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HEALTHCARE SIMULATION TUTORIAL: METHODS, CHALLENGES, AND OPPORTUNITIES

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ABSTRACT

Simulation in healthcare is becoming an increasingly important methodology for systems improvement projects. For any given project, the simulation methodology to be used is highly application-dependent. The majority of healthcare simulation models are performed with one of three methodologies: discrete-event simulation, system dynamics, or agent-based modeling. In this tutorial we will present examples of real-world projects applied using each method. These examples, some taken from our own research, will range from complex disease progression and social determinants of health to problems in resource planning, scheduling, and allocation. We will also discuss simulation challenges unique to healthcare such as privacy and security; regulation; IRB approval; data quality, availability, and collection; interdisciplinary collaboration and facility access. Finally, we will present our thoughts on emerging opportunities for healthcare simulation such as perioperative care; coordination across the care continuum; population health management; patient health belief and behavior; and emerging healthcare regulation and policy.

1 INTRODUCTION

Due to the complexity of the healthcare system, simulation models have become an increasingly important methodology for modeling healthcare problems. Simulation models are capable of modeling the relationships between the healthcare system, facilities, providers, patients, caregivers, and other stakeholders. By modeling a real-world health system or process over time, healthcare managers and policymakers can better understand and evaluate the impact of their decisions without causing unnecessary risk to patients or placing an unnecessary burden on the healthcare system. Enhanced computing capabilities and graphics allow for an ever increasing complex analysis of healthcare models with meaningful and informative graphical displays for the decision-makers. Furthermore, simulation modeling has become a universal methodology and decision tool that is increasingly understood by a variety of collaborators, regardless of their background and expertise.

The specific healthcare application drives the selection of the most suitable simulation methodology. The majority of healthcare simulation models are performed using one of three methodologies: discrete-event simulation, system dynamics, or agent-based modeling. Discrete-event simulation models are best for analyzing patient and process flows and the capacity and utilization of healthcare resources. System dynamics models are most suitable for analyzing healthcare policy decisions and agent-based models are useful for a large variety of decisions, but especially those requiring individual or population level analysis. In this tutorial, we further describe the simulation methodologies, cite applications from the literature,

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suggest a list of commonly used software, and provide a more detailed example of a real-world problem using each of the simulation methodologies. However, designing, developing, and validating healthcare simulation models is not without its challenges. There are many obstacles to developing quality informative, and reliable healthcare simulation models such as data privacy and security, facility access, regulations, and interdisciplinary collaborations. Yet, healthcare simulation models have the potential to provide important insight on disease management interventions, preventative measures, health behaviors, coordination across the care continuum; these future research opportunities are discussed later in this tutorial.

The rest of this tutorial is organized as follows. Section 2 describes the three simulation methodologies and provides real-world examples of each. Section 3 discusses simulation challenges unique to healthcare while Section 4 shares our thoughts on emerging opportunities for healthcare simulation. Finally, Section 5 gives concluding remarks.

2 SIMULATION METHODOLOGIES AND EXAMPLES

For each of the three simulation methodologies, we provide further details on their unique characteristics, discuss the type of healthcare problems most suitable for the simulation methodology, cite specific applications from the literature, list the most commonly used simulation software, and provide a detailed example applying each specific simulation methodology.

2.1 Discrete-Event Simulation

Discrete-event simulation models are driven by events which occur at discrete points in time and mark a change in the state of the system. Discrete-event simulation models are commonly used for modeling healthcare problems at the tactical or operational level of decision-making (Marshall et al. 2015). In a healthcare setting, they are most practical for performance improvement and design decisions that aim to improve process or patient flow, manage hospital or clinic capacity, schedule staff, analyze scheduling procedures, utilize ancillary services, or allocate resources (Hamrock et al. 2013; Jun, Jacobson, and Swisher 1999). The basic building blocks of discrete-event simulation models include entities, events, and queues (Marshall et al. 2015). Entities include resources, locations, arrival rates, service times, and flow patterns. Patients are the most common entities modeled in a healthcare discrete-event simulation model but others include schedules, medication, and other supplies (Hamrock et al. 2013).

There are many commercial vendors for discrete-event simulation software; however, some of the most commonly used include ProModel (ProModel Corporation, Allentown, PA), Arena (Rockwell Automation, Milwaukee, WI), AnyLogic (The AnyLogic Company, St Petersburg, Russian Federation), and Simio (Simio, St. Sewickley, PA). Discrete-event simulation models are useful as an evaluation tool because they can be customized to collect performance measures such as patient throughput, waiting times, and resource utilization. These performance measures inform healthcare decision-makers of the impact on design changes in the healthcare model, but discrete-event simulation models alone do not determine optimal solutions. This is especially true for multi-criteria decision-making (Jun, Jacobson, and Swisher 1999).

2.1.1 A Discrete-Event Simulation Model for Outpatient Appointment Scheduling

We developed a discrete-event simulation model for outpatient appointment scheduling at a primary care clinic. The objective was to examine scheduling methodologies that provide same day access for a designated patient population while allowing acceptable access to the remaining patient population. The model was designed to predict the operational performance of the clinic under different demand patterns and staffing scenarios. Specifically, decision-makers have a user interface that allows the clinic to set patient arrival rates, no-show rates, percentage of sick patients, patient characteristics (e.g., priority levels), appointment durations, physician's work schedule, and preferred capacity levels by patient type. The model predicts performance measures such as the average patient request-to-appointment time, clinic utilization, and physician overtime. Figure 1 depicts the discrete-event simulation model input, animation, and output for outpatient appointment scheduling; further details are available in Alvarado, Li, and Lawley (2015).

The simulation model provides a great tool for clinics to improve operational efficiency and patient satisfaction. This work is significant because clinic managers can test various scheduling strategies with minimal costs and risks before implementation in the clinic. Specifically, the clinic can experiment with different physician schedule hours and capacity limitations by patient type. They can also analyze how changes in the appointment duration, no-show rates, and arrival rates impact the clinic's utilization, throughput, and patient waiting times.

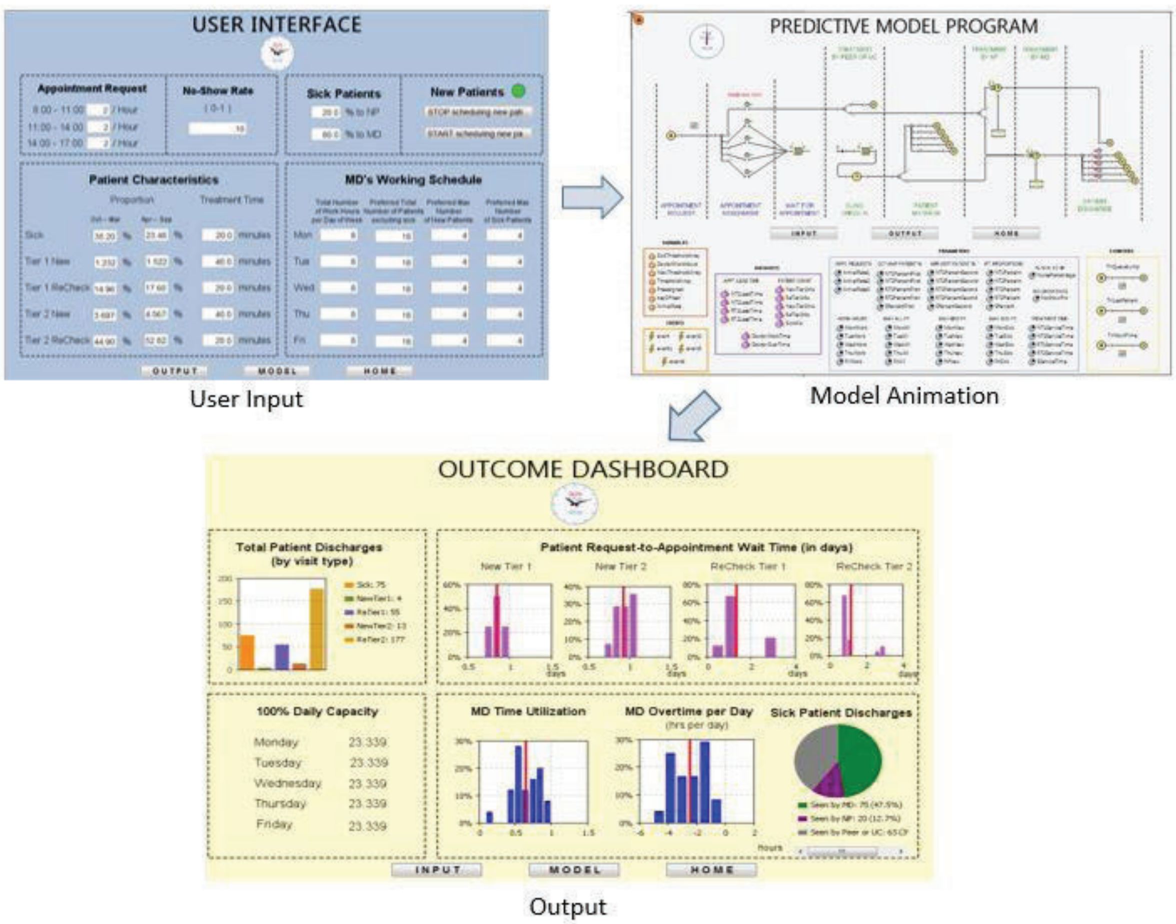

Figure 1: User interface of the discrete-event simulation model for outpatient appointment scheduling.

2.2 System Dynamics

System dynamics is a simulation modeling methodology for complex and nonlinear relationships of a system in order to understand behaviors over time. Feedback loops, stocks, and flows are the fundamental building blocks of a system dynamics model. A stock is an accumulation of inflow and outflow over time, where flow is a rate of change per unit time. Feedback loops are used to show a circular relationship of variables in the system. They operate in continuous time and often use differential equations to explain the relationship between entities. Typically, system dynamics models are less costly in data requirements and skills needed for model design and development (Marshall et al. 2015). System dynamics models are useful for recognizing behavioral patterns in a system, gaining insight into the processes of a system, and identifying leverage points for system redesign to reproduce a given behavior. System dynamics models are highly suitable for strategic planning such as informing healthcare policy on screening and prevention policies, disease intervention tasks, and capacity in a large healthcare system (Milstein, Homer, and Hirsch 2010). The most popular commercial software choices for developing system dynamics models include AnyLogic (The AnyLogic Company, St Petersburg, Russian Federation), Ithink/Stella (ISEE Systems, Lebanon, NH), Powersim (Powersim Software, Nyborg, Norway), and Vensim (Ventana Systems, Harvard, MA).

2.2.1 A System Dynamics Model for Diabetes Prevalence

Jones et al. (2006) developed a system dynamics model to project the growth of diabetes at the national level until 2015 and used the model to evaluate the impact of various large-scale interventions (e.g., enhancing clinical management of diabetes, increasing management of prediabetes, reducing the prevalence of obesity). Figure 2 shows an overview of their model structure. In the model, the national population progresses through a series of stocks that represent different health levels related to diabetes, including normal blood glucose, prediabetes, uncomplicated diabetes, and complicated diabetes. In addition, all the prediabetes and diabetes populations are further divided into diagnosed or undiagnosed categories. They calibrated the system dynamics model using a variety of nationwide large data sets such as the National Health Interview Survey, the National Health and Nutrition Examination Survey, and the Behavioral Risk Factor Surveillance System.

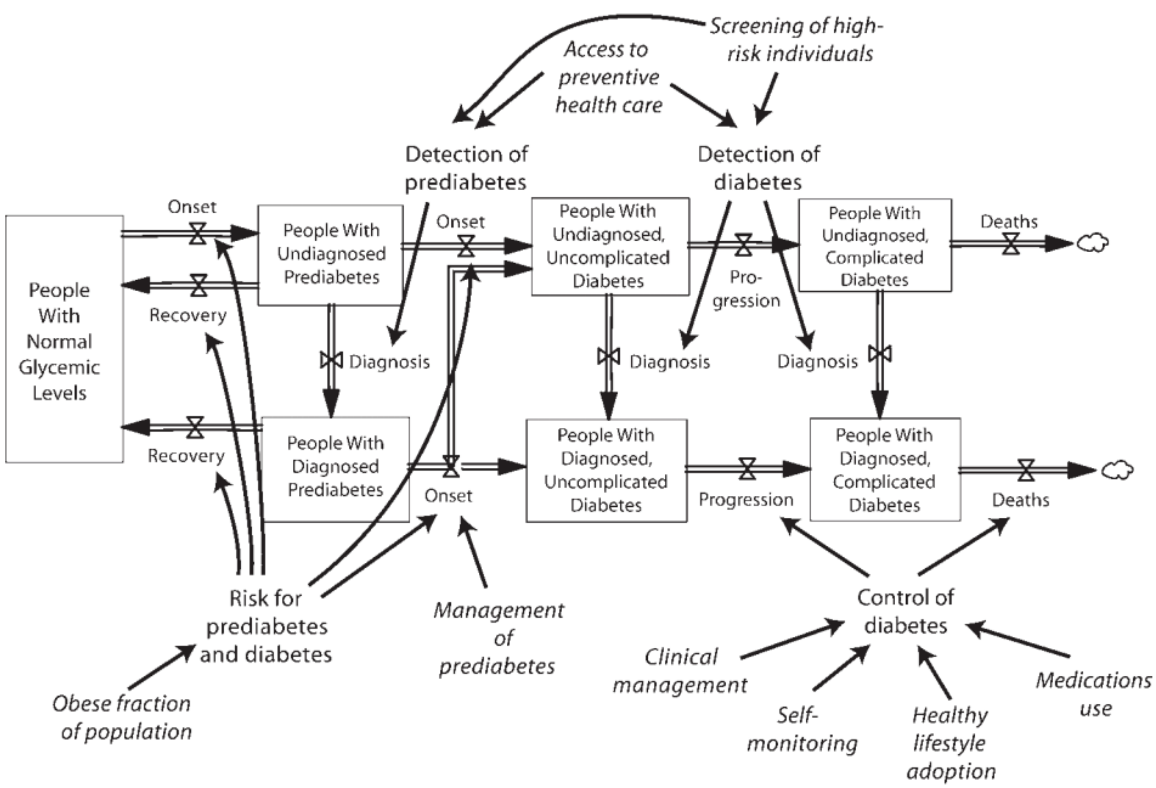

Figure 2: Structure of the system dynamics model of diabetes (Jones et al. 2006).

In a follow-up study, Milstein et al. (2007) used the system dynamics model to examine the plausibility of the *Healthy People 2010* (United States Public Health Service 2000) objective of reducing the prevalence of diagnosed diabetes. They accounted for the recent increase in the prevalence of obesity and predicted that it would be unlikely to achieve a reduced prevalence of diabetes in a short term. Based on an in-depth analysis of the simulation results, they found that, in addition to the increasing new case of diabetes, both the increased diabetes diagnosis rate and decreased diabetes mortality rate contribute to the resistance of reversing the growing trend of diabetes in the short term.

2.3 Agent-based Modeling

Agent-based modeling studies system-level emergent phenomena through explicitly simulating individual health and behaviors (Epstein 2006). Agent-based models are flexible in capturing real-world phenomena because agents can represent a large set of properties such as interactive, dynamic, heterogeneous, stochastic, adaptive, and mobile (Bonabeau 2002). Compared to discrete-event simulation and system dynamics, agent-based modeling is usually used to solve problems in which individual level behaviors and interactions are of critical importance and data on heterogeneous characteristics of individuals are available (Macal and North 2010).

Agent-based modelers used to program their models using programming languages such as Java and C++ due to the lack of specialized agent-based modeling software package. In recent years, a number of agent-based software have appeared—including AnyLogic (The AnyLogic Company, St Petersburg, Russian Federation), NetLogo (The Center for Connected Learning and Computer-Based Modeling, Northwestern University, Chicago, IL), Repast (Argonne National Laboratory, Lemont, IL), Swarm (Swarm Development Group, Santa Fe, NM)—which simplified the model development process and facilitated the use of ABM in the healthcare field. It is worth noting that these software packages usually require modelers to embed programming codes (e.g., Java in AnyLogic) into them to realize some more sophisticated functions and, thus, programming a complex agent-based model is still considered a highly technical job.

Barnes, Golden, and Price (2013) reviewed a selected body of literature on the application of agent-based models in healthcare operations management. They presented examples of using agent-based models to improve patient flows in both operating rooms and emergency departments, as well as two innovative applications of agent-based models to improve the implementation of healthcare technologies such as radio-frequency IDs and electronic health records. In public health and medicine, agent-based models have been mostly used to simulate the epidemics of infectious diseases (e.g., influenza, sexually transmitted diseases) compared to chronic diseases (Kumar et al. 2013). By generating populations of different characteristics and incorporating rules that govern disease transmissions, agent-based models can capture the entire course of a disease outbreak and evaluate the impact of alternative interventions at different scales (e.g., local, global). For example, Lee et al. (2010) developed an agent-based model of the H1N1 influenza and used the model to design the most effective control strategies in the workplace. In addition, agent-based models have been used to study the diffusion of health behaviors (e.g., drinking, dietary behaviors) in a social network (Gorman et al. 2006; Li, Zhang, and Pagán 2016).

Recently, agent-based models have been increasingly used to study chronic diseases and inform public health policies to curb the growing global chronic disease epidemic. Nianogo and Arah (2015) provided a systematic review of agent-based models of chronic diseases (e.g., diabetes, cardiovascular disease) and health behaviors (e.g., smoking, walking, alcohol use). They found that agent-based models are being slowly adopted by health researchers with an interest in chronic disease and a systematic and rigorous guideline is needed to facilitate the use of this simulation tool in chronic disease management and health policy-making. Li et al. (2016) provided a narrative review on the use of agent-based models in three types of chronic diseases, including diabetes, cardiovascular disease, and obesity. They elaborated on the advantages of agent-based models over other simulation models and current barriers for a wide adoption of the simulation tool, as well as pointing out new research directions specific to each of the three chronic diseases.

2.3.1 An Agent-Based Model of Cardiovascular Disease to Inform Intervention Design

We developed an agent-based model of cardiovascular health and evaluated the impact of different hypothetical lifestyle interventions on cardiovascular diseases (i.e., myocardial infarction, stroke) in the long term (Li et al. 2014a). The detailed model structure can be found in Li et al. (2014a). Briefly, each agent (person) is defined according to seven behavioral and health factors, including smoking, physical activity, diet, body weight, cholesterol, blood pressure, and blood glucose. The agents age and change their behavioral and health status dynamically as the simulation runs. The rules and transition probabilities that determine the agent's behaviors were estimated from published studies. In addition, the model provides an interface that allows users to define the population of their interest and conduct simulated trials by predicting the long-term outcomes of different interventions (Figure 3). The user interface also facilities communication between modelers and decision-makers because it can present model outcomes in an animated, visualized way.

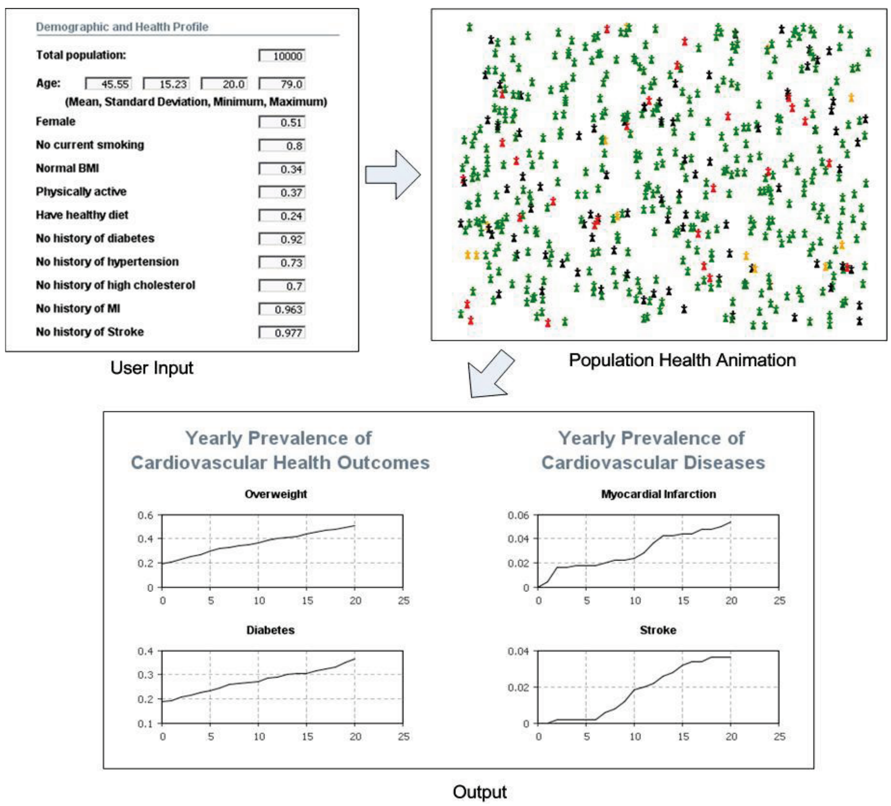

Figure 3: User interface of the agent-based model of cardiovascular health.

Our agent-based model of cardiovascular health can be used to promote evidence-based decision making for local health departments and inform population health management for primary care clinics (Li et al. 2015; Li et al. 2014b). For example, we simulated populations from four areas of New York State and compared the potential impact of a hypothetical lifestyle intervention that promotes healthy diet, physical activity and smoking cessation on population health outcomes across these different areas (Li et al. 2015). We found the same intervention may result in different levels of population health improvement for different areas, which need to be considered by local health departments when designing their prevention strategies. In another study, we projected the short- and long-term impact of a similar lifestyle program for populations of particular interest to care providers such as the US Medicare-age population (i.e., insured adults aged ≥65 years) and populations with one or more chronic health conditions (Li et al. 2014b). The projected results can help primary care clinics better design their population health management programs.

3 CHALLENGES

To effectively conduct quality healthcare research using simulation models, there are a number of challenges that must first be considered and overcome. For modelers and researchers within an academic institution, these challenges can significantly prevent data collection and delay the progress of the model development; for healthcare administrators and clinicians, these challenges can hinder effective communication and collaboration with simulation modelers and impede timely implementation of the decisions and policies learned from the simulation model. Next, several of these challenges are discussed in further detail.

3.1 Regulation

Healthcare providers must adhere to numerous, complex regulations on privacy rights, research, fraud prevention and detection, freedom of information, employment, and more. These regulations are in place to protect the patients, ensure quality healthcare, and improve healthcare delivery. However, the regulations may sometimes be burdensome or impractical (Barnet et al. 2014). Ensuring that all regulations are met implies that data acquisition may be a complex, time-consuming process due to privacy and security, facility access may be limited due to safety precautions, approvals are needed for human subjects research, and more.

3.2 Privacy and Security

Recent, reliable data is typically required as input for any type of simulation model to define parameters, scenarios, and attributes in order to verify and validate the model. This need for real health and clinical data may present a challenge due to national privacy and security laws. The Privacy Rule under the Health Insurance Portability and Accountability Act (HIPPA) was enacted in 1996 to protect medical and other health information. The HIPPA Privacy Rule defines limits on who can view, send, and receive patient health information. The implication is that much of the patient specific data must be de-identified by removing patient identifying information (e.g., name, address, and phone numbers) before it can be provided to researchers for inclusion in simulation. For more guidance on methods of de-identification of protected health information in accordance with the HIPPA Privacy Rule, visit the US Department of Health and Human Services (2015) website.

3.3 IRB Approval

To develop simulation models that involve human subjects research, Institutional Review Board (IRB), approval is required to ensure that the research is conducted in accordance with all federal, institutional, and ethical guidelines. Typically, IRB approval is required if data needs require intervention or interaction with an individual or requires identifiable private information. There are exemptions for minimal risk projects such as those involving educational settings, surveys/interviews and existing data. However, this research still requires confirmation of exempt status from the IRB and does not negate the need for consent of subjects. All investigators, students, and researchers must complete a mandatory training prior to submitting an IRB application, which are reviewed monthly. Failure to obtain proper IRB approval is a federal violation that can prevent publication of the research results and even jeopardize the accomplishment of the entire project. Understanding the IRB application process and timeline is crucial to the development of research project datasets.

3.4 Interdisciplinary Collaboration

Collaboration between simulation modelers and clinicians (or public health practitioners) are usually difficult due to different training backgrounds and views about healthcare problems. For example, simulation modelers tend to focus on methodological rigor and innovation when tackling a problem, while clinicians tend to focus on real-world solutions. Simulation modelers are oftentimes data-driven and think about system-level performance, while clinicians rely heavily on knowledge and experience and care more about individual outcomes. Moreover, simulation modelers have to add simplifying assumptions to the model to make it manageable, while these assumptions may oftentimes seem “wrong” in a clinician’s eyes. All of these differences could become potential barriers for an important interdisciplinary collaboration. Therefore, effective and effective communication as well as deep respect to other people’s disciplines are needed to build a good collaborative relationship and develop simulation models that are both methodologically rigorous and practically useful.

3.5 Data Quality, Availability, and Collection

One of the grandest challenges to developing, verifying, and validating simulation models is accessing and collecting data of high quality. Some healthcare organizations may not have automated data collection for the specific type of information required in a simulation model. Thus, modelers and healthcare administrators should consider this potential challenge early in the design of the simulation model. In some instances, it will be necessary to plan for manual data collection. Manual data collection is time intensive and oftentimes requires facility access, which is discussed in the next section. Furthermore, manual data collection is highly subjective to human errors. For example, the collected data may have inaccurate recording times, missing information, or inconsistent recordings. Thus, it is necessary to review and understand the data, clean the data due to poor quality recordings, and format the data to prepare as input to the simulation model.

3.6 Facility Access

Facility access is a crucial step in developing a healthcare simulation model. Depending on the specific healthcare application area, the system, process, facility layout, procedure, and more must be well understood during the model development phase to ensure that it is an accurate abstraction of reality. This step requires facility access (or shadowing) to gain knowledge and understanding of the problem being modeled. Obtaining facility access can be challenging unless the right clinical collaborators have been identified. However, depending on the extent in which facility access is needed to design, develop, and populate the simulation model, even the time and authority of the clinical collaborators may be limited. In these instances, it may be necessary to consider alternatives such as using smaller data sets, utilizing other researchers (e.g., students or interns), or possibly even negotiating short-term employment opportunities (e.g., consultants) with the healthcare system to obtain proper clearance for facility access.

4 OPPORTUNITIES

Compared to statistical models and mathematical programming models that are also widely used by operations researchers and other types of analysts, simulation models are more flexible in (1) capturing real-world phenomena with a high level of granularity, (2) evaluating alternative interventions by conducting “what-if” analyses, (3) studying the interactions between populations and their environment, and (4) projecting long-term outcomes and identifying emergent phenomenon that may not be apparent to decision-makers. There are several continuing and emerging healthcare care areas that lend themselves well to design, development, and analysis using healthcare simulation models. In this section, we discuss opportunities in perioperative care, population health management, patient health belief, and behavior, and emerging healthcare regulation and policy.

4.1 Perioperative Care

Perioperative care refers to three phases of surgery (preoperative, intraoperative, and postoperative) before, during, and after an operation. The preoperative care phase is the time before an operation in which tests are performed on the patient or surgery preparation occurs (e.g. fasting). Intraoperative care is the period during surgery that includes transportation to the operating room, anesthesia, surgery, and transfer to the post anesthesia care unit. Finally, postoperative care is the period after surgery which begins with the post anesthesia care unit and may even extend beyond discharge from the post anesthesia care unit. Discrete-event simulation of perioperative can emphasize process improvement activities such as patient flow, scheduling rules of bed utilization, sequencing of surgical operations, or determining the optimal bed capacity (Azari-Rad 2010). Simulation models of perioperative care allow healthcare managers to test and evaluate new ideas without posing risk to the patient.

4.2 Coordination across the Care Continuum

The continuum of care (or care continuum) is the system-level concept that guides and tracks patients over time through a comprehensive array of health services spanning all levels and intensity of care (Young et al. 2014). The care continuum involves healthcare services from birth until the end of life. The scope and scale of the care continuum lends itself well to system dynamics modeling or even agent-based modeling. With these models one can analyze the burden or overcrowding of different healthcare services (e.g., long-term care, emergency departments, assisted living) due to interventions or policies in the healthcare system. System dynamics models have been applied to modeling the continuum of care for osteoarthritis (Vanderby et al. 2015).

4.3 Population Health Management

Population health management (PHM) focuses on the use of different approaches to improve not only the health outcomes of a given group of individuals but also the distribution of health outcomes within a given population. Strategies to improve population health within healthcare delivery systems include better access and coordination of services for both low-risk and high-risk individuals as well as working with community partners to address key factors that impact population health such as the level of social support and the structure of the physical environment. Preventive, population-based interventions addressing issues such as physical inactivity or poor nutrition can really make a difference in improving population health while helping control healthcare costs. Given the multiple—and oftentimes interrelated—factors impacting population health, simulation models may help to identify novel strategies to improve health outcomes.

In addition, current risk assessment tools rely on standard statistical models to identify correlations in somewhat limited administrative datasets, which may be unable to capture the complexity of risk and disease progression. Multiple cohort studies have consistently demonstrated that risk factors for chronic conditions act synergistically rather than independently, indicating that risk factors combine to produce a higher absolute risk of disease than would be expected if each acted on an individual independently. This complex process makes standard statistical models that assume independence of observations or unidirectional causality less effective at exploring relationships between factors and outcomes. Simulation models, instead, has the potential to provide new insights about individual behavior and disease progression in great detail and, thereby, be useful to assess the impact of population health management interventions and present risks and costs proactively and dynamically.

4.4 Patient Health Belief and Behavior

The patient health belief model is used to explain why individual patients may accept or reject preventative service or adopt healthy behaviors. It was developed to understand why patients take preventative health actions and to understand their motivation in seeking health services. The health belief models assume that patients will take preventative health actions to reduce the risk of developing a health condition with undesirable consequences (The Health Belief Model 2016). By using a health belief model, healthcare decision-makers can develop an understanding of preventative health behaviors, patient motivation, and consequences of undesirable behaviors to design more effective interventions. System dynamics simulation models can be used for understanding system level policy decisions and their impacts on patient health. Agent-based models can also allow more detailed understanding at the patient population level of the impact of intervention policies and patient behaviors. Using healthcare simulation models, policy-makers can evaluate whether certain policies will motivate a patient population to comply with healthy behaviors.

4.5 Emerging Healthcare Regulation and Policy

Healthcare regulation and policy are continually evolving over time. In recent years, the U.S. healthcare system has seen a number of proposed changes with the introduction of the Affordable Care Act. The long-term impact of policies from the Affordable Care Act is not well understood and are still being refined today. Mandated changes in health insurance policies now require coverage of existing conditions, hospitals must reduce hospital readmissions for certain conditions or face reimbursement penalties, and the entire healthcare system is moving from fee-for-service to payments based on the quality of healthcare delivered. The impact of system-level changes can be better understood using healthcare simulation models, particularly with system dynamics models or agent-based models. Furthermore, healthcare policies directly affecting the general population such as preventative screenings and vaccinations can be analyzed with agent-based simulation models. Changes to the delivery of care, logistics, and procedures can be best analyzed with discrete-event simulation models. All of these present opportunities for analysis using healthcare simulation models, and understanding these system level changes can better inform decision-makers of the impact on the healthcare system and patients.

5 CONCLUSIONS

The use of healthcare simulation models provides the opportunity to address many challenging healthcare problems at the strategic, tactical, and operational levels. The specific application lends itself to the selection of discrete-event, system dynamics, or agent-based model simulation methodologies. Although not discussed in this tutorial, mixed methods simulation models combine two or more of the simulation methodologies. AnyLogic is one software that supports the development of mixed method simulation models. Healthcare problems at the strategic level often involve health policy and can be modeled using system dynamics or agent-based models. Problems at the tactical level involve managerial decisions while problems at the operational level involve logistics and procedures; both of which can be modeled using agent-based models or discrete-event simulation. Additionally, when specific individual level behaviors and interactions are of critical importance to the simulation, then agent-based models should be used. There are several challenges to developing quality, informative, and reliable healthcare simulation models such as data privacy and security, facility access, regulations, and interdisciplinary collaborations. Each of these challenges can limit the data availability or slow the development of the simulation model. However, healthcare simulation models have the opportunity to provide important insight on disease management interventions, preventative measures, health behavior, coordination across the care continuum, and healthcare policy and regulation.

REFERENCES

The Health Belief Model. EuroMed Info. Accessed May 1, 2016. http://www.euromedinfo.eu/the-health-belief-model.html/.

Alvarado, M., Li, Y. and Lawley, M. 2015. "A Discrete-Event Simulation Model for Outpatient Appointment Scheduling." 2015 AnyLogic Conference . Accessed June 2016. http://www.anylogic.com/upload/conference/2015/ presentations/texasaandm.pdf.

Azari-Rad, Solmaz. 2010. "Perioperative Process Improvement Using Discrete Event Simulation." Master's thesis, Graduate Department of Mechanical and Industrial Engineering, University of

Toronto., https://tspace.library.utoronto.ca/bitstream/1807/24534/1/AzariRad_Solmaz_A_20096_MASc_Thesis.pdf. Accessed May 1, 2016.

Barnes, S., B. Golden, and S. Price. 2013. "Applications of Agent-Based Modeling and Simulation to Healthcare Operations Management." *In Handbook of Healthcare Operations Management,* 45-74. Springer.

Barnet, S., M. Gamble, H. Punke, E. Rappleye, E. Rizzo, and T. Rosin. 2014. "10 Challenges and Opportunities for Hospitals in 2015." *Becker's Hospital Review.* Accessed May 1, 2016. http://www.beckershospitalreview.com/hospital-management-administration/10-challenges-and-opportunities-for-hospitals-in-2015.html.

Bonabeau, E. 2002. "Agent-Based Modeling: Methods and Techniques for Simulating Human Systems." *Proceedings of the National Academy of Sciences*, no. suppl 3: 7280-7287.

Epstein, J.M. 2006. *Generative Social Science: Studies in Agent-Based Computational Modeling.* Princeton University Press.

Gorman, D.M., J. Mezic, I. Mezic, and P.J. Gruenewald. 2006. "Agent-Based Modeling of Drinking Behavior: A Preliminary Model and Potential Applications to Theory and Practice." *American Journal of Public Health* 96(11): 2055-2060.

Hamrock, E., J. Parks, J. Scheulen, and F.J. Bradbury. 2013. "Discrete-Event Simulation for Healthcare Organizations: A Tool for Decision Making." *Journal of Healthcare Management* 58(2): 110.

Jones, A.P., J.B. Homer, D.L. Murphy, J.D. Essien, B. Milstein, and D.A. Seville. 2006. "Understanding Diabetes Population Dynamics through Simulation Modeling and Experimentation." *American Journal of Public Health* 96(3): 488-494.

Jun, J., S. Jacobson, and J. Swisher. 1999. "Application of Discrete-Event Simulation in Health Care Clinics: A Survey." *Journal of the Operational Research Society* : 109-123.

Kumar, S., J.J. Grefenstette, D. Galloway, S.M. Albert, and D.S. Burke. 2013. "Policies to Reduce Influenza in the Workplace: Impact Assessments Using an Agent-Based Model." *American Journal of Public Health* 103(8): 1406-1411.

Lee, B.Y., S.T. Brown, P.C. Cooley, R.K. Zimmerman, W.D. Wheaton, S.M. Zimmer, J.J. Grefenstette, T. Assi, T.J. Furphy, and D.K. Wagener. 2010. "A Computer Simulation of Employee Vaccination to Mitigate an Influenza Epidemic." *American Journal of Preventive Medicine* 38(3): 247-257.

Li, Y., N. Kong, M. Lawley, and J.A. Pagán. 2014a. "Assessing Lifestyle Interventions to Improve Cardiovascular Health Using an Agent-Based Model." *In Proceedings of the 2014 Winter Simulation Conference,* edited by A. Tolk, S. Y. Diallo, I. O. Ryzhov, L. Yilmaz, S. Buckley and J. A. Miller, 1221-1232. Savannah, GA: Institute of Electrical and Electronics Engineers, Inc.

Li, Y., N. Kong, M. Lawley, L. Weiss, and J.A. Pagán. 2015. "Advancing the Use of Evidence-Based Decision-Making in Local Health Departments with Systems Science Methodologies." *American Journal of Public Health* 105(S2): S217-S222.

Li, Y., D. Zhang, and J.A. Pagán. 2016. "Social Norms and the Consumption of Fruits and Vegetables Across New York City Neighborhoods." *Journal of Urban Health* 93(2): 244-255.

Li, Y., N. Kong, M.A. Lawley, and J.A. Pagan. 2014b. "Using Systems Science for Population Health Management in Primary Care." *Journal of Primary Care & Community Health* 5(4): 242-246.

Li, Y., M.A. Lawley, D.S. Siscovick, D. Zhang, and J.A. Pagan. 2016. "Agent-Based Modeling of Chronic Diseases: A Narrative Review and Future Research Directions." *Preventing Chronic Disease* 13: E69.

Macal, C.M., and M.J. North. 2010. "Tutorial on Agent-Based Modelling and Simulation." *Journal of Simulation* 4(3): 151-162.

Marshall, D.A., L. Burgos-Liz, M.J. IJzerman, W. Crown, W.V. Padula, P.K. Wong, K.S. Pasupathy, M.K. Higashi, and N.D. Osgood. 2015. "Selecting a Dynamic Simulation Modeling Method for Health Care Delivery Research—Part 2: Report of the ISPOR Dynamic Simulation Modeling Emerging Good Practices Task Force." *Value in Health* 18(2): 147-160.

Milstein, B., A. Jones, J.B. Homer, D. Murphy, J. Essien, and D. Seville. 2007. "Charting Plausible Futures for Diabetes Prevalence in the United States: A Role for System Dynamics Simulation Modeling." *Preventing Chronic Disease* 4(3): A52.

Nianogo, R.A., and O.A. Arah. 2015. "Agent-Based Modeling of Noncommunicable Diseases: A Systematic Review." *American Journal of Public Health* 105(3): e20-e31.

United States Public Health Service. 2000. *Healthy People 2010.* Washington (DC): US Dept. of Health and Human Services.

US Department of Health and Human Services. 2015. *Guidance regarding Methods for De-Identification of Protected Health Information in Accordance with the Health Insurance Portability and Accountability Act (HIPAA) Privacy Rule* .

Vanderby, S.A., M.W. Carter, T. Noseworthy, and D. Marshall. 2015. "Modelling the Complete Continuum of Care using System Dynamics: The Case of Osteoarthritis in Alberta." *Journal of Simulation* 9(2): 156-169.

Young, B., Clark, C., Kansky, J. and Pupo, E. 2014. "Definition: Continuum of Care." HIMSS. Accessed May 1, 2016. http://www.himss.org/ResourceLibrary/genResourceDetailPDF.aspx?ItemNumber=30272.

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