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DECISION ANALYTIC MODELING IN HEALTH CARE DECISION MAKING

Oversimplifying a Complex World?

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Abstract

The need to choose among alternatives instead of allowing the market to make choices has led health care professionals to rely on scientific information as an aid in decision making. Mathematical modeling is one of the increasingly common tools used over the past three decades to produce new information. But we have used almost exclusively noncomplex models to help analyze complex systems problems. The need to integrate the complexity of the interactions of clinical, quality of life, and economic attributes into such models can no longer be ignored. The opportunity is available to use existing complex systems modeling techniques for health care questions to improve the quality of study outputs, which can, in turn, help produce more rational decisions.

Keywords: Decision Modeling, Complex Systems

We do not allow impersonal economic market forces to make most decisions on efficient use of health care resources for reasons of equity, distributive justice, and market failure (i.e., insufficient information to make rational choices). But resource limitations still compel us to choose among alternatives. We rely instead on information derived from scientific study as a substitute for the economic market to help us make health system quality/cost trade-offs. This method of decision making is being used at the level of individual patients and physicians, even with limited knowledge of population-based probabilities and confidence limits, and with uncertainty of outcome when applying population statistics to individual patients. These data, when available, focus primarily on efficacy and safety, and then occasionally on other outcomes, such as effectiveness, cost, and quality of life.

Even the availability of best information does not guarantee the best (or even a good) decision. Nor does sound information necessarily lead to improved health, more equitable distribution of resources, economically more efficient allocation of medical care processes, or greater patient satisfaction. Using good data only increases the likelihood of the desired outcome. Uncertainty in health care is a particular problem because benefits, risks, and costs are often unknown; one simply

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cannot estimate with confidence the likely health, economic, and quality-of-life consequences for populations or individuals of alternative combinations of resource inputs without large quantities of good data. There are usually both clinical (effects on clinical outcomes) and economic (effects on cost and quality of life) uncertainty in health care decision making, and thus many decision analyses estimate value, i.e., quality and cost outcomes and trade-offs among likely alternative interventions. Finally, even the best information is only a tool, helping decision makers choose among options given social, political, and economic environments and preferences.

DECISION ANALYSIS MODELS

Decision analytic modeling expresses in mathematical terms a description of known or expected reality, whether of a disease state, treatment process, or entire episode of illness and care. It allows us to estimate a range of expected outcomes by varying assumptions about the relationship among population, disease, health care processes, and attendant probabilities of events occurring. Decision analysis, like every research tool, works best when assumptions and inputs are grounded in fact. In both Bayesian and classical contexts, the accuracy of prediction is dependent upon assumptions concerning: a) the current state of reality and the interaction of factors bearing importantly on that reality; and b) stated or inherent probabilities of events occurring.

This tool has been used increasingly in health care during the past three decades. Its two basic uses are to predict outcomes from described or assumed reality and influences on it (e.g., comparing health care strategies or interventions) and to generate new hypotheses for further study.

THE ISSUE

There are two main components of any decision analysis model: the logic system and assumptions that describe the reality or problem being studied, and the probabilities of discrete events occurring. The goal of this paper is to focus on issues related to describing reality (first principles), for it is here that we are currently most deficient in health services research.

It is our contention we in health services research too frequently make predictions based on oversimplified models. This oversimplification leads to additional uncertainty in the level of confidence that we can have in the results. Other fields such as physics, astronomy, economics, meteorology, and chemistry have for decades constructed very complex nonlinear models of complex systems; biology and medicine as well now frequently use complex systems models, for example, in explaining how the brain works. The complex models used in these fields also simplify reality, but not nearly as much as in health services research. The development of modeling tools combined with increased, easily accessible computational power means health services researchers no longer need be restricted to noncomplex models with a relatively small number of descriptors or processes and input-output relationships of a simple mathematical form.

Complex systems models can be used in exactly the same manner as noncomplex systems decision analytic models. They are tools to integrate or synthesize information. Their ultimate purpose is to assist decision makers by reducing uncertainty, whether one physician for his or her patients or a medical care system for its population.

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DEFINITIONS

Complex Systems

A *complex system* is one in which the relationships between inputs and outputs are nonlinear and in which the interactions are complicated and convoluted. Such systems are usually characterized by an enormous number of inputs and an even larger number of interactions, making it difficult to predict accurately all important outcomes.

Examples of complex systems would include:

1. Predicting the weather
   Inputs: Historic and current temperature, humidity, barometric pressure, time past vernal equinox, etc., at many locations.
   Output: Weather at a specific time and place.
2. Treatment outcomes
   Inputs: Patient and family characteristics, diagnoses, medical history, diagnostic test results, treatment options, type of payer, quality of life, personal preferences, employment characteristics, cost, etc., over time.
   Output: Effects on disease, adverse reactions, changes in quality of life, function, cost at a specific time after treatment.

Linear

A relationship between inputs and outputs is *linear* if the output is a sum of constant multiples of the inputs. For example, the equation

$$output = a*input_1 + b*input_2 + c*input_3$$

describes a linear relation in which parameters a, b, and c are constants, each constant multiplies an input, and the results are summed. The effect on the output of changing an input is easily predictable.

Nonlinear

Nonlinearity is used to describe any relationship between inputs and outputs that is not linear. For example, the equation

$$output = a(time)*input_1 + b(time)*input_2*input_3^{c(\mathrm{time})}$$

is nonlinear, where a, b, and c do not have to be constants but can be variable, e.g., as a function of time, and the coefficients can be squares, cubes, square roots, logarithms, etc. Results are not restricted to being summed but can be combined in any way. It might not be possible even to express the output as a function of the inputs in one equation. Nonlinear input–output relations can be complex or noncomplex. For example, the interactions among patient and family characteristics, diagnoses, medical history, test results and treatment options, and their effects on the course of a disease such as breast cancer are nonlinear and probably a combination of noncomplex and complex components.

THE TOOLS

Use of complex systems is well under way in microbiology, genetics, and medical research. New paradigms have been developed to address issues of complex systems in diverse areas of basic biology and clinical medicine (Table 1).

Table 1. Examples of Use of Complex Systems Modeling in Medicine

Paradigm	Learning by example
Technique	Neural networks
Application	Predict 5- and 10-year survival of people with carcinoma of the breast or colorectal carcinoma
Example	Complex systems model that included the same variables as the standard predictive model (TNM), gave significantly more accurate predictions than the TNM staging system. Adding anatomic and demographic variables to the complex systems model gave even more accurate predictions (3).
Paradigm	Nonlinear rates of change
Technique	System of nonlinear differential equations
Application	Simulating the dynamics of HIV in humans to predict immune response and viral load changes in lymphocytes and long-lived infected cells after treatment.
Example	Complex systems model predicted the time scales in which combination therapy would reduce plasma viral loads by three logs and clear HIV from the body (21).
Paradigm	Rule-based reasoning dependent on nearest neighbor interaction
Technique	Cellular automata
Application	Estimate effect of myocardial infarction and ischemia on induction of ventricular fibrillation
Example	Complex systems model showed that ischemia can cause ventricular fibrillation and then death, even when ischemia involves only limited parts of the myocardium (2).

Other complex systems models in medicine include using neural networks for improved prediction of risks in pregnancy (16), ranking perinatal variables influencing birthweight (13), and 1-year recurrence and patient survival for esophago-gastric junction cancer (19). Neural networks have also been applied in radiology and laboratory medicine for image analysis and signal processing (10;17), and gerontology and physiologic aging (14). Models using cellular automata described how capillary sprout network forms in response to tumor angiogenesis factors (4), and predicted phenotypic characteristics of HIV strains in lymph tissue reservoirs (18;28). Process theory has been adapted in psychiatry to explain normal personality development and psychopathology (15;24). Thermodynamic models and bifurcation processes have been used to explain bipolar disease (25). Chaos theory in cardiology determined cardiovascular health by predicting heart rate dynamics and power (12;23).

Insufficiencies of Existing Noncomplex Models

The need to enlarge our methodological armamentarium is compelling because exclusive reliance on noncomplex models is insufficient to understand the simultaneous and multiple interaction effects of medical interventions, delivery systems, and payment mechanisms with individuals and populations. For example, all clinical and cost-effectiveness models of alternative treatment strategies for eradicating *Helicobacter pylori* to cure peptic ulcer disease (PUD) have been noncomplex (linear) models. Nearly all ignored comparison of empirical treatment strategies of general physicians with those of directed diagnostic and treatment algorithms of specialist gastroenterologists, and thus were applicable to only a small percentage of all patients, and ignored that patients who visit general physicians with symptoms

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suggestive of PUD are likely different than those who are referred to the specialist (11;29). In addition, these noncomplex models incorrectly assumed that curing disease also cured symptoms, as an important number of patients continue to have symptoms after ulcer cure and *H. pylori* eradication. Only one set of models even included symptoms as a motivation for patient and physician behavior and began the analysis with the initial visit, thus capturing a fuller array of processes, costs, and outcomes over time (8;9). Integrating factors that bear on symptoms from all related upper gastrointestinal diseases in any PUD model is likely to lead to better outcome estimates. Additionally, none of the models integrated any aspects of delivery systems, physician payment and patient out-of-pocket expenses, or willingness to pay for diagnosis and care, factors that likely have as much power to influence as specific medical modalities.

Much of the current U.S. breast cancer screening policy rests on a series of greatly detailed noncomplex (linear) models flowing from clinical studies of varying quality (5;6). Even though there have been declines of breast cancer mortality in young subpopulations for 4 years (1), it is difficult to relate reliably these declines to increased screening and early diagnosis, simply because the current models do not describe or integrate accurately the nonlinear, and likely complex, interactions among changing definitions of disease, improved technology to diagnose disease, population awareness, insurance payment policies, service availability, screening, genetic predisposition, biology of disease, environmental factors, and changing treatment effects. If prevention, diagnosis, and treatment of breast cancer are as complex a problem as we suspect, then accurately predicting outcomes will require complex systems analysis. We cannot know, *a priori,* whether models that include these factors and allow for more complex interactions among factors would give more accurate predictions, but we would expect them to do so.

Use of Complex Systems Modeling in Health Services and Systems Research

A few complex systems models have been used in health services research. Examples include the health manpower planning model by Yett et al. (31) and the national forecasting model of Feldstein and Roehrig (7) in the U.S. health system. Both were inaccurate in prediction. Another example is the use of frontier analysis in the generally successful work of Schinnar et al. (26;27) in predicting utilization and cost in the delivery of mental health services. Finally, catastrophe/complexity theory was used in the clinical/epidemiologic area to show that anorexia nervosa and bulimia were the same disease but occurred at different times during its natural history (20).

Potential Use of Complex Systems Modeling in Decision Making

Expanding knowledge of multiple risk factors for coronary artery disease (CAD) provides an opportunity to examine the usefulness of complex systems models in improving the understanding of the important effects of social, medical, and economic changes related to CAD on disease outcomes, especially considering the hundreds of risk factors identified. In fact, the large number of associated risk factors may make many models including all such risk factors difficult to interpret, if not altogether meaningless. In their most basic forms, many models from the last three decades tested the link among CAD, the risk of disease complications such as myocardial infarction or stroke, and effects of treatment to modify risk factors so as to improve clinical and economic outcomes. All were (noncomplex) linear models, although many made use of nonlinear risk functions such as those from the Framingham Heart Study. Re-estimating outcomes using other potentially important risk factors, such as changing homocystine levels, the role of chronic infection, and C-reactive protein, while also accounting for improving or worsening of other risk factors, such as hypertension, insulin-dependent diabetes, unstable angina, and heart failure, compliance with multiple medication regimens, availability of diverse treatments, role of incentives used by managed care organizations or Medicare, and others, will make prediction even more complicated. Further, any CAD model would need to include multiple disease states of the most important risks such as hypertension and diabetes, and the fullest possible group of important interactive effects of prevention, treatment (including adverse side effects), and rehabilitation on clinical, quality-of-life, and economic outcomes. At the very least, noncomplex and linear models cannot adequately examine these interactive effects (30).

CONCLUSION

While the underpinning of all modeling is simplification, the key to successful modeling is defining the simplest models that give accurate and useful predictions. A noncomplex, even linear, model can be extraordinarily useful in health services research if it gives good predictions. However, it is the nature of the problem that determines the model used. Complex systems modeling approaches and analytic techniques provide alternatives for increasing the level of complexity, and hence, of accuracy of prediction. This is not to suggest that complex systems modeling guarantees correct prediction, but rather that it can increase the likelihood of correct prediction.

Noncomplex models are limited for many reasons (28). First, the observed (macroscopic) phenomena are assumed to be caused by a single or small set of variables (microscopic), and there is assumed to be a simple relationship between cause and effect. While this assumption is valid and useful for understanding some conditions, such as Down's syndrome, a form of mental retardation caused by a specific genetic change, the relationship, for example, between carcinoma of the breast and genetic mutations, is not so simple. Environment, diet, age, and other risk factors, along with payment policies and access to specific services, and their complex interactions, may have equal or greater importance than family history and genetic factors in disease development and successful outcome of treatment.

A second reason that noncomplex models can be limiting is that reducing the description of reality to a low order set of (deterministic) equations can be insufficient to ensure predictability of the system. Too simplified a model can lead to a loss of complex interaction among variables that has an important effect on model results. Variability of results among studies thus may not be due to sampling error or environmental differences, but rather to ignoring an important nonlinear rule of the system's behavior. Complex nonlinear models allow us to examine large sets of variables with multiple and complex interactions so as to ensure predictability of the system. Predictability is a prerequisite, of course, for increasing the likelihood that a policy will have the desired effects.

In the 18th century, the French economist François Quesnay developed the first economic input–output model describing a complex system (22). We in health services research and technology assessment have been slow to adopt and diffuse new methods of information production and dissemination to improve effectiveness and efficiency of decision making. The need for greater accuracy of prediction is

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arising now at the same time as our understanding of problem complexity increases. We are further slowed by decision makers, such as legislators and formulary committees, who do not have the knowledge to interpret and apply the research and policy results. Wider use of complex systems models should be our next methodological adaptation, along with educating users of research results. The ultimate test of the value of complex models in health care will be determined by the quality of their output. If their predictions are materially better than those of noncomplex models, their use is more likely assured.

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