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Abstract

Conventional evaluation of health care interventions often neglects the wider health system impacts that can be critical for achieving desired health system goals. As such, traditional health technology assessment (HTA) and modeling methods are often of limited usefulness when applied to complex health systems. Health care delivery systems are inherently complex consisting of multiple tiers of interdependent subsystems and processes that are adaptive to changes in the local environment and behave in a non-linear fashion. Often, researchers and health care decision makers either underestimate or fail to consider the interactions amongst the people, processes, technology, and facility designs. Health care delivery system interventions need to incorporate the dynamics and complexities of the health care system context in which the intervention is delivered.

This report presents three dynamic simulation modeling methods to evaluate system interventions for health care delivery: agent-based modeling (ABM); discrete event simulation (DES); and system dynamics (SD) modeling. In contrast to conventional evaluations, a dynamic systems approach incorporates the complexity of the system and anticipates the upstream and downstream consequences of changes in complex health care delivery systems. It is a primer for researchers and decision makers working in health care delivery science and implementation that face complex challenges to providing effective or efficient care delivery that can be addressed with system interventions.

This report provides an overview of these modeling methods and examples of health care system interventions where such methods could be useful. The report assists researchers and decision makers in deciding whether these simulation methods are appropriate to address specific health systems problems through an eight-point checklist (SIMULATE). The report also directs readers to other resources for further education on the topic of modeling for system interventions in the emerging field of health care delivery science and implementation. Upon reviewing this report, readers should be able to identify if these simulation modeling methods are appropriate to answer the problem they are addressing and to recognize the differences between these methods and other modeling approaches used typically in HTA applications.
Introduction

Health care delivery systems are inherently complex and fragmented social systems consisting of multiple providers and payers responsible to deliver health care services to patients in defined regions [1-3]. Social systems are different from other systems in that people make decisions, interact amongst themselves and also interact with other parts of the system, i.e., interdependent. It is hard to plan health care services in this kind of complex system because decisions and choices by people are dynamic, i.e., can change over time and, interactions between parts of the system and with other systems are adaptive, i.e., can change. In the era of patient-centered care, customizing care delivery to the needs of individual patients further escalates the complexity of health care delivery systems [4-9].

This complexity challenges decision makers to evaluate interventions to improve the effectiveness and efficiency of health care delivery due to emergent behavior, i.e., the potential intended and unintended consequences.

Recent advances in computing and data analytics make it possible to simulate the impact of system interventions on healthcare delivery systems without costly and time consuming direct experimentation. The results of such simulation models can anticipate the degree of effectiveness of a novel system intervention as well as its cost-effectiveness.

This task force report presents dynamic simulation modeling methods to evaluate system interventions for health care delivery. It is a primer for researchers and decision makers that face complex challenges to deliver effective and efficient care. Based on experience from the fields of industrial engineering and operations research, three dynamic simulation modeling methods are well suited for and commonly applied to these types of problems: agent-based modeling (ABM), discrete event simulation (DES), and system dynamics (SD) modeling [9-13].

The report provides an overview of these dynamic simulation modeling methods and examples of health care system interventions where such methods could be useful. It is intended to assist researchers and decision makers in deciding whether these simulation methods are appropriate to address specific health systems problems. We present an eight-point checklist (SIMULATE) as a tool to assist in determining if these dynamic simulation modeling methods are suitable to address the problem of interest. The report also directs readers to other resources for further education on the topic of modeling system interventions in the emerging field of health care delivery science and implementation. Upon reviewing this report, readers should be able to identify if these simulation modeling methods are appropriate to
answer the problem they are addressing and to recognize the differences of these methods from other modeling approaches.

**Definitions of concepts and terminology**

In the field of complexity science, complexity is a property of a system, not an intervention [14]. A complex system is one that is adaptive to changes in its local environment, is composed of other complex systems, e.g., the human body, and behaves in a non-linear fashion, i.e., change in outcome is not proportional to change in input [15]. Moreover, the behaviour of the system as a whole is different from that of its parts or components. Understanding this emergent behaviour is part of understanding a complex system.

*Simple* systems consist of tasks that can be answered as ‘yes’ or ‘no’, whereas *complicated systems* consist of tasks that are based on ‘if/then’ algorithms. *Complex systems* consist of tasks that are relationally dependent events with unpredictable outcomes [16].

Health care consists of multiple complex systems. For instance, complex systems in health care delivery include primary care, specialists, outpatient facilities, hospitals, and long term chronic care facilities. This framework of complexity can be useful for delineating simulation modeling applications to systems depending on the level of complexity (Table 1).

**Table 1: Concepts & Terminology Definitions**

<table>
<thead>
<tr>
<th>Term</th>
<th>Definition</th>
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<tbody>
<tr>
<td>Complex System</td>
<td>A system that is adaptive to changes in its local environment, is composed of other complex systems, behaves in a non-linear fashion and exhibits emergent behaviour [14].</td>
</tr>
<tr>
<td>Emergent Behaviour</td>
<td>Also known as emergence, refers to the novel and coherent structures, patterns, an properties that arise from the interaction of the parts of a complex system and take place at the system scale rather than at the component’s scale [17].</td>
</tr>
<tr>
<td>Health Care Delivery Systems</td>
<td>Health care delivery systems represent a continuum of providers in primary, secondary and tertiary care, as well as payers that grant patients access to affordable, quality care in defined</td>
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regions. They are inherently complex entities, consisting of multiple tiers of interdependent subsystems and processes, as well as varying degrees of private and public elements throughout different regions [16].

Overview of Dynamic Simulation Modeling Methods

This report focusses on three dynamic simulation modeling methods that are well suited for and commonly applied to health care delivery problems: agent-based modeling (ABM); discrete event simulation (DES); and system dynamics (SD) modeling.

System Dynamics (SD) is a simulation modeling method used for representing the structure of complex systems and understanding their behavior over time. It was developed in the 1950s by Jay Forrester at the Massachusetts Institute of Technology when faced with managerial problems at General Electric. From manual simulations of the stock-flow-feedback structure of the production plants, including the existing corporate decision-making structure for hiring and layoffs, Forrester was able to show that the employment instability was due to the internal structure of the firm, not an external force such as the business cycle. In 1961, Forrester published the first book in the field, Industrial Dynamics [18].

The core elements of SD are feedback, accumulation (stocks), rates (flows) and time delays. Stocks are accumulations or aggregations of something, e.g., people, beds, oxygen. Flows are rates; these feed in and out of stocks and have the same units of stocks per time unit, e.g., people per hour, beds per year, oxygen per minute. An important concept in SD is nonlinearity. This concept is tied to the existence of feedback processes. It means that an effect is seldom proportional to the cause.

One of the core assumptions in SD is that the behaviour of the system is due to its structure, not external forces or factors. Although SD models can be formulated at many different levels of detail, such models in health care are most traditionally aggregate, in the sense that they characterize the population in terms of sizes of subpopulations rather than at an individual level. Thus, rather than tracking specific persons on a longitudinal basis, such models provide a cross-sectional view of a system by counting over time the number of people exhibiting particular combinations of characteristics or in particular, e.g., health states. In general terms, SD can produce patterns and trends, as well as mean values. The patterns and trends resulting from simulation experimentation with different policies or strategies (“what if” questions) can be analysed by modellers and stakeholders to inform decision making.
**Discrete-event Simulation (DES)** is a simulation method used to characterize and analyze queuing processes and networks of queues where there is an emphasis in the utilization of resources [19] developed in the late 1950s by K.D. Tocher while working in the operational research group at United Steel Companies in the United Kingdom. Tocher was faced with constructing a simulation model of one of the steel plants [20]. Most problems or questions that DES can help analyze are those regarding resource utilization and queues, i.e., wait times.

The core concepts in DES are events, entities, attributes, and resources. An event is a something that happens at a certain time point in the environment and that can affect resources and/or entities. Entities are objects that have attributes and consume resources while experiencing events. Attributes are features or characteristics unique to an entity. They can change over time or not. Resources are objects that provide a service to an entity. Queues are another important concept in DES. Queues occur when several entities compete for a specific resource for which there is a constraint. At a more technical level, time is discrete, and change happens when an ‘event’ occurs.

In healthcare specifically, DES can be useful to analyze effects on health-related outcomes. DES is also useful for problems where it is particularly relevant to be able to capture the changing attributes of entities, e.g., patients, and where the processes to be characterized can be described by events [21].

The outputs of DES are generally mean values and distributions of values. Individual entities are followed through simulated processes enabling event traceability. This methodology generates high level of insight about the problem and system under study at logistic/operational level. Outputs of DES can be interpreted or used for system performance indicators such as resource utilization, wait times, number of entities in queues, and throughput of services or products. Also, scenarios with different strategies and policies (“what if” questions) can be tested. The mean values or distributions can be thought of as accurate; however, not necessarily optimal.

**Agent Based Modeling (ABM)** is a simulation method for modeling dynamic, adaptive, and autonomous systems [22]. It is employed to discover systems by using ‘deductive’ and ‘inductive’ reasoning. At the core of an ABM model, there are ‘autonomous’ and ‘interacting’ objects called agents. Agents are social and interact with others and they live in an environment and their next actions are based on the current state of the environment. In addition, an agent senses its environment and behaves accordingly based on defined decision rules. Agents may have explicit goals to maximize or minimize, may learn and adapt themselves based on experience.

In 1971, Thomas Schelling used ABM to propose a theory to explain the persistence of racial segregation even though the legal and cultural environment was one of growing tolerance. Using a
basic ABM model with simple if-then statements, (e.g., individuals will tolerate racial diversity, but will not tolerate being in a minority in their locality), he was able to show via colored squares on a matrix, that segregation will still be the equilibrium situation.

The three core concepts that form the basis for ABM are: agency, dynamics, and structure [23]. Agency means that agents, e.g., patients, have goals, beliefs and can act. These agents can move through space and time, interact with each other, learn, and disseminate new learnings to other agents in their social network. Dynamics means that both the agents and their environment can change, develop, or evolve over time. Structure is emergent from agent interaction. For example, how human populations will tend to aggregate in certain locations based on pre-defined behaviors that have been coded into the agents. All of the above factors can be modelled.

The widest use of ABM related to population health has been to model large-scale anthropogenic or natural disasters, such as a chemical spill, infectious disease outbreak, fire, hurricane, or flooding. The response of the affected population is driven by available information about the event, behaviors, e.g., evacuation, and containment strategies, e.g., vaccination or quarantine [24].

ABM is a rapidly maturing health modeling technique well suited to addressing public health planning and policy needs, as well as health care infrastructure investment decisions. The attainment of specific population health goals can be simulated at the population level, and the specifics of investments needed to achieve these goals can be investigated in a more detailed fashion. Primary goals can be defined by disease outcomes, efficiency measures, return on investment, or costs [25].

The strength of interpretation of ABM results lies in the conduct of sensitivity analyses. By varying the interventions applied to the health care system, (e.g. introducing a new diabetes prevention program versus lowering the co-pay for diabetes medications). ABMs can be a powerful tool to test assumptions, assist planning, and forecast the effects of different health system scenarios on population health.

**Why is Dynamic Simulation Modeling Relevant to Health Care Delivery Research in Complex Systems?**

Health care delivery systems are inherently complex, characterized by nonlinearities, feedback loops, and large numbers of variables that evolve dynamically over time. Simulation models can help identify the critical functional and relational aspects of a system. Thus, simulation modeling allows us to understand why a system behaves the way it does as a function of its organization and the relationships amongst components of the system.
More recently, with the focus on patient-centered care, the complexity has increased in these systems. The Institute of Medicine’s seminal report, “Crossing the Quality Chasm: A New Health System for the 21st Century”, highlights patient-centered care as a necessary component of good practice, emphasizing the importance of continuous health relationships, knowledge sharing, and free information flow across segments of the health care system [5]. According to Berwick’s Triple Aim, health care system improvement requires the simultaneous pursuit of three aims in iterative cycles: improving both the experience of care and the health of populations, and reducing per capita costs of health care [26].

A dynamic simulation model can help address these conflicting goals and complements the increased focus on patient centeredness as a research priority. Providers are now challenged with implementing evidence-based practices, such as checklists, but lack the facility to incorporate patient preferences [27, 28]. Simulation modeling methods of complex systems can capture patient preferences to simulate patient and provider behavior as well as anticipating the outcomes of behavioral interactions.

In the context of healthcare delivery, a patient-centered approach requires an understanding of the multiple and diverse determinants of health outcomes and patient experience. Modeling these relationships and interdependencies at the system level, can provide a comprehensive view of the drivers that improve the quality of the patient visit experience, such as shortened waiting times, quality of information, and access to care. Care pathways can be designed to better reflect patient preferences for certain sub-groups, such as risk tolerance for therapies [29], the avoidance of side effects [30], potential adherence to therapeutic regimens, or demographics and past medical history [31]. In the complex interactions between doctors and patients, simulation modeling may also yield insights into revealed versus stated preferences.

Health care delivery systems are continually evolving as they strive to balance quality care against resource constraints. However, classic health economic models do not account for the multiple constraints facing health care systems. Constraints are imposed on the health care system in many ways: provider budgets, patient out-of-pocket spending, physical space and facility designs, staff numbers, delivery processes, workflow productivity, access to technology, and time. Designing health care systems that deliver value will require these types of new approaches [32].

What/How can simulation modeling contribute to design and evaluation of health care delivery system interventions?
In the Medical Research Council’s framework for the evaluation of interventions, an intervention is “built up from a number of components, which may act both independently and inter-dependently.” Consequently, it can be challenging to determine what aspect(s) of the intervention effect change in the system [14].

When evaluating interventions, the Medical Research Council report emphasizes that it is necessary to consider the wider ramifications of intervening and to be aware of the interaction that occurs between components of the intervention, as well as between the intervention and the context in which it is implemented. This includes the operations, structures, and relationships that exist in each setting and the implications that contextual effects have for designing and evaluating interventions.

Dynamic simulation modeling methods are useful in the design and evaluation of health care systems and the interventions needed to resolve their inherent problems. Many of the advances in disease diagnosis, treatment and care are implemented, without addressing the unintended or unanticipated consequences of these interventions at the system level.

In fact, interventions that are implemented to address difficult challenges in health care sometimes fail to solve persistent problems or create new problems. This phenomenon is known as policy resistance: the tendency for interventions to be defeated by the system’s response to the intervention itself [33]. Dynamic simulation models enable evaluators and policy makers to account for and identify policy resistance in a system and design and test interventions that can overcome this phenomenon.

It is widely accepted in health care that generating reliable scientific evidence requires conducting experiments, comparing and differentiating hypotheses and obtaining results that are replicable [33, 34]. However, generating reliable scientific evidence becomes more difficult as complexity increases and is not always feasible due to ethical, physical, or technical reasons. Simulation models are virtual worlds that offer decision makers the capability of conducting experiments and evaluating system interventions.

<table>
<thead>
<tr>
<th>What is simulation modeling used for?</th>
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**Health Care Delivery Research in Complex Systems**
- Model building process and simulation are learning processes themselves
- Identify critical functional and relational aspects in complex systems.
- Understanding system behavior as a function of its organization (structure).
- Shift paradigms and mental models

**Design and Evaluation of Health Care Delivery System Interventions**
- Evaluate intended and unintended consequences of an intervention using “what if...?” scenarios
- Tool for designers (e.g. policy design, system design and re-design) that is more prescriptive in nature by informing decision making.
Simulation models provide low risk and low cost laboratories to learn and gain understanding about health care systems and the effects that interventions may have on them.

Dynamic simulation modeling methods test ‘what if’ scenarios that can then be used to estimate the upstream and downstream outcomes associated with systems of care that are too complex to anticipate based upon piecemeal analyses of the system components. In the virtual world of the simulation model, decision makers can push the system to extreme conditions, extend time of observation, strengthen and relax assumptions, which is often impossible or infeasible in the real world. Simulation models provide immediate feedback to decision makers, allowing them to gain years of simulated experience and knowledge about the system and interventions by revealing dynamics and mechanisms that are otherwise not obvious [35, 36].

Traditional approaches and statistics provide descriptive ways of measuring and testing individual relationships. As massive amounts of data are collected and warehoused, the descriptive analyses are replaced by predictive models, which strive to foretell the future. Dynamic simulation modeling takes it one step further to become prescriptive in nature, such that the models prescribe what actions/interventions to take, based on scenarios tested through experiments [37, 38].

Through simulation modeling, decision makers can observe effects that interventions can have on different parts of the system concurrently; it engages decision makers into systems thinking and to focus on interdependencies—broadening their perspective on the problem and enhancing their understanding of interventions in the context of the overall system [3, 35]. Hence, decision makers are forced to develop intuition about the system and how it really works, thereby informing the design of the system and interventions realistically and more accurately [35, 38-40].

System redesign is an essential step to achieving sustainable implementation of evidence-based practice interventions across the care continuum and dynamic simulation modeling can inform the adoption of evidence based patient care practices. Suppose for example, that policy makers are considering a new centralized system for the intake of patients with joint pain and disability due to long waiting times to access appropriate arthritis care. Redesigning the referral process can be informed by dynamic simulation modeling.

Arthritis, most commonly osteoarthritis (OA) and rheumatoid arthritis (RA), is a frequent cause of joint pain and disability, and is associated with a significant societal burden, in terms of both morbidity and costs. Early recognition and intervention prevents or minimizes permanent, irreparable joint damage.

which results in functional impairment. Ensuring timely access to appropriate and effective care is the first step in preventing the deleterious, progressive effects of these diseases.

A centralized intake referral system involves pooling of patients on waiting lists to create a single first-come, first-serve, but severity prioritized queue, from which patients are directed to an appropriate service provider [41]. In theory, pooling patient referrals for assessment and triage should help decrease the variability in the system and improve access to arthritis care [42]. But, a central intake system can be structured in a variety of ways, and the impact of different structures on patient outcomes and costs are not obvious. Dynamic simulation modeling allows policy makers to evaluate these different structures and alternative scenarios [43]. This ability to evaluate system design and the intended and unintended consequences of implementing alternative interventions is a critical, but largely missing, tool in health services delivery research.

Nonetheless, there are challenges to using and implementing dynamic simulation models. Some of the challenges are the need of specialized skills in simulation modelling, e.g., operations research, engineering, computer science. Data requirements for the models can be difficult to fulfill due to lack of access to certain data, costs associated with data acquisition, and data availability. Nevertheless, these models provide an advantage since their structure will not be limited by the available data and they can be used to do exploratory analyses until the additional data can be incorporated. It may be difficult at times to communicate how these models are built and the details of their mathematical structure. This can sometimes be interpreted by users, i.e., policy makers, as lack of transparency. However, these structures and sophisticated calculations are necessary to adequately represent the problem and to obtain accurate results.

What are the Differences between Health Economic Models in Health Technology Assessment and Dynamic Simulation Models in Health Care Delivery Systems?

HTA is defined as "the systematic evaluation of the properties and effects of a health technology, addressing the direct and intended effects of this technology, as well as its indirect and unintended consequences, and aimed mainly at informing decision making regarding health technologies.” Traditionally, health economic models used in HTA are based on clinical evidence and perform analyses of economic consequences of that specific technology compared to usual care. The standard metric used in HTA is cost-effectiveness - the ratio of the incremental cost to the incremental benefit (often measured as quality-adjusted life years) of a single or multiple interventions.

Most HTA reports have a limited scope with regard to the consequences to the health care delivery system. For planning, design and evaluation of health care delivery system interventions, dynamic

.simulation models can capture the feedback loops that reflect interactions amongst the operations, structures, and relationships in the health care system and evolve dynamically over time. Conventional evaluation of interventions in health care is often limited because it neglects these wider health system impacts that could be critical for achieving desired health goals.

For instance, a health economic model comparing tissue engineered and biodegradable gels for repair of small cartilage defects might evaluate the clinical effectiveness in terms of cost per quality adjusted life years and economic consequences (budget impact) compared to physiotherapy, surgery, or watchful waiting. However, for health care planning and delivery, other questions may arise, such as the required health care facilities to deliver this minimally invasive therapy, and the change in hospital service due, for instance, to a delay of whole joint replacement in case of severe osteoarthritis. In addition, the health system is likely to adopt minimally invasive interventions, but the diffusion may differ widely between regional health facilities, depending on interaction between health care payers, providers, and physicians. The impacts of such interactions are not typically accounted for in HTA.

A systems approach anticipates the upstream and downstream consequences of changes in the health care system. This enables health service planners to identify upstream and downstream points of leverage through experimentation with various ‘what if’ scenarios without actually having to implement the policy first. Dynamic simulation modeling is used to model interventions before the cost-intensive design and development and implementation phases. Thus, effects on patient care, the health care system, as well as health economics aspects can be estimated and anticipated [44].

Characteristics of Dynamic Simulation Modeling Methods Relevant to Health Care Delivery System Problems

Dynamic simulation modeling can be applied to a range of health care delivery system problems:

a) Simulation modeling can estimate consequences of health care delivery system interventions

Many interventions in health care have impacts on the health care delivery system that are not typically considered in health economic models. Simulation modeling can better estimate the downstream and upstream consequences once a health policy or delivery intervention is implemented, accounting for feedback loops and interdependencies to characterize the adaptive nature of the health care delivery system. These models can also be used to dynamically estimate the consequences of demographic change, or, for instance, ageing of the population [45].

b) Simulation modeling allows the incorporation of behavioral aspects and personalized health care decisions
One of the advantages of simulation models is that they are flexible in the definition of either “health states” or “events” [46, 47]. This enables a more realistic representation of the unique pathways of individual patients through the health care system as well as the health states they currently experience. Patients make decisions about when they will see a doctor, if they will comply with their medication regimen, or if they are willing to co-pay for expensive treatment. Simulation models in general, and agent-based modeling in particular, allow flexibility to incorporate the dynamics of people making decisions affecting population health outcomes, and thus efficient planning of health care interventions. Pombo-Romero et al. developed an agent-based model to show social interaction to explain the use and diffusion of new drugs in a regional healthcare system [48]. Such agent-based models account for behavioral interactions between patients, physicians and pharmacists regarding prescriptions.

c) Simulation models are flexible to consider consequences of co-morbidities and health care utilization

Most health economic models assume an underlying disease for which a treatment is evaluated. However, many people with chronic diseases suffer from multiple morbidities and experience multiple episodes of interactions with the health care system. Simulation models may also incorporate subroutines to model physiological interactions in the body that affect treatment outcomes and healthcare demand. For instance, Sabounchi et al. created a systems dynamics model specific to weight gain and obesity in women undergoing fertility treatment [49]. The model includes several physiological subsystems that may affect body weight.

The potential advantage is that networks of related diseases can be defined similar to networks of underlying genetic mutations and networks of social activities [50]. If such underlying physiological responses networks can be identified and modeled, the consequences of healthcare delivery interventions on the health system can be evaluated more precisely taking into account time dependency.

d) Simulation models can consider the spatial consequences of a health care delivery intervention

Many health care interventions also have a spatial component, such as infectious disease policies [51] or remote health services like tele-monitoring. If health services are delivered at home, or if general hospitals specialize into health care centers, this has a large impact on the amount of patients travelling to health care facilities. At the least, it will impact the case-mix of patients in the hospital, and simulation modeling can be applied to estimate the consequences on hospital admissions and support further capacity planning [52].
One specific application is queuing and waiting list management in hospitals. Troy and Rosenberg used a simulation model to determine the need for ICU beds for surgery patients [53]. The background for the study was an increase in the number of patients admitted to the hospital for emergency care as the hospital developed into a tertiary care facility. The increase in acute patient admissions has led to an increase in the need for ICU beds. Simulation modeling was used to estimate the required number of ICU beds based on available surgeons and expected number of patients admitted to the hospital.

e) Simulation modeling addresses system problems that are too complex to enable an analytic solution.

Health care consists of multiple complex systems. The inherent feedback loops that reflect interactions and interdependencies amongst the operations, structures, and relationships in the health care system evolve dynamically over time and cannot always be captured in an analytic solution. But simulation methods can be used to model such relationships.

Different kinds of health care delivery problems where simulation modeling approaches are valuable

The feasibility and relevance of simulation modeling methods to inform health system planning and decision making for improving system efficiency have been demonstrated [54]. The specific selection of the appropriate simulation modeling method depends on a number of factors, such as whether the problem is specific to individuals or groups, the level of the problem (strategic, tactical, or operational) and whether stochastic or deterministic solutions are sought [22]. This will be the subject of a subsequent Task Force report.

Table 2. Examples of Problems addressed with simulation modeling methods to evaluate complex Health Care Delivery Interventions

<table>
<thead>
<tr>
<th>System Level</th>
<th>Types of Problems</th>
<th>Problem Example</th>
</tr>
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<tbody>
<tr>
<td>Strategic level</td>
<td>Policy</td>
<td>Informing regional or national policy regarding implementation of a centralized intake system for referral to an appropriate provider for assessment and specialist consultation if needed, for patients with musculoskeletal pain.</td>
</tr>
<tr>
<td>Tactical level</td>
<td>Management</td>
<td>Wait time management for referral for a specific service e.g., consultation with orthopaedic surgeon or rheumatologist</td>
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The literature on the applications of simulation modeling in health care is large and growing rapidly—although most applications continue to be in the traditional operations research areas of scheduling, transportation, queuing theory, allocation of resources, etc. [54]. The following examples illustrate how these dynamic simulation modeling methods have been applied to health care delivery problems and interventions:

- The Mayo Clinic’s Center for the Science of Health Care Delivery has applied health care delivery systems thinking to redesign its practices, particularly in the domains of cardiac surgery [55] and outpatient practice [56]. The Center used discrete event simulation to predict the minimum number of beds needed to meet Mayo Clinic quality standards of care. The model incorporated assumptions about surgery growth and new patient recovery protocols, as well as smoothing surgery schedules and transferring long-stay patients from the intensive care unit. The model predicted bed supply requirements 30% lower than the traditional bed planning approach. System dynamics modeling was used for high level planning of primary care staffing that incorporated new care delivery modes. The model allowed for “what-if” scenarios to be evaluated, showing projected access performance for measures such as time to appointment and corresponding staffing requirements.

- Another example is the ReThink Health model. This system dynamics model simulates the behavior of a health system —tracking changes in health status, utilization, and costs. It has been used to analyze various health policy strategies (expanding health insurance coverage, delivering better preventive and chronic care, and improving environmental conditions) to reduce deaths and improve the cost-effectiveness of interventions [9, 57]. (Milstein’s 2011 paper was awarded Public Health Systems Research Article of the Year by Academy Health.) For example, Milstein et al. (2010) report on the use of the model to evaluate five different health reform policy proposals. The results demonstrated that expanding health insurance and improving the quality of health care delivery would improve health status but would do so at higher cost and health

In contrast, policies focused on strengthening primary care would improve health status, reduce inequalities, and lower costs. Such divergent outcomes would be extremely difficult to predict (not to mention quantify) without the aid of a simulation model [9].

In Ontario, the median waiting time for total hip and knee joint replacements in Ontario was greater than 6 months, longer than clinically appropriate. To inform decisions to reduce waiting times and improve waiting list management, the team developed a discrete event simulation model of the Ontario total joint replacement system to evaluate the effects of 4 management strategies on waiting times: (1) reductions in surgical demand; (2) formal clinical prioritization; (3) waiting time guarantees; and (4) common waiting list management. Using the DES model, they concluded that if increases in the number of surgeries provided (supply) increased by less than 10% per year, demand would need to be reduced by at least 15% to reduce waiting times to clinically acceptable levels within 10 years. Clinical prioritization was found to improve the number of patients receiving surgery in severity-specific wait periods. However, implementing general wait time guarantees would only shuffle wait times among patients [58].

GE Healthcare has applied agent-based modeling, combining demographic, economics and epidemiological data, to support resource allocation decisions about the optimal delivery of care [25]. For example, in India, two government censuses and a socio-economic survey were integrated and used to simulate the expansion of India’s healthcare infrastructure.

Initially, the simulations had been limited to cardiovascular disease diagnosis and treatment within the Andhra Pradesh region. Cardiovascular disease is an increasing health issue in India and a priority for the Indian Ministry of Health —with 2.58 million Indians predicted to die from the disease each year by 2020. Data visualization methods were used to detail the highest concentration of disease, which could then be overlapped over the existing or potential future healthcare infrastructure. Such visualizations allow healthcare scenarios over time to be compared, allowing for optimal future planning. In the future there are plans to evaluate expanding the tool to cover other disease areas and adapt for use in other markets outside India.

The Alberta Health Services Bone and Joint Strategic Clinical Network was seeking a sustainable solution to balancing access, effectiveness and efficiency in delivering health services to patients with osteoarthritis across the continuum of care. A system dynamics model was used to inform system-wide planning for osteoarthritis of the hip and knee [59, 60]. This model contained a complex set of interactions among system components including initial osteoarthritis diagnosis and care, specialist assessment, medical management, surgical management, post-surgery rehabilitation characterized
by a variety of feedback loops. Other important variables included funding levels and the supply of orthopedic surgeons.

Comparison and contrast of key simulation modeling methods (SD, DES, ABM) with other modeling methods (e.g., optimization, Markov models) – differences and complementarities

Simulation models in the sense that we are discussing here (dynamic simulation) are distinguished by their explicit representation of system states and the mechanisms of its evolution over time. Such states might, for example, include the health status and risk behaviors of population members, cumulative societal cost and quality adjusted life years. In contrast to the situation for analytic models — where the trajectories associated with system evolution are specified as an explicit function of time — for simulation models, this evolution is implicitly characterized by specification of the rules governing that system evolution.

Such rules aspire to characterize the posited “physics” of the system, describing causal drivers hypothesized to characterize “how the system works”. The International Society of Pharmacoeconomics and Outcomes Research (ISPOR) and the Society for Medical Decision Making (SMDM) published seven ISPOR-SMDM Modeling Good Research Practices Task Force Reports providing guidance on state-transition models, such as Markov models [61-67].

The resulting simulation models—like the systems that they characterize—are often non-linear in character, a feature with several implications. First, the non-linearity of the models and systems characterized implies that understanding the behavior of the system to a portfolio of interventions requires simulating those interventions together, so as to capture situations where such interventions work synergistically and compete with one another. In contrast to Markov models, which are commonly used to characterize evolution of isolated cohorts—simulation model non-linearity generally implies that individuals or cohorts cannot be simulated as solitudes, but must instead be simulated in a population context.

Second, the non-linearity leads such models to exhibit emergence, where the behavior of the whole can be very distinct from—and cannot be reduced to—that of its parts. Such emergent behavior is often surprising, counter-intuitive, and often differs strikingly across temporal and spatial scales. Third, while Markov models and linear systems models can be solved to provide a “closed form” (analytic) description of the system’s evolution a priori, to understand simulation models, analytic solutions are in general not possible, and to derive dynamics of the system requires executing the rules governing the system over time in a mechanistic fashion accounting for the dynamics in the system.
There is a large variety of simulation models, some of which share similar capabilities. We focus on three primary types in this report: system dynamics modeling, discrete event simulation modeling and agent based modeling; selected based on their suitability to address problems in health care delivery systems and ability to simulate dynamically the interactions between operations, structures, and relationships in the health care system.

Individual-based simulation modeling—modeling formulated at the level of individual agents or actors—is associated with two major traditions: 1) micro-simulation—originating in economics and emphasizing evolution based on empirically grounded, statistical relationships, and 2) agent-based modeling—originating in computer science and traditionally depending on algorithmic and rule-based formulations in richer, dynamic, environments. While their origin, emphasis, and preferred patterns of practice differ, the methods overlap in content and underlying concepts, and we consider them here together. In accordance with growing practice, we refer to both below as “agent-based models”.

There are many other types of related simulation modeling methods. Reflecting the important role networks have come to play in many agent-based models, we further consider aspects of dynamic social network analysis as specializations of agent-based models. Similarly, we consider diverse compartmental modeling techniques, such as those prevalent in mathematical epidemiology since its inception in the 1920s, under the rubric of system dynamics. Furthermore, simulation models can be used to evaluate and optimize a health care intervention given constrained resources. For example, optimization models can consider the demand for imaging in the context of the limited availability of imaging capacity and scanning time to optimize the use of imaging services. Likewise, these modeling studies can be applied to improve scheduling and hence, to minimize waiting time for patients [68].
Table 3. Comparison between dynamic simulation models and other types models

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Dynamic Models</th>
<th>Markov Models</th>
<th>Analytic Models</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mode of Description</td>
<td>Implicitly (via rules or state equations)</td>
<td>Implicitly (via transition matrices)</td>
<td>Closed-form expressions</td>
</tr>
<tr>
<td>Indexing</td>
<td>Time and space</td>
<td>Time</td>
<td>Varies</td>
</tr>
<tr>
<td>Linearity</td>
<td>Generally non-linear</td>
<td>Linear</td>
<td>Generally derivable only for linear systems</td>
</tr>
<tr>
<td>Solution procedure</td>
<td>Simulation</td>
<td>Closed-form solution or simulation</td>
<td>Direct Evaluation</td>
</tr>
<tr>
<td>Population character</td>
<td>Generally open population</td>
<td>Cohorts</td>
<td>Varies</td>
</tr>
</tbody>
</table>

SIMULATE Checklist

The SIMULATE checklist developed by this ISPOR task force guides researchers in determining if dynamic simulation modeling is appropriate to address the problem. The checklist identifies eight elements that characterize simulation modeling methods and differentiate them from other modeling approaches, such as Markov Models and decision trees. The more elements that are indicated, the more likely simulation modeling is required or will be a more efficient approach to inform the problem.

<table>
<thead>
<tr>
<th>SIMULATE</th>
<th>Does your problem require:</th>
</tr>
</thead>
<tbody>
<tr>
<td>System</td>
<td>Modeling multiple events, relationships and stakeholders representing healthcare delivery processes?</td>
</tr>
<tr>
<td>Interactions</td>
<td>Including non-linear or spatial relationships amongst stakeholders that influence behaviors and make outcomes in the system difficult to anticipate?</td>
</tr>
<tr>
<td>Multilevel</td>
<td>Modeling a healthcare delivery problem from Strategic, Tactical or Operational perspectives?</td>
</tr>
<tr>
<td>Understanding</td>
<td>Modeling a complex problem to improve patient-centered care that cannot be solved analytically?</td>
</tr>
<tr>
<td>Loops</td>
<td>Modeling feedback loops that change the behavior of future interactions and the consequences for the delivery system?</td>
</tr>
<tr>
<td>Agents</td>
<td>Modeling multiple stakeholders with behavioral properties that interact and change the performance of the system?</td>
</tr>
<tr>
<td>Time</td>
<td>Time-dependent and dynamic transitions in a healthcare delivery system, either between or within healthcare system levels or in health status change?</td>
</tr>
<tr>
<td>Emergent</td>
<td>Considering the intended and unintended consequences of health system interventions to address policy resistance and achieve target outcomes?</td>
</tr>
</tbody>
</table>
System. The decision problem in the checklist includes the entire healthcare delivery system. This includes different healthcare entities and patients moving through the system. For example, cardiovascular patients may transition from outpatient settings to the hospital when they have an acute myocardial infarction (AMI), subsequently be discharged to rehabilitation therapy, and then finally return to the outpatient setting once more.

Interactions. Patient behaviors, such as medication adherence, diet and exercise may have a non-linear relationship with their risk of cardiac events and it is certainly the case that health care expenditures for cardiovascular patients are nonlinear and highly skewed. As a result, the aggregate implications of patient health behaviors for the healthcare system are extremely difficult to anticipate. Similarly, patient geographic location may have strong influences on whether they are sent to a local hospital when they have an event versus being treated in a coronary artery bypass grafting (CABG) facility with the latest technology for treating patients with an AMI.

Multilevel. The treatment of cardiovascular disease is important at several levels of the health care system. At an operational level, patient behaviors have a strong impact on their risk of events, as does their interaction with the health care system itself (their doctor, local emergency room, hospital, etc.). Accumulating the experience of many patients can help to inform the development of decision rules to maximize the efficiency and effectiveness of care provided subject to the characteristics of a particular patient’s case, spatial proximity to different types of health care providers, etc. This is the tactical level. Finally, at a strategic level, attempts to maximize the cost-effectiveness of cardiovascular care must account for patient behaviors, nonlinearity of healthcare expenditures, and interactions with health care providers. The data must be accumulated over the entire cardiovascular patient population served by the healthcare system to evaluate policies that will lead to the most cost-effective care.

Understanding. The complexity of systems characterized by nonlinearities, interactions among system components, behaviors of agents (e.g., patients and doctors) makes it very difficult to anticipate outcomes associated with particular changes to the system such as treatment protocols for a patient arriving in the emergency room with an AMI. Traditional modeling approaches such as Markov models, decision trees, and multivariate methods can be helpful in understanding pieces of a system but are not generally adequate to understand outcomes at a system level.

Loops. Systems of cardiovascular care have integrated loops that may feed forward or feed backward. For instance, a surviving patient who has experienced an AMI can learn to modify their medication adherence, exercise and diet behaviors. This, in turn, affects their subsequent risk of a future event and associated health care utilization such as re-hospitalizations.
The system may also integrate feedback loops, which actually implies the system learns or adapts from previous experiences or from new policy interventions. For instance, physicians may change prescribing choices as new medications enter the market or new evidence about existing treatments arises.

**Agents.** Patients, doctors, and informal care providers are all examples of agents that interact with one another and other components of the health care system. Patient behavior at any time $t$ is influenced by the consequences of their experiences in previous periods, their expectations for the future, their interactions with their physician, the rehabilitation therapist and the informal care provider who helps them maintain their independence when the return home. Similarly, the treatment choices of physicians are influenced by the outcomes of their previous patients, availability of alternative treatment options, expansion of evidence in the literature, and many other factors. Each of these behavioral responses is, in itself, very complex but their interaction makes it virtually impossible to anticipate outcomes without the use of simulation methods.

**Time.** Time is an inherent component of any health care system. One cardiovascular patient might spend 50+ years putting on weight and failing to take their statin and blood pressure medicine before ending up in the hospital with an AMI. Their hospital stay might last 15 days before they are sent to the rehabilitation center for another week. Finally, they return home, modify their diet and medication behaviors and live for another 40 years. Another patient with a similar profile might return home but develop depression and continue their poor health behaviors—eventually developing congestive heart failure and dying 5 years later.

**Emergence.** Nonlinearities and interactions among agents over time and space can lead to such complexity that it is only possible to understand the performance of the system through simulation. Emergent behaviors can range from valuable innovations to unfortunate events. Policy resistance is related to emergence. Due to the complexity of the system a particular policy intervention may fail because policy makers do not fully understand its mechanisms and cannot anticipate certain consequences or effects that may emerge. For instance, the introduction of electronic medical records (EMRs) might be expected to improve the information available to physicians when making treatment decisions. However, physicians may resist using EMRs because they feel that it interrupts their interaction with the patient during the care process.
Summary and Conclusion

The translation of evidence into policy and clinical care through implementation in the health care system are core issues facing health care delivery system transformation around the world. Implementing evidence based practices can be achieved through simulation modeling to redesign health care delivery systems and improve patient outcomes and health system performance [6]. Traditional health technology assessment and modeling methods are often of limited usefulness when applied to health systems. The hierarchical relationship between the health system, providers and the patient manifests a level of complexity that can be captured using dynamic simulation modeling methods.

Although dynamic simulation modeling methods are widely used in industrial and business operations to optimize processes and improve effectiveness and efficiency, they are still relatively new in health applications [36]. Recently, there has been notable growth of studies applying simulation modeling methods in health research and health system management. The feasibility and relevance of these methods to inform health care delivery system planning and decision making for improving system efficiency have been demonstrated [54].

In this report, we have provided an overview of dynamic simulation modeling methods and examples of health care system problems where such methods could be useful. We differentiate dynamic simulation modeling methods from other types of modeling approaches used typically in HTA applications. The eight-point checklist (SIMULATE) can be used to assist in determining if dynamic simulation modeling methods are an appropriate modeling approach to address the specific health care delivery problems of interest. Key characteristics that suggest simulation modeling is required or will be a more efficient approach to inform the problem include: a complex problem with non-linear or spatial relationships among stakeholders in the context of a system characterized by emergent behavior.

In a subsequent report, we will describe each of the three dynamic simulation modeling methods (system dynamics, discrete event simulation and agent based models) and present good practice guidelines to support the application of simulation modeling methods in health.
References

24. IPLER. *Information Products Lab for Emergency Response (IPLER)*. 2008 January 10, 2014; Available from: [http://ipler.cis.rit.edu/node/1?_sm_au_=iVV0HQk2ZV57r4kR](http://ipler.cis.rit.edu/node/1?_sm_au_=iVV0HQk2ZV57r4kR).
30. Mohamed, A.F., et al., Avoidance of weight gain is important for oral type 2 diabetes treatments in Sweden and Germany: patient preferences. (1878-1780 (Electronic)).
31. Schneider, A., et al., Importance of gender, socioeconomic status, and history of abuse on patient preference for endoscopist. (1572-0241 (Electronic)).
41. Bungard, T.J., et al., Cardiac EASE (Ensuring Access and Speedy Evaluation) - the impact of a single-point-of-entry multidisciplinary outpatient cardiology consultation program on wait times in Canada. (1916-7075 (Electronic)).
48. Pombo-Romero, J., C.J. Varela Lm Fau - Ricoy, and C.J. Ricoy, Diffusion of innovations in social interaction systems. An agent-based model for the introduction of new drugs in markets. (1618-7601 (Electronic)).
49. Sabounchi, N.S., et al., *A novel system dynamics model of female obesity and fertility*. (1541-0048 (Electronic)).


51. !!! INVALID CITATION !!!


53. Troy, P.M. and L. Rosenberg, *Using simulation to determine the need for ICU beds for surgery patients*. (1532-7361 (Electronic)).


