering analysis, discrete event simulation, and system dynamic modelling. These examples cover clinical issues as well as hospital and broader health policy concerns.

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[1] Some modelling methods are explained in greater detail at: http://www.systemswiki.org/index.php?title=Simulation_Methods.

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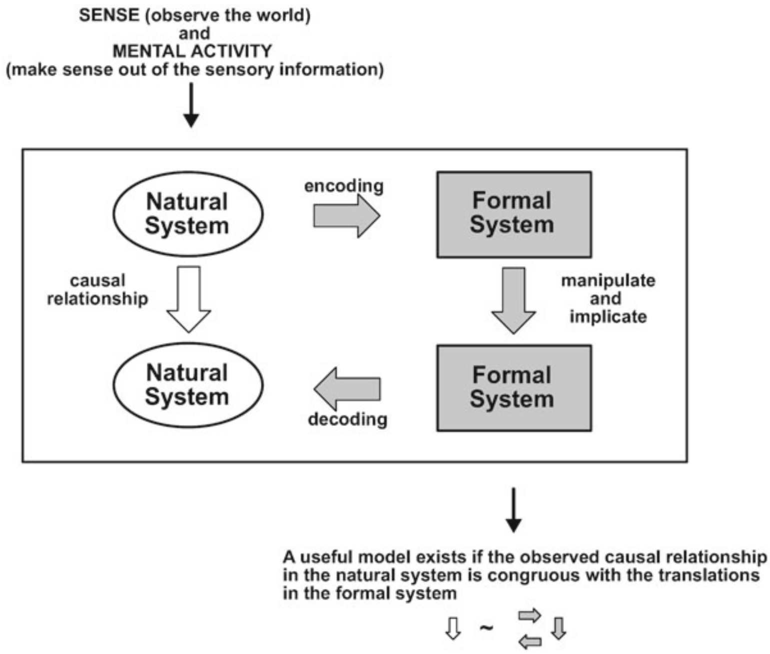


Fig. 6.1 “Real world” and “Mental world”

6.2 Concepts of Modelling

Understanding problems and finding solutions “that work” will require an appreciation of the system’s agents and context. Representing problems and their solutions can involve different means, like storytelling, the use of metaphors, mathematical formulas or computational models, as illustrated in Fig. 6.2.

Donna Meadows [5] synthesised the key features of thinking in systems in the following way:

- A system is a set of elements or parts that is coherently organised and interconnected in a pattern or structure that produces a characteristic set of behaviours, often classified as its function or purpose,

and its underpinning principles include:

- A system is more than the sum of its parts
- Many of the interconnections in systems operate through the flow of information
- The least obvious part of the system, its function or purpose is often the most crucial determinant of the system
- System structure is the source of system behaviour. System behaviour reveals itself as a series of events over time. This pattern of events over time is system behaviour

We model problems before deciding on a course of action so we can avoid making big mistakes and having confidence that our actions are more likely to be effective. Guiding principles for modelling are:

- Don’t solve the wrong problem
- Don’t apply the wrong solution
- Don’t cause worse problems
- Avoid unintended consequences
- Provide a safe place for experiments and discussion

At its most basic, modelling involves the plotting of a system diagram, influence diagram, multiple cause diagram, and a sign graph diagram, the latter identifying feedback loops within the system (Fig. 6.3). Each of the agents in a multiple cause/sign graph diagram can be given values that reflect their characteristics (stocks and flows) and behaviours (feedback loops), and running such a computational model repeatedly with different assumptions will elaborate the potentially best solution to the modelled problem (explored in detail later in this chapter).

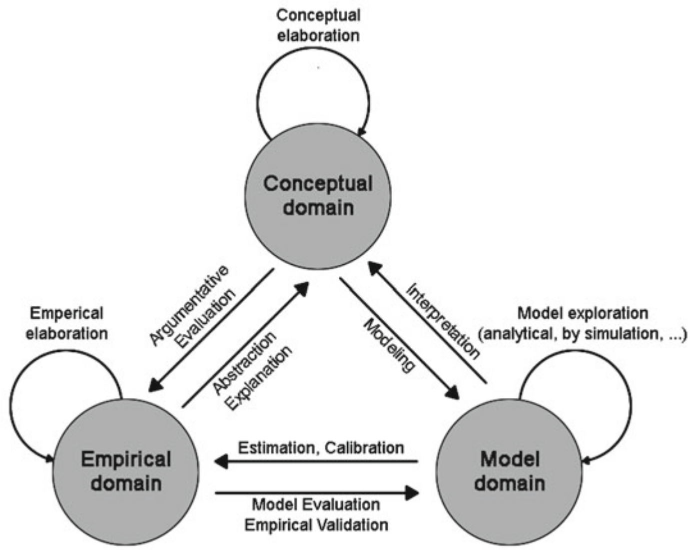


Fig. 6.2 We can **share representations of our mental models** by telling stories, drawing pictures or maps or making scale 3D models. We can represent how things change over time by using metaphors and successive snapshots or storyboards, or use mathematical or computational models to describe behaviour over time

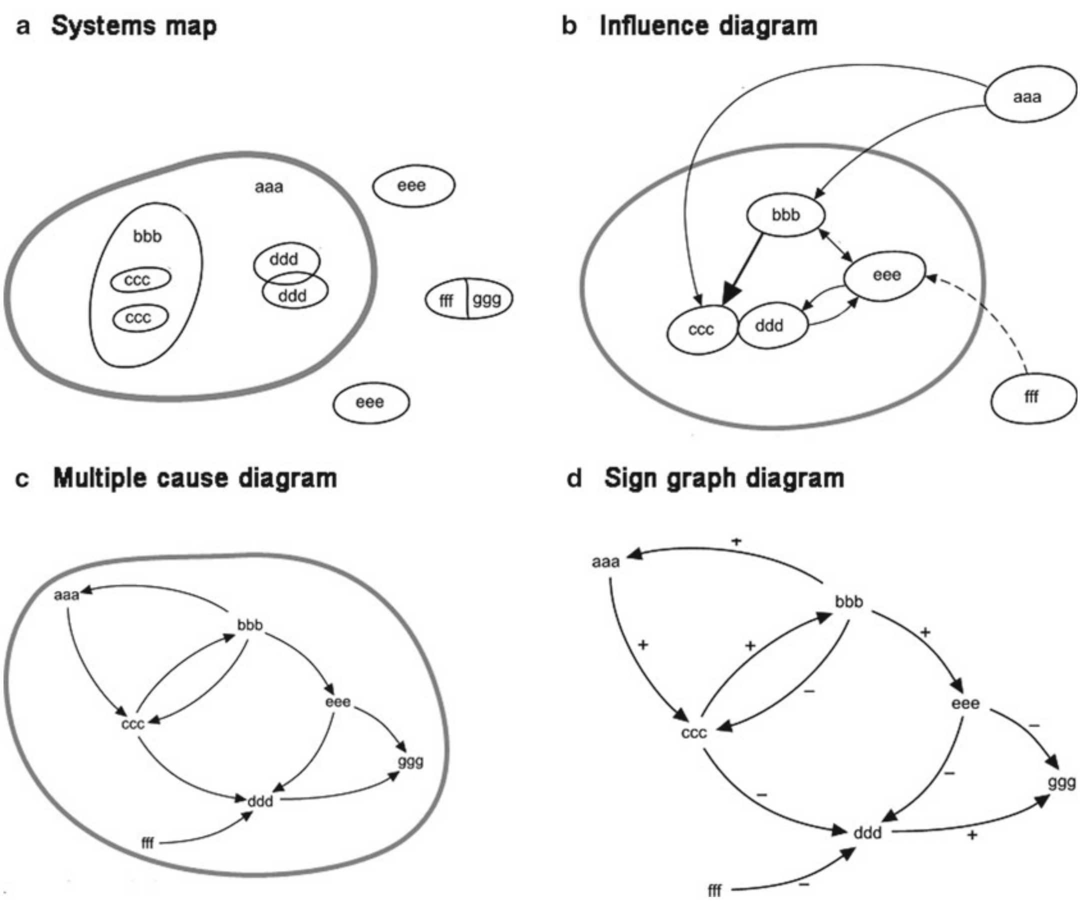


Fig. 6.3 Mapping system dynamics: a system map (**a**) provides an overview of the system and its components; the influence diagram (**b**) conceptualises the main structural features and their relationships; the multiple cause diagram (**c**) analysis main relational causes within the system; and the sign graph diagram (**d**) provides the direction of influence amongst variables, "+" indicates an influence in the same direction, "−" an influence in the opposite direction

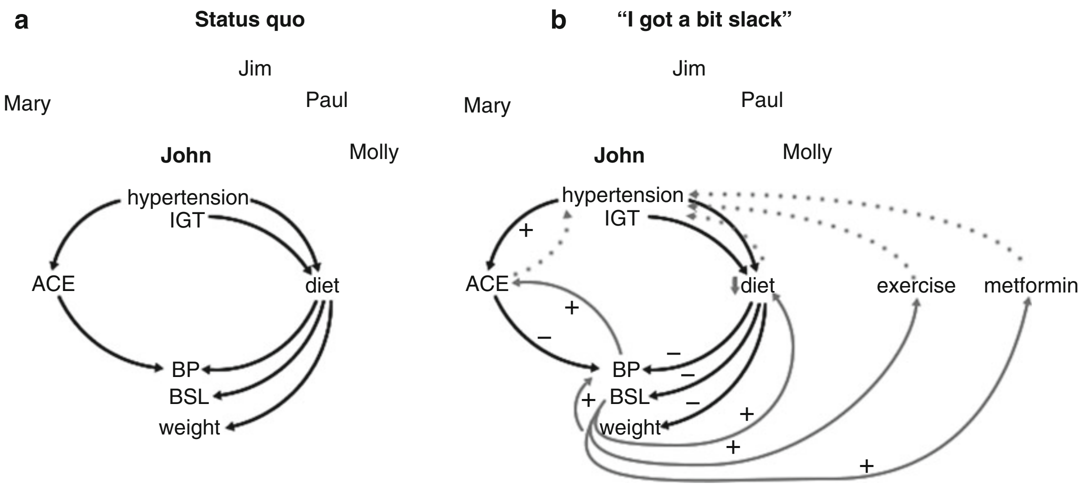


Fig. 6.4 *Left*: the dynamics of the past 9 months, *right*: the changing dynamics at the time of this consultation

In Jay Forrester's words:

> *Through an appropriate simulation model, one should know the structure causing the problem, should know how the problem is created, should have discovered a high-leverage policy that will alter behaviour, should understand the reasons why the low-leverage policies will fail, should be able to explain how strongly defended policies within the system are actually the cause of troubles, and should be able to argue for better alternative policies.*

6.3 De-mystifying Modelling: The Example of the Patient-Centred Consultation

This clinical case study illustrates how we "intuitively" model the clinical interactions in day-to-day practice. It explicitly shows how based on available information, limited time, beliefs, or intuition, we can reach quite different but legitimate conclusions about the patient's problems. Resulting outcomes depend on our sophistication in documenting "*a system* and *interpret its interconnections*".

6.3.1 The Presenting Problem

John is a 63-year-old married man who has three children—Jim, Paul and Molly, who no longer live at home. John has been retired for 18 months. He presents for his regular check-up of his hypertension and impaired glucose tolerance. For the past 9 months his blood pressure had been controlled with an ACE inhibitor, and he had followed a strict diet to control his weight and maintain normal blood glucose levels.

Today his BP is 175/105, his weight has increased by 5 kg and his random sugar level is 13.5 mmol/l. When hearing of the changes in his results he admits to having been "a bit slack" during the last few months (Fig. 6.4—left).

Drawing John in a system diagram highlights some critical points—one can believe John on face value, and explain his deterioration based on the pathophysiological mechanisms and manage him by alteration of his medications (Fig. 6.4—right), ***or*** one may think that this is a bit unusual for John, and one might better make a few more enquiries.

Further questioning reveals that John believes it must have to do with his intermittent abdominal pains and his reflux. He had not mentioned this before since he usually successfully self-manages these symptoms with a couple of over-the-counter H2-receptor blockers. Here the consultation has reached a critical point—his new symptoms may indicate a new disease which could be further investigated (Fig. 6.5—left), or it may represent just another symptom of his "true" illness.

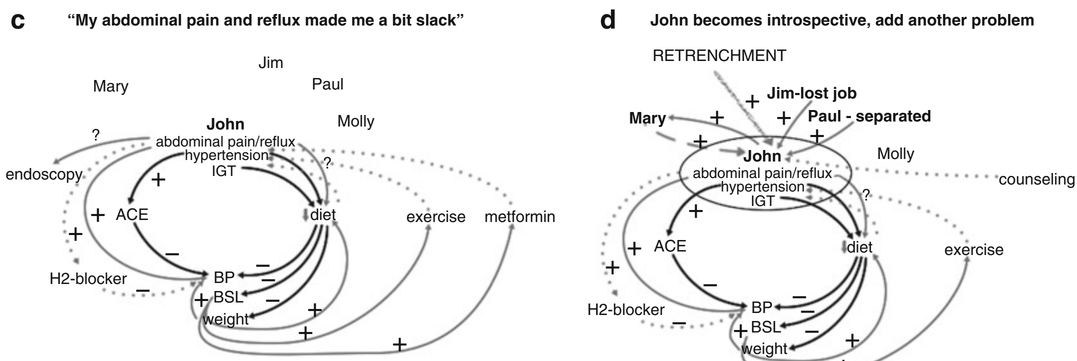


Fig. 6.5 *Left*: further symptoms complicating the clinical picture; *right*: a new insight changes the dynamics

Closer enquiries about the onset of his abdominal pains and his reflux allow John to become more reflective. He states that he is bored with his life since having been forced to retire early, he is having regular fights with his wife, and he is really worried about his two sons. John recently got retrenched from an executive position in a multi-national cooperation, and Paul has separated from his partner and children. John states that he has started smoking again and is having six standard drinks of alcohol most nights (Fig. 6.5—right).

These additional features lead to another critical point in the consultation – is the stress a separate issue, or do all of John's different complaints and his deterioration fit together?

6.3.2 Clinical Interpretation

The different perspectives of John's illness can be classified in the biomedical tradition as the biomedical mechanisms of disease, the social and mental determinants of health and illness, and the patient's construction of meaning of the health/illness experience [6]. John is a patient with multiple threats to his illness experience—peptic ulcer disease, cardiovascular disease, impaired glucose tolerance, marital problems, adjustment disorder, unhealthy lifestyle habits, and worries about his children. John's illness narrative has multiple interconnected (i.e. complex) strands.

6.3.3 System Dynamic Interpretation

As the system analysis confirms, *stress*[2] is the common focal point of all of John's problems—*retirement*, *marital problems* and *worries* relating to his son's life—even though his main complaint is abdominal pain. Increasing *stress* will increase his *marital problems*,[3] which in turn will further increase his *stress*, and vice versa decrease in *stress* will decrease his *marital problems*[4] which will decrease his *stress*. Following other relationships indicate that increased *stress* will lead to increased *alcohol consumption*, which on the one hand will increase his *carbohydrate intake* and increase his *IGT* and this in turn will increase his *stress*, and on the other it will decrease *mucosal protection*[5] which in turn will increase his *ulcer/reflux* symptoms and increase his *stress*. Following the relationship to *smoking* highlights the synergistic effects on his *ulcer/reflux* symptoms, and following the endocrine stress response shows the synergistic effects on his cardiovascular, endocrine and gastric symptoms (Fig. 6.6).

Modelling has helped to understand and communicate all of the various relationships between

[2] All variable names appear in *italic*.

[3] "+" sign next to the arrow indicates that the change in the variable at the tail of the arrow results in a change of the variable at the head of the arrow in the same direction.

[4] Again "+" sign as the change occurs in the same direction.

[5] Here we have a "–" sign as the change will result in a change in the opposite direction.

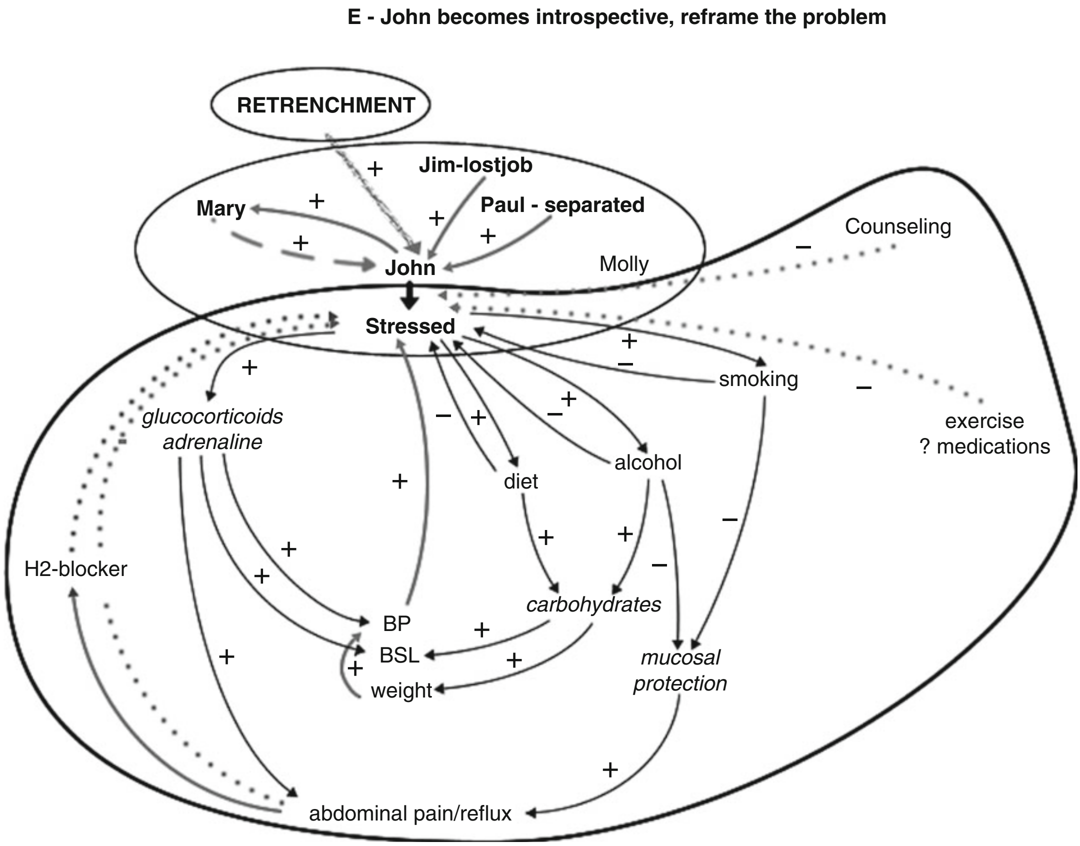


Fig. 6.6 The dynamics within the different system domains of John's illness

John's symptoms. It has allowed us to consider various possible options of acting, and in the end has allowed us to identify the correct problem and avoided unintended consequences that might have made his illness worse. All of this may seem obvious; nevertheless, it illustrates the pragmatic application of systems and complexity thinking to clinical practice.

6.4 Introduction to Dynamic Modelling

So far we have explored the structural dimensions and relationships of models; in this section we explore the dynamic interplay between the behaviours of a system's agents. *System dynamics modelling* was developed at MIT by Jay Wright Forrester in the 1950s. It arose from the insight that problem behaviours over time are produced by systemic structures.

6.4.1 Dynamic Complexity Produces Unintended Consequences

There is a persistent preoccupation with cost, quality, and access in health care, despite many practice and policy changes over the years. Sterman, in a NIH Videocast[6] has described the qualities of these persistent complex health problems which resist policy solutions as:

[6] **Videocast/Podcast** at http://videocast.nih.gov/Summary.asp?file=13712.

- Dynamic
- Tightly coupled (connected)
- Governed by feedback (with delays)
- Non-linear
- Multi-scale
- Self-organising
- Adaptive
- Evolving

This dynamic complexity refers to surprising behaviour over time—everything is connected to everything else in a meaningful way, and interactions occur on multiple timescales. Hence the hallmark of dynamic complexity is *unintended consequences*. The problems either resist all solutions (policy resistance or gridlock, where large changes have small effects), or show "tipping points" where small changes have large effects. This non-linearity can also be manifested as "sensitive dependence on initial conditions". Other writers distinguish between complex and complicated. Ravel instructed his music students, "Your playing should be complex, but never complicated." Complicated mechanisms, sometimes referred to as static or structural or operational complexity, hold few surprises, whereas dynamic or behavioural complexity is considered puzzling or *surprising*. Of course surprise depends on the understanding of the person surprised.

Another type of complexity is called analytic or evaluation complexity, where problems and causes are fuzzy and indistinct and values and views are so contested there is no way even to agree on a framework to analyse the issue. This is the territory of "*unknown unknowns*" and distinguishes uncertainty from risk. Risk is considered quantifiable, whereas uncertainty is not.

6.4.2 Mental Models Limit Learning from Shared Experience

Mental models are our way of making sense of the world, they are the beliefs inside our heads that we use to explain what we see and give us the confidence to act well. We are capable of many levels of abstraction and we act quickly using *fast but fallible* decision-making rules. Sterman again lists some of the problems with mental models as:

- Focus on "here and now"
- Stop at a single simple explanation
- Ignore feedback loops
- "Get it wrong" for
  - Chance and uncertainty
  - Time delays
  - Accumulations
  - Non-linearities

These mental models of cause and effect are learnt from our individual past experiences and from hearing and reading the stories and thoughts of others. They are therefore personal, disconnected and fail to take account of complex dynamic nonlinear feedback interactions.

Fragmented disciplines, the jargon language of management and confusion of concepts and diversity of values make these mental models difficult to describe, share and improve. To avoid embarrassment we mix with like-minded people. We value focussed analytical *tunnel vision* that ignores complexity, rather than more *imaginative synthetic* ways to reason and plan what to do in a complex world. This can lead to limiting our ways of knowing and learning by isolating parts of the world rather than exploring connections.

We tend to focus on fixing processes that fall within our narrow range of expertise and span of control rather than seeking explanations in independent interactions. As *interdependencies* increase, so does the likelihood that a given action will generate unintended consequences that may unfold over distant space and time. The more unintended consequences that are generated, the less likely it is that the intended consequences of the action will be achieved and/or sustained.

The *conflicting mental models* of health and healthcare in the heads of participants drive the health system as much as the external institutions and rules that were shaped by mental models of past leaders. From this viewpoint the health system is seen as a strife of interests, or an endless conflict among countervailing powers. Indeed it is a lot like the challenge of climate change.

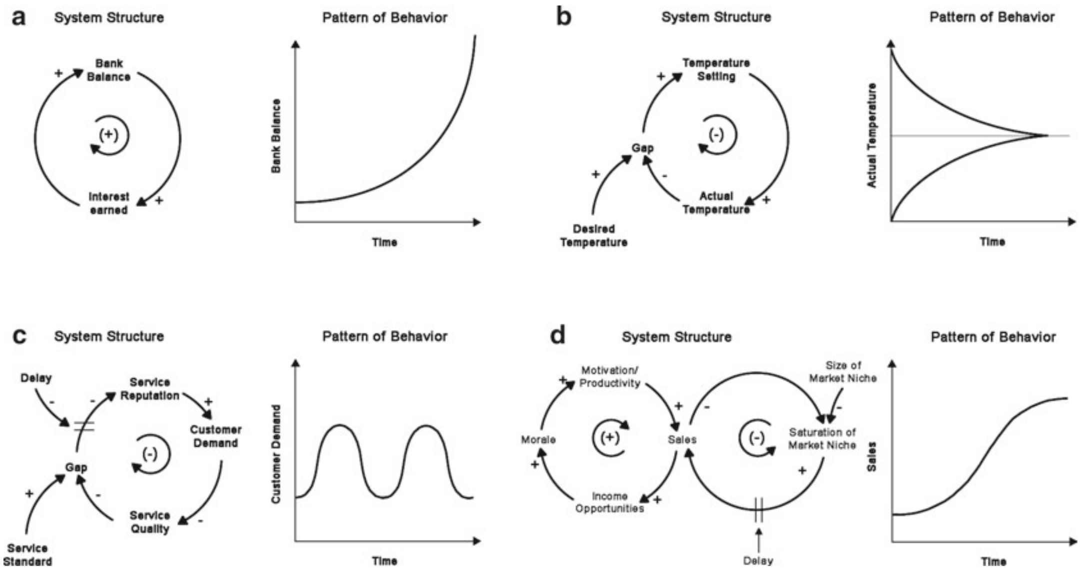


Fig. 6.7 Common system dynamic behaviours. A feedback loop is a closed chain of causal connections from a stock, through a set of decisions or rules or physical laws or actions that are dependent on the level of the stock and back again through a stock to change the stock. (**a**) Positive feedback loop—positive feedback effects are called runaway loops or reinforcing feedback, a small change over time results in large changes; (**b**) Negative feedback loop—negative feedback effects are called self-balancing, they are both a source of stability and resistance to change. Often actions taken do only show immediate results, … things take time. Delays make a system likely to oscillate between two states (**c**), and if delay is considered, changes can be anticipated and result in more controlled fashion of change (**d**)

6.4.3 Information Feedback and Circular Causation

We perceive states of the world, and we act on this information based on our beliefs or mental models, including our understanding of causes and effects. The logic people use to make decisions (converting information into action) that make sense in one part of a system may not be reasonable or desirable within a broader context or when seen as part of the wider system. So the *bounded rationality* of each actor in a system may not lead to decisions that further the welfare of the system as a whole. The system dynamics method aims to avoiding these unintended consequences of clinical policy and management interventions due to their feedback effects. Figure 6.7 illustrates some of the common system structures and their dynamic behaviour.

6.4.4 We Need Better Tools to Help Us Share Our Deep Knowledge of Cause and Effect

We need tools and methods *to shape the future and build consensus about taking effective action*, tools to help us *think clearly*, to explain, design and manage complex social and technical systems. This chapter explores the potential for using concept maps and computer models to help us agree on how to shape a challenging future. It is about computer-assisted thinking, synthesis and experimenting and *learning from virtual experience*. It introduces basic *complex systems science and engineering* methods and applies them to a range of health and health care problems using *maps* and *models* we have found useful in the past.

6.5 Application of Modelling in Healthcare

Having outlined the developments and principles of systems and modelling, we now briefly outline the application of these methods to healthcare problems. The first example describes the analysis of practice populations using cluster analysis, the second analyses the phenomenon of overcrowding of emergency departments with discrete event simulation, and the remaining two introduce system dynamics modelling in the context of chronic kidney disease and the interface of community and hospital care of the elderly.

6.5.1 Clustering: Primary Care Consultations

Little is known about the systems context of primary care consultations. A primary care practice system comprises five distinct domains—the health care system, patients and doctors as individuals, the doctor–patient interactions and consultation outcomes. In turn each domain or subsystem consists of specific variables that all interact and influence each other through feedback (Fig. 6.8) [7].

Clustering analysis was used to identify patterns of relationships between the system variables. Clustering analysis, using the Viscovery SOMine software package (Eudaptics), is based on Kohonen's Self Organising Map [8]. Self-organisation refers to a type of neural network that classifies data and discovers relationships within the dataset without any guidance during learning (unsupervised learning). The basic principle of identifying those hidden relationships is that, if input patterns are similar, they should be grouped together. Two inputs are similar if the distance between the two inputs is small. The result of this analysis is provided in Fig. 6.9 and show seven distinct patterns of distribution of the variables. Each pattern describes well-known patient characteristics and behaviours amongst different physicians [7].

Clustering provides a static, rather than dynamic, picture of the system's past behaviour and thus has limitations in terms of drawing inferences for its

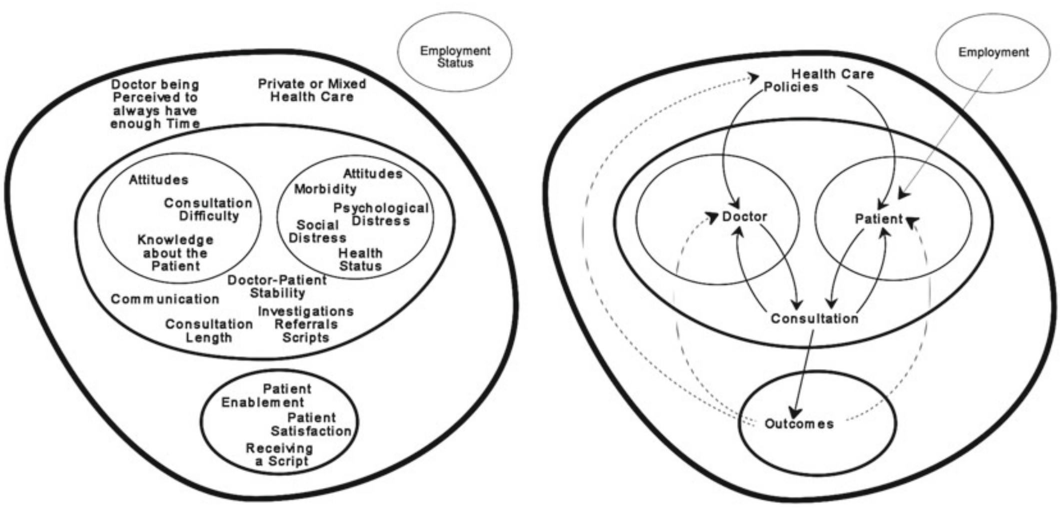


Fig. 6.8 System diagram and influence map of the Consultation System. Explanation: the system map provides a snapshot of the variables of the system at a point in time, and certain variables are grouped into subsystems. The influence diagram describes the main structural features of the system and highlights the important relationships that exist between systems variables. The employment variable belongs to a different system hence sits outside the boundaries of the "consultation system"

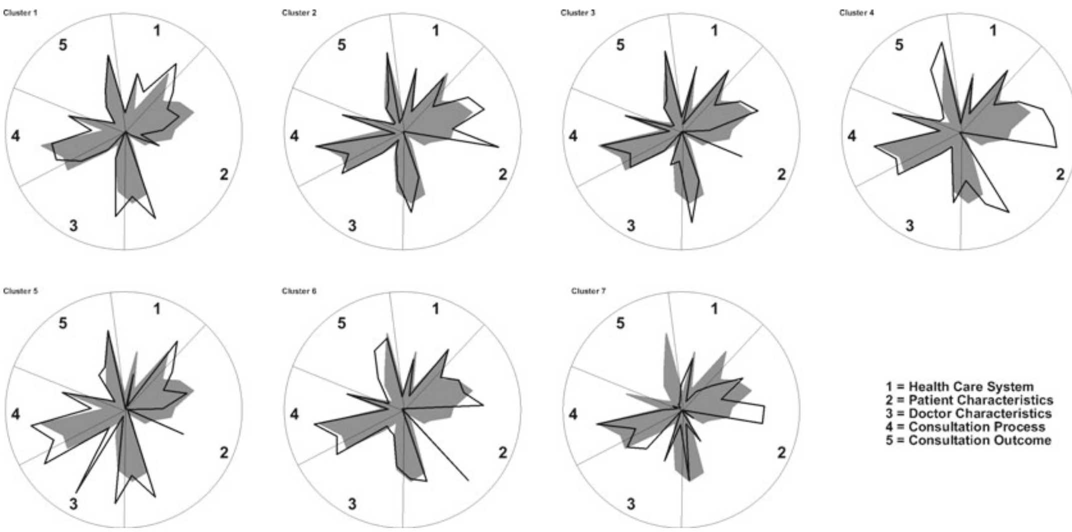


Fig. 6.9 Magnitude of cluster differences (*transparent leaves*) from the population mean (*grey leaf*). The different characteristics of the study population as a whole compared with its subgroups are easier understood in a visual fashion. The outlines of the transparent leaves show the magnitude of differences of each variable and domain compared with the whole population. The shapes of the transparent leaves highlight even more clearly how distinctively different the seven subgroups are

future behaviour. However the approach utilised in this study provides health care reformers with a basis for hypothesis formulation when considering structural and/or process changes.

6.5.2 Modelling Emergency Department Overcrowding with Discrete Event Simulation

Emergency departments (EDs) are becoming one of the dominant sources of care and an important route for admission into hospitals [9]. In recent years a large increases in presentations to emergency departments [10] has coincided with reduced healthcare budgets which has led to frequent ED blockage crises. ED blockage crises are characterised by considerably longer waiting times, ambulance diversion/bypass, and, ultimately, compromised quality of patient care. The health and political impact of these crises instigated efforts to ensure patient waiting and treatment times were minimised and ambulance "bypass" being eliminated. While such efforts have met with some success, large gaps in the understanding of ED operations remain.

The "always open" and "ready for any eventuality" nature of EDs make demand forecasting extremely complex and uncertain. While there is a well-recognised pattern to daily demand, the relative predictability of the average number of patient presentations each hour does not simplify demand estimation [11]. Even if patient numbers can be determined, the demographic mix of patients is usually wide and can vary. Patients may be of any age or either sex, have a full spectrum of ailments and injuries from life-threatening to minor and range from lucid to unresponsive [12, 13]. Ceglowski et al. [14] contextualise ED operations by looking at three main functions:

1. Availability for patients seeking care, regardless of time of day and number of patients
2. Reception and management (including treatment) of patients (both urgent and non-urgent)
3. Disposition of patients once their treatment is complete

Simulation studies have formed a large component of the drive to understand and improve emergency departments (ED) operations within the healthcare system. System dynamic simulations described earlier in this chapter, have looked at the interaction of ambulance services with the

ED, and the role of hospital policy on treatment time in ED [15]. Discrete-event simulation (DES) is particularly suitable for process systems modelling. The process systems context surrounds most of the applications of DES where effective representation of individual entities, attributes, decisions and events throughout the process of care, while explicitly modelling the randomness, are particularly important. The majority of models have used generalied distributions to describe arrival rates, lengths of stay and treatment times for ED simulation and optimisation purposes [16–18]. Jun et al. [19] surveyed the uses of Discrete Event Simulation over the past 20 years in healthcare clinics ranging from individual practices to EDs.

This case study [14] describes the experience at the Emergency Department (ED) in one of Melbourne's metropolitan teaching hospitals.[7] This emergency department is typical in setting and complexity [12]. There is a constant stream of patients into the emergency department with a range of ailments and urgencies. While the number of patients arriving each hour is reasonably well characterised, patients levels of urgency, gender, or age at any time of day and day of the year is subject to major uncertainty.

6.5.2.1 Treatment-Focused Groups of ED patients

In trying to model the uncertain nature of ED operations, one approach to simplify the situation is by grouping "similar" ED patients under the Casemix principle. Similar cases are assumed to be treated alike and to utilise a particular set of resources [20–22]. ED casemix variously suggest that cost of treating ED patients correlates to patient urgency, disposition (whether treated and discharged home or admitted to hospital) and age. However, the process-of-care grouping of patients attending emergency departments remains particularly difficult because of the broad range of demographics and clinical presentations [21].

The use of *non-parametric methods* for grouping of patients was explored by Isken and Rajagopalan [23] and Ceglowski et al. [14]. This technique, being based on data for every patient, suffers less from the depth and breadth limitations of traditional data- or knowledge-sampling approaches, and can identify non-obvious groupings of patients,

Ceglowski et al. [14] obtained 56,906 de-identified records of all ED presentations of 1 year at one Melbourne metropolitan hospital. The records contained demographic information as well as details of the visit such as "presentation problem", key time points, disposition, and of medical procedures undergone by patients during that visit.

After some preliminary data investigations, a hypothesis was formed that patients could be grouped according to the medical procedures most often performed together. A non-parametric method called self-organising maps (SOM) [24] was employed to find groups of patients with minimal intra-group diversity and maximal inter-group separation. SOM generally employs large data sets, works well with many input variables and produces arbitrarily complex models unlimited by human comprehension [25]. SOMs provide a visual understanding of patterns in data through a two-dimensional representation of all variables. Viscovery SOMine, the software tool used in this analysis, employs a variant of Kohonen's Batch-SOM [24] guided by Ward's classic Hierarchical Agglomeration algorithm [26] to determine the optimal number of clusters.

Figure 6.10 shows the distinct groups of patients who underwent particular groups of procedures. These groups of medical procedures represented the core treatment pathways. Nineteen groups of procedures accounted for treatment of all patients whose treatment involved two or more procedures. Each of the groups, or clusters, represents a pattern of treatment.

The resulting clustering model underwent extensive validation which provided the confidence that the groups of patients reflected true clinical presentations and provided a good representation of treatment activities within the ED. The obtained treatment groups were then incorporated into a Discrete Event Simulation model.

[7] Interested readers are referred to the publications by Ceglowski et al. [14].

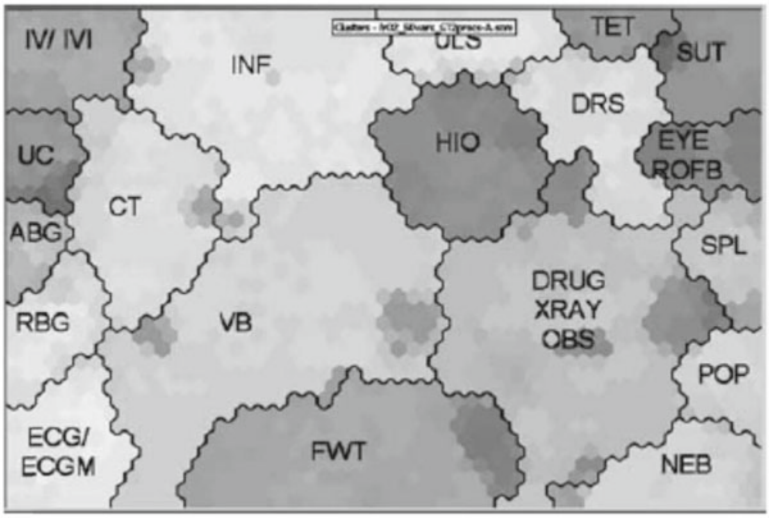


Fig. 6.10 Screenshot of the SOM treatment clusters in Viscovery SOMine. Input variables have been compressed into two dimensions and separated by boundaries. The clusters are labelled according to the procedure that is dominant (typically all patients in that cluster have that procedure and other, allied procedures).
Treatments on the right-hand side relate to accident victims, with treatments including tetanus injections (TET), dressings (DRS), sutures (SUT), eye injuries (EYE, ROFB), splints (SPL) and Plaster of Paris (POP). Those on the left relate more to illness. Examples are treatments that include tests of arterial blood gases (ABG) or random blood glucose (RBG), monitoring of echocardiograms (ECG/ECGM) and intravenous drug infusion (IVI)

6.5.2.2 Treatment-Focused Discrete Event Simulation

Discrete Event Simulation studies in EDs commonly break the ED into sub-units, assign patients to urgency categories and use these to prioritise access to resources. They generally approximate patient arrival rates and regulate patient flow by events such as completion of triage, admittance to an ED bed and review by doctors [27–34]. In trying to model the uncertain nature of ED operations, analysts have simplified the situation by grouping ED patients, developing unique process charts for each patient group (often including the duration of investigative activities such as imaging and tests, and the frequency of connections between the activities), and using generalised distributions to describe arrival rates, lengths of stay and treatment times in simulation and optimisation models [16, 17].

The model described by Ceglowski et al. [14] seeks to complement conventional scale models by providing a high-level, abstracted view of ED operations. The treatment-focused Discrete Event Simulation approach encourages a systems-wide view by concentrating on how patient and treatment differences affect queue times. The treatment grouping introduced earlier is useful in this abstraction of ED utilisation.

Since patient registration and triage are well understood and largely optimised, it is reasonable to model only the stage between patient placement in a treatment bed and their physical departure from the ED. This simplifies the system to consideration of whether treatment sites (most commonly ED beds) are physically occupied. Queues develop if all sites are occupied. The benefit of this simplified "state-based" view is that many variables become extraneous. For instance, patient bed times may vary according to the people involved in the treatment (interns or experienced doctors, for example), or admission of patients to virtual "short stay units" within the ED which may result in the ED meeting its performance obligations. Variability owing to doctors' differences is difficult to cater for in a conventional ED model. By using total bed time, it becomes unnecessary to gather these data, provided a high-level view of the ED is acceptable.

The model was designed to generate a large variety of patient types according to urgency, treatment and disposal. The use of urgency and disposal variables were occasioned by Casemix studies that had indicated the importance of these on patient grouping [35]. Patients arrived in the ED bed queue at rates dictated by the data. They were apportioned urgencies and disposal within urgency according to historic distribution. Patients of each urgency/disposal type were streamed into one of the 20 treatment pathways according to the distribution profiles noted for that urgency/disposal/treatment combination. At this point, the patient carried urgency, treatment and disposal labels that jointly defined the patient type. Patient type provided a framework for building the model and subsequent analysis. Discrete distributions were specifically developed for 161 patient types (99% of patients) and generalised distributions were used for the remaining 1% of patient types that occurred rarely (Fig. 6.11).

In the model, as in real life, patients queued for suitable beds if all beds were occupied. If access to treatment has been compromised at any time, a queue for beds develops. Waiting time may then exceed the thresholds stipulated by the national triage scale for a given triage category. Patient bed time (the total time for which they occupy a bed) was drawn from historic distributions for that urgency, treatment and disposal combination. Bed time was an input to the system and queue time was regarded as an output of the system. Generalised distributions had to be developed for bed turnover based on expert opinion.

The model was implemented in Simul8 (Version 11 from the Simul8 Corporation) through sequences of virtual workstations and queues and underwent extensive validation and verification (see footnote 7).

Data Mining led to patients being grouped by similarity of treatment. These groups were used in an abstract representation of the ED as a system that was either available or full. Ceglowski et al. [14] identified factors that impacted on access to treatment by analyzing what happened when the system was full. The queues formed often but were generally not long either in duration or in number of patients. However, in several instances long queues formed analogous to those experienced in the ED when the system became blocked (unable to accept any new patients for treatment). In studying these instances, it became apparent that system blockage depended on the combination of patient types within the system. Patient types that were characterised by long bed times were implicated in the blockage, as would be expected.

The most important finding was that the *combination* of number of patients and long bed time was significant. A simple weighting of the number of patients in each patient type with the average bed time for that patient type showed that certain patient types were occupying ED beds for a disproportionate time. It is notable that the heaviest users were all awaiting admission to a hospital ward. The data records that the decision to admit these patients was made early in their treatment, but the ED was forced to continue treating them because of the delay in moving them to a hospital ward. The treatment and symptoms of these patients give an indication of which wards were implicated in the admission delay.

6.5.3 System Dynamics Modelling

System dynamics is a formal method of computer modelling using stocks, flows and information feedback loops.[8] Using the example of dialysis we first introduce the principles of system dynamics modelling.

6.5.3.1 Stocks and Flows

Suppose someone asked you the question: Please explain how the number of people on long term renal replacement therapy will change over the next 20 years. How would you answer?

[8] For a brief introduction and references see http://www.systemswiki.org/index.php?title=System_Dynamics; http://www.systemswiki.org/index.php?title=System_Dynamics_Methodology.

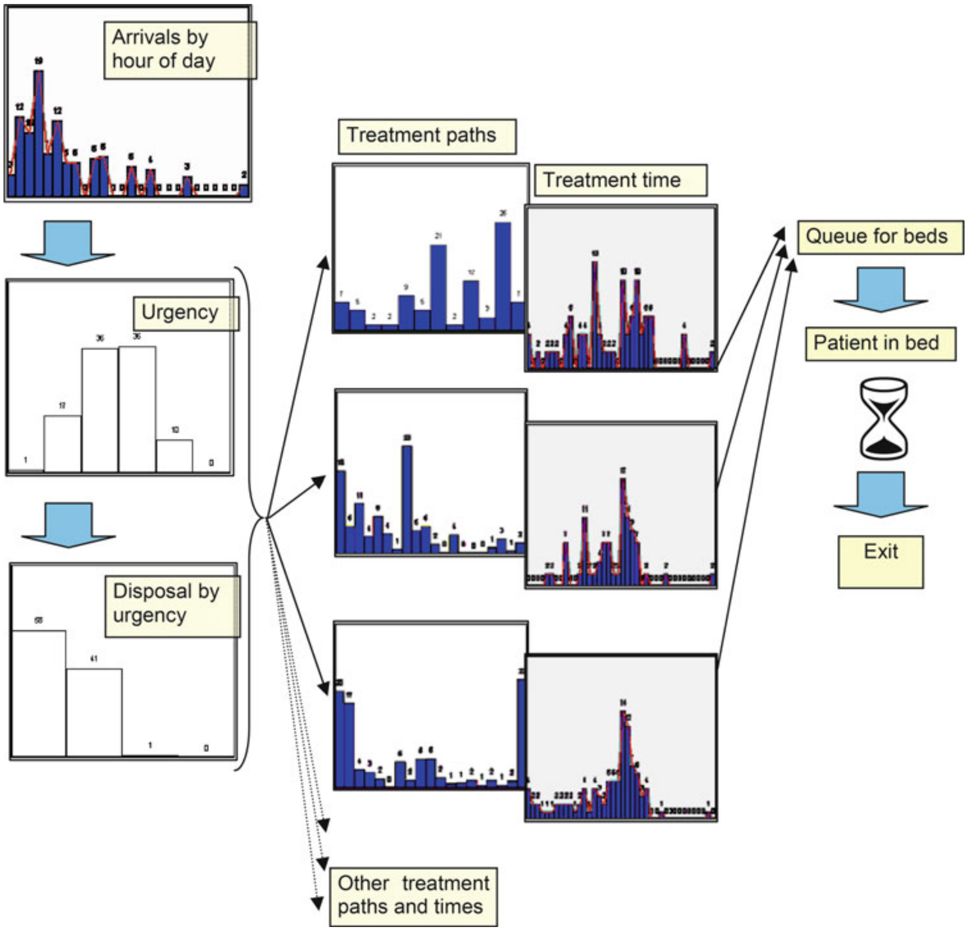


Fig. 6.11 Schematic of the simulation. Rather than following the physical movement of patients the simulation tracks the state of ED treatment sites as being "occupied" or "free". Queues result when all treatment sites are occupied (irrespective of other resource considerations). The bulk of the simulation is dedicated to allocation of appropriate urgency, disposal, treatment cluster and bed time labels to patients. While patient types are generic by urgency, disposal and treatment cluster, patient bed time is individual

This is the way a system dynamics thinker and modeller might answer.

You can consider the number of people now on dialysis as a bathtub of water with an inflow tap of new dialysis patients per year and an outflow drain of deaths per year on dialysis. Similarly, consider the current number of transplanted patients as the level of water in another bathtub. Most people who flow into the transplant bathtub are an outflow drain from the dialysis bathtub. Some people may also be transplanted without being dialysed, particularly live donor transplants. This extra inflow into transplants is represented as a tap of transplants with no dialysis flowing in each year. Now the outflow from the transplant bathtub can again be transplant deaths per year. But also people with transplants can flow back to the dialysis bathtub at the rate of the number of graft failures per year (Fig. 6.12).

This bathtub thinking, called stock-flow thinking, is a key component of system dynamics.

6.5.3.2 A SD Simulation Model of Dialysis and Transplant Patients

We will now construct a simple computer model based on real world data.

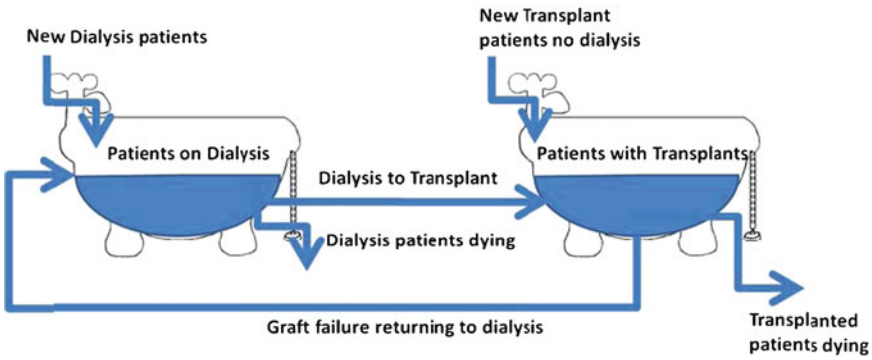
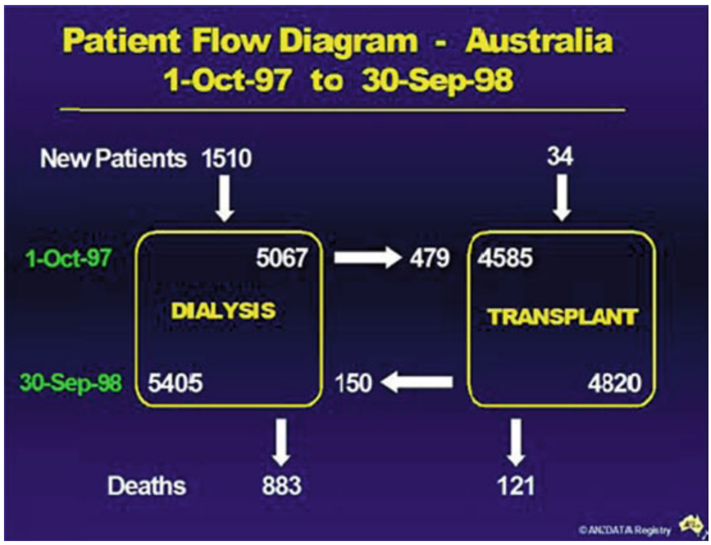


Fig. 6.12 Bathtub model of stocks and flows

Fig. 6.13 Patient flow of patients requiring renal replacement therapy—Australia 1997–1998



A stock flow representation has been used by the Australasian dialysis and transplant data registry, ANZDATA (http://www.anzdata.org.au), for many years in their annual reports, as a patient flow diagram (Fig. 6.13).

The calculations are as follows:

1. The stock of dialysis patients at the end of year (5405) = Number at beginning of year (5067) plus inflows of new patients during the year (1510) plus inflows from transplant to dialysis during the year (150) minus the outflows of Deaths during the year (883) minus the outflows from dialysis to transplant during the year (479)
2. 5045 = 5067 + (1510 + 150 − 883 − 479)
3. This can be written as a differential equation:

DIALYSIS(t) = DIALYSIS(t − dt) + (New_Patients + Tx_Failures − Deaths_Dx − Dx_to_Tx) × dt

Several SD modelling tools are available to convert stock flow maps into model equations. Here is a stock-flow map of Renal Replacement Therapy produced using ithink/STELLA software (Fig. 6.14).

We can generalise this pattern of calculations by calculating the flows in terms of the fractional change in the relevant population. New patient and transplant rates are usually reported in rates per million of the general population per year and death and graft failure rates are usually reported as fractions of the stock of dialysis or transplant patients per year. We use connectors (between

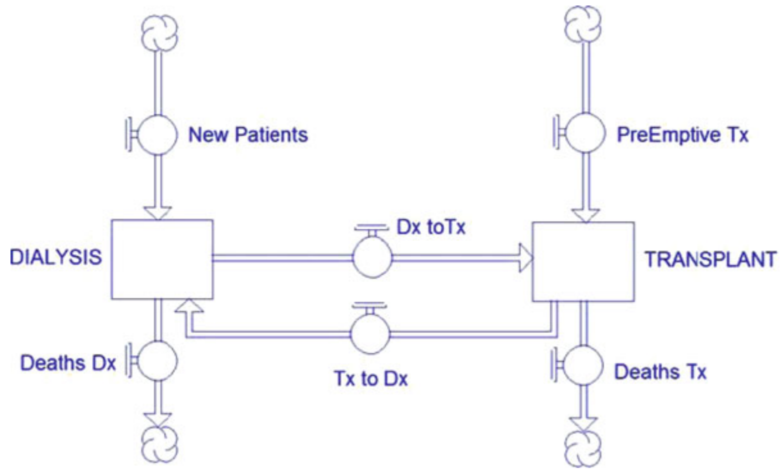


Fig. 6.14 Stock-flow map of renal replacement therapy

stocks) and converters (which alter the flow rates) to show these relationships on the stock flow map (Fig. 6.15).

We can add some additional structure to perform calculations of these key parameters. Here we have added a population stock and population increase flow to calculate the size of the future population (Fig. 6.16).

Calibrating the model initial stock and parameter values from historical data since 1994 provides us with an executable model that produces behaviour over time. We can then add a user interface with sliders to vary the parameters in the model and to conduct what-if virtual experiments. The results of two sets of virtual experiments are show below.

Modelling the Effect of Changing Acceptance Rate of New Patients Onto Dialysis

First we explore the effect of varying the percentage growth in the acceptance rate above and below the historical rate of 6% per year from 2003. There are four simulation runs shown (Fig. 6.17):

1. No change 6% growth rate (the base case) (blue)
2. Decrease to 3% growth rate (brown)
3. Decrease to 0% growth rate (mauve)
4. Increase to 10% growth rate (green)

The results from these four runs show a spread of numbers on dialysis at mid 2010 from 8,000 to 16,000 and a spread of acceptance per million population in 2010 from 90 to 210 per year.

Modelling the Effect of Varying Transplant Rates

In another set of virtual experiments we vary the transplant rate, taking a period of five years to reach the new rate. The four simulation runs shown are (Fig. 6.18):

1. No change in the rate of 26 kidney transplants per million population pa (blue)
2. Increase to 34 kidney transplants per million population pa (brown)
3. Increase to 50 kidney transplants per million population pa (mauve)
4. Decrease to 17 kidney transplants per million population pa (green)

If we take into account that the quality of life and annual cost of treatment are better for transplanted patients than patients on dialysis then the better course to follow is to increase the kidney transplant rate.

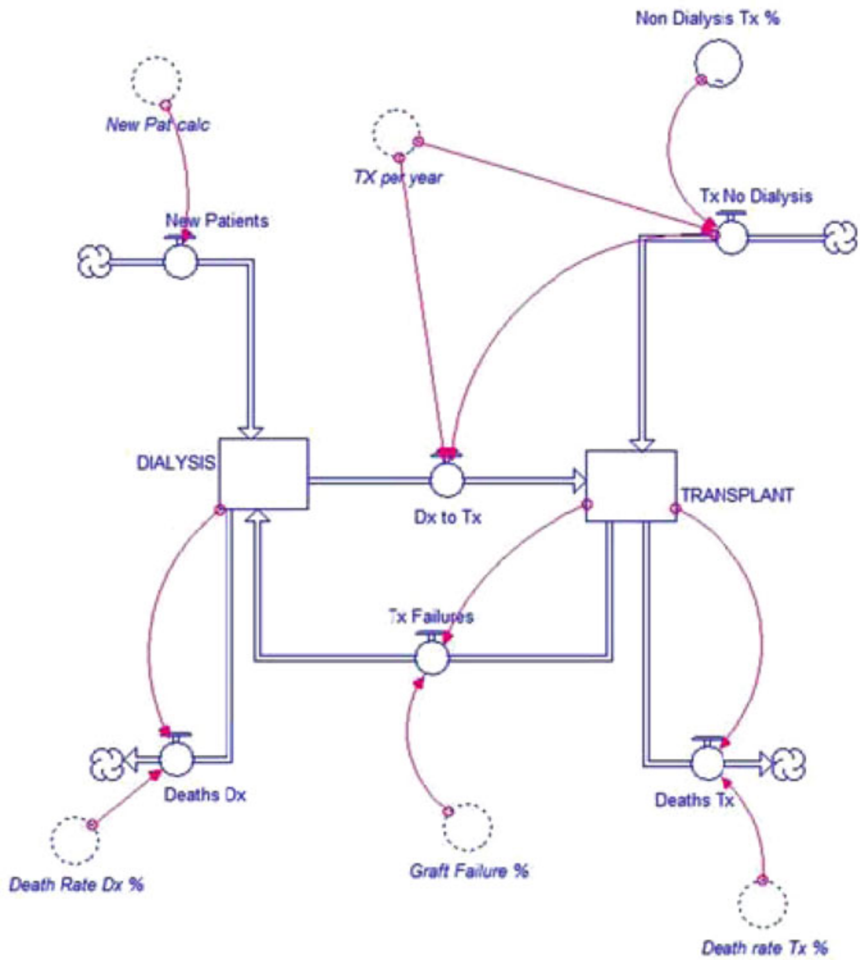


Fig. 6.15 A visual representation of the inflows and outflows (*thick arrows*) of patients on renal replacement therapies, stocks or boxes on dialysis or with a functioning transplant. The flow rates are calculated using the round circle auxiliary variables, and the *red* connectors show the variables used to calculate the flow rates

6.5.3.3 Modelling at Different Scales

Dialysis and Transplant dynamics

Here we will represent our stock flow model of renal replacement therapy as a causal loop diagram, using the online tool Insightmaker (http://insightmaker.com/insight/317) Firstly we construct the individual links inherent in the above bathtub model. Note that an inflow has a same link to its stock, and outflow has an opposite link to its stock (Fig. 6.19).

Note in the above diagram, taken from the SD model, the dialysis death rate and the acceptance rates are represented as exogenous time trends or forcings. Can you identify any other exogenous causes or variables in the diagram? (Graft failure rate, Organ donor rate and Population).

Another key feature of a good SD model is that all changes are endogenous. Another way to describe this is that the model is causally closed. For example, we can simply hypothesise that an

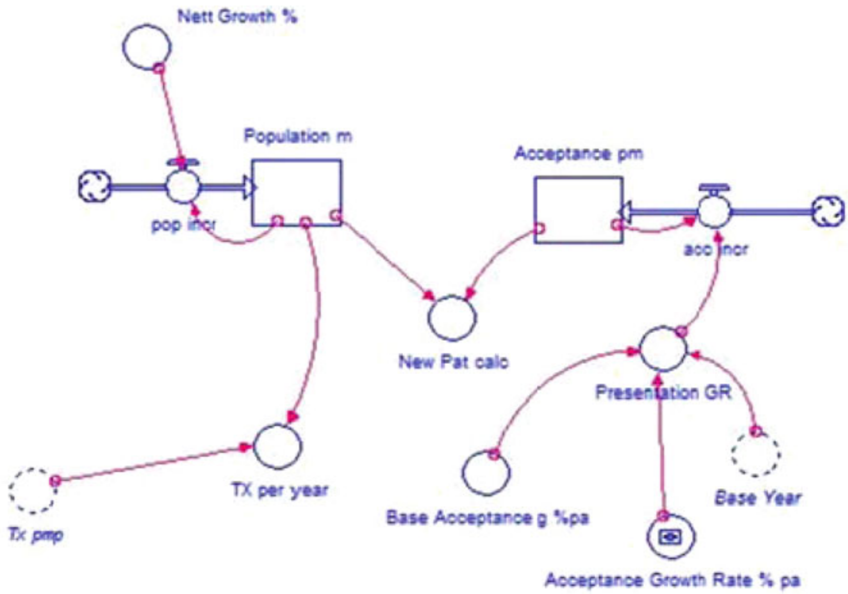


Fig. 6.16 Additional structure used to calculate growth in flow rates based on per million population (pmp). New patients accepted onto dialysis are driven by changes in the acceptance rate pmp from a base year and by the change in underlying population. The acceptance growth rate % pa can be varied using a slider to perform what-if simulation runs

increase/decrease in dialysis death rate will tend to reduce/augment the acceptance rate as dialysis becomes less/more attractive. Here is one way to close some of the loops, keeping the focus on deaths in this diagram. The diagram above suggests some additional possibilities for producing a causally closed system, by considering the influences that might change organ donor rates and the links between acceptance rate and dialysis death rate. These extra loops can be considered as dynamic hypotheses, and the exact loops we explore depend on the surprising situation we are trying to explain. For instance in Australia the growth in acceptance rate slowed and the number of new transplants with no dialysis increased more than expected. Closing the loops can provide potential explanations of these non-linear effects. This plausible explanation is described as a dynamic hypothesis (Fig. 6.20).

Here we have explicitly labelled some plausible balancing loops and reinforcing loops as possible explanations for observed non-linear trends in people on renal replacement treatment. Several other simple balancing loops are left unlabelled. Note we have explicitly shown the stocks as boxes.

Labelled Reinforcing Loops

Dialysis and transplant learning effects: The dialysis death and graft failure rates fall over time as the techniques improve with experience. This increases the number of people on renal replacement therapy over time. Another reinforcing loop is the possibility of successive grafts, which tends to increase the number of people on both dialysis and transplant. The final reinforcing loop is the delayed effect on organ donation rate of the number of people living with transplants, labelled as transplant success diffusion.

Labelled Balancing Loops

To explain what limits the number of people on dialysis we have introduced the concepts of session treatment time as the limiting resource. To manage this resource we can either ration the number of people accepted on to dialysis, labelled as rationing places, or we can reduce the time

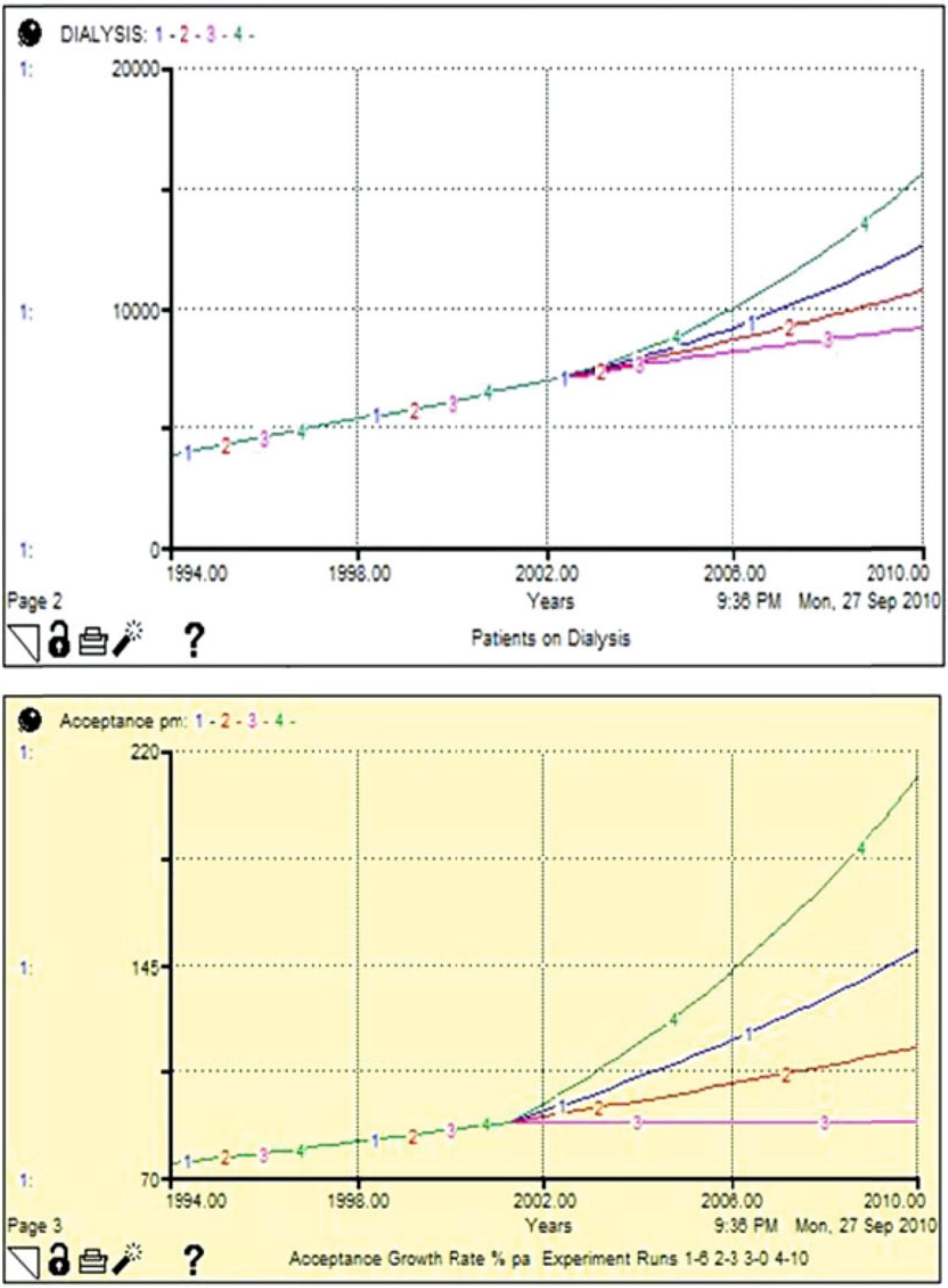


Fig. 6.17 Model results for number of patients on dialysis and acceptance rate onto dialysis per million population by calendar year. The acceptance growth rate is varied at 2001. Graph run 1 remains at 6% growth pa, Graph run 2 is at 3% growth rate, Graph 3 is at 0% growth rate and Graph 4 is at 10% growth rate. This results in a range of patients on dialysis in 2010 from 8,000 to 16,000

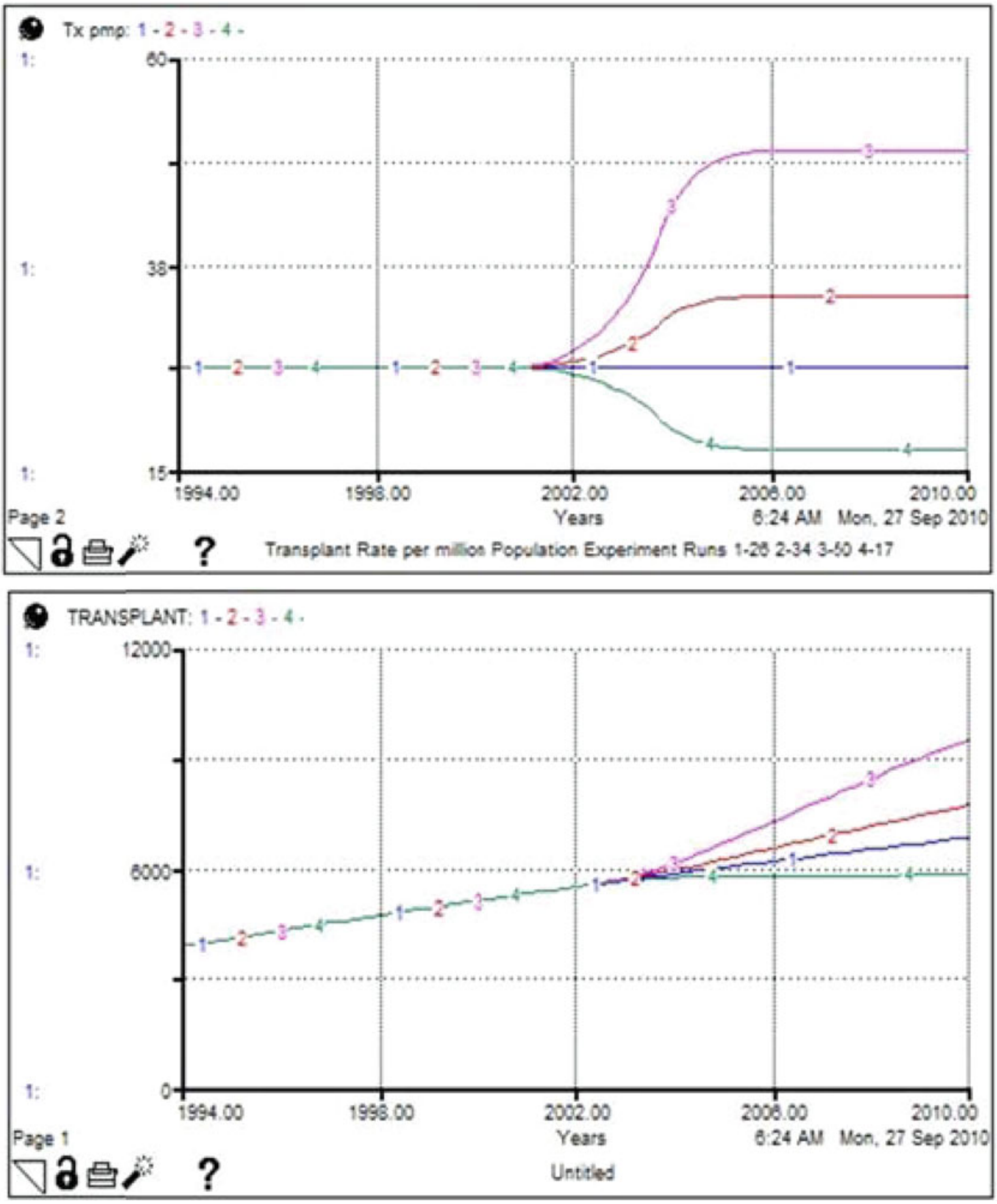


Fig. 6.18 Model results for changing transplant rates

spent on dialysis for each patient, labelled as cutting corners.

We can use these causal loop diagrams to explain the results of our models or to develop plausible dynamic hypotheses which can guide future extensions to the model and data gathering to test these models empirically.

However there are many other concepts that could be used to represent the dynamics of this complex system. We can zoom out to include

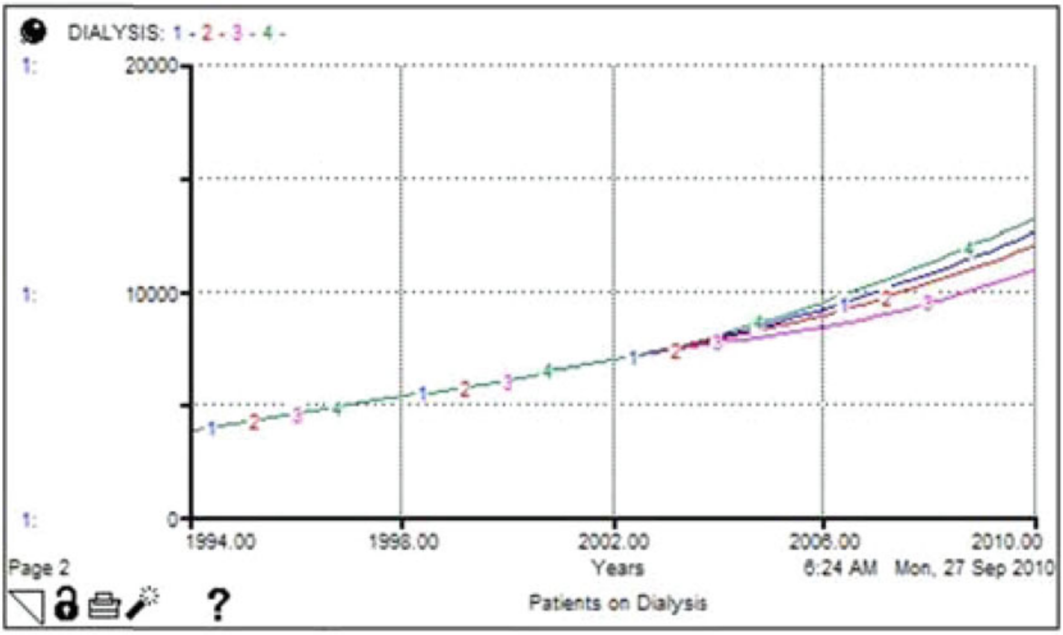


Fig. 6.18 continued

people with progressing chronic kidney disease prior to being accepted on to a dialysis programme. People involved in the technical detail of dialysis might want to explore the contribution of dialysis adequacy. Therefore the purpose of the model is an important determinant of the way we choose to represent the dynamics of a system.

Chronic Kidney Disease Dynamics

Of course the need for Dialysis is mostly driven by the number of people who have progressive forms of kidney disease, including glomerulonephritis and diabetes. The flow of people through early and late stages of chronic disease can also be represented using system dynamics models.

The key chronic kidney diseases that produce end stage renal failure in many countries are glomerulonephritis and diabetic nephropathy and their onset and progression can be delayed by screening and effective management of risk factors including hypertension, proteinuria and glycaemic control. The above generic pattern can be adapted to these specific diseases and interventions, similar to Motohashi's approach [36]. Rather than the original stock-flow diagram, the model here is represented as causal loops and explicit stocks[9] (Fig. 6.21).

You may wish to identify flows and label more loops and add the effects of other limited resources, such as funding.

Organ Donation and Transplantation Dynamics

Where possible the preferred renal replacement therapy seems to be a combination of self-managed dialysis and kidney transplantation. Of course the transplantation rate is limited by the availability of live and deceased donors. Here we will introduce a slightly different conceptualisation to explore ways to increase the transplantation rate. In this view we consider the stock of transplantable organs in the general population. These can be added to by births and in migration of transplantable organs or by advances in technology that make more organs capable of being transplanted. Perhaps transplantable organs may also be grown from stem cells in the future.

[9] More detail of the model is available online at http://insightmaker.com/insight/1003.

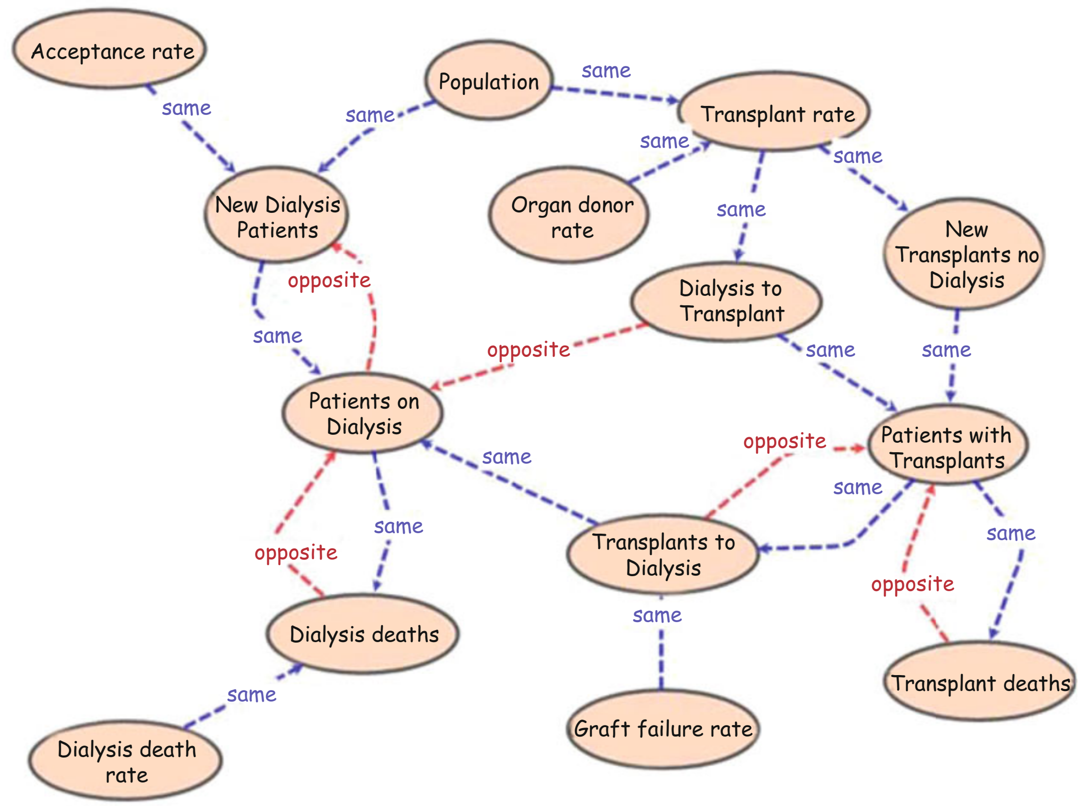


Fig. 6.19 Causal loop diagram of renal replacement therapy

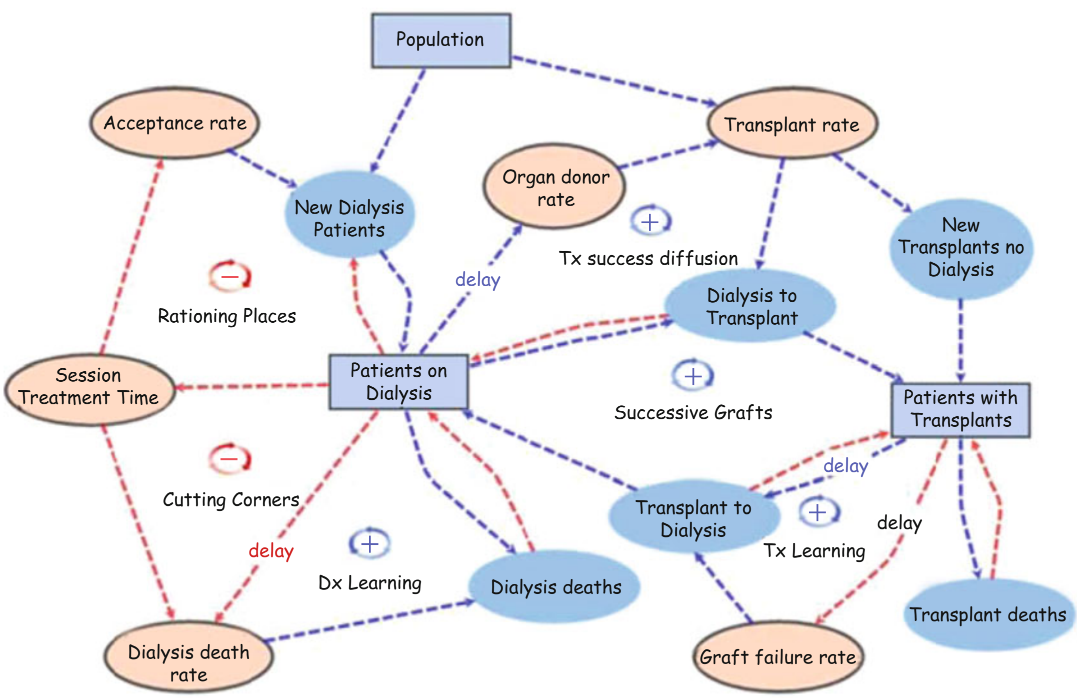


Fig. 6.20 Identifying reinforcing (positive) and balancing (negative) feedback loops

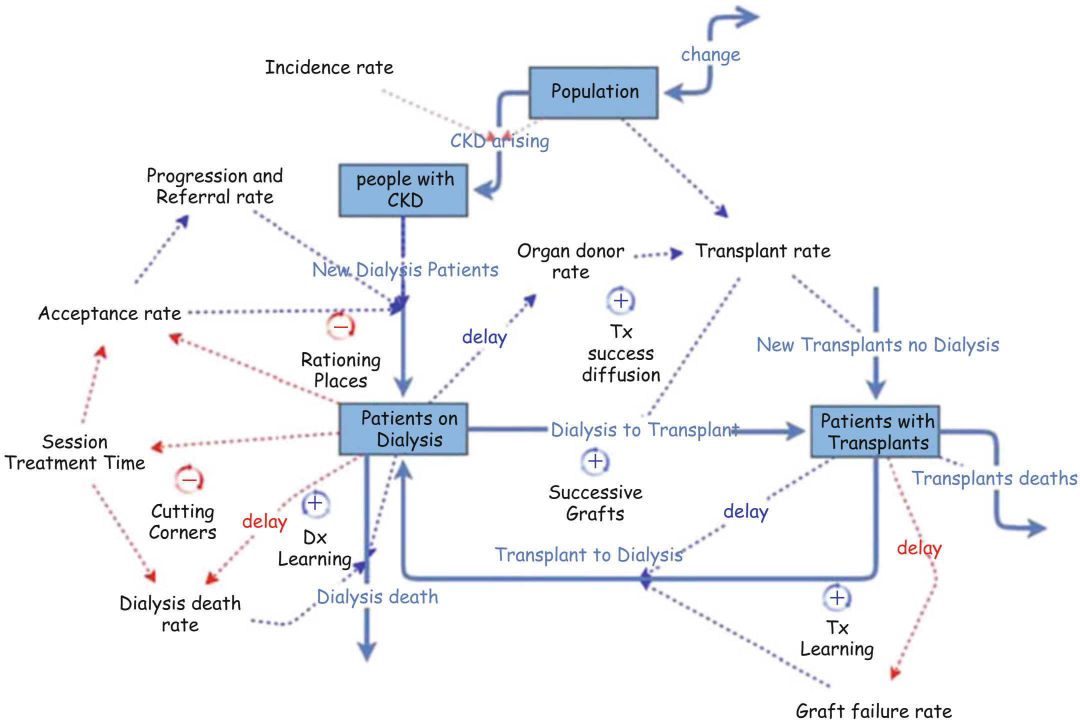


Fig. 6.21 Renal transplant dynamics

These organs mostly become no longer transplantable by the organs ageing beyond the time they are considered transplantable, or by dying without being donated. This pool of transplantable organs in people is also depleted by organs failing and people becoming potential transplant recipients. This stock of organs failed in transplantable recipients can be removed by death or by replacing organs.

By the act of donating by live and deceased donors, organs can flow outside the body, be potentially stored and then flow into the bodies of recipients. They will remain there until the death of the recipient or the failure of the graft. Graft failure takes the organ back to the organs failed in transplantable recipients, where they are again removed by dying or being retransplanted.

The diagram below shows these organ flows and the potential feedback effect of increasing donor age reducing the life of the transplanted organ[10] (Fig. 6.22).

This organ flow representation shows the ways transplantable organs are generated and are consumed by ageing, death and organ failure. Transplantable organs can flow from a donor to a recipient, with a variable time spent outside the body. This forms a basis for discussing places to intervene to promote the flow of organs to recipients and to increase the time organs spend as functioning and transplantable entities.

Zooming in on Dialysis Modality Selection

Consider a model whose purpose is to explore how to best match the supply of dialysis facilities to the demand for dialysis.[11]

The broad context, as we have previously shown, includes understanding the drivers of demand for dialysis, including both population

[10] More detail of the model is available online at http://insightmaker.com/insight/323.

[11] This section is taken from unpublished work of my NZ colleague David Rees and Ahmad Azar's papers and conference presentations (GM).

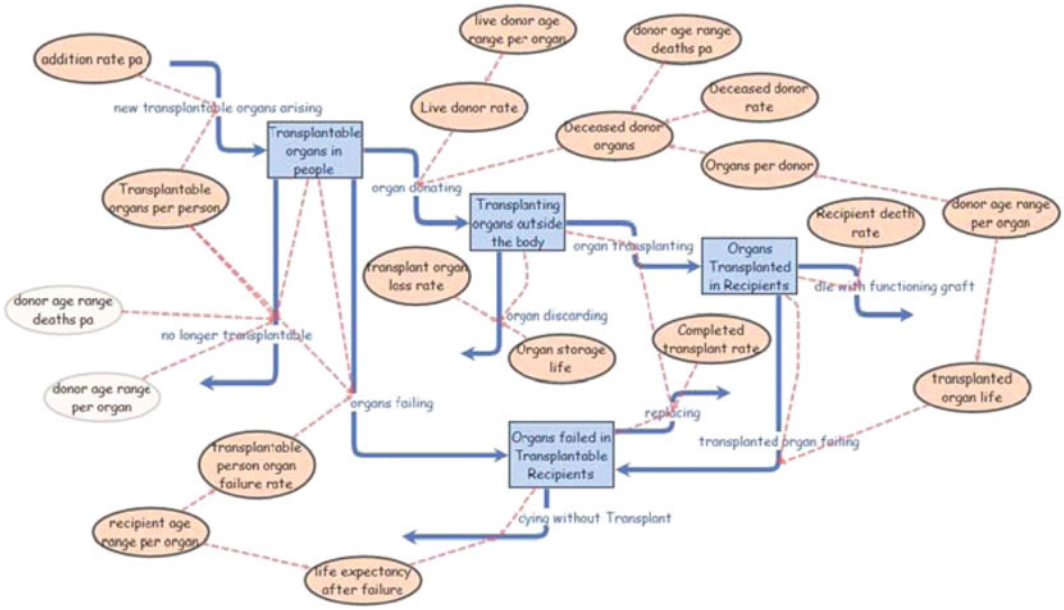


Fig. 6.22 Organ donation and transplant dynamics

dynamics and kidney disease dynamics including diabetes and other risk factors. On the supply side, the availability and configuration of resources, including technologies, specialised staff and funding determines the quality of services and therefore the patient and medical preferences for different dialysis options. Key decisions include provision of shared facilities, the availability of resources for prevention of progression of chronic kidney disease, early specialist referral and vascular access surgery which interact with the age, co-morbidity and social conditions of the population that need dialysis. Again, the availability of live and deceased kidney donors will also affect dialysis treatments and outcomes.

At a more detailed level, dialysis adequacy affects the morbidity, quality of life and mortality and attractiveness of different modality options. Intradialytic session length and filtration interact with interdialytic management of fluid balance, nutrition and anaemia. Some of these concepts are included in the following diagram (Fig. 6.23).

Another constraint which could be added to the above diagram is the interaction between costs benefits and resources. This is indicated above by the links among population, resources for prevention and dialysis resources. You may wish to modify this diagram to add loops, stocks and flows.[12]

More Detailed Models: Pros and Cons

The models already presented contain only a few stocks. Like all compartmental models we assume perfect mixing within each stock. If we are interested in the differences within stocks, we can divide or array the stock into multiple dimensions. One common way to array stocks is by age and gender, since in epidemiology and public health we often have detailed data by age and gender. This increases the accuracy of our model, but it may detract from understanding the feedback dynamics of the situation. Age-specific mortalities

[12] More detail of the model is available online at http://insightmaker.com/insight/318.

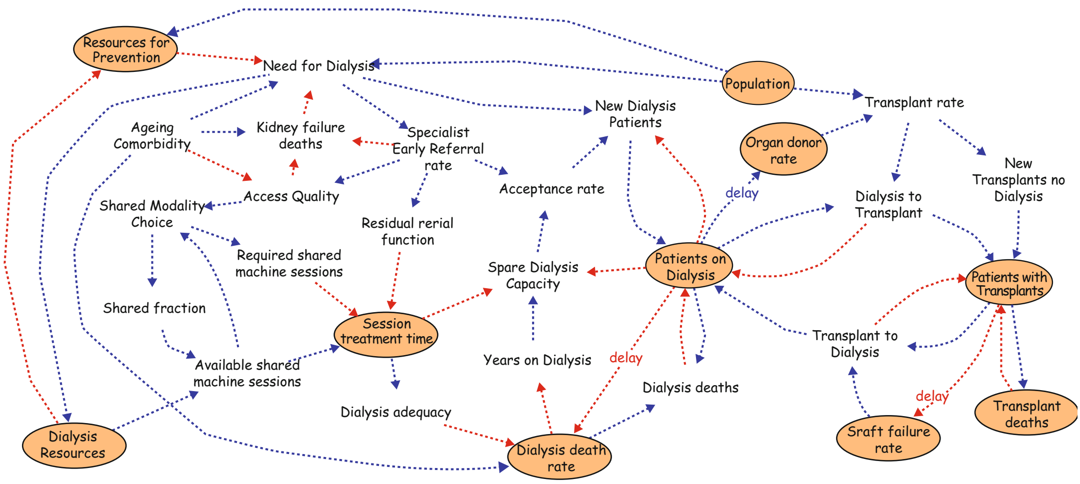


Fig. 6.23 Detail of the interactions among resources for dialysis and prevention and the drivers of the number of patients on dialysis. Key management variables are the session treatment time, the choice of shared dialysis modality (e.g. centre-based hemodialysis rather than home-based) and the referral and acceptance rates. *Blue arrows* represent same and *red arrows* represent opposite influences

are important in quantifying costs and benefits, particularly using quality adjusted life years and health adjusted life expectancy as measures of population health. Specifically modelling policies for accepting elderly people on dialysis may require this more detailed level of analysis. Other problems may require zooming out to include a much broader context, including both drivers of demand and constraints on supply. In general, the interacting components include the population, people with health conditions, patients in care, clinical services workload, workforce, facilities, technology and funding sources [37].

6.5.4 Understanding the Flows of Older Patients Between Hospital and Aged Care

6.5.4.1 A Hospital View

The simple view of improving patient flows through care locations is that more beds are needed. However when more beds were added to emergency departments, flows became worse [38]. In hospital wards the available beds are generally constrained by staff costs, together with inflexible budgets and staffing practices. Beds are perceived to be blocked by older patients waiting weeks for discharge into aged care residences. Control of aged care places generally belongs outside health care, in the aged or social care sector. One solution to hospital congestion is to give priority to admitting patients from hospitals into aged care residences. However this is resisted by aged care proprietors, since these patients are often the most unprofitable. The funding arrangements are designed to provide an acceptable level of care and constrain the growth in government expenditure. Eric Wolstenholme in the UK has described many patient flow improvements as fixes that fail (http://bit.ly/u1KwVv),[13] and these failures lead to chronically unsafe care, which he calls "coping but not coping" [39]. The key interactions are represented in the following causal loop diagram using Insightmaker (Fig. 6.24).

A Stock and Flow diagram of formal and informal coping policies is shown below, from http://bit.ly/vKuRFk. Formal adjustments to

[13] An unfolding of the arguments in the paper and link to the Insight is available on the Systemwiki website.

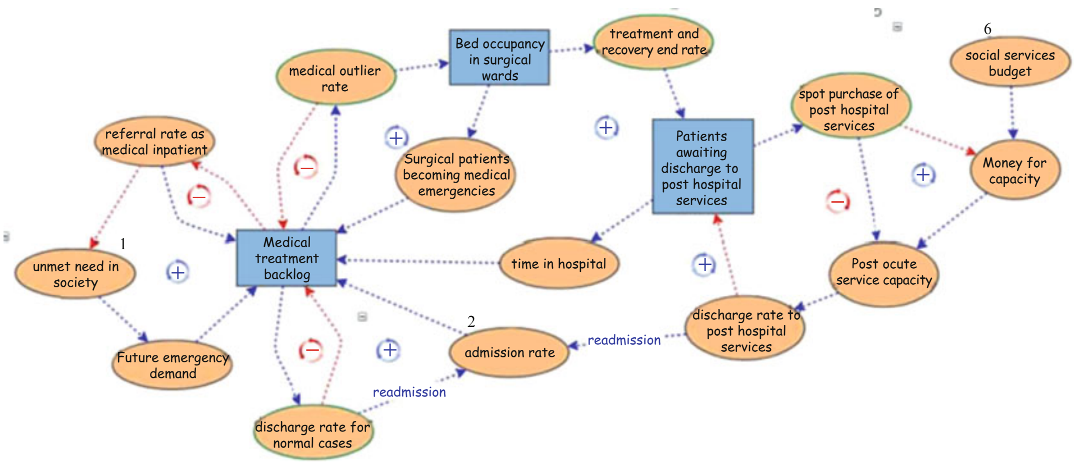


Fig. 6.24 Causal loop representation of variables (*ovals*) that influence the main stocks (*blue boxes*) involved in adjusting to changes in demand for medical inpatient treatment. The variables operate at the pre-hospital, in-hospital and post-hospital phase of care

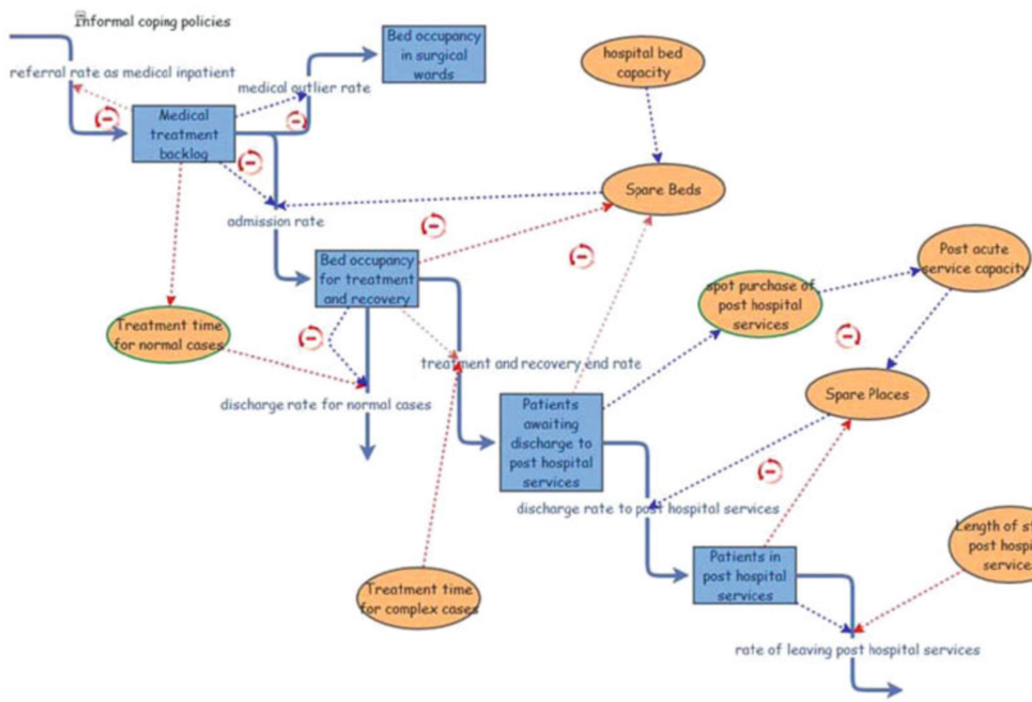


Fig. 6.25 A stock and flow diagram representation of formal and informal coping policies to managing changes in medical inpatient demand

capacity and flow rates interact with informal workarounds, including changes in referral and discharge thresholds, and placement of medical outliers in surgical wards. These workarounds then delay the use of formal long term adjustments in capacity (Fig. 6.25).

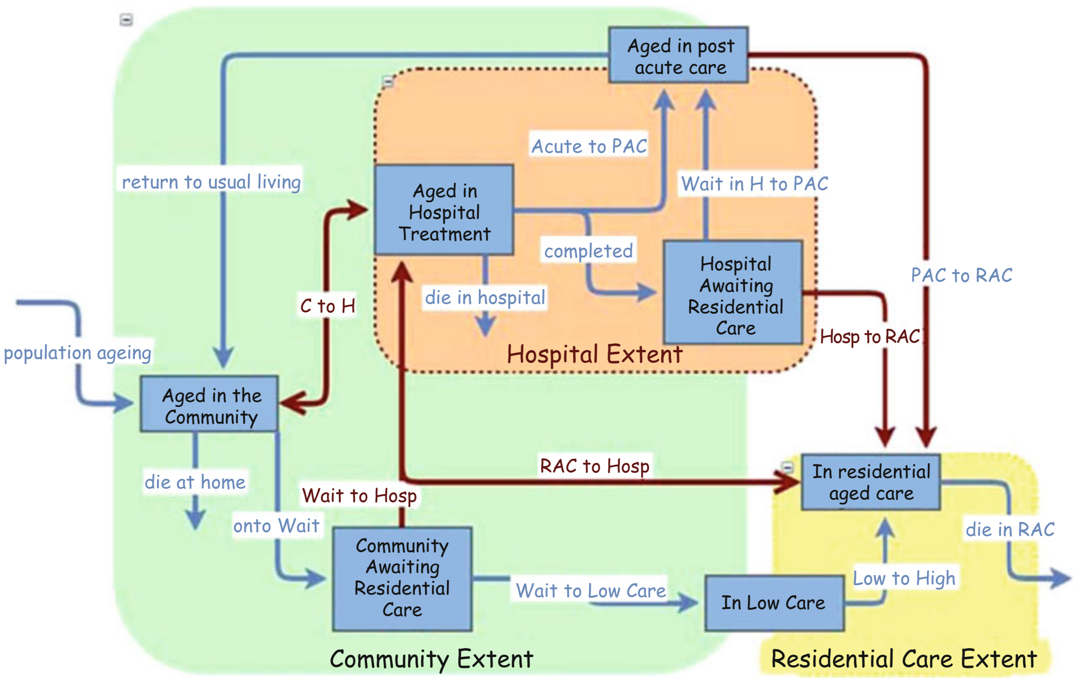


Fig. 6.26 A stock and flow diagram of flows of aged care patients between the community, acute hospital, post acute care (PAC) and residential aged care (RAC)

6.5.4.2 A Systems View of Aged Care

Based on experience with national, regional and district models of the acute aged care interface [40] we constructed a simplified model to help people understand the downstream effects associated with population ageing swamping the current systems of care across the community, hospitals and aged care sectors. A Stock and Flow diagram can be found at http://bit.ly/sLMfp8 (Fig. 6.26).

We have two groups of people waiting for aged care places, one in hospital and the other in the community (at home). The key downstream dilemma is to manage these inflows into residential aged care. This becomes increasingly difficult if quality improvements within aged care prolong life and reduce the death rate outflow from residential aged care (RAC). From the hospital point of view, the best short term fix is for RAC to admit patients from hospital as a priority. However this causes increased waits in the community and eventual increased flows of older people into hospital for treatment. Another perverse incentive is that in order to remain financially viable, aged care residences must have a flow of people through low care and so prefer to upgrade an existing resident from low to high care rather than admit a new high care patient from hospital. Virtual experiments show that intermediate post acute care (PAC) options only have lasting effects if they increase the rate of flow of return to usual living in the community. Hence the increasing demand due to baby boomers and reduced informal carers in the community requires a focus on managing expectations and services around what constitutes usual cared living in the community. The increasing complex detail is also unfolded at http://bit.ly/sLMfp8. A downloadable ithink simulation model is at http://bit.ly/u3zQn8. Detailed models are calibrated with data from many sources and include an interactive user interface which can be used to perform virtual "what-if" experiments.

Ithink/STELLA Model Output Showing Living Arrangements Output, Control Panel Options and Cost Changes over time and ability to perform what-if experiments (Figs. 6.27 and 6.28).

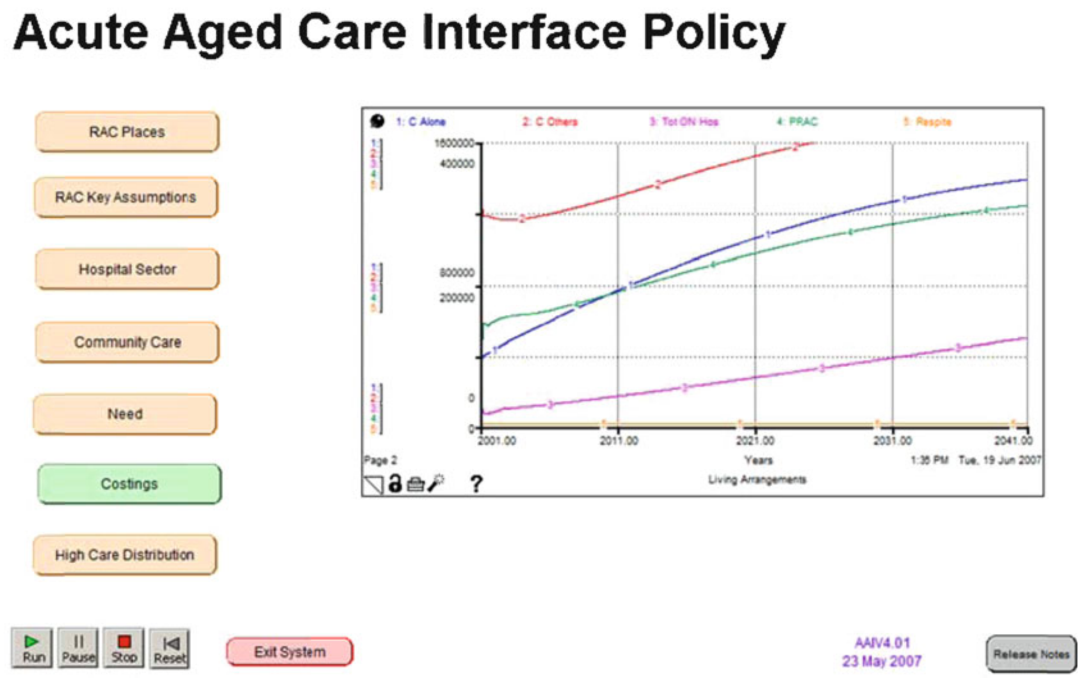


Fig. 6.27 Graphical user interface used to perform simulation experiments for exploring policies at the acute aged care interface. The left hand buttons link to detailed sector experiments and the graph shows the number of people in community, hospital, permanent and respite care by calendar year

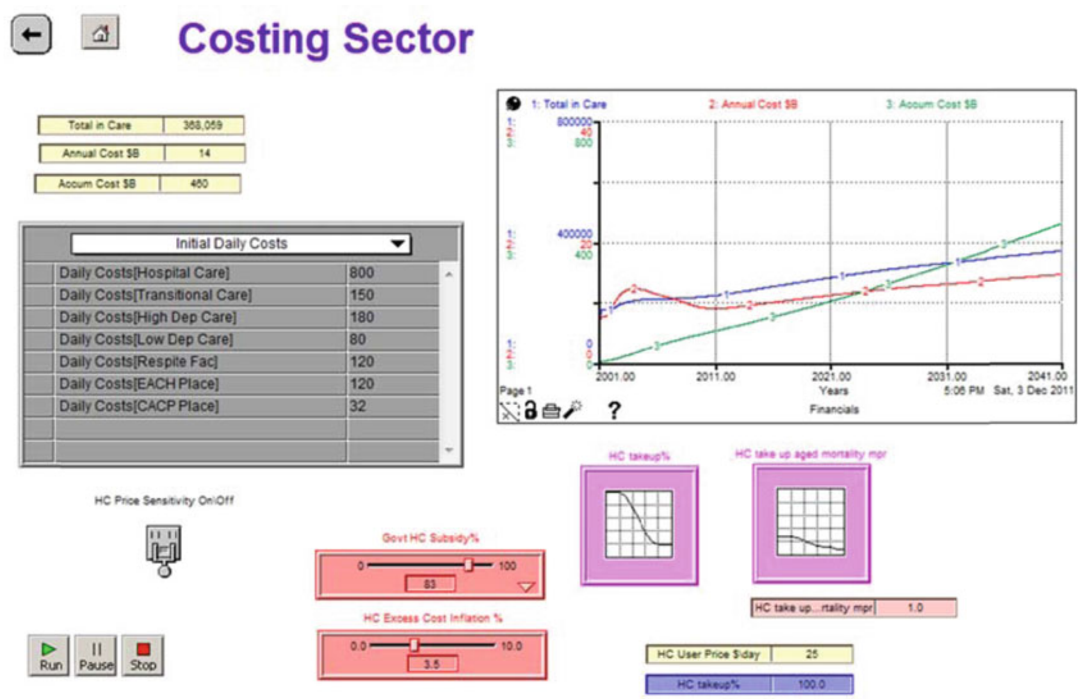


Fig. 6.28 The Costing Sector Aged Care Policy User Interface showing grey tables, pink graphical and red slider variables than can be modified to show the effect on the graphical outputs of total people in care, annual and accumulated costs by calendar years. (http://www.systemswiki.org/index.php?title=Acute_to_Aged_Care_ithink_Models)

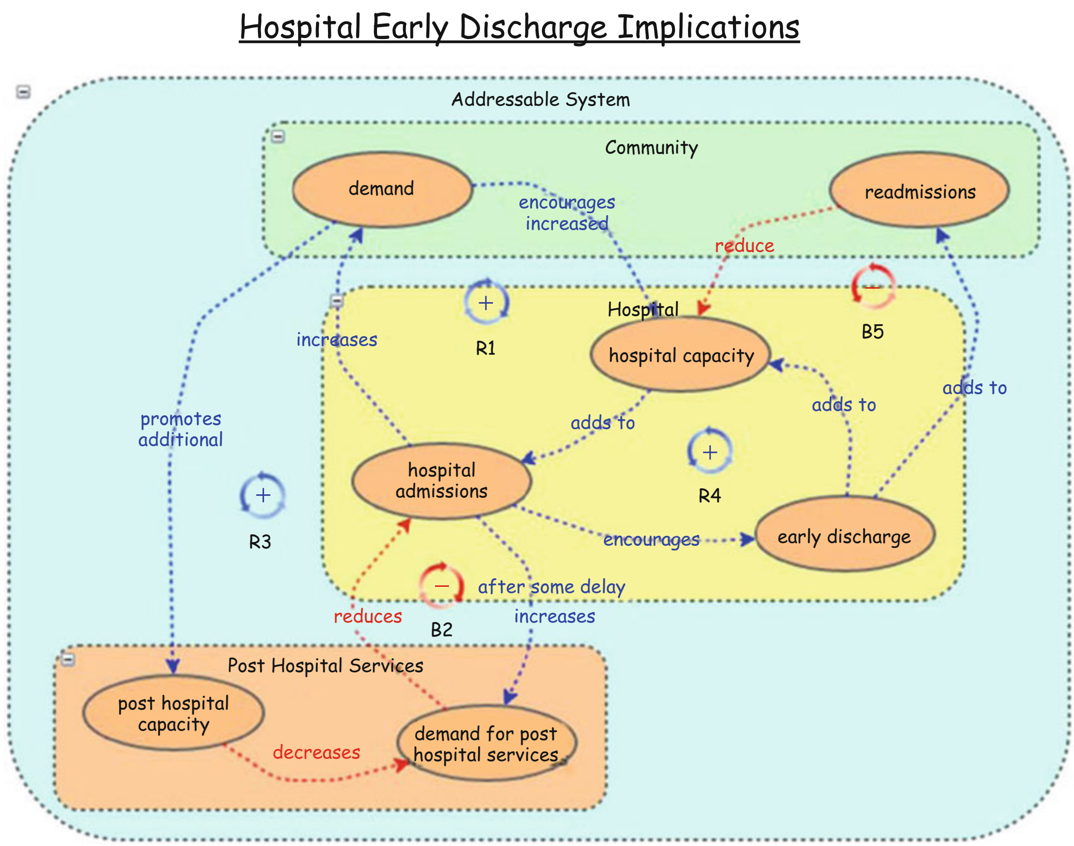


Fig. 6.29 Eric Wolstenholme's generic archetype of the implications of early hospital discharge described at http://bit.ly/svAofc

Based on these kinds of experiences in many projects, the insights gained from virtual experiments and real world experience can be expressed in insightful causal loop diagrams, such as the following generic archetype from Eric Wolstenholme [39] (Fig. 6.29).

The prevent versus treat dilemma can be extended to the whole health system, and communicated using Rich Picture diagrams, as in the following example adapted from Jack Homer, Gary Hirsch and Bobby Milstein's [41] US work on chronic illness in a complex health economy (Fig. 6.30).

6.6 Conclusions

> *"Models are not perfect," says Syd Levitus. "Data are not perfect. Theory isn't perfect. We shouldn't expect them to be. It's the combination of models, data, and theory that lead to improvements in our science, in our understanding of phenomena."*
>
> http://earthobservatory.nasa.gov/Features/OceanCooling/page5.php accessed Nov 12 2008

Forrester has set the standard for system dynamics models in his books on industrial, urban and world dynamics. He recently described what makes a good system dynamics model as the following:

1. The description starts with a clear statement of the system shortcoming to be improved.
2. It displays a compact model that shows how the difficulty is being caused.
3. It is based on a model that is completely endogenous with no external time series to drive it.
4. It argues for the model being generic and descriptive of other members of a class of systems to which the system at hand belongs.

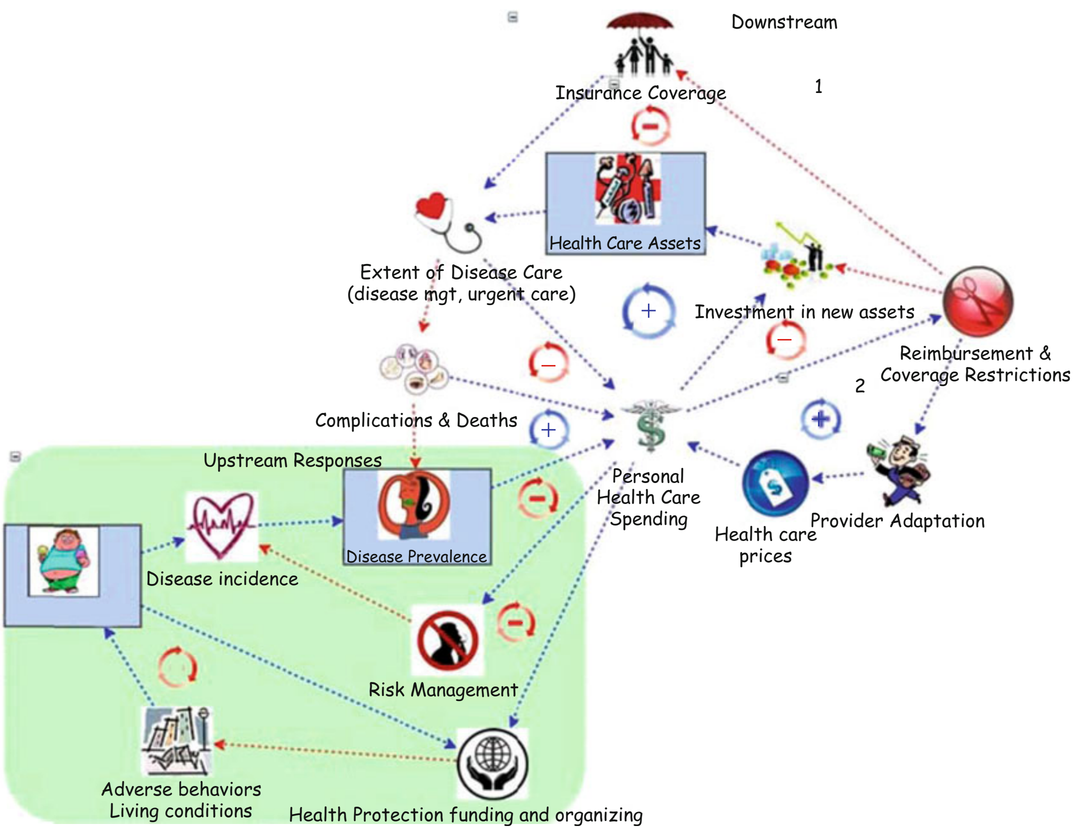


Fig. 6.30 A rich picture representation of the upstream and downstream interventions for managing chronic care in the US Health Care System. This example is unfolded progressively at http://bit.ly/wUnNxq

5. It shows how the model behaviour fits other members of the class as policies followed by those other members are tested.
6. It arrives at recommended policies that the author is willing to defend.
7. It discusses how the recommended policies differ from past practice.
8. It examines why the proposed policies will be resisted.
9. It recognises how to overcome antagonism and resistance to the proposed policies.

Forrester ISDC Plenary Session Boston 2007 and SD List 12 Feb 2008.

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