SYSTEMS ANALYSIS TOOLS IN HEALTHCARE DECISION MAKING

THE ROLE OF SYSTEMS ANALYSIS TOOLS TO INFORM HEALTHCARE DECISION MAKING

By

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ABSTRACT

Background and Objectives: Tools designed for systems analysis (SA) can link the different levels of healthcare by modeling the interacting, interrelated and interdependent components. The objective of this thesis was to investigate the use of discrete event simulation (DES) to help inform decision making.

Methods:

Project 1: A new method is developed in which physicians and their delegates are modeled using DES as interacting pseudo-agents when simulating a hospital emergency department (ED).

Project 2: Using a SA approach, we examined the referral patterns, healthcare utilization, time intervals and patient flow to identify rate limiting steps that may lead to delayed surgical candidacy and epilepsy surgery at the Hospital for Sick Children (SickKids) in Toronto, Ontario.

Project 3: A DES model was developed of the surgical evaluation and surgery process and its associated constraints at SickKids to inform decision making at both the institutional and provincial levels. Once validated, the model was used to evaluate the effect of alternative resource capacities on waiting times.

Results:

Project 1: Neglecting the interaction between physician and delegates in the ED could result in misleading conclusions with respect to physician utilization and waiting times.

Project 2: We found that only 5.7% of the eligible population was referred annually for surgical evaluation and that children waited on average 1-2 years for surgery. Through mapping of patient flow and resource utilization we were able to identify multiple barriers to surgery.

Project 3: The findings support the recommendations to the province by directing requested funds to identified resources that would decrease waiting times.

Conclusions: SA tools can be used to make decisions that are generalizable to all levels of healthcare. Adopting the use of these tools increases the uptake of evidence in decision making and provides useful and critical information to develop comprehensive policies for improved healthcare.

PREFACE

This thesis is a “sandwhich thesis”, which combines three individual projects prepared for publication in peer-reviewed journals. One of the papers is published, one of the papers is resubmitted for final approval and the third is in submission. The contributions of Morgan Elizabeth Lim to all papers in the thesis include: developing the research ideas and research questions, performing the analyses, interpreting the results, writing the manuscripts, submitting the manuscripts for publication and responding to reviewer comments. The work in this thesis was conducted between fall 2009 and fall 2012.

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Thank you to my fellow HRM colleagues for all those late nights and joining me on this journey, specifically, Ilia Ferrusi, Natalia Diaz-Granados, Sameer Parpia, Deirdre DeJean, and Nathan Souza. I am grateful for the privilege of having worked with them and I hope we will continue to work together in the future.

Last, but not least, I would like to thank my family and friends who played a critical role in getting me to this point. I missed a lot of holidays, birthdays and celebrations. Thank you for being so understanding. Thank you to Ameet Zalera and Evelyn Paik for being the most supportive friends anyone could ask for and keeping me sane.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

ABM	Agent-based modeling
CI	Confidence Interval
CTAS	Canadian Triage Acuity Scale
DES	Discrete Event Simulation
ED	Emergency Department
EMS	Emergency Medical Services
EMU	Epilepsy Monitoring Unit
ESCC	Epilepsy Specific Care Centres
FIFO	First In First Out
FMRI	Functional Magnetic Resonance Imaging
IEEG	Invasive Electroencephalography
ISPOR	International Society for Pharmacoeconomics and Outcomes Research
LOS	Length of Stay
MEG	Magnetoencephalography
MRE	Medically Refractory Epilepsy

MRI	Magnetic Resonance Imaging
NPA	Neuropsychological Assessment
OHTAC	Ontario Health Technology Advisory Committee
SickKids	The Hospital for Sick Children in Toronto
SUDEP	Sudden Unexpected Death of Epilepsy
VEEG	Video Electroencephalography

CHAPTER 1

Introduction of the thesis

General Introduction

The process of decision making in healthcare is challenged by the complexity of the healthcare system. Decision-makers are faced with producing guidance based on heterogeneous evidence (scientific and colloquial), multiple stakeholder interests and constrained resources or budgets. The objective is often to maximize both patient outcomes and operational efficiency (i.e. organization of resources within a constrained budget) at one or more levels of healthcare provision. As a result, there is a need for a paradigm shift towards approaching problems from a holistic perspective.

In healthcare, our approach is focused heavily on reductionist methods, meaning complex problems are reduced into smaller problems that are simpler to analyze. This approach continues to pervade in the medical sciences (i.e. diagnosis and treatment), epidemiology and the evaluation of health technologies. Reductionist methods frequently neglect the interacting, interrelated and interdependent components that exist between the parts; for example, hospital emergency department (ED) wait times are not simply a function of the bottlenecks within the ED, but may be a symptom of inpatient bed holding, which may be a symptom of organizational practice. As a result, it is important to combine these aspects of healthcare management with a more comprehensive approach.

Systems Analysis

A systems analysis approach encompasses the multiple components of a problem in order to consider dynamic relationships and predict unintended consequences and emergent behaviour due to feedback (portion of the output returns to affect input) and nonlinearity (output not directly proportional to input). It is used widely in many disciplines such as engineering, operations research, biology and economics, and is ideal for the examination of healthcare systems. Health services are generally organized and delivered as 'silos' of fragmented care by individual institutions [1]. In Ontario, the move towards delivering care through Local Health Integration Networks and hospital networks (e.g. University Health Network) means we need to focus on collaboration across disciplines, settings, institutions and governments. The regionalization of services is not specific to Ontario[2]. Throughout most of Canada, services are planned and delivered by smaller geographic areas. Systems analysis encourages these collaborations in addition to ongoing and iterative learning, and transformational leadership [3]. These dimensions closely align with already established health research approaches such as participatory research and integrated knowledge translation [4]. They seek to engage and integrate the end user into a collaborative research process with the overarching goal of producing knowledge and translating it into action [3,4].

Systems Analysis in Healthcare

In the evaluation of healthcare provision, emphasis is placed on the clinical (e.g. effectiveness and safety), economic (e.g. costs and resource utilization) and patient-centered (e.g. quality of life and patient preferences) domains while the organization of services is often left to administration. For example, when determining to fund the use of a diagnostic imaging test for a certain indication, evaluation is centered on diagnostic accuracy and the cost of administering the test, however, capacity constraints (i.e. how many patients can be scheduled to use the diagnostic imaging machine during operating hours) are often neglected. A systems analysis approach acts as a bridge between the clinical, economic, patient-centered and organizational domains to incorporate the clinical pathway with the organization and delivery of care. Additionally, it acts as a mechanism to integrate interests and information from multiple levels of the healthcare system (Figure 1): micro (evidence based clinical practice), meso (institutional rules), and macro (government policies) [5]. Tools designed for systems analysis can link the different levels of healthcare by modeling the interacting, interrelated and interdependent components. These models allow decision makers to understand the effects of implementing changes on the clinical, economic, patient-centered and organizational domains while also considering the effects on multiple policy levels (i.e. direct effects of a provincial policy on the institution).

Recently, systems analysis tools have demonstrated their potential to improve healthcare system performance at the hospital level through quality improvement (QI) programs such as Lean, Six Sigma and the Theory of Constraints [6-8]. These QI programs are a combination of mapping the process or flow of patients, information or equipment, statistics and management practices and are focused predominantly on behaviour change. The success of these programs can be partially attributed to relationships built between the project team and stakeholders (i.e. management and clinicians) through the process of formulating the problem, mapping the care pathway, and collecting and analyzing the data. Statistical methods are used to detect variability in processes, however, more comprehensive tools are necessary to evaluate both the patient care pathway and the delivery of healthcare in order to analyze organizational efficiency, trade-offs (e.g. between departments), costs, and health outcomes. Mathematical models are a specific subset of systems analysis tools applied to the improvement of healthcare systems which have the capacity to analyze complex and large healthcare systems to derive strategies to improve outcomes. They have been used to address a number of healthcare issues: forecasting demand, appointment and resource scheduling, resource allocation, patient flow, programme evaluation, and public health [9-11].

Systems Analysis Tools: Mathematical Models

Mathematical models involve mapping a system or process from the real world to a more simplified but more realistic representation using a set of variables and equations. They can be prescriptive or descriptive [12]. Prescriptive models optimize an objective function (e.g. benchmarks) based on a set of decision variables (e.g. number of physicians). Examples of prescriptive models include optimization techniques such as linear and integer programming, and metaheuristics such as genetic algorithm and ant-colony optimization. These models are useful when an objective function is present, however, they do not provide a detailed understanding of a system's operational behaviour inherent in a descriptive model [12].

Developing and validating a descriptive mathematical model is an iterative process that requires the collaboration of multiple stakeholders. Figure 2 presents an outline of the process. The initial phase of formulating the problem involves collaboration between key stakeholders to ensure all perspectives are considered to set common goals and targets and to gain buy in from leadership.

It involves sequentially mapping and understanding the patient care pathway, identifying potential capacity limitations, and data availability. The selection of the most appropriate mathematical model to be used is based on the above and model assumptions in addition to analyst familiarity with the technique and the model's ability to estimate appropriate performance measures to address the formulated problem. Following selection of the mathematical modeling technique a conceptual model is developed alongside data collection. These two phases are linked in that the conceptual model informs what data to collect, however, data availability will constrain the breadth of the conceptual model. The level of data necessary also depends on the chosen mathematical model (e.g. patient level or averages). Once the conceptual model has been validated with the stakeholders the mathematical model is programmed either using a programming language (e.g. Java) or pre-packaged simulation software (e.g Arena®). The development of the mathematical model can be a lengthy process as it also requires internal and external validation as well as calibration. Once the model is finalized, experiments can be run (e.g. what if scenarios) and the outputs analyzed. Acquiring buy in from leadership through collaboration also facilitates cooperation between different staff levels to aid in the development of a conceptual model and data collection, for example, consulting with physicians and nurses to determine the patient flow in a clinic.

Mathematical models can be classified based on a number of assumptions: analytical or simulation, deterministic or stochastic, cohort or individual, time advance mechanism, outcomes/performance measures, diagrams, resource constraints, memory, level of data abstraction and validation methods. Table 1 provides a detailed description of these model assumptions and why they may be relevant to modeling healthcare systems. Table 2 outlines different mathematical models based on these assumptions.

A number of algorithms for choosing the appropriate method have been developed [13,14], however the choice of mathematical model is dependent on a well formulated problem and the outcome/performance measures needed to inform decisions. Once there is an in-depth understanding of the problem through conversations with the decision-makers a modelling technique can be chosen based on the model assumptions (Tables 1 and 2). For instance, if decision-makers are interested in understanding short term effects of a treatment where the patient is either sick or dead we might choose a decision tree. Perhaps we may be evaluating a more complicated problem such as how to organize emergency medical services in the region to decrease response time so we might choose discrete event simulation. The last row of Table 2 provides insight on what mathematical model to choose. Stahl [14] proposed selecting the mathematical model based on the following criteria (which also align with the assumptions in Table 2): population level (cohort versus individual), interactivity between patients (e.g. infection), treatment of time (i.e. cumulative versus instantaneous, treatment of space (e.g. organization of resources in a clinic), resource constraints (i.e. limited resources), and agent autonomy (i.e. does the patient have the freedom to make choices or are the choices predefined).

The decision tree and state-transition models are mainly used for economic evaluations of health technologies (e.g. cost-effectiveness studies) where resource utilization is calculated into the costing. Decision trees are useful for informing problems with a short term time horizon and simple care pathways with limited health states. Markov models can be used to address problems with longer time horizons, various health states, recurrent events and when memory is unimportant (i.e. does not track the history of the patient). Both decision trees and Markov models do not explicitly model resource utilization (i.e. no capacity constraints) or time and therefore cannot provide useful performance measures such as waiting times. State-transition microsimulation models are slightly more flexible in that they are able to model patients at the individual level so that each patient can follow a different pathway. Alternatively, it is possible to build memory into the model so that the patient’s history can dictate the pathway. However, the inability to model capacity constraints and time makes it an ineffective technique to model at the micro or meso level.

The remaining mathematical models (queuing model, system dynamics, agent-based modeling and discrete event simulation) are able to incorporate resource capacity constraints and time in order to estimate appropriate performance measures. Queuing models are characterized by an arrival process (e.g. distribution), an inter-arrival rate (e.g. time between patient arrival), a queue discipline (e.g. first in first out), a server (e.g. physician) and service time (e.g. treatment time). They are useful for simple systems because as complexity is added the analytical solutions become less attainable.

System dynamics models are based on the fundamental principle that system structure determines behaviour [15]. This type of analysis is composed of a qualitative assessment of the relationships between system elements, information, organizational boundaries and strategies, illustrated using a feedback loop diagram [11]. This is followed by a quantitative assessment to examine system behaviour changes over time using a stock-flow diagram based on underlying differential equations. Systems dynamics models are helpful for strategic planning of large populations, however, they lack memory and patient individuality [11]. For these reasons they are not ideal for modeling operational details.

Agent-based modeling is a bottom-up technique that models a heterogeneous population of agents and their interactions to determine emergent behaviour and detailed movement patterns. Agents can be people or objects with characteristics that are governed by a set of rules (e.g. optimize health) and can learn and adapt. However, because behaviour is defined at the individual level there is no defined global behaviour (i.e. defined patient pathway). Their use in systems analysis may be limited because these models have no concept of queues and flows [16].

Due to the limitations associated with system dynamics and agent-based modeling the most widely used healthcare is discrete event simulation (DES). DES is a network of queues (e.g patients waiting for a physician) for services (e.g. surgical procedure) that entities (e.g. patients) flow through and attributes determine their pathway [17]. An event occurs at an instant in time that changes the state of the system. The simulation keeps track of current and future events in an event calendar [18]. Time is continuous and controlled by a simulation clock which lurches forward from one event to the next. Entities are the dynamic objects in the model. They move around and queue for resources. In healthcare, the entity is often the patient. DES uses queuing theory to represent the queues. This means that each queue has an arrival process, queue discipline (how individuals behave in queue), a server (resource that serves the entity), and service time distribution. Attributes are user defined values associated with individual entities. Entities have the same set of attributes but with different values (e.g. acuity levels). Services are provided by resources and are considered an area of constraint as there is a capacity associated with the resource (e.g. beds and physicians). Outputs of the model can be performance based (i.e. wait times, resource utilization and number waiting in queue) or user defined (e.g. surgical outcomes and utility). Additionally, DES can incorporate travelling time, such as time it takes a patient to walk from one area of a clinic to another.

DES is used to understand operational details of a disease or system (e.g. patient flow), when patient history is important (e.g. re-assessment), when change over time is important, when patients are competing for resources and when there is interaction between entities (e.g. infectious disease). Despite the flexibility of DES, there remain some methodological issues when addressing healthcare planning problems. Specifically, DES analysts continue to view hospitals and health clinics like factories where the patient is the driver [19]; for example, patients queue for services from physicians. Once the physician has completed treatment on the patient, the physician immediately begins treatment on the next patient in queue. This is an inaccurate depiction of reality for two reasons: 1) physicians have a skill hierarchy where he/she may not perform a task that may be performed by another delegate (e.g. treating high acuity patients over low acuity) and 2) physicians also utilize their time performing indirect patient related tasks (e.g. teaching and charting). To overcome these issues it is possible to use agent-based modeling. However, the purpose of agent-based modeling is to observe emergent behaviour and detailed movement patterns and are limited because they have no concept of queues and flows. Conversely, it is possible to model human resources as agents within a DES.

DES continues to be a favoured tool for healthcare systems analysis [20], however its application focuses mainly on the operational efficiency of individual clinics or institutions [9,10,21]. The use of DES to bridge multiple levels of healthcare (Figure 1) has yet to be explored. This thesis addresses this issue through the development of two DES models: a hospital emergency department that links the micro (clinical practice) with the meso (healthcare delivery) and an institutional level surgical evaluation process that links the micro, meso and macro. The models were developed in collaboration with multiple institutions and stakeholders to generate information that could be used by decisions makers at multiple levels of healthcare.

Outline of the Thesis

This is a sandwich thesis of three papers addressing the role of systems analysis tool DES to inform healthcare decision making. The first paper addresses a methodological issue using a DES model of a hospital emergency department (ED) (Chapter 2). The second and third papers present the application of DES to a provincial level healthcare planning problem (Chapters 3 and 4). Overall conclusions and directions for future research are presented in Chapter 5.

In Chapter 2 we present an approach to overcome the methodological issue of modeling healthcare staff as homogeneous resources who only interact with the patient. A new method is developed in which physicians and their delegates are modeled using DES as interacting pseudo-agents in a hospital ED. They are pseudo-agents because they are entities with embedded decision logic as opposed to full agents with full autonomy. This new approach is compared with the traditional approach of ignoring interaction between the physician and delegates. A model without the complexity of the ED is first created in order to validate the programming used to create the pseudo-agents. Upon validation, the new approach is implemented and compared with the traditional approach in an ED model informed by data from an academic hospital from Hamilton, Ontario, Canada. Results highlight the importance of integrating interactions between physicians and delegates when modeling the ED. This presents a novel contribution to the literature as it has never been done.

In Chapters 3 and 4 a systems analysis approach is used to inform health policy that may lead to increased access to care for children with medically refractory epilepsy (MRE) in Ontario. In 2007, the Ontario Health Technology Advisory Committee (OHTAC), a standing advisory subcommittee of the Health Quality Ontario Board that makes evidence-based recommendations to the Ontario health care system and the Ministry of Health and Long-Term Care about the best health technologies in Ontario [22], recommended the conduct of a field evaluation to determine the substitutive role of magnetoencephalography (MEG) for invasive electroencephalography (iEEG) for the surgical treatment of medically refractory epilepsy (MRE). During the study design process, two major issues were identified. First, it was determined that the use of MEG could occur at various stages of the surgical evaluation process but that iEEG was used at the time of resective surgery. As a result, this evaluation could not be completed in isolation from the surgical evaluation process. Secondly, it was discovered that surgical candidates were waiting 1 to 2 years for a surgical decision and up to an additional year for surgery, suggesting important capacity related issues. Therefore, in order to properly address this question it was necessary to understand the patient flow and resource capacity issues associated with the surgical evaluation and surgery process.

To address these issues, a systems analysis approach was chosen for two reasons. One being that the surgical evaluation process involves multiple levels of the healthcare system (Figure 1) as referrals are made from across the entire province, diagnostic testing and surgery occurs within the hospital and patient outcomes are needed to determine effectiveness. The other being that, it was important to capture feedback and system performance measures such as resource utilization and wait times in order to identify strategies to increase access to care. The field evaluation was conducted at the Hospital for Sick Children (SickKids) in Toronto, the primary referral centre for children with MRE in Ontario [23].

Chapter 3 presents the results of a retrospective chart review conducted to collect data based on 463 children referred for surgical evaluation at SickKids. We examine the referral patterns, healthcare utilization, time intervals and patient flow to identify rate limiting steps that may lead to delayed surgical candidacy decision-making and epilepsy surgery. The analysis shows that from first seizure onset approximately 4.6 years passes before MRE children are referred for surgical evaluation. As a result, children not only continue to live with a reduced quality of life but are also at higher risk of neurodevelopmental, behavioural and social development problems associated with uncontrolled seizures [24-26]. We also estimated that only 5.7% of the eligible children with MRE annually are evaluated for candidacy for surgical treatment and that time from referral to surgery ranged from 1.1 to 1.6 years. Of those who went to surgery, 95% had a reduction in seizure frequency and 74% were seizure free 1 year post-surgery. Because surgery is shown to be effective in eliminating seizures, it is essential to decrease time to treatment. This study was used to form the basis for a more complex analysis to investigate strategies to increase access to epilepsy surgery.

A DES model was developed of the surgical evaluation and surgery process and its associated constraints at SickKids to inform healthcare decision making at both the institutional and provincial levels (Chapter 4). In collaboration with SickKids, the model was developed in several phases: mapping patient flow, programming the simulation software, and estimating model inputs. Model validation included consultation with key stakeholders at SickKids, software debugging and goodness-of-fit with the system. We examined strategies to meet the following waiting time benchmarks: 30 days to epilepsy monitoring unit (EMU), 1.5 years to surgery with invasive monitoring and 1 year to surgery without. Results demonstrated that the increasing the following resources met these goals most efficiently: 2 EMU beds, 2 invasive monitoring surgeries and 6 non-invasive monitoring surgeries per year and limiting the number of repeat seizure conferences to 2. Using these results may increase the confidence of decisions by the institution because it reduces uncertainty about choices concerning resource allocation while also focussing on the patient. At the provincial level, this information can be used to justify increased funding for specific resources. More importantly, because the surgical evaluation and surgical processes are similar for adults, this model can be extended to include the adult institutions and linked together in order to create a provincial model.

Lastly, in Chapter 5 we summarize the key findings, limitations and implications of the thesis. We conclude with directions for future research. The thesis shows the integration of qualitative and quantitative data to optimize patient centered outcomes with the goals of the government and institution. First we report that pseudo-agent based modeling in DES is an effective method of modeling interactions of the physician and delegates in the hospital ED. It demonstrates the importance of accurately modeling physician relationships and the roles in which they treat patients. Second we report how the system analysis of the surgical evaluation process at an academic paediatric quaternary-referral centre shows that only a limited number of children with MRE in Ontario are being assessed for surgical candidacy and that each stage of the surgical evaluation process presents its own resource constraints contributing to delays. Third, we report how the DES model of the surgical evaluation process at the paediatric centre identified bottlenecks and presented strategies to reach the goal of decreasing wait times to surgical evaluation resources and surgery. We anticipate that using these models may increase the confidence of decisions made by decision makers as it reduces uncertainty about choices concerning resource allocation while also focussing on the patient.

References

1. Simpson SH. Of silos and systems: the issue of regionalizing health care. *Can J Hosp Pharm* .2011;64(4):237-40.

2. *Health Care in Canada 2000: A First Annual Report*. Ottawa (ON):Canadian Institute of Health Information. 2000. Available: https://secure.cihi.ca/free_products/Healthreport2000.pdf (accessed 2013 May 24).

3. Swanson R, Cattaneo A, Bradley E, Chunharas S, Atun R, Abbas K, et al. Rethinking health systems strengthening: key systems thinking tools and strategies for transformational change. *Health Policy and Planning* .2012;27(Suppl 4):iv54-iv61.

4. Canadian Institutes of Health Research. Guide to Knowledge Translation Planning at CIHR: Integrated and End-of-Grant Approaches. *Canadian Institutes of Health Research* 2012 Jun 12. Available: http://www.cihr-irsc.gc.ca/e/documents/kt_lm_ktplan-en.pdf (accessed 2013 Mar 28).

5. Battista R, Lance J-M, Lehoux P, Regnier G. Health technology assessment and the regulation of medical devices and procedures in Quebec. *International Journal of Technology Assessment in Health Care* .1999;15(3):593-601.

6. Holden R. Lean Thinking in Emergency Departments: A Critical Review. *Annals of Emergency Medicine* .2011;57(3):265-78.

7. DelliFraine J, Langabeer J, Nembhard I. Assessing the Evidence of Six Sigma and Lean in the Health Care Industry. *Quality Management in Health Care* .2010;19(3):211-25.

8. Wright J, King R. We All Fall Down: Goldratt's Theory of Constraints for Healthcare Systems. Great Barrington: The North River Press Publishing Corporation; 2006

9. Jun JB, Jacobson SH, Swisher J. Application of discrete-event simulation in health care clinics: A survey. *Journal of the Operational Research Society* .1999;50:109-23.

10. Fone D, Hollinghurst S, Temple M, Round A, Lester N, Weightman A, et al. Systematic review of the use and value of computer simulation modelling in

population health and health care delivery. *Journal of Public Health Medicine* .2003;25(4):325-35.

11. Brailsford S. System Dynamics: What's in it for healthcare simulation modelers.*Proceedings of the 2008 Winter Simulation Conference*; 2008: 1478-83.

12. Sinreich D, Marmor Y. Emergency department operations: The basis for developing a simulation tool. *IIE Transaction* .2005;37:233-45.

13. Brennan A, Chick S, Davies R. A taxonomy of model structures for economic evaluation of health technologies. *Health Economics* .2006;15:1295-310.

14. Stahl J. Modelling Methods for Pharmacoeconomics and Health Technology Assessment. *Pharmacoeconomics* .2008;26(2):131-48.

15. Brailsford S. Tutorial: Advances and challenges in healthcare simulation modelling.*Proceedings of the 2007 Winter Simulation Conference*; 2007: 1436-48.

16. Siebers PO, Macal CM, Garnett J, Buxton D, Pidd M. Discrete-event simulation is dead, long live agent-based simulation! *Journal of Simulation* .2010;4:204-10.

17. Law A, Kelton W. Simulation Modeling and Analysis. Third Edition McGraw Hill; 2000

18. Kelton W, Sadowski R, Swets N. Simulation with Arena. 5th Edition McGraw-Hill; 2010

19. Hay A, Valentin EC, Bijlsma RA. Modeling Emergency Care in Hospitals: A Paradox - The Patient Should Not Drive the Process.*Proceedings of the 2006 Winter Simulation Conference*; 2006: 439-45.

20. Lim M, Nye T, Bowen J, Hurley J, Goeree R, Tarride JE. Mathematical Modeling: The Case of Emergency Department Waiting Times. *International Journal of Teachnology Assessment in Health Care* .2012;28(2):93-109.

21. Gunal M, Pidd M. Discrete evnt simulation for performance modelling in health care: a review of the literature. *Journal of Simulation* .2010;4:42-51.

22. Ontario Health Technology Assessment Committee. OHTAC Recommendation: Functional Brain Imaging. Toronto: Ontario Ministry of Health Technology Advisory Committee: Health Quality Ontario; 2007.

Available: http://www.health.gov.on.ca/english/providers/program/ohtac/tech/recommend/rec_fbi_012507.pdf

23. Bowen JM, Snead OC, Hopkins RB, Elliott I, Burke N, Atkin J, et al. Diagnostic evaluation of infants, children and adolescents with epilepsy for surgery candidacy and the role of magnetoencephalography (MEG) [Report No. FEEAP-HTA013a-2011.REP]. Hamilton (ON): Programs for Assessment of Technology in Health, St. Joseph's Healthcare Hamilton/McMaster University; 2011. Available: http://www.path-hta.ca/Libraries/Reports/MEG_OHTAC_report.sflb.ashx

24. Huttenlocher PR, Hapke RJ. A follow-up study of intractable seizures in childhood. *Ann Neurol* .1990;28(5):699-705.

25. Vasconcellos E, Wyllie E, Sullivan S, Stanford L, Bulacio J, Kotagal P, et al. Mental retardation in pediatric candidates for epilepsy surgery: the role of early seizure onset. *Epilepsia* .2001;42(2):268-74.

26. Ibrahim GM, Fallah A, Albert GW, Withers T, Otsubo H, Ochi A, et al. Occipital lobe epilepsy in children: characterization, evaluation and surgical outcomes. *Epilepsy Res* .2012;99(3):335-45.

Figure 1: Bridging the different levels of healthcare using a systems analysis approach

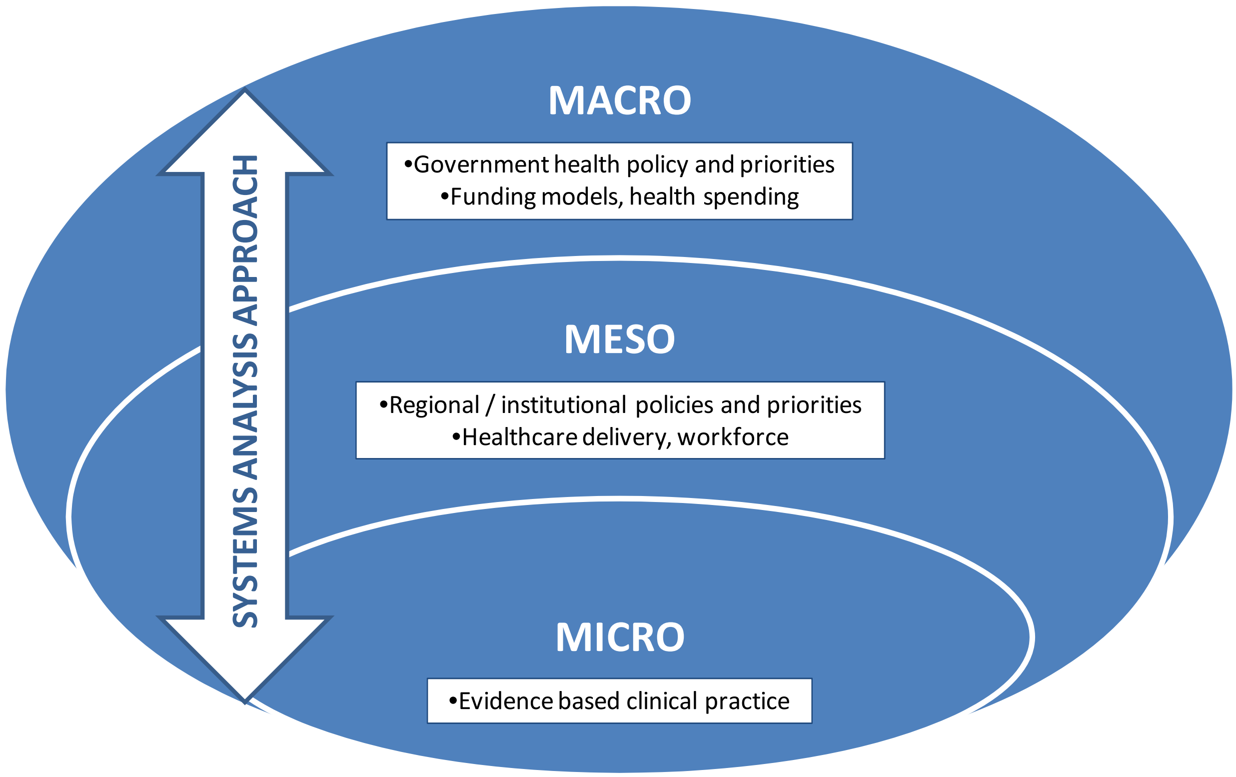
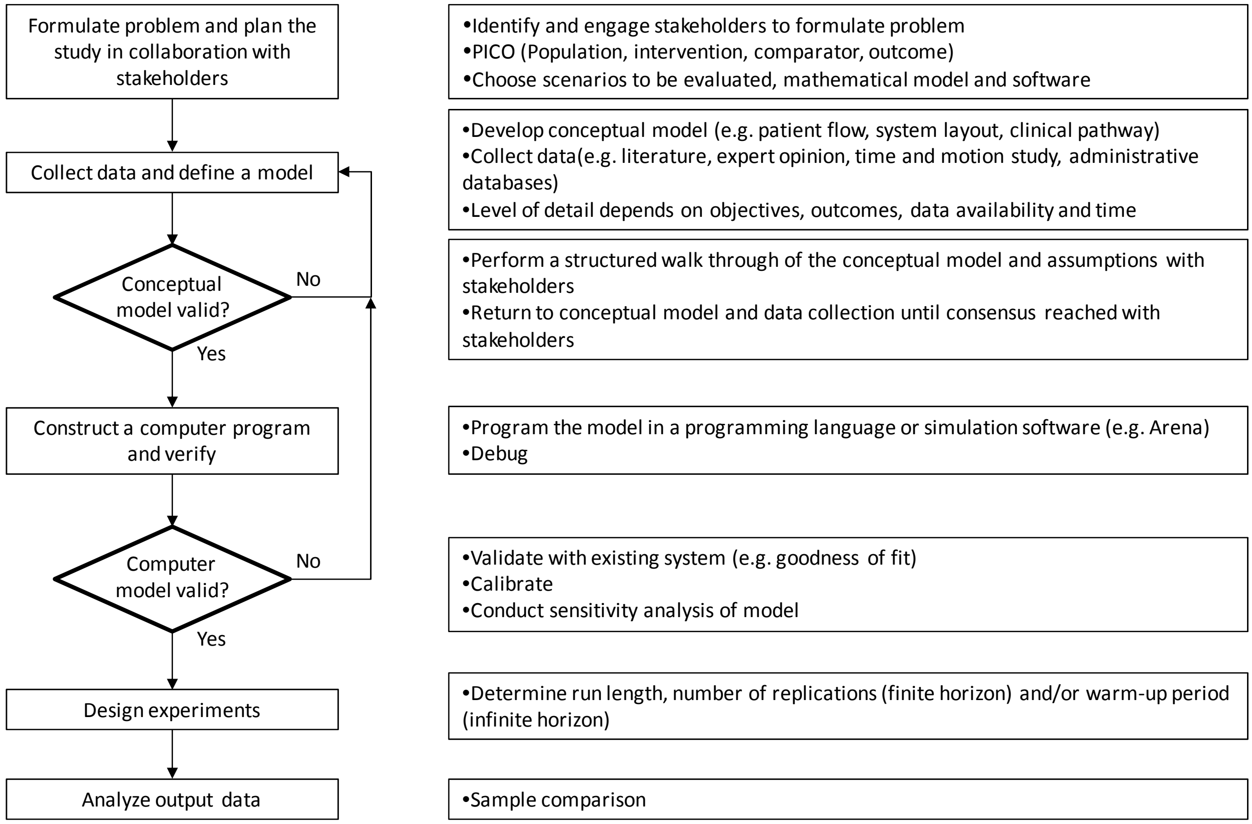


Figure 2: Steps in developing and validating a descriptive mathematical model



Adapted from Law & Kelton. *Simulation Modeling and Analysis*. Third Edition. 2000.

Table 1: Description of different mathematical model assumptions

Model assumption	**Description**	**Significance to healthcare modeling**
Analytical or simulation	• Analytical solutions are mathematical models with obtainable closed-form solutions, meaning it solves in terms of common functions from a given generally accepted set. • Simulation is the process of numerically exercising the model through state changes over time to see how the inputs will affect the output measures of performance.	Analytical solutions are tractable when the model is relatively simple, however, a more complex (I.e. realistic) model requires the use of simulation to estimate a solution.
Deterministic or stochastic	• A deterministic model does not contain any probabilistic (i.e. random) components and will result in a fixed outcome given initial conditions. • A stochastic model allows for random variation where inputs are estimated using probability distributions.	Healthcare is frequently characterized by uncertainty and variability (e.g. arrival rate), requiring a stochastic approach.
Cohort or individual	• A cohort characterizes the average patient experience from a population with the same attributes. • Individual level models are based on variability between patients and their history and attributes dictate their pathway.	Choice depends on whether patient variability and history is important.
Time advance mechanism	• Discrete - variables change at discrete points in time (i.e. countable sets that have distinct separated values such as integers). • Continuous - variables change smoothly with respect to time and therefore involve differential equations. • Cycles - variables change at specified time points (e.g. 6 months)	Dictates how time advances and the measure of performance the model outputs: probability (what is the probability there are zero patients in the system?), rate (what is the rate at which patients are being processed by triage) or percentile (what is the percentile of patients who have exited the system in less than 4 hours?)

Adapted from Lim M, et al.. International Journal of Technology Assessment in Health Care. 2012;28(2):93-109.

Table 1 continued: Description of different mathematical model assumptions

Model assumption	Description	Significance to healthcare modeling
Outcomes and performance measures	• Measures are based on the underlying mathematical equations. See discrete vs. continuous.	Dictates choice of mathematical model in order to meet objective.
Diagrams	• Diagrams lay out the model logic and aid communication between the doer and the decision-makers.	They provide a level of transparency and allow the decision-maker to visualize what is being modeled.
Resource constraints	• Individuals move through a system and utilize a set of finite resources. The ability to integrate simultaneous use of multiple resources is dependent on the model type.	The analyst may want to model simultaneous resource use (e.g. patient may need to meet with both a nurse and physician at the same time.)
Memory	• Memory describes how individual characteristics and past events can affect an individual's pathway in the model.	Memory can be thought of as a patient's medical history, where past events in the model can dictate future pathways.
Level of data abstraction	• Individual level or aggregate level (i.e. means) are used to populate a model.	Data availability can affect choice of mathematical model.
Validation	• Ensures the model is an accurate representation of the system under study. • External validity is a non-statistical type of validity that determines if the model conceptually represents the system. • Internal validity is represented by quantitative techniques that are used to test overall validity and of various components, typically accomplished with graphical plots and goodness of fit test.	To inform policy, validation is essential to ensuring the model outputs will be representative of the system.

Adapted from Lim M, et al.. International Journal of Technology Assessment in Health Care. 2012;28(2):93-109.

Table 2: Mathematical modeling techniques by model assumption

Model Assumptions	**Decision tree**	**State-transition: Markov Model**	**State-transition: Microsimulation**	**Queuing model**
Analytical or simulation	Analytical	Analytical	Simulation	Analytical
Deterministic or stochastic	Deterministic	Stochastic	Stochastic	Stochastic
Cohort or individual	Cohort	Cohort	Individual	Cohort
Time advance mechanism	No	Cycles	Cycles	Continuous
Outcomes/Performance measures	Averages	Averages	Averages	Probabilities, average times
Diagrams	Decision tree	State transition, influence diagram	State transition, influence diagram	Flowchart
Resource constraints	No	No	No	Single
Memory	Yes	No	Can be built in	No
Level of data abstraction	Low	Depends on number of states	Depends on number of states	Low
Validation	Expert opinion, GoF, historical data	Expert opinion, GoF, historical data	Expert opinion, GoF, historical data	Expert opinion, GoF, historical data
Suggest to use corresponding model technique when:	Short time horizon, simple care pathway, limited health states, cohort	Short to lifetime time horizon, multiple health states, recurrent events, cohort	Short to lifetime time horizon, multiple health states, recurrent events, patient history dictates pathway, individual level	Simple care pathway, resource constraints, waiting times, cohort

GoF – Goodness of Fit. Adapted from Lim M, et al. International Journal of Technology Assessment in Health Care. 2012;28(2):93-109.

Table 2 continued: Mathematical modeling techniques by model assumption

Model Assumptions	**System dynamics**	**Agent based modeling**	**Discrete event simulation**
Analytical or simulation	Simulation	Simulation	Simulation
Deterministic or stochastic	Deterministic	Stochastic	Stochastic
Cohort or individual	Cohort	Individual	Individual
Time advance mechanism	Continuous	Discrete or Continuous	Continuous
Outcomes/Performance measures	Probabilities, average times	Percentiles, average and total times, network (cluster) identification	Percentiles, average and total times
Diagrams	Causal loop, stock-flow	Flowchart, network diagram, relationship map	Influence diagram, flowchart, design layout
Resource constraints	Single	Multiple	Multiple
Memory	No	Yes	Yes
Level of data abstraction	Low	High	High
Validation	Expert opinion, historical data	Expert opinion, GoF, historical data	Expert opinion, GoF, historical data
Suggest to use corresponding model technique when:	Complex care pathway, feedback, resource constraints, cohort	Complex care pathway, interaction between patients (i.e. infection), patient can make autonomous choices, resource constraints, physical organization of resources, individual	Complex care pathway, interaction between patients (i.e. infection), resource constraints, physical organization of resources, individual

CHAPTER 2

Simulating an emergency department: The importance of modeling the interactions between physicians and delegates in a discrete event simulation

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ABSTRACT

Background: Computer simulation studies of the emergency department (ED) are often patient driven and consider the physician as a human resource whose primary activity is interacting directly with the patient. In many EDs, physicians supervise delegates such as residents, physician assistants and nurse practitioners each with different skill sets and levels of independence. The purpose of this study is to present an alternative approach where physicians and their delegates in the ED are modeled as interacting pseudo-agents in a discrete event simulation (DES) and to compare it with the traditional approach ignoring such interactions.

Methods: The new approach models a hierarchy of heterogeneous interacting pseudo-agents in a DES, where pseudo-agents are entities with embedded decision logic. The pseudo-agents represent a physician and delegate, where the physician plays a senior role to the delegate (i.e. treats high acuity patients and acts as a consult for the delegate). A simple model without the complexity of the ED is first created in order to validate the building blocks (programming) used to create the pseudo-agents and their interaction (i.e. consultation). Following validation, the new approach is implemented in an ED model using data from an Ontario hospital. Outputs from this model are compared with outputs from the ED model without the interacting pseudo-agents. They are compared based on physician and delegate utilization, patient waiting time for treatment, and average

length of stay. Additionally, we conduct sensitivity analyses on key parameters in the model.

Results: In the hospital ED model, comparisons between the approach with interaction and without showed physician utilization increase from 23% to 41% and delegate utilization increase from 56% to 71%. Results show statistically significant mean time differences for low acuity patients between models. Interaction time between physician and delegate results in increased ED length of stay and longer waits for beds.

Conclusion: This example shows the importance of accurately modeling physician relationships and the roles in which they treat patients. Neglecting these relationships could lead to inefficient resource allocation due to inaccurate estimates of physician and delegate time spent on patient related activities and length of stay.

INTRODUCTION

Overcrowded emergency departments (ED) are an ongoing issue for hospital staff, healthcare administrators, policy makers and patients. With increasing patient demands on these services and constricting budgets, administrators are in search of practical and implementable solutions (e.g. staff scheduling and resource allocation) to minimize patient waiting time and increase throughput. Methods of computer simulation have often been employed to model ED activity because it allows researchers to analyze the effects of re-organizing resources in the ED without making potentially costly changes.

A review of 29 studies identified four mathematical modeling techniques used to evaluate waiting times in the ED[1]: analytic queuing models (n=3), system dynamics (n=2), discrete event simulation (DES) (n=22), and agent-based modeling (ABM) (n=2). DES was the most frequently (75%) used modeling technique. Compared to analytic queuing models and system dynamics, DES is capable of modeling more complex non-linear systems (e.g. feedback) while taking into account patient history, staff scheduling and multiple resource constraints. It is a process-oriented model that is represented by a network of queues for services that a patient flows through where attributes determine the pathway of the patient. The drawback is that modelers continue to view the hospital like a factory where the patient is the driver[2]. In a DES model, patients queue, are triaged and wait for a resource (e.g. bed, physician) based on their acuity levels (e.g. high priority patients are served first). Once that resource (e.g. physician) has completed processing (e.g. treating patient) it immediately moves onto the next patient. This is an unrealistic depiction of ED care because physicians have a skill hierarchy where a physician will most likely not perform a task that can easily be performed by a delegate such as a medical student, resident physician, physician assistant, or nurse practitioner. A number of studies have argued for the inclusion of skill-based specification which would allow a physician or delegate to prioritize tasks and produce a more realistic result [2,3].

Process-oriented models also tend to neglect indirect patient-related tasks that physicians are required to perform (e.g. teaching, consultation with a specialist, charting, and discussions with the patient's family). In the review [1], only one previous DES study attempted to include multi-tasking by fragmenting physicians and nurses into several parts where each part represented a task [4]. Consequently, this study did not incorporate interaction between the physician and their delegates, which is a common limitation in previous simulation studies of the ED.

These indirect patient-related tasks play an even larger role when modeling a teaching hospital because a large portion of the ED staff is comprised of physician trainees. The physician trainee's function is to both treat patients and learn from senior staff. Despite these differences, the interactions between trainees and physicians are frequently neglected. If included, trainees are often modeled similarly to physicians where the only difference exists in the assessment/treatment time [4-7]. However, previous research has found that the presence of trainees in the ED is positively associated with an increased patient length of stay (LOS) [8,9] and that trainees exhibit poor time management when faced with overcrowding [10,11]. Time and motion studies [12,13] have estimated that approximately 30% of a physician's time is actually spent with the patient (e.g. examining and treating) while the remainder is spent on other tasks such as teaching, charting, interactions with the nursing staff and addressing family member concerns. As such, ignoring indirect patient demands by ignoring the interactions between physicians and their delegates may result in an overestimation of staff resource availability and thus provide inaccurate estimates of resource utilization (percent of scheduled time spent with patient) and patient LOS.

To overcome some of these issues, analysts have used agent-based modeling (ABM). Agents can represent people (e.g. patients, physicians), services (e.g. diagnostics) and the environment in which they operate and are governed by a set of goals (e.g. minimize time spent with patient) and behaviours (e.g treat).

Agents are able to make autonomous decisions, interact with each other and exhibit proactive behaviour based on their internal goals [[14]]. As such, the purpose of ABM models is to model at the individual level and observe the emergent behaviour and detailed movement pattern. The application of ABM to evaluate healthcare problems is still relatively new compared to the use of DES. Previous work has explored the use of ABM to model different ED physician staffing schedules [[15]], patient diversion strategies [[16]], and differing radiology process times [[17]]. Only one model identified accounting for differing levels of staff expertise [[18]], however, as indicated by the authors, this model is still in its first cycle of development.

ABMs are also difficult to implement because these types of models are often based on theories or subjective data (e.g. expert opinion) and few user friendly software exist for enthusiasts who are not expert programmers [[14]]. Nonetheless, an agent's deliberative process is inherently discrete and using an event-based approach (as opposed to discrete time) eases the integration of agents interacting (when they should), which may be more representative of reality [[19]]. When modeling the ED, pure ABMs may be limited because there is no concept of queues and flows and would need to be combined with DES [[14]].

To overcome these issues, a new method was developed to model a hierarchy of heterogeneous interacting pseudo-agents in a DES, where pseudo-agents are entities with embedded decision logic[20]. The purpose of this study is to present an alternative approach where physicians and their delegates in the ED are modeled as interacting pseudo-agents in a DES and to compare it with the traditional approach ignoring such interactions. To the best of our knowledge, this approach of using interacting pseudo-agents has never been implemented when modeling the ED using DES.

METHODS

This new approach of modeling physicians and their delegates as interacting pseudo-agents is first validated before being implemented in an ED DES model. Results are compared to the traditional approach without interaction. The following provides a description of the interacting pseudo-agents approach and the models used to compare this new approach with the traditional way of modeling the ED without interactions between physicians and their delegates. The models are built using the Arena® Simulation Software, version 13.9 (Rockwell Automation).

Development of the Interacting Pseudo-Agents Approach

Physicians and delegates are considered pseudo-agents because they are modeled as entities with embedded hierarchical decision-logic as opposed to being true autonomous agents found in pure ABM. To model interactions, separate entities are created for the physician and delegate. Each entity is assigned a new set of resource states: idle (waiting for a patient), assessing patient (only for delegate to develop treatment plan), consulting (with each other), or treating patient. The interaction occurs once the delegate has assessed a patient and requires consultation with the physician about the treatment plan. The model assumes that at anytime one physician and one delegate are scheduled. Decisions made by the physician and delegate are summarized below.

1. Physician: There is one attending physician in this model per shift. The role of the physician is to treat patients and produce orders (i.e. laboratory work, xray, discharge/admit) which dictate the pathway of the patient. Their other role is to aid delegates with their patient assessments. The physician attends to patients of a higher priority before anything else. If there are no high priority patients in queue for treatment then the physician will attend to any delegates who are waiting for guidance with their patient assessments. If there are no high priority patients or delegates who need assistance then they will treat a low priority patient.

2. Delegate: There is one delegate in this model. Their role is to assess and treat patients with a low priority. Once they have developed a treatment plan they must check with the physician before proceeding to treatment.

Figure 1 represents the states and state transitions of the physician and delegate. In this approach there is one queue for patients. The physician and delegate entities are held in a hold block until a signal is sent to release them. There are two signals: one is sent to both the physician and delegate to alert that there is a patient waiting in the queue and the other is sent to the physician from the delegate to alert that the delegate is waiting for a consult.

Validation of the Interacting Pseudo-Agents Approach

A simple model without the complexity of the ED is created in order to validate the building blocks (programming) used to create the pseudo-agents and their interactions. Using a simple model controls for any differences that might arise as a result of system feedback as opposed to the programming. The objective of the validation exercise is to compare the outputs from the same model built using first the conventional blocks (i.e. physician as a resource with no interactions with delegates) and secondly the new building blocks modeling the physician and delegate as entities with interaction. If the blocks representing the interaction are disabled, then the results should be similar with the model built using the conventional blocks (i.e. no interactions). This should hold true because, in both models, the physician will treat all high priority before low priority patients and delegates will only treat low priority patients. Once the interaction blocks are enabled, there should be an increase in resource utilization and waiting time for low priority patients because the physician has to consult with the delegate about the patient’s treatment plan before proceeding.

The following assumptions are used for the model developed to validate this new method. Patients enter the model and then queue for treatment. Once treatment is complete the patient is discharged from the model. Approximately 5 patients arrive per hour (20% high acuity and 80% low acuity) with an exponentially distributed inter-arrival rate. The only processing time is related to treatment time which is assumed to be 20 minutes for high acuity patients and 10 minutes for low acuity patients. An additional 10 minutes is added to the treatment time when the patient is processed by a delegate. In the interacting pseudo-agent approach it is assumed that delegates spend 5 minutes interacting with the physician before returning to the patient. An additional 5 minutes is added to implement any instructions by the physician. All simulations are run for a 24 hour warm-up period and then for 24 hours over 500 replications.

Resource utilization (percentage of scheduled time spent on patient related activities which includes consultation for the interacting pseudo-agent approach) and time to disposition based on acuity and whether treated by a physician or delegate were compared for three sets of outputs : 1) using the conventional building blocks , 2) using the new building blocks without the interaction between physician and the delegate and, 3) using the new building blocks with the interaction between physician and the delegate . The assumption behind the validation exercise is that comparisons (1) and (2) should be comparable in terms of percentage of time spent on patient related activities and that differences should exist with outputs from (3).

Implementation of the Interacting Pseudo-Agents Approach in a Hospital Emergency Department

Once validated, the interacting pseudo-agent approach is implemented in a more realistic representation of a DES model of a hospital ED. The following presents the assumptions of the ED model which is informed by data from an academic hospital from Hamilton, Ontario, Canada.

Process overview: The ED is open 24 hours and is responsible for triage and treatment of approximately 50,000 patients a year. Figure 2 presents the basic patient flow through the ED and the point in the patient flow where the interacting pseudo-agents approach is incorporated into the model. The patient arrives as a walk-in or by ambulance and proceeds to triage. The patient is triaged by the triage nurse and then registered by the clerk. In this hospital, the patient can only be admitted to the ED when both the charge nurse and a bed are available. If both are unavailable the patient is seated in the waiting room and enters a queue. In some cases, a patient may voluntarily leave the ED without being seen after a prolonged wait. However, for the vast majority of patients, the patient is placed in a bed and assessed by the nurse when they become available. Once the nurse assessment is complete, the patient is placed in queue to see the physician or the delegate depending on the patient's acuity. When available, the physician assesses the patient and produces orders: 1) send for diagnostics, 2) send for laboratories (i.e. blood work) or 3) treat. If a laboratory is ordered the patient will wait in bed until a bedside nurse is available to draw blood. The patient does not have to wait for results before proceeding. If radiology is ordered the patient is sent to the radiology room which is located in the ED. After radiology the patient returns to the same bed. After treatment the patient is either admitted to the hospital or discharged from the ED.

Entities: There are three types of entities in this model: 1) patients, 2) physician, and 3) delegate. The physician and delegate are modeled as entities only in the interacting pseudo-agent approach. Patients are triaged into one of five categories according to the Canadian Triage and Acuity Scale (CTAS) where level one is the most severe: level 1 (resuscitation), level 2 (emergent), level 3 (urgent), level 4 (less urgent) and level 5 (non-urgent)[[21]]. Because CTAS 1 and 2 patients are treated similarly in the model, results are reported as high (CTAS 1 and 2) and low (CTAS 3, 4, and 5) acuity. The physician treats all patients with priority given to CTAS 1 and 2 and the delegate only treats low acuity patients.

Input data: Patient arrival times and probabilities used in the hospital ED model are derived from a hospital administrative database with information on each patient that arrives in the ED. Patient arrival is based on a schedule derived from the data (separate for walk-in and ambulance) that changes hourly and daily to account for peak and non-peak times. Figure 3 presents the average number of patient arrivals by weekday and hour. An exponential distribution is used to distribute the arrivals over each hour. Data and time stamps are entered manually into a centralized database by ED staff (e.g. clerks, nurses, and physicians). Data is used from 15,196 patients collected between April and July 2010. Process times are derived from a time and motion study (n=85) conducted in the ED over a 24 hour period. Table 1 and Table 2 summarize the inputs as well as the probability distributions used in the model to reflect the variation associated with the mean values. In Table 1, triage nurse and registrar capacity is based on an hourly schedule. In Table 2, the probabilities of having blood work or being sent to radiology is dependent on CTAS level but are independent of each other. Distributions are derived using Arena's input analyzer, which fits probability distribution functions to the data.

Initialization and analysis: To avoid initialization bias, a warm-up period was chosen using Welch's method[[22]]. The model is simulated over multiple replications for an extended period where key performance measures are recorded. The moving averages of these measures are graphed over time. Once the average stabilizes there is no longer initialization bias and the model reaches a steady state. This is considered the warm-up period and statistics begin recording after this time point. Analysis of simulation outputs is performed using the batch means method, where only one simulation run is executed. Data accrued during the warm-up period are deleted and the remainder of the run is divided into batches and each batch average represents a single observation. Arena has a built-in batching algorithm[[23]] that performs the analysis and provides a batched mean average with 95% confidence intervals (CI) in a report.

Comparison of Outputs between the Interacting Pseudo-Agent Approach and the Approach Without Interaction

The purpose of this comparison is to evaluate the performance of the approach with interacting pseudo-agents compared to the approach without interaction in terms of resource utilization, patient waiting time for assessment and treatment and flow time. Resource utilization is defined as the percentage of scheduled time spent on patient-related activities which includes assessment, treatment and interaction time (i.e. consultation). The following time intervals are estimated for the patient and reported by acuity level and whether treated by physician or delegate: arrival to bed (includes waiting time for triage and bed), waiting time for physician or delegate based on acuity, process time for assessment, treatment, and consultation and average total LOS. Model outputs are compared with two-sample t-tests using Arena's output analyzer. To better understand the effect of various changes on the operation of the ED system, sensitivity analyses are conducted on several key parameters including patient demand, number of beds and nurses, and consultation time.

RESULTS

The following reports on the validation of the interacting pseudo-agents approach and the comparison of this approach and the approach without interaction when implemented in a hospital ED informed by real data.

Validation results

Table 3 presents the results of the validation of the interacting pseudo-agent approach implemented in a simple model. As expected, physician and delegate utilization (64% and 72% respectively) is similar between the approach without interaction and the interacting pseudo-agent approach when the interaction between physician and delegate is disabled. Likewise, time to disposition for low and high acuity patients are identical between the two approaches. Once the interaction between physician and delegate is enabled in the pseudo-agent approach, there is an increase in resource utilization for the physician and delegate (25% and 21% respectively). The time to disposition is similar in high acuity patients because they are first priority over teaching. In contrast, low acuity patients are processed slower because they must wait in queue while the physician processes high acuity patients or teaches the delegate. When seen by a delegate low acuity patients are processed the slowest because extra time is taken for the delegate to go over the treatment plan with the physician and then to administer said treatment.

Comparison of Outputs between the Interacting Pseudo-Agent Approach and the Approach Without Interaction

Results from the warm-up analysis showed average output stabilization after 40 days. The model was run for one replication of 420 days which was long enough to provide enough observations to calculate 95% CIs using the batched means methods. Table 4 reports outputs comparing the interacting pseudo-agents approach and the approach without interaction when implemented in a hospital ED model. Similar to results in Table 3, the utilization increases when the interaction between physician and delegate is incorporated. When compared to the model without interaction, physician utilization increases by approximately 78% (from 23% to 41%) while delegate time increases by 27% (from 56% to 71%). Additionally, in the model with interaction, the physician remains idle (i.e. waiting to perform a task) on average 7 minutes before seeing a patient, whereas the delegate remains idle 10 minutes on average. A short waiting time is estimated for patients waiting for assessment and treatment from the physician or delegate. Despite this short waiting time, they are still statistically different between approaches, implying that patients do wait longer when the physician and delegate are assigned other patient related tasks (i.e. consultation). Patient time spent with the physician is similar between models because the treatment time input remains the same, however, patient time with the delegate increases (14.5 minutes to 24.5 minutes) because the delegate must consult with the physician before proceeding with treatment. In turn, this increases LOS which results in a longer queue for beds. Statistically significant differences are observed for average LOS between the two approaches for all low acuity patients, however, a statistically significant difference is not observed for high acuity patients. This is most likely due to the variation between time to admission and time to discharge.

Sensitivity Analysis

Sensitivity analysis is conducted on several parameters: the patient walk-in arrival rate is decreased by half, consultation time between the physician and delegate is increased, time to treat the patient is increased and the number of resources is increased (beds, charge nurses and bedside nurses). Table 5 reports on the results of the sensitivity analysis. Physician and delegate utilization increases when consultation time is increased but remains the same when resources are increased. Time from arrival to bed for high acuity patients does not vary significantly for all analyses, however, low acuity patients are placed in a bed quicker when the number of beds and bedside nurses is increased. As a result, these resource changes also lead to a decrease in average LOS. This may indicate that the number of beds and bedside nurses are limiting the flow of patients through the ED model. Increasing consultation time (i.e. interaction time) increases patient waiting time for the physician (4.49 for high acuity and 5.28 minutes for low acuity) and delegate (3.31 minutes). This translates into a longer time from arrival to bed for low acuity patients because it takes longer to discharge patients

Discussion/Conclusion

The ED is a complex environment that involves a number of interactions between patients and staff. Relationships between physicians and their delegates are also an important part of the overall ED process, perhaps more so in teaching hospitals. The objective of this study is to introduce an approach to modeling physicians that incorporates both embedded decision logic and physician interaction when modeling the ED. This interacting pseudo-agent approach is first validated using a simple model before being implemented in a more comprehensive hospital ED model informed by data from a Canadian academic hospital. Comparison between the model with interaction and the model without interaction showed that resources are less idle and lower acuity patients are processed slower because of consultation time. These results are corroborated by the literature that show decreased throughput when delegates are working. In the ED model, physician utilization increases from 23% of scheduled time to 41% when the interaction is modeled. This physician utilization is similar to those found in two separate time and motion studies documenting emergency physician time utilization. Friedman et al.[24] observe that direct patient related physician utilization is 28% and that teaching medical students and residents accounts for 5.8%. Hollingsworth et al.[13] found 32% of physician utilization was related to direct patient related activities and 6.3% was related to teaching, however, percentage of time spent on teaching is most likely an underestimate as only interactions with senior residents was recorded which would bring it closer to our results.

Using an interacting pseudo-agents based approach in DES can be particularly beneficial if the purpose of the simulation model is to derive optimal staff scheduling as this approach provides a more accurate representation of scheduled resource utilization and patient throughput. It is also possible to extend this method to other delegates (e.g. nurse practitioners, medical students, interns and physician assistants) to incorporate breaks and shift length for scheduling or to model more complex decision making to determine bottlenecks in patient flow. In the ED setting, the role of physician delegates is to assist with patient treatment under the supervision or in consultation with the physician. As such, interaction with physician delegates consumes a significant amount of the physician's time which needs to be modeled.

If time and resources are available, a full ABM model can be built rather than embedding decision logic in entities in a DES. This method models patients, physicians and nurses as separate agents where each operate under a different set of rules and interact more like a real ED. The drawback is that an ABM model takes longer to build as it is more complex and requires more data and knowledge of decision rules than other simulation techniques. Although the use of ABM in healthcare is gaining in popularity, it remains limited by the unavailability of commercial software and analysts with expertise in ABM. This may explain why DES is more commonly chosen to model the ED. The International Society for Pharmacoeconomics and Outcomes Research and the Society for Medical Decision Making Modeling Good Research Practices Task Force[[20]] advocates using DES to model more complex interactions between individuals which can be extended to modeling interactions between physicians and delegates in this study.

Our results show that it is important to model these types of interactions when simulating EDs. Despite its strengths, a few limitations are associated with this study. Both junior and senior delegates are not modeled as we assume that senior delegates function as an attending physician. This assumption is corroborated by an attending emergency physician. In reality, senior delegates are capable of treating patients of all acuity levels with minimal supervision and they also spend a portion of their time teaching junior delegates. Although our model reflects agent decisions that occur in an academic institution, we acknowledge that this may differ between hospitals. Results must also be used with caution as the hospital ED model does not incorporate the entire patient flow or possible variations in routing (e.g. multiple diagnostic tests and re-assessments) due to data limitations. Excluding re-assessment may result in an underestimate of total LOS and resource utilization. Some complexities of the ED are also not included in the model such as high acuity patients by-passing triage and jumping queue for a bed. However, our sensitivity analysis showed that high acuity patients are not greatly affected in the model when changes are made. Additionally, only one delegate shift was illustrated, whereas it is possible for multiple delegates to be working the same shift. Increasing the number of delegates would most likely also increase patient LOS. It is also worth noting that inputs estimated using the time and motion study was based on a small number of observations (n=85). Finally, since the objective of this study is to develop and validate a new modeling approach before comparing it in a hospital ED, we did not focus on comparing the outputs of the ED model with the observed data. Rather we aimed to show that simulation studies which did not model interactions between physicians and delegates may be misleading.

Implementation using commercially available software may not be as desirable as coding a program oneself, however, it presents a viable option for analysts unfamiliar with coding. In terms of scalability, modeling resources as interacting pseudo-agents in a DES may become overly complicated if the objective is to assess interactions among a large variety of staff. Despite these limitations, this study presents for the first time, an approach to model interactions between physicians and delegates and results indicates important differences in resource use and time intervals when compared to methods not modeling such types of interactions.

Future work would be to increase the complexity of the model to incorporate re-assessments and multiple diagnostic pathways. It would also be informative to create interacting pseudo-agents for nurses and residents, medical students and interns. Nurses and physicians spend a significant amount of time consulting about the patient as the nurse is responsible for monitoring patient vitals. Residents, medical students and interns require differing amounts of the attending physician's time which detracts from the patient, therefore it would be important to incorporate these staff members in the model to more precisely measure physician utilization.

In conclusion, the pseudo-agent based approach provides a more realistic representation of the emergency department. Our results indicate that modeling the interaction between physician and delegate can have an impact on predicted patient throughput and waiting time. In light of these results, future DES modeling of the ED setting should incorporate interaction between physician and delegate by modeling them as pseudo-agents.

COMPETING INTERESTS

The authors declare no competing interests.

AUTHOR'S CONTRIBUTIONS

ML developed the discrete even simulation models, performed the data analysis and drafted the manuscript.

AW, RG and JET contributed to the development of the discrete event simulations model, interpretation of the data analysis, and manuscript revisions.

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References

1. Lim M, Nye T, Bowen J, Hurley J, Goeree R, Tarride JE. **Mathematical Modeling: The Case of Emergency Department Waiting Times**. *International Journal of Technology Assessment in Health Care* 2012;28(2):93-109.

2. Hay A, Valentin EC, Bijlsma RA. **Modeling Emergency Care in Hospitals: A Paradox - The Patient Should Not Drive the Process**. *Proceedings of the 2006 Winter Simulation Conference*; 2006: 439-45.

3. Raunak M, Osterweil L, Wise A, Clarke L, Henneman P. **Simulating patient flow through an emergency department using process-driven discrete event simulation**. *2009 ICSE Workshop on Software Engineering in Health Care (SEHC 2009)*;2009: 73-83.

4. Gunal M, Pidd M. **Understanding accident and emergency department performance using simulation**. *Proceedings of the 2006 Winter Simulation Conference*; 2006: 446-52.

5. Komashie A, Mousavi A. **Modeling Emergency Departments Using Discrete Event Simulation Techniques**. *Proceedings of the 2005 Winter Simulation Conference*; 2005: 2681-5.

6. Mahapatra S, Koellig C, Patvivatsiri L, Fraticelli B, Eitel D, Grove L. **Pairing emergency severity index level triage data with computer aided**

system design to improve emergency department access and throughput. *Proceedings of the 2003 Winter Simulation Conference*; 2003: 1917-25.

7. Santibanez P, Chow VS, French J, Martin PL, Tyldesley S. **Reducing patient wait times and improving resource utilization at British Columbia Cancer Agency's ambulatory care unit through simulation**. *Health Care Management Science* 2009;12:392-407.

8. Lammers RL, Roiger M, Rice L, Overton DT, Cucos D. **The effect of a new emergency medicine residency program on patient length of stay in a community hospital emergency department.** *Acad Emerg Med* 2003;10(7):725-30.

9. Salazar A, Corbella X, Onaga H, Ramon R, Pallares R, Escarrabill J. **Impact of a resident strike on emergency department quality indicators at an urban teaching hospital**. *Acad Emerg Med* 2001;8(8):804-8.

10. Bush SH, Lao MR, Simmons KL, Goode JH, Cunningham SA, Calhoun BC. **Patient access and clinical efficiency improvement in a resident hospital-based women's medicine center clinic**. *Am J Manag Care* 2007;13(12):686-90.

11. Shayne P, Lin M, Ufberg JW, Ankel F, Barringer K, Morgan-Edwards S, et al. **The effect of emergency department crowding on education: blessing or curse?** *Acad Emerg Med* 2009;16(1):76-82.

12. Chisholm CD, Whenmouth LF, Daly EA, Cordell WH, Giles BK, Brizendine EJ. **An evaluation of emergency medicine resident interaction time with faculty in different teaching venues.** *Acad Emerg Med* 2004;11(2):149-55.

13. Hollingsworth JC, Chisholm CD, Giles BK, Cordell WH, Nelson DR. **How do physicians and nurses spend their time in the emergency department?** *Ann Emerg Med* 1998;31(1):87-91.

14. Siebers PO, Macal CM, Garnett J, Buxton D, Pidd M. **Discrete-event simulation is dead, long live agent-based simulation!** *Journal of Simulation* 2010;4:204-10.

15. Jones SS, Evans RS. **An Agent Based Simulation Tool for Scheduling Emergency Department Physicians**. *AMIA Annual Symposium Proceedings*. 2008: 338-42.

16. Laskowski M, McLeod RD, Friesen MR, Podaima BW, Alfa AS. **Models of emergency departments for reducing patient waiting times**. *PLoS ONE [Electronic Resource]* 2009;4(7):e6127.

17. Wang L. **An Agent-Based Simulation for Workflow**. *Proceedings of the 2009 IEEE Systems and Information*; 2009: 19-23.

18. Taboada M, Cabrera E, Iglesias ML, Epelde F, Luque E. **An Agent-Based Decision Support System for Hospitals Emergency Departments**. *Procedia Computer Science* 2011;203(4):1870-9.

19. Michel F, Ferber J, Drogoul A: In *Multi-Agent Systems and Simulation: A Survey of the Agent Community's Perspective*. Edited by Uhrmacher AM, Weyns D. Boca Raton, FL, USA: Multi-Agent Systems: Simulation and Applications CRC Press. Taylor and Francis Group; 2009: 3-52.

20. Karnon J, Stahl J, Brennan A, Caro JJ, Mar J, Möller J, et al. **Modeling using discrete event simulation: a report of the ISPOR-SMDM Modeling Good Research Practices Task Force--4**. *Value in Health* 2012;15(6):821-7.

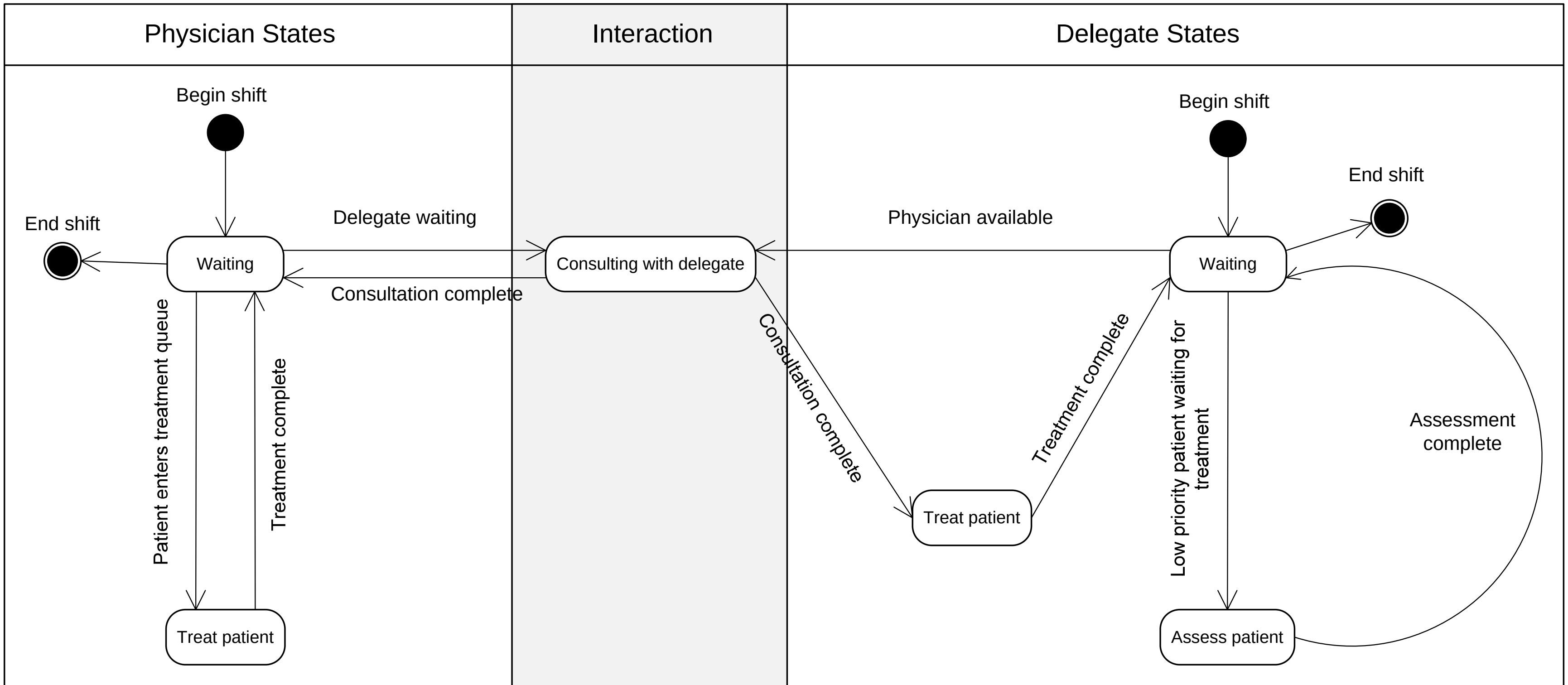
21. Beveridge B, Clarke B, Janes L, Savage N. Thompson J, Dodd G, Murray M, Nijssen-Jordan C, Vadeboncoeur A, Canadian Association of Emergency Physicians. *CTAS Implementation Guidelines*. Access on March 21, 2012. http://caep.ca/resources/ctas/implementation-guidelines.

22. Heidelberger P, Welch P. **Simulation run length control in the presence of an initial transient**. *Operations Research* 1983;31(6):1109-44.

23. Kelton WD, Sadowski RP, Sturrock DT. *Simulation with Arena. 4*. New York: McGraw Hill; 2007

24. Friedman S, Elinson R, Arenovich T. **A study of emergency physician work and communication: A human factors approach**. *Israeli Journal of Emergency Medicine* 2005;5(3):35-42.

Figure 1: Possible physician and delegate states and state transitions



<u>Physician decision logic</u>
If patient queue > 0 & patient is high acuity, then treat patient
    If treatment complete, then return to waiting
If delegate waiting for consult, then consult with delegate
    If consultation complete, then return to waiting
If patient queue > 0 & patient is low acuity, then treat patient
    If treatment complete, then return to waiting

<u>Delegate decision logic</u>
If patient queue > 0 & patient is low acuity, then assess patient
    If assessment complete, then wait for physician
If waiting for consult & physician waiting, then consult with physician
    If consultation complete, then treat patient
    If treatment complete, then return to waiting for patient

Figure 2: Hospital emergency department patient flow

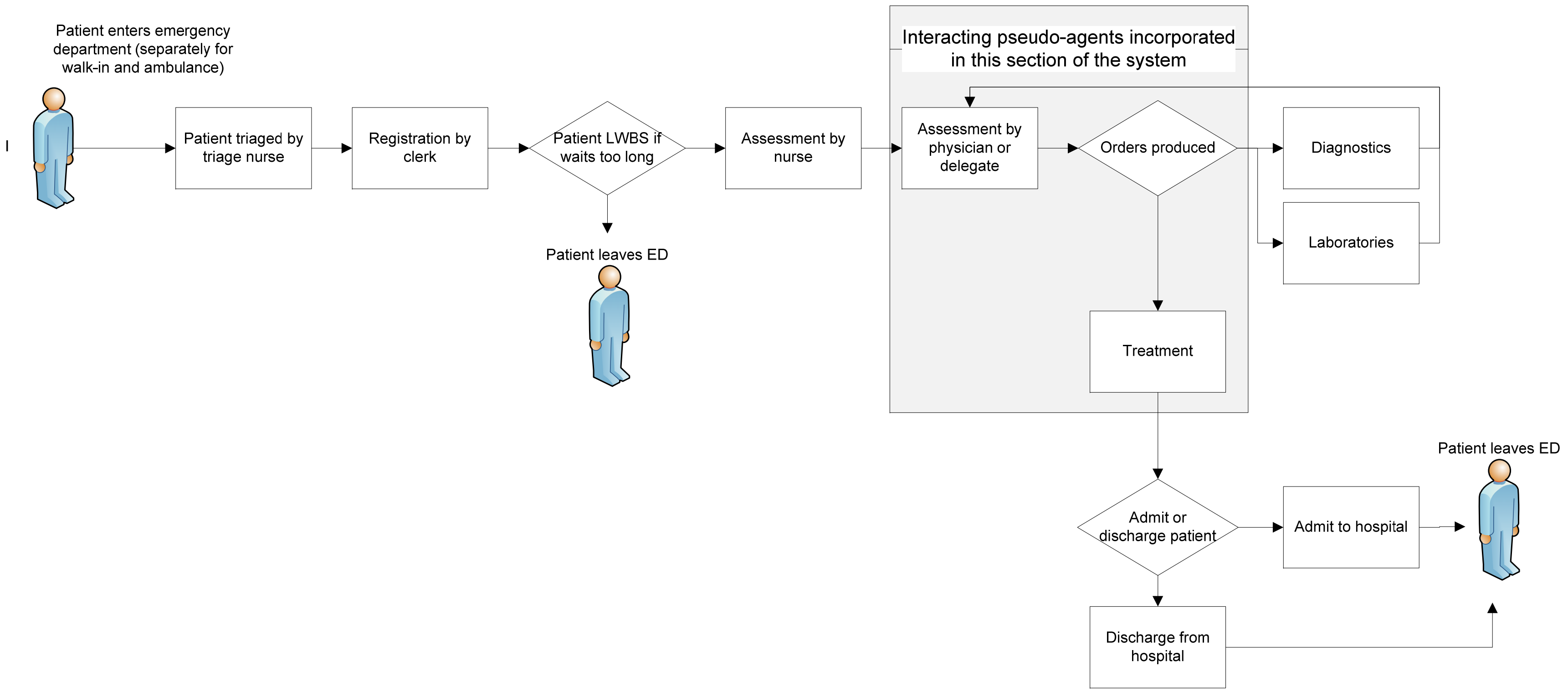


Figure 3: Weekday patient arrival Pattern over a 24 hour period

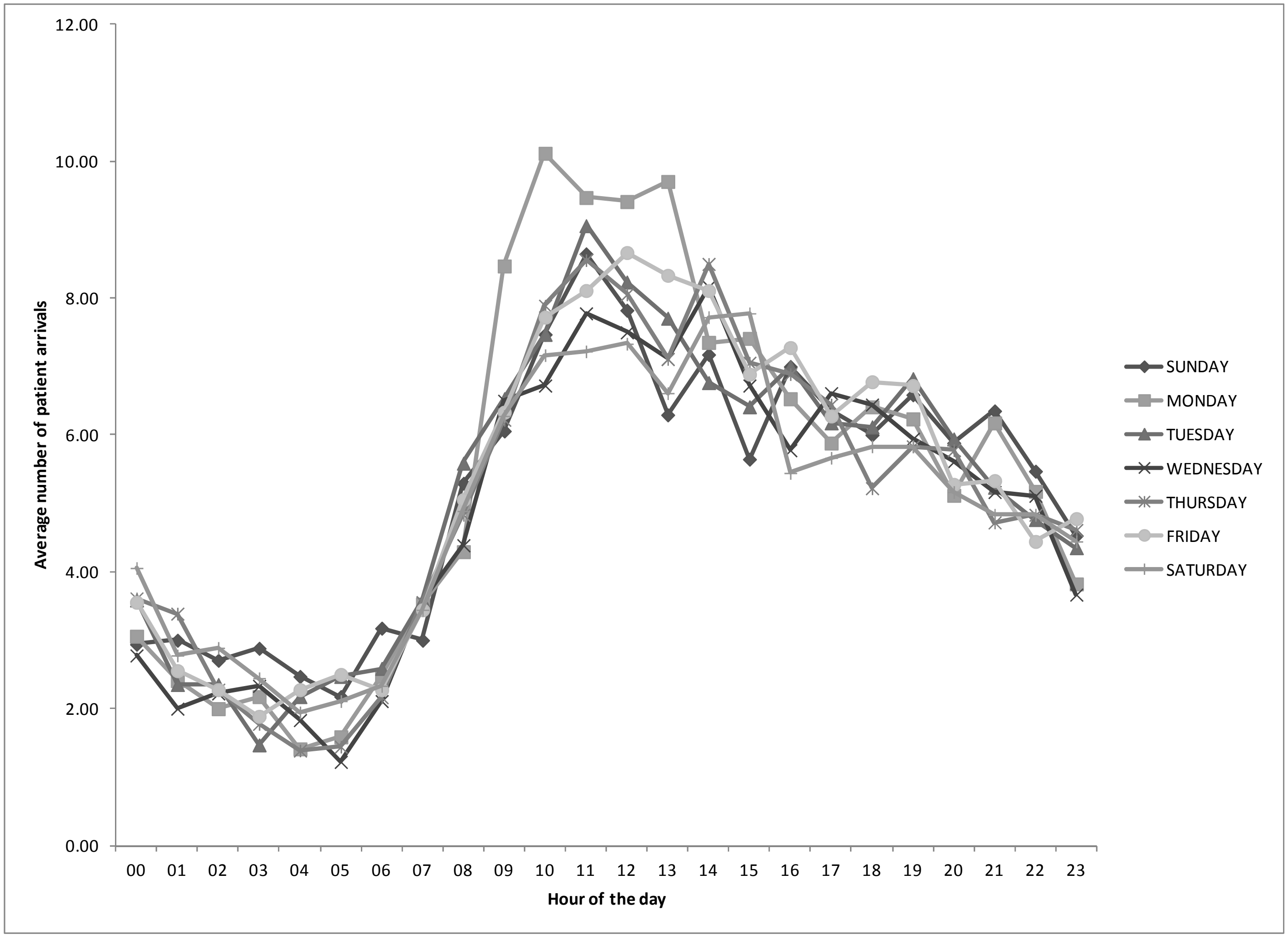


Table 1: Input data

Resource	Capacity†	Process Time (minutes)	Distribution
Triage Nurse	1 or 2	10	Poisson
Registrar	1 or 2	2	Lognormal
Bedside Nurse	2		
Assessment		10	Beta
Draw blood		4	Triangular
Discharge		10	Triangular
Charge Nurse	1		
Physician	1		
Treatment (high priority)		9	Triangular
Treatment (low priority)		4	Triangular
Consultation		4.5	Triangular
Delegate	1		
Treatment (low priority)		4	Triangular
Consultation		4.5	Triangular
Beds	5	NA	
Radiology‡	1	9	Beta

All inputs were estimated based on the time and motion study except radiology

†Based on schedule, ‡Estimation from administrative data

Table 2: Probability inputs to the model

	All	CTAS 1	CTAS 2	CTAS 3	CTAS 4	CTAS 5
Probability of patient with CTAS level		0.01	0.16	0.56	0.25	0.02
Probability of patient receiving radiology		0.82	0.07	0.48	0.28	0.18
Probability of patient having blood work		0.85	0.73	0.51	0.19	0.01
Probability of leaving without being seen						
< 30 minutes	0.01					
30 - 60 minutes	0.02					
60 - 120 minutes	0.1					
120 - 180 minutes	0.2					
180 - 300 minutes	0.3					
> 300 minutes	0.4					

Inputs estimated from administrative data

Table 3: Validation results of the interacting pseudo-agent approach

Performance measure	Without interaction		Pseudo-agent (interaction disabled)		Pseudo-agent (interaction enabled)	
Utilization*						
Physician	0.64	(0.63, 0.65)	0.64	(0.63, 0.65)	0.89	(0.88, 0.90)
Delegate	0.72	(0.72, 0.72)	0.72	(0.72, 0.72)	0.93	(0.93, 0.93)
Time to disposition (minutes)						
Physician (High acuity)	26.97	(26.68, 27.26)	26.97	(26.68, 27.26)	28.42	(28.13, 28.71)
Physician (Low acuity)	18.92	(18.41, 19.43)	18.92	(18.41, 19.43)	83.97	(78.37, 89.57)
Delegate (Low acuity)	28.13	(27.61, 28.65)	28.13	(27.61, 28.65)	110.94	(105.15, 116.73)

*time for teaching or learning only included in pseudo-agent model

(95% confidence intervals)

Table 4: Results comparing two approaches using the hospital emergency department model

Performance measure	Value (95% CI)		Difference (SD)
Utilization**			
Physician - Without interaction	23%		
With interaction	41%		18%
Delegate - Without interaction	56%		
With interaction	71%		15%
Time from arrival to bed (minutes)			
High acuity - Without interaction	20.39	(20.06, 20.72)	
With interaction	21.47	(21.19, 21.75)	1.08* (0.26)
Low acuity - Without interaction	68.94	(62.87, 75.01)	
With interaction	88.49	(80.36, 96.62)	19.55* (1.47)
Patient waiting time for physician or delegate (minutes)			
Physician (high acuity) - Without interaction	0.49	(0.44, 0.54)	
With interaction	1.02	(0.96, 1.08)	0.53* (0.04)
Physician (low acuity) - Without interaction	0.56	(0.55, 0.57)	
With interaction	1.49	(1.46, 1.52)	0.93* (0.02)
Delegate (low acuity) - Without interaction	0.15	(0.14, 0.16)	
With interaction	0.52	(0.49, 0.55)	0.37* (0.01)
Patient time with the delegate (minutes)			
Delegate (low acuity) - Without interaction	14.50	(14.5, 14.5)	
With interaction	24.51	(24.48, 24.54)	10.01* (0.01)

*statistically significant at the 5% level, **includes interaction time

CI – confidence interval, SD – standard deviation

Table 4 Continued

Performance measure	Value (95% CI)		Difference (SD)
Average total length of stay (minutes)			
Physician (high acuity) - Without interaction	85.91	(85.15, 86.67)	
With interaction	86.83	(85.88, 87.78)	0.92 (0.61)
Physician (low acuity) - Without interaction	118.54	(111.3, 125.78)	
With interaction	136.99	(128.47, 145.51)	18.45* (1.31)
Delegate (low acuity) - Without interaction	114.84	(108.32, 121.36)	
With interaction	142.07	(135.48, 148.66)	27.23* (1.36)
All low acuity patients - Without interaction	116.66	(110.49, 122.83)	
With interaction	138.91	(130.86, 146.96)	23.1* (0.94)

*statistically significant at the 5% level, **includes interaction time

CI – confidence interval, SD – standard deviation

Table 5: Sensitivity analysis results

Parameter	Utilization		Time from arrival to bed (minutes)		Average total length of stay (minutes)		
	Physician	Delegate	High Acuity	Low Acuity	Physician (High Acuity)	Physician (Low Acuity)	Delegate (Low Acuity)
Base case	41%	71%	21.47 (21.19,21.75)	88.49 (80.36,96.62)	86.83 (85.88,87.78)	136.99 (128.47,145.51)	142.07 (135.48,148.66)
Patient walk-in arrival (1/2)	26%	57%	15.84 (15.61,16.07)	18.99 (18.50,19.48)	77.39 (76.12,78.66)	58.25 (57.39,59.11)	74.33 (73.74,74.92)
Number of beds (from 5 to 10)	41%	70%	17.60 (17.13,18.07)	31.06 (28.53,33.59)	92.92 (90.70,95.14)	89.68 (84.69,94.67)	100.76 (96.96,104.56)
Number of charge nurses (from 1 to 2)	41%	70%	19.99 (19.08,20.90)	71.68 (55.45,87.91)	83.56 (80.51,86.61)	117.98 (101.96,134)	127.13 (106.55,147.71)
Number of bedside nurses (from 2 to 3)	41%	70%	18.79 (18.46,19.12)	39.88 (37.25,42.51)	78.91 (77.87,79.95)	78.79 (75.76,81.82)	91.73 (89.36,94.10)
Consultation time (5 to 15 minutes)	66%	86%	22.65 (22.25,23.05)	130.32 (111.79,148.85)	89.71 (88.76,90.66)	179.36 (161.17,197.55)	197.56 (177.78,217.34)

(95% confidence intervals)

CHAPTER 3

Access to Surgery for Paediatric Patients with Medically Refractory Epilepsy: A Systems Analysis

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HIGHLIGHTS

- Annual percent of potentially eligible population who actually have surgery is only 1%
- Time from first seizure to EMU referral was approximately 4.6 years.
- Time from EMU referral to surgery 1.6 years with iEEG and 1.1 years without iEEG.
- Surgical patients: 95% reduced seizure frequency and 74% seizure free one year post-surgery.

Abstract

Purpose: A systems analysis perspective was undertaken to evaluate access to surgery for children with medically refractory epilepsy (MRE) in Ontario, the largest province in Canada. The analysis focused on the assessment of referral patterns, healthcare utilization, time intervals and patient flow to determine surgical candidacy in children with MRE. The purpose of this systems analysis study was to identify rate limiting steps that may lead to delayed surgical candidacy decision and surgery.

Methods: Prolonged video electroencephalography (vEEG) is the common entry point into the process for all potential epilepsy surgery candidates. Therefore, a single centre retrospective chart review of children and adolescents referred to the epilepsy monitoring unit (EMU) for vEEG monitoring at the primary referral centre for paediatric epilepsy surgery in the province. Basic demographic and referral data were abstracted for all screened cases. Included cases were: 1) Age <19 years old at time of first EMU admission, 2) Date of EMU admission between April 1, 2004 and March 31, 2006 and 3) Referral for elective vEEG and/or overnight with vEEG greater than 8 hours duration. Data were collected on number of seizure conferences, surgical candidacy, surgical outcomes (seizure free and seizure reduction), resource utilization, and recorded time stamps for each event to estimate system delays.

Results: During the two-year period, 463 patients were referred to the EMU of whom 349 received prolonged vEEG (>8 hours). Forty five percent (n=160) of patients came to seizure conference for discussion of their data, of whom 40% (64/160) were considered surgical candidates. Time from first seizure to EMU referral was approximately 4.6 years. Time from referral to admission and admission to first seizure conference were approximately 103 days and 71 days respectively. From initial EMU referral to surgery ranged from 1.6 to 1.1 years depending on whether the patient required invasive monitoring with intracranial EEG. Overall, 95% of surgical patients had a reduction in seizure frequency, 74% were seizure free after one year post-surgery.

Significance: Referral rates for surgical assessment are low relative to the estimated number of children living with MRE in Ontario, less than 2%. Hence, only a limited number of children with this disorder in the province of Ontario who could benefit from epilepsy surgery are being assessed for surgical candidacy. The majority of Ontario children with MRE are not being provided the potential opportunity to be seizure free and live without functional limitations following surgical intervention. These data document the critical need for health system redesign in Ontario, the goal of which should be to provide more consistent and just access to evidence-based medical and surgical care for those citizens of the province who suffer from epilepsy.

Keywords: Epilepsy, epilepsy surgery, drug resistance, resource utilization, surgical assessment

INTRODUCTION

Approximately one third of children with epilepsy will have medically refractory epilepsy (MRE) (Kwan P & Brodie MJ, 2000) with all of its attendant and comorbid difficulties in learning, behaviour, motor, and social skills (Drewel EH, Bell DJ, & Austin JK, 2009; Jones JE et al., 2008; Elliott et al., 2012).The surgical treatment of epilepsy in children with MRE has been shown to be efficacious in a significant number of patients, both in terms of decreasing seizure frequency and improvement in quality of life (Tellez-Zenteno JF, Dhar R, & Wiebe S, 2005; Hauptman et al., 2012; D'Argenzio et al., 2012; Elliott et al., 2012). However, despite the mounting evidence supporting the effectiveness of surgery for patients with MRE (Wiebe & Jette, 2012), there remain barriers in access to this potentially curative treatment modality. Studies continue to show long seizure duration (5.7 years and greater) preceding epilepsy surgery (Harvey AS, Cross JH, Shinnar S, & Mathern BW, 2008). Even in adults, there are estimates of between 19 to 22 years before referral for evaluation of surgical candidacy (Gilliam F et al., 1999; Choi H, Carlino R, Heiman G, Hauser WA, & Gilliam FG, 2009; Wiebe S, Blume WT, Girvin JP, & Eliasziw M, 2001). These long delays suggest that there are a significant number of patients who could have been treated as children, thereby sparing them the neurodevelopmental, behavioural, and social development problems associated with years of uncontrolled seizures (Huttenlocher & Hapke, 1990; Vasconcellos et al., 2001). Health related quality of life is well known to be impaired in children with epilepsy (Elliott, Lach, & Smith, 2005; Wu, Ding, Wang, & Hong, 2010), who have higher rates of behavioural, cognitive, emotional, social and academic disorders than healthy children or children with other chronic health conditions (Austin, 1989; Austin, Risinger, & Beckett, 1992; Austin, Huster, Dunn, & Risinger, 1996; Dunn, Austin, & Huster, 1999; Williams et al., 2003; Rodenburg, Stams, Meijer, Aldenkamp, & Dekovic, 2005).

In Canada, Ontario is the largest province with a population of approximately 13 million. In this province epilepsy afflicts an estimated 70,000 people of whom 10,000 are children. Twenty-one thousand of these Ontarians are estimated to have MRE of whom 3,143 are children (Statistics Canada, 2012; Tellez-Zenteno, Pondal-Sordo, Matijevic, & Wiebe, 2004; Wiebe, Bellhouse, Fallahay, & Eliasziw, 1999). In 2007, the Ontario Health Technology Advisory Committee (OHTAC), a standing advisory subcommittee (physicians, allied health professionals, ethicists, health economists, and hospital administrators) of the Health Quality Ontario Board that makes evidence-based recommendations to the Ontario health care system and the Ministry of Health and Long-Term Care about the best health technologies in Ontario (Health Quality Ontario, 2012) estimated that approximately 1.6% of the eligible population were receiving surgical treatment of their MRE and that significant wait times of over a year were associated with obtaining diagnostic testing to evaluate surgical candidacy (Ontario Health

Technology Advisory Committee, 2007). In order to improve access to care, OHTAC recommended an evaluation of system capacity associated with the decision of surgical candidacy for children with MRE and surgical intervention where indicated (Bowen et al., 2011).

Conducting a systems analysis is necessary to capture the relationships and between the different components of the evaluation and surgical process. A systems analysis approach enables the identification of gaps and bottlenecks in the organization and delivery of care for the entire process. Therefore, using a systems analysis perspective, the following study examines the referral patterns, healthcare utilization, time intervals and patient flow to identify rate limiting steps at the primary referral centre in the province that may lead to delayed surgical candidacy decision making and epilepsy surgery.

METHODS

Setting

Data was collected from the Hospital for Sick Children (SickKids) in Toronto Ontario. This institution was chosen, because it is the only referral centre in Ontario for children with MRE throughout the province who may be candidates for the surgical treatment of their epilepsy. In Canada, we have a publicly funded healthcare system where delivery is organized by the province. The center in this study is the only centre in the province for surgical evaluation and surgery (no privately funded centre running parallel), therefore there no other center exists for comparison. The study was reviewed by the Research Ethics Boards of both St. Joseph's Healthcare Hamilton, Ontario, Canada and SickKids.

Evaluation of Surgical Candidacy at SickKids

Figure 1 outlines both the stages of data collection and the evaluation process for surgical candidacy (Go C & Snead OC 3rd, 2008). The central part of the process is a multidisciplinary seizure conference where members of the epilepsy surgery team gather weekly to examine all of the clinical, diagnostic, and psychosocial data associated with each potential surgical candidate in order to reach a consensus as to whether the child should be eliminated from consideration, undergo further diagnostic testing, or proceed to surgery with or without invasive intracranial monitoring which may include subdural and/or depth electrodes. The seizure conference is a central process as the patient can be directed towards multiple pathways. The members of the team who participate in this weekly seizure conference include neurologists, neurosurgeons, clinical neurophysiologists, neuroradiologists, nurses, social workers, neuropsychologists, and psychiatrists. The point of entry into this process of evaluation for epilepsy surgery candidacy is the epilepsy monitoring unit (EMU) to which the children are initially referred in order to undergo prolonged video electroencephalography (vEEG). Any paediatric neurologist in Canada is able to refer to the EMU, however, they do not accept referrals from paediatricians or family doctors. Patients must first be referred to neurology before they can be referred to the EMU. The children remain in the EMU until one or more seizures are captured by the vEEG, a period that may last up to five days. Following the EMU visit, some patients may be considered ineligible for surgery based upon seizure semiology and/or EEG findings. The remainder are presented for discussion at seizure conference. Further diagnostic evaluation may also be completed as a component of the initial pre-surgical assessment either prior to, or following the first seizure conference depending on clinical circumstances. It is now the current standard that evaluation always includes magnetic resonance imaging (MRI), magnetoencephalography (MEG), neuropsychological assessment (NPA) and functional MRI (fMRI), the latter being done if the child is able to cooperate, however, at time of data collection it was almost always the case that these diagnostic tests were assigned. We (Ibrahim et al., 2012) and others (Kakisaka et al., 2012; Wu et al., 2012), have found MEG to be an extremely useful diagnostic modality in the non-invasive localization of the epileptic focus in patients with MRE who are being considered for epilepsy surgery. Therefore, we use it routinely in this regard. When patients require further diagnostic testing in order to reach a surgical decision, re-discussion takes place at consecutive conferences until all data is available to determine appropriate treatment decision. At the final seizure conference a complete review is conducted of the patient's medical history and seizure history followed by a review of the vEEG as well as results from all diagnostic imaging studies, including fMRI as well as NPA data. If surgery is recommended, patients are scheduled for surgery at SickKids. If indicated by the seizure conference consensus decision, intracranial EEG (iEEG) monitoring is done preparatory to a final surgical decision. If no iEEG is indicated, the child proceeds straight to the surgery recommended by the seizure conference consensus. Surgical patients are routinely evaluated in the ambulatory neurology clinic in follow-up every six months for a minimum of two years. However in this study, we present clinical outcome data following epilepsy surgery up to one year, as not all children at the time of the review had follow-up beyond this period.

Study Design

The study was composed of 2 phases: screening for study inclusion and full chart abstraction for those meeting the inclusion criteria. A retrospective medical chart review was conducted of both manual and electronic charts of children and adolescents (further referred to as patients) referred to the EMU for a vEEG at SickKids. Health practitioners familiar with the current evaluation process completed the data abstraction. The study was completed in 2 phases: screening for study inclusion and full chart abstraction for those meeting the inclusion criteria.

Phase 1: All medical charts were screened for those children referred to the SickKids EMU between April 1, 2004 and March 31, 2006 for inclusion in the study and basic demographic and referral data were abstracted (e.g., sex, date of birth, previous EMU referral, residence) for all screened cases. To be included for further data abstraction, cases had to meet the following criteria: 1) Diagnosed as having MRE, 2) Age <19 years old at time of first EMU admission, 3) Date of EMU admission is between April 1, 2004 and March 31, 2006 and 4) Referral for elective vEEG and/or overnight with vEEG greater than 8 hours. The time horizon for selection of the medical charts were based on an estimate of 2-3 years from EMU admission to surgical intervention and to increase likelihood that surgical candidates identified in the chart review would have at least 1 year of clinical follow-up data available after surgery.

Phase 2: For all patients meeting the inclusion criteria, data were abstracted from vEEG reports (duration and seizure types), EMU reports (reason for vEEG, who requested vEEG), seizure conference reports (includes a detailed summary of the patients' complete seizure and medical history, diagnostic test results, procedures and recommendations for surgery), diagnostic reports, surgical reports (related diagnostic tests and appointments, surgery type, use of iEEG, complications and post-operative care and follow-up), neurology clinical notes, general letters, and any additional physician notes. Additionally, all dates associated with EMU referrals and admissions, diagnostic tests, medical appointments and surgeries were abstracted. For patients who did not proceed to seizure conference after vEEG, no further information was abstracted as these individuals were not seen further at SickKids. Further chart abstraction was completed for patients who returned to the EMU and had subsequent vEEGs, EMU reports or seizure conference reports. Seizure conference recommendations related to surgical candidacy were abstracted from each available conference report and assigned into one of the following status categories: (1) surgical candidate (2) not a surgical candidate (3) not a surgical candidate at this time (further technical diagnostic testing and investigations required). When available, subsequent family decision and acceptance of the management strategy was abstracted. Surgical resection location (temporal lobectomy, temporal or extratemporal lesionectomy, temporal or extratemporal cortical resection, hemispherectomy, corpus callosotomy, other, and no resection) and iEEG status were abstracted from hospital records.

Outcomes

Information from the medical chart review was used to describe geographic and demographic referrals to the EMU at SickKids, the clinical evaluation process, the sequence and timing between diagnostic tests, as well as associated healthcare resource utilization. Resources included diagnostic tests, neuropsychological evaluations, seizure conferences, medical appointments (e.g. specialists, social work, and neurology clinic), surgical procedures and follow-up visits and are recorded as frequency counts. Dates were used for calculation of time intervals between appointments (e.g. number of days from EMU referral to admission). Type of surgical intervention was recorded for patients undergoing surgery. Long-term surgical clinical outcomes included seizure status and seizure frequency (day, week or month). Surgical outcomes were evaluated as the proportion of seizure free patients and the proportion with reduced seizure frequency between baseline (i.e. initial EMU referral) and one year post-surgery. Time intervals were reported as medians along with the minimum and maximum to inform the distribution of the data. Median differences were tested using the Kruskal-Wallis rank test. Discrete variables were reported as percentages while continuous variables were reported as means with standard deviations. Paired Student's t test was used to determine statistically significant mean differences in baseline characteristics, proportions of surgical outcomes before and after surgery.

RESULTS

Between April 1, 2004 and March 31, 2006, 463 children were referred to the EMU at SickKids, mainly from within the province of Ontario (96.5%) with some out of province referrals (2.2%) from Newfoundland & Labrador, Prince Edward Island, New Brunswick and British Columbia. Out of country referrals (1.3%) included patients from Barbados, Nigeria, Mexico and Trinidad. The average age at time of referral was 8.7 years ranging from less than 1 to 18 years where 56.4% of referrals were male. Of the 463 patients, 114 (24.6%) received a vEEG lasting less than 8 hours and therefore did not meet study inclusion criteria and no further information was collected. The remaining 349 (75.4%) cases had prolonged vEEG and were followed for the remainder of the study.

Referrals to the EMU were made by a neurologist (91.1%), neurosurgeon (3.7%), or other healthcare practitioner (5.2%). Estimates for seizure frequency and seizure duration at EMU admission, vEEG duration and mean age at first seizure and EMU referral and admission can be found in Table 1. Following the EMU, 189 (54.2%) patients were not considered surgical candidates and did not proceed to seizure conference.

The remaining 160 cases proceeded to seizure conference for review by the team of specialists described above. Figure 2 illustrates the flow of patients for surgical candidacy assessment. Following seizure conference, patients proceeded based on their surgical candidacy status. If surgical candidacy was ruled out by the data the patient was not considered a surgical candidate and no further assessment was undertaken. If the child was deemed a surgical candidate, they were scheduled directly for surgery. If the localization of the seizure focus to be resected remained uncertain, the patient was sent for further diagnostics recommended by the epilepsy surgery team and another seizure conference was scheduled. One child did not require a seizure conference as the need for surgical intervention was apparent based on the child's initial presentation. Overall, 64 patients were considered surgical candidates and 56 (n=26 with iEEG) proceeded to surgery. Patients dropped out due to family decision (n=4) or were lost to follow-up (n=4). At surgery, 3 patients were found to be ineligible for resection because of involvement of eloquent cortex in the seizure onset zone (were included for follow-up calculation), 1 child died post-surgery of sudden unexpected death of epilepsy (SUDEP) and 1 was lost to follow-up.

The median time between first seizure and first EMU referral was 4.6 years while the time from EMU referral to admission was 103 days. For those who underwent surgery the median time from EMU referral to surgery was 1.1 years for those who did not receive iEEG and 1.6 years for those who did. Further reporting of time between various evaluation stages and surgery are presented in Table 2. A statistically significant difference was found between median time from EMU admission to first seizure conference for those who became surgical candidates. Following a recommendation for surgery at seizure conference, the time for the family response after discussions with their neurologist took a median of 52.5 days with some families responding the next day and others waiting up to a maximum of 303 days.

Healthcare resource utilization was recorded for diagnostic tests and medical appointments. Prior to EMU admission, patients were primarily referred for MRI, MEG and EEG. Of those who went for surgery, 75% of diagnostic tests were MRI, MEG, fMRI or NPA. The mean number of tests that occurred between seizure conference 1 and 2, seizure conference 2 and 3 and seizure conference 3 and 4 were 2.2, 1.9 and 2.0 tests respectively with MRIs being the most frequently repeated test. Total number of diagnostic tests and average time from ordering the test to completion can be found in Table 3. Surgical candidates received more diagnostic tests than non-surgical candidates, primarily fMRIs and NPAs. Some patients had repeated diagnostic testing. Specifically, for the patients who were determined to be surgical candidates, 56 out 64 cases (88%) had at least one test repeated, while 40% of seizure conference cases had tests repeated. The need to conduct a second MRI was required in 66% of the patients who were surgical candidates however a repeat MEG was needed in only 22% of patients who were surgical candidates. Medical visits included visits to neurosurgeons, epileptologists, psychiatry, orthoptics, neurologists, social workers, and opthamologists as well as visits for assessment and treatment of functional limitations (vision, mobility, etc) that may have been present. The median time to see a neurosurgeon was 105 days.

Long-term clinical outcome data showed a statistically significant reduction ($p<0.05$) in baseline seizure frequency at one year post surgery. Data revealed

95% of surgical patients had a reduction in seizure frequency after one year of which 74% were seizure-free. Surgical outcomes by surgical resection location are in Table 4. Three patients showed an increase in seizure frequency one year post surgery. Mean seizure frequency declined from 3.6 per day to 0.36, showing a 90% reduction.

DISCUSSION

This study evaluated the complex process at SickKids used to determine the candidacy of children with MRE for surgical treatment of their epilepsy by capturing information regarding resource utilization and time between the various stages of assessment. With an assumed prevalence of 3,143 children with MRE in Ontario, this study identified an estimated annual referral rate of only 5.6%. Compounding the low referral rate is the prolonged delay between first seizure and referral to the EMU for evaluation of surgical candidacy of 4.6 years with a maximum time of 16.2 years, which is consistent with reported delay in other studies (Choi H et al., 2009; Wiebe S et al., 2001; Gilliam F et al., 1999; Harvey AS et al., 2008). Low referral rate and/or delayed referral for epilepsy surgical assessment may indicate a lack of awareness and education among family practitioners and neurologists about the potential benefit of epilepsy surgery (McLachlan RS, 2001; Swarztrauber K, 2004; Swarztrauber K, Dewar S, & Engel J Jr, 2003; Theodore et al., 2006), a situation that is not unique to Ontario (Jette et al., 2012).

A number of misconceptions in the medical community about epilepsy surgery have contributed to low referral rates for pre-surgical assessment. Among these is uncertainty towards referring very young children for epilepsy surgery evaluation (Jette et al., 2012), in spite of data indicating the value of surgery in very young children (Sugimoto et al., 1999; Gowda et al., 2010; Dunkley et al., 2011) and the imperative to provide surgical treatment for those children with MRE who are candidates as early as possible to avoid all the developmental, behavioural, and social comorbidity of chronic long standing MRE (Vendrame et al., 2009). This reluctance to refer very young children is also supported by our study findings which shows that only 19% of the children referred to the EMU are in the youngest age group. Additionally, outcomes often defined by primary care practitioners, as well as many neurologists, as acceptable seizure control being occasional seizures as an adequate response to medication are no longer appropriate since the current goal of treatment of epilepsy in both adults and children is seizure freedom with no side effects (Lowenstein, 2011). This is supported by the deficient knowledge of epilepsy treatment among neurologists and primary care practitioners (Theodore et al., 2006) and the continued behaviour of prescribing medications to patients with epilepsy who could potentially be cured with surgical treatment because of misconceptions towards the risks of benefits of treatment (Swarztrauber K, 2004). For example, in Sweden, guidelines recommending epilepsy surgery have existed since 1991, however, there is a lack of referral for surgery with 58% of non-referred patients being candidates for evaluation (de Flon, Kumlien, Reuterwall, & Mattsson, 2010). Attitudes and awareness within the medical community of the value of epilepsy surgery to treat MRE may be limiting the use of this therapeutic modality, access to surgery also may be limited by both system capacity and organization of services (Labiner et al., 2010).

With newer diagnostic technologies and the ability to identify surgical candidates at an earlier stage in the treatment paradigm, the standard of care has moved towards specialized epilepsy centres to both diagnose and treat these patients (Labiner et al., 2010). For this reason, specialized epilepsy centres need to be equipped with appropriate resources including, diagnostic equipment, operating room space and staff expertise to properly diagnose and treat patients in a timely manner. As indicated by our data, patients with MRE who are candidates for epilepsy surgery flow through a complex process for evaluation, where each stage may present its own resource constraints (i.e. number of beds) that could contribute to delays. In order to provide appropriate and timely care to epilepsy patients it is essential to identify the potential factors that may lead to diagnostic or treatment delay. Some of these factors were revealed by our data.

Time to seizure conference varied due to access to other diagnostic testing (i.e. MRI, MEG, NPA, fMRI) ordered prior to seizure conferences. Diagnostic completion times between seizure conferences varied depending on the diagnostic test and ranged anywhere from 1 day (i.e. emergency case) to 390 days. Each incremental diagnostic evaluation contributed to the total time to surgical candidacy decision which also depended on the number of seizure conferences required. In particular, MEG is a diagnostic imaging test that typically requires young children to be sedated under general anaesthesia, meaning that the use of MEG is not only limited by the number of patients referred, but also by the number of available anaesthesiologists (Ochi A & Otsubo H, 2008). Because time to diagnostic completion is a much wider system issue due to competing referrals from other disease areas, there is a potential to decrease the number of repeat tests by decreasing diagnostic delay time. Multiple diagnostic evaluations were required for the determination of surgical candidacy with 88% of surgical candidates requiring repeated evaluation, primarily multiple MRIs. Repeat tests may occur because of changes in seizure characteristics over time, re-evaluation based on results from other diagnostic tests, requirement for specific diagnostic test protocols for epilepsy, and overall wait times for other evaluations and assessments. Reducing the time to diagnostic evaluation and coordination of test protocols between diagnostic centres across the province may help reduce the need for repeat diagnostic evaluation.

For those children who were identified as surgical candidates the median times from EMU admission to surgery were 1.6 years (iEEG) and 1.1 years (no iEEG). In comparison a recent publication by Wright et al. (Wright JG & Menaker RJ, 2011) found that in 2009, 23% of paediatric neurosurgeries were completed past their target in Ontario. Those authors also found that surgical interventions in other subspecialties such as dentistry, ophthalmology, plastic surgery and oncology had a greater proportion of surgeries completed beyond their target time.

Despite the rigour of our study, there are a few limitations. We did not compare our results with another institution because our study site is the only referral centre in the province offering both surgical evaluation and surgery. It would be possible to use a centre from another province, however, the delivery of healthcare differs by province which would bias the comparison. Additionally, because Canada has a publicly funded healthcare system there is no privately funded centre running in parallel. As a result, our findings may not be as generalizable to privately funded settings. Other factors such as health insurance or ethnicity may be associated with time to surgery (Baca et al., 2013). Aligned with other centres (de Oliveira, Santos, Terra, Sakamoto, & Machado, 2011; Turon-Vinas et al., 2010; Hemb et al., 2010; Zupanc et al., 2010; Mikati et al., 2010) our outcomes appear comparable. Given the use of MEG in our study site and the varying skill set of the team (i.e. epileptologist, clinical neurophysiologist and neurosurgeon), there is no rigorous statistical method to make such a comparison. The reported time interval of first seizure to EMU referral reflects a combination of time for the treating physician to make the referral and waiting time for an appointment with the paediatric neurologist and paediatric epileptologist. Data was not collected to discern between the time intervals, however, the time from entering the epilepsy program after being seen by the specialist to the EMU referral is negligible since virtually all children seen who are epilepsy candidates are immediately referred to an EMU. We were also unable to collect time of MRE diagnosis to calculate the time from MRE diagnosis to EMU referral as this information was not recorded in the charts. Despite this limitation we predict a wide variation would exist in any such data due to variations in how long a child is treated and with how many drugs before being considered as having MRE (Berg AT 2006;Go C & Snead OC 3rd 2008). Additionally, one year following surgery, 74% of our patients were seizure free, the caveat being that one year follow-up is not optimal to determine outcomes of epilepsy surgery. The Engel scale was also not captured as part of this study, however, previous experience with children from the same centre showed that 74% of surgical patients with a mean follow-up of 67 months were in Engel Class I (Benifla et al., 2006). A separate study at the same centre also found that 77% of children included in their study had a good postsurgical (Engel Class I to IIIa) seizure outcome after a mean follow-up of 27 months (RamachandranNair et al., 2007).

However, these results from our field evaluation were presented to OHTAC who, in light of our data, felt that there was a compelling need to increase access to epilepsy surgery in Ontario. As a result an Ontario Provincial Epilepsy Strategy Working Group was formed to provide a provincial perspective and to compile province-wide data from both paediatric and adults centres of care (Ontario Health Technology Advisory Committee, 2012). The Working Group has recommended the integration and standardization of delivery of care, decision support and clinical information systems through the organization of currently existing epilepsy specific care centres (ESCC) into district and regional services. Based on the Working Group's recommendations and an economic analysis conducted using findings from this study (Bowen, Snead, Chandra, Blackhouse, & Goeree, 2012), OHTAC endorsed implementation of a provincial strategy.

Any changes in delivery of care will impact referral rates and patterns as well as resource utilization. To properly plan such a wide re-organization of services it would be beneficial to examine the inter-relationship between ESCCs using a systems thinking perspective, considering the complex and dynamic nature of the different levels of healthcare delivery (Ontario Health Technology Advisory Committee, 2012). For example, how will the addition of EMU beds in one specific region of Ontario affect referral patterns from another region? Such changes can be quantified using systems analysis tools such as mathematical or simulation models. By mapping the clinical pathways and flow of patients with epilepsy through the current system, a simulation model can be developed to help inform the planning process and illustrate the feedback of any changes made to the evaluation process. For example, the time from EMU referral to admission was 3 to 4 months in this study, however, if referral rates increase due to increased awareness about epilepsy surgery this would in turn increase time to admission. A simulation model could predict by how much and estimate the number of resources needed to meet the increased demand.

CONCLUSION

This study has examined issues related to children with MRE who are potential candidates for epilepsy surgery. Specifically, we examined referral patterns and delays, healthcare resource utilization and surgical clinical outcomes. Referral rates for surgical assessment are low relative to the estimated number of those living with MRE in Ontario. Few children are being assessed for surgical candidacy and thus are not being provided the potential opportunity to be seizure free following surgical intervention. The future creation of ESCCs in Ontario will provide opportunities to streamline care and increase access to essential services to those suffering from this debilitating condition. The ultimate goal is to put into place a comprehensive, evidence-based system of care for all those adults and children in the Province of Ontario who suffer from epilepsy, a system that is just with timely accessibility to quality evidence-based medical and surgical care for all.

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Disclosure of conflict of interest

None of the authors has any conflict of interest to disclose.

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Reference List

Austin, J. K. (1989). Comparison of child adaptation to epilepsy and asthma. *J Child Adolesc Psychiatr Ment Health Nurs, 2*(4), 139-144.

Austin, J. K., Huster, G. A., Dunn, D. W., & Risinger, M. W. (1996). Adolescents with active or inactive epilepsy or asthma: a comparison of quality of life. *Epilepsia, 37*(12), 1228-1238.

Austin, J. K., Risinger, M. W., & Beckett, L. A. (1992). Correlates of behavior problems in children with epilepsy. *Epilepsia, 33*(6), 1115-1122.

Baca, C. B., Vickrey, B. G., Vassar, S., Hauptman, J. S., Dadour, A., Oh, T. et al. (2013). Time to pediatric epilepsy surgery is related to disease severity and nonclinical factors. *Neurology, 80*(13), 1231-1239.

Berg AT. Defining intractable epilepsy. *Advances in Neurology,* 97, 5-10. 2006.

Benifla, M., Otsubo, H., Ochi, A., Weiss, S. K., Donner, E. J., Shroff, M. et al. (2006). Temporal lobe surgery for intractable epilepsy in children: an analysis of outcomes in 126 children. *Neurosurgery, 59*(6), 1203-1213.

Bowen, J. M., Snead, O. C., Chandra, K., Blackhouse, G., & Goeree, R. (2012). Epilepsy care in Ontario: an economic analysis of increasing access to epilepsy surgery. *Ont Health Technol Assess Ser [Internet], 12*(18), 1-41.

Bowen, J. M., Snead, O. C., Hopkins, R. B., Elliott, I., Burke, N., Atkin, J. et al. (2011). *Diagnostic evaluation of infants, children and adolescents with epilepsy for surgery candidacy and the role of magnetoencephalography (MEG)*. Report No. FEEAP-HTA013a-2011.REP. Hamilton (ON): Programs for Assessment of Technology in Health, St. Joseph's Healthcare Hamilton/McMaster University

Choi H, Carlino R, Heiman G, Hauser WA, & Gilliam FG. (2009). Evaluation of duration of epilepsy prior to temporal lobe epilepsy surgery during the past two decades. *Epilepsy Res, 86*(2-3), 224-227.

D'Argenzio, L., Colonnelli, M. C., Harrison, S., Jacques, T. S., Harkness, W., Scott, R. C. et al. (2012). Seizure outcome after extratemporal epilepsy surgery in childhood. *Dev.Med.Child Neurol., 54*(11), 995-1000.

de Flon, P., Kumlien, E., Reuterwall, C., & Mattsson, P. (2010). Empirical evidence of underutilization of referrals for epilepsy surgery evaluation. *Eur J Neurol, 17*(4), 619-625.

de Oliveira, R. S., Santos, M. V., Terra, V. C., Sakamoto, A. C., & Machado, H. R. (2011). Tailored resections for intractable rolandic cortex epilepsy in children: a single-center experience with 48 consecutive cases. *Childs.Nerv.Syst, 27*(5), 779-785.

Drewel EH, Bell DJ, & Austin JK. (2009). Peer difficulties in children with epilepsy: association with seizure, neuropsychological, academic, and behavioral variables. *Child Neuropsychol, 15*(4), 305-320.

Dunkley, C., Kung, J., Scott, R. C., Nicolaides, P., Neville, B., Aylett, S. E. et al. (2011). Epilepsy surgery in children under 3 years. *Epilepsy Res., 93*(2-3), 96-106.

Dunn, D. W., Austin, J. K., & Huster, G. A. (1999). Symptoms of depression in adolescents with epilepsy. *J Am Acad Child Adolesc Psychiatry, 38*(9), 1132-1138.

Elliott, I., Kadis, D. S., Lach, L., Olds, J., McCleary, L., Whiting, S. et al. (2012). Quality of life in young adults who underwent resective surgery for epilepsy in childhood. *Epilepsia, 53*(9), 1577-1586.

Elliott, I. M., Lach, L., & Smith, M. L. (2005). I just want to be normal: a qualitative study exploring how children and adolescents view the impact of intractable epilepsy on their quality of life. *Epilepsy Behav, 7*(4), 664-678.

Gilliam F, Kuzniecky R, Meador K, Martin R, Sawrie S, Viikinsalo M et al. (1999). Patient-oriented outcome assessment after temporal lobectomy for refractory epilepsy. *Neurology, 53*(4), 687-694.

Go C, & Snead OC 3rd. (2008). Pharmacologically intractable epilepsy in children: diagnosis and preoperative evaluation. *Neurosurg Focus, 25*(3), E2.

Gowda, S., Salazar, F., Bingaman, W. E., Kotagal, P., Lachhwani, D. L., Gupta, A. et al. (2010). Surgery for catastrophic epilepsy in infants 6 months of age and younger. *J.Neurosurg.Pediatr., 5*(6), 603-607.

Harvey AS, Cross JH, Shinnar S, & Mathern BW. (2008). Defining the spectrum of international practice in pediatric epilepsy surgery patients. *Epilepsia, 49*(1), 146-155.

Hauptman, J. S., Pedram, K., Sison, C. A., Sankar, R., Salamon, N., Vinters, H. V. et al. (2012). Pediatric Epilepsy Surgery: Long-term 5-Year Seizure Remission and Medication Use. *Neurosurgery, 71*(5), 985-993.

Health Quality Ontario. (2012). About the Ontario Health Technology Advisory Committee. *Health Quality Ontario*. Retrieved from http://www.hqontario.ca/evidence/evidence-process/about-the-ontario-health-technology-advisory-committee

Hemb, M., Velasco, T. R., Parnes, M. S., Wu, J. Y., Lerner, J. T., Matsumoto, J. H. et al. (2010). Improved outcomes in pediatric epilepsy surgery: the UCLA experience, 1986-2008. *Neurology, 74*(22), 1768-1775.

Huttenlocher, P. R., & Hapke, R. J. (1990). A follow-up study of intractable seizures in childhood. *Ann Neurol, 28*(5), 699-705.

Ibrahim, G. M., Fallah, A., Albert, G. W., Withers, T., Otsubo, H., Ochi, A. et al. (2012). Occipital lobe epilepsy in children: characterization, evaluation and surgical outcomes. *Epilepsy Res, 99*(3), 335-345.

Jette, N., Quan, H., Tellez-Zenteno, J. F., Macrodimitris, S., Hader, W. J., Sherman, E. M. et al. (2012). Development of an online tool to determine appropriateness for an epilepsy surgery evaluation. *Neurology, 79*(11), 1084-1093.

Jones JE, Austin JK, Caplan R, Dunn D, Plioplys S, & Salpekar JA. (2008). Psychiatric disorders in children and adolescents who have epilepsy. *Pediatr Rev, 29*(2), e9-14.

Kakisaka, Y., Iwasaki, M., Alexopoulos, A. V., Enatsu, R., Jin, K., Wang, Z. I. et al. (2012). Magnetoencephalography in fronto-parietal opercular epilepsy. *Epilepsy Res, 102*(1-2), 71-77.

Kwan P, & Brodie MJ. (2000). Early identification of refractory epilepsy. *N Engl J Med, 342*(5), 314-319.

Labiner, D. M., Bagic, A. I., Herman, S. T., Fountain, N. B., Walczak, T. S., & Gumnit, R. J. (2010). Essential services, personnel, and facilities in specialized epilepsy centers--revised 2010 guidelines. *Epilepsia, 51*(11), 2322-2333.

Lowenstein, D. H. (2011). Interview: the National Institute of Neurological Diseases and Stroke/American Epilepsy Society benchmarks and research priorities for epilepsy research. *Biomark.Med, 5*(5), 531-535.

McLachlan RS. (2001). Commentary on epilepsy surgery in Canada. *Can J Neurol Sci, 28*(1), 4-5.

Mikati, M. A., Ataya, N., Ferzli, J., Kurdi, R., El-Banna, D., Rahi, A. et al. (2010). Quality of life after surgery for intractable partial epilepsy in children: a cohort study with controls. *Epilepsy Res, 90*(3), 207-213.

Ochi A, & Otsubo H. (2008). Magnetoencephalography-guided epilepsy surgery for children with intractable focal epilepsy: SickKids experience. *Int J Psychophysiol., 68*(2), 104-110.

Ontario Health Technology Advisory Committee. (2007). *OHTAC Recommendation: Functional Brain Imaging*. Toronto: Ontario Ministry of Health Technology Advisory Committee: Health Quality Ontario

Ontario Health Technology Advisory Committee. (2012). *OHTAC Recommendation: Care for Drug-Refractory Epilepsy in Ontario*. Toronto: Ontario Ministry of Health Technology Advisory Committee: Health Quality Ontario

RamachandranNair, R., Otsubo, H., Shroff, M. M., Ochi, A., Weiss, S. K., Rutka, J. T. et al. (2007). MEG predicts outcome following surgery for intractable epilepsy in children with normal or nonfocal MRI findings. *Epilepsia, 48*(1), 149-157.

Rodenburg, R., Stams, G. J., Meijer, A. M., Aldenkamp, A. P., & Dekovic, M. (2005). Psychopathology in children with epilepsy: a meta-analysis. *J Pediatr Psychol, 30*(6), 453-468.

Statistics Canada. (2012). *Population and dwelling counts, for Canada, for provinces and territories, 2011 and 2006 censuses (tables). Population and Dwelling Count Highlight Tables. 2011 Census*.

Sugimoto, T., Otsubo, H., Hwang, P. A., Hoffman, H. J., Jay, V., & Snead, O. C., III. (1999). Outcome of epilepsy surgery in the first three years of life. *Epilepsia, 40*(5), 560-565.

Swarztrauber K. (2004). Barriers to the management of patients with surgically remediable intractable epilepsy. *CNS Spectr, 9*(2), 146-152.

Swarztrauber K, Dewar S, & Engel J Jr. (2003). Patient attitudes about treatments for intractable epilepsy. *Epilepsy Behav, 4*(1), 19-25.

Tellez-Zenteno JF, Dhar R, & Wiebe S. (2005). Long-term seizure outcomes following epilepsy surgery: a systematic review and meta-analysis. *Brain, 128*(Pt 5), 1188-1198.

Tellez-Zenteno, J. F., Pondal-Sordo, M., Matijevic, S., & Wiebe, S. (2004). National and regional prevalence of self-reported epilepsy in Canada. *Epilepsia, 45*(12), 1623-1629.

Theodore, W. H., Spencer, S. S., Wiebe, S., Langfitt, J. T., Ali, A., Shafer, P. O. et al. (2006). Epilepsy in North America: a report prepared under the auspices of the global campaign against epilepsy, the International Bureau for Epilepsy, the International League Against Epilepsy, and the World Health Organization. *Epilepsia, 47*(10), 1700-1722.

Turon-Vinas, E., Lopez-Casas, A., Palacio-Navarro, A., Donaire, A., Garcia-Fructuoso, G., Rumia, J. et al. (2010). [Five years' experience in a paediatric epilepsy unit]. *Rev Neurol, 51*(8), 451-460.

Vasconcellos, E., Wyllie, E., Sullivan, S., Stanford, L., Bulacio, J., Kotagal, P. et al. (2001). Mental retardation in pediatric candidates for epilepsy surgery: the role of early seizure onset. *Epilepsia, 42*(2), 268-274.

Vendrame, M., Alexopoulos, A. V., Boyer, K., Gregas, M., Haut, J., Lineweaver, T. et al. (2009). Longer duration of epilepsy and earlier age at epilepsy onset correlate with impaired cognitive development in infancy. *Epilepsy Behav., 16*(3), 431-435.

Wiebe S, Blume WT, Girvin JP, & Eliasziw M. (2001). A randomized, controlled trial of surgery for temporal-lobe epilepsy. *N Engl J Med, 345*(5), 311-318.

Wiebe, S., Bellhouse, D. R., Fallahay, C., & Eliasziw, M. (1999). Burden of epilepsy: the Ontario Health Survey. *Can J Neurol Sci, 26*(4), 263-270.

Wiebe, S., & Jette, N. (2012). Pharmacoresistance and the role of surgery in difficult to treat epilepsy. *Nat.Rev.Neurol., 8*(12), 669-677.

Williams, J., Steel, C., Sharp, G. B., DelosReyes, E., Phillips, T., Bates, S. et al. (2003). Anxiety in children with epilepsy. *Epilepsy Behav, 4*(6), 729-732.

Wright JG, & Menaker RJ. (2011). Waiting for children's surgery in Canada: the Canadian Paediatric Surgical Wait Times project. *CMAJ, 183*(9), E559-E564.

Wu, D. Y., Ding, D., Wang, Y., & Hong, Z. (2010). Quality of life and related factors in Chinese adolescents with active epilepsy. *Epilepsy Res, 90*(1-2), 16-20.

Wu, X. T., Rampp, S., Buchfelder, M., Kuwert, T., Blumcke, I., Dorfler, A. et al. (2012). Interictal magnetoencephalography used in magnetic resonance imaging-negative patients with epilepsy. *Acta Neurol Scand*.

Zupanc, M. L., Rubio, E. J., Werner, R. R., Schwabe, M. J., Mueller, W. M., Lew, S. M. et al. (2010). Epilepsy surgery outcomes: quality of life and seizure control. *Pediatr Neurol, 42*(1), 12-20.

Figure 1: Overview of process to determine surgical candidacy and data collection points

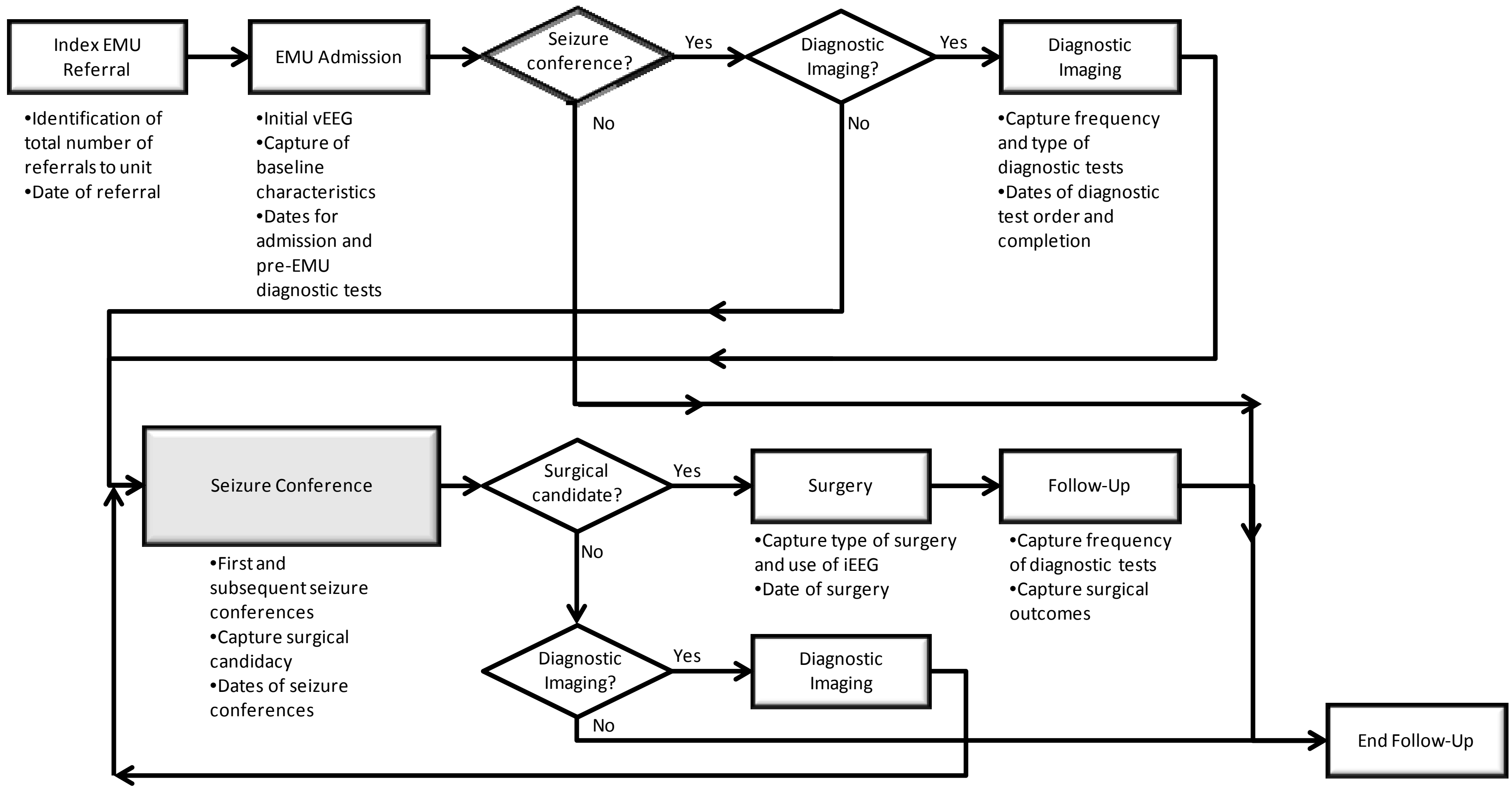

Figure 2: Flow diagram of children referred to seizure conference for assessment of surgical candidacy

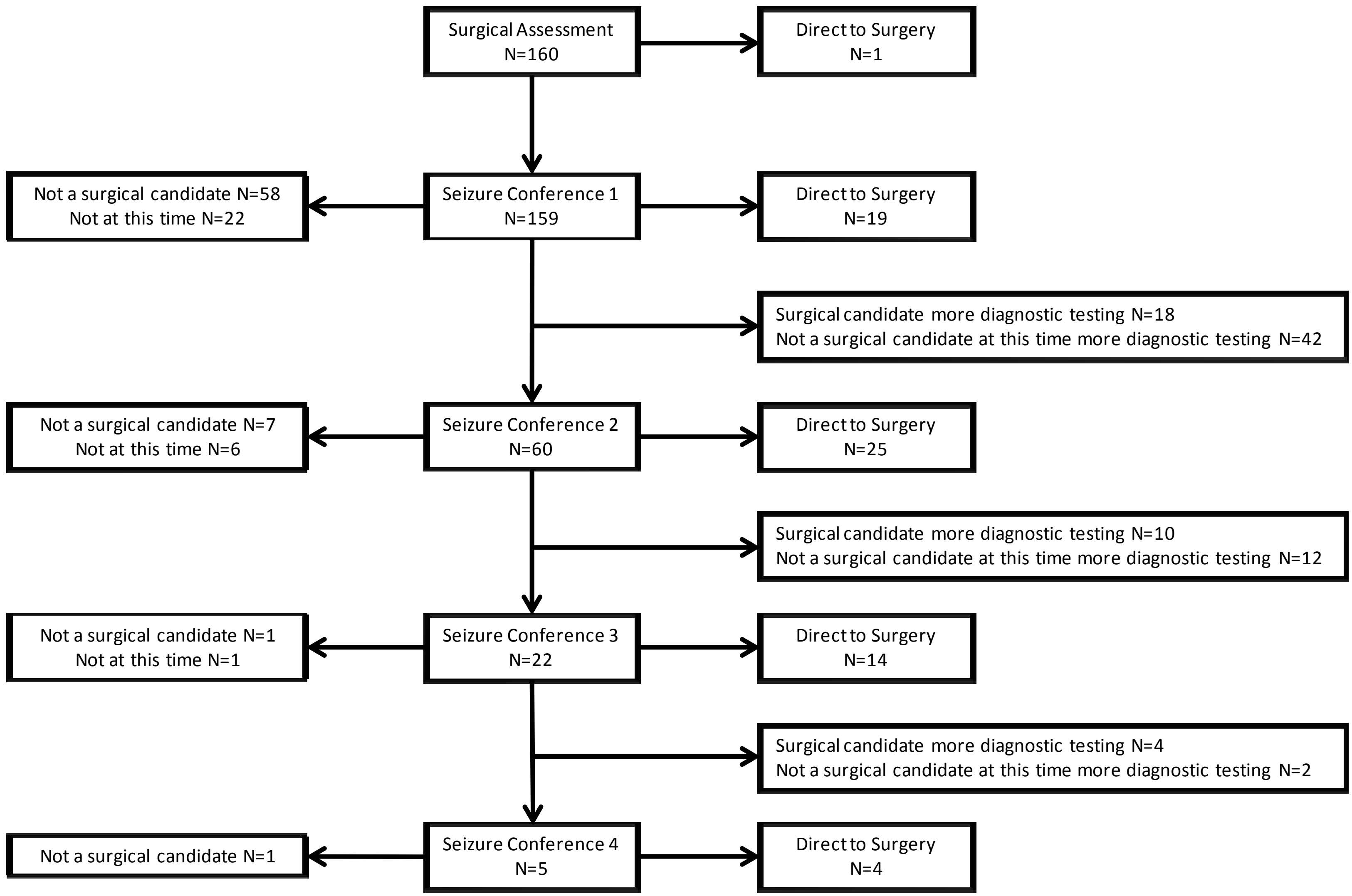

Table 1: Demographics and video electroencephalography characteristics

	Did not proceed to seizure conference	Seizure conference		Overall	p-value
		Not a surgical candidate	Surgical candidate		
	n=59	n=104	n=56	n=219	
Age at first seizure	5.02 (4.1)	4.07 (3.85)	4.92 (4.72)	4.53 (4.16)	0.32
Age at EMU referral	10.15 (4.50)	9.84 (4.29)	10.13 (5.15)	9.99 (4.52)	0.89
Age at EMU admission	10.49 (4.48)	10.11 (4.27)	10.34 (4.86)	10.27 (4.47)	0.86
Duration of vEEG days†	1 (1,5)	3 (1,4)	3 (1,8)	2 (1,8)	0.40
Seizure frequency per day	3.60 (5.73)	4.48 (11.52)	3.67 (5.44)	4.05 (8.91)	0.80
Seizure duration (minutes)†	0.5 (0.03,240)	1.0 (0.03,60)	1.0 (0.03,7)	1.0 (0.03,240)	0.23

Mean (SD), † median (min, max)

Table 2: Time intervals between first seizure and epilepsy monitoring unit and seizure conferences

Time Interval	(% n)	No seizure conference n=59	Seizure conference: Not a surgical candidate n=104	Seizure conference: Surgical candidate n=56	Overall n=219	p-value
First seizure to first EMU referral (years)		3.83 (0.26,15.88)	5.35 (0.04,14.12)	3.71(0.01,14.14)	4.59 (0.01,15.88)	0.55
Age group (years)						
<5	(19%)	0.9 (0.26,3.07)	1.65 (0.19,5.90)	0.82 (0.01,2.48)	1.11 (0.01,5.9)	
6 to 10	(38%)	3.45 (0.65,10.43)	5.18 (0.04,9.9)	5.54 (1.75,8.45)	4.9 (0.04,10.43)	
11 to 15	(34%)	8.31 (0.76,12.89)	10.67 (0.3,14.12)	6.67 (0.3,14.14)	8.87 (0.3,14.14)	
16, 17	(9%)	3.64 (1.94,15.88)	7.0 (1.05,13.15)	4.5 (0.63,8.0)	4.2 (0.63,15.88)	
Index EMU referral to EMU admission (days)		121 (0,266)	93 (0,431)	88 (0,326)	97 (0,431)	0.36
EMU admission to 1st SC (days)			65 (4,555)	86 (2,1423)	71 (2,1423)	0.02*
1st to 2nd SC (days)			238 (71,954)	168 (0,441)	182 (0,954)	0.42
2nd to 3rd SC (days)			224 (140,308)	154 (45,693)	182 (45,693)	0.09
3rd to 4th SC (days)			99 (77,140)	560 (28,574)	140 (28,574)	0.51
Surgical candidacy to surgery (days)				139 (2,992)		
First seizure to surgery (years)				5.3 (0.7,16.6)		
Index EMU referral to surgery (years)						
iEEG				1.6 (0.02,3.3)		
no iEEG				1.1 (0.04,4.3)		

Median (min, max), *statistically significant at the 5% level

EMU- Epilepsy Monitoring Unit, SC – Seizure Conference, iEEG – intracranial electroencephalography

Table 3: Total diagnostic tests completed and time to completion

Diagnostic Test	Pre-EMU	Between seizure conferences: Non-surgery cases	Between seizure conferences: Surgery cases	Post-operative	Follow-up	Total	Time to completion†
	n	n	n	n	n	n	median (min, max)
MRI	197	18	27	10	40	292	102 (1, 370)
EEG	168	0	2	5	51	226	175 (0, 651)
Full sequence MRI	0	1	8	0	128	137	118 (15, 392)
CT	28	1	0	92	9	130	15 (0, 126)
MEG	45	25	48	0	9	127	77 (3, 443)
NPA	19	6	28	0	12	65	139 (14, 400)
fMRI	13	7	27	0	1	48	120 (36, 456)
vEEG	22	1	12	0	2	37	61 (0, 441)
PET	8	3	0	0	0	11	116 (65, 166)
Other	25	2	23	0	3	53	

†Time intervals do not include post-operative. Time to completion = time between test ordered and performed

MRI-magnetic resonance imaging, EEG-electroencephalography, CT-computer tomography, MEG-magnetoencephalography, NPA-neuropsychological assessment, fMRI-functional MRI, vEEG-video EEG, PET-positron emission tomography

Table 4: Clinical outcomes – Seizure freedom and reduction at one year

		% seizures post-surgery relative to baseline		
Surgery	N	None (n)	Reduced (n)	More (n)
Temporal Lobectomy	22	82 (18)	9 (2)	9 (2)
Temporal and Extratemporal Lesionectomy†	24	75 (18)	21 (5)	4 (1)
Temporal and Extratemporal Cortical Resection	2	50 (1)	50 (1)	
Hemispherectomy	2	50 (1)	50 (1)	
Corpus callosotomy‡	2	0	100 (2)	
No Resection‡	1	100 (1)	0	
Overall	53	74 (39)	21 (11)	6 (3)

† post-operative mortality (n=1), ‡ no follow-up data available (n=2)

There were 51 for follow-up

CHAPTER 4

A Discrete Event Simulation Model to Evaluate Access to Surgery for Children with Medically Refractory Epilepsy

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Abstract

Background: Timely access to surgery for children with medically refractory epilepsy (MRE) is imperative as neurodevelopmental, behavioural, and social development problems are associated with years of uncontrolled seizures and poor quality of life. The purpose of this research is to develop and validate a discrete event simulation (DES) model of the current system for determination of epilepsy surgery candidacy in children with MRE at the primary provincial children's hospital and to evaluate strategies to decrease waiting times and meet proposed benchmarks.

Methods: In collaboration with the Hospital for Sick Children (SickKids) in Toronto, Canada, a DES model was developed in several phases: mapping patient flow, programming the simulation software (Arena®), and estimating inputs using data from a retrospective chart review. Model validation included consultation with key stakeholders at SickKids, debugging, and goodness-of-fit with the system. Model outputs were defined as total time to surgery and waiting time. Simulation analysis was conducted on resources to inform the development of alternate resource configurations to increase access and meet benchmarks.

Results: Clinical care was described by 4 modules: Epilepsy Monitoring Unit (EMU) (the entry point for diagnostic evaluation), multimodal diagnostic assessment, multidisciplinary seizure conference (SC), and surgery. Based on the analyses of different resource capacities the following increases in resources were found to meet the institution's goals: 2 EMU beds (30 days), 2 invasive monitoring surgeries (1.4 years) and 6 non-invasive monitoring surgeries (1 year), and limiting the number of repeat SCs to 2.

Conclusions: This study presents a DES model that can be used for operational planning. It identified bottlenecks and proposed the efficient resource configurations to reach the goal of improving access by decreasing waiting times.

INTRODUCTION

Epilepsy is a common neurological disorder that affects approximately 0.6% of Canadians with 15,500 newly diagnosed cases a year, ranking higher than diseases such as colon cancer [1]. Diagnosis will occur before the age of 10 in 55% of those afflicted [1]. In Ontario (population of 13 million), approximately 65,000 individuals suffer from epilepsy of which 10,000 are children [2]. One third of those with epilepsy will be unresponsive to 2 or more anti-seizure medications; defined as having medically refractory epilepsy (MRE) [3]. Left uncontrolled, MRE dramatically affects the quality of life of both those and the families of those afflicted through learning disabilities, behavioural problems, loss of motor functions and psychiatric disorders [4-6]. At the healthcare system level, MRE costs eight times more than those with controlled epilepsy [7].

Surgery to treat MRE has been shown to be effective in seizure remission and reduction while improving quality of life [5,8-10], however, despite strong evidence supporting the efficacy of surgery in this regard, many of those suffering from MRE who are potential candidates for epilepsy surgery continue to go untreated. In 2010, only 3.75% (430 adults and 309 children) of those with MRE were evaluated for surgery [11] and less than 2% of the eligible population received surgery [12]. Even with a referral, children with MRE are faced with prolonged waiting times for evaluation of surgical candidacy and surgery [13]. Considering the number of neurodevelopmental, behavioural, and social development problems associated with years of uncontrolled seizures [14], timely access to treatment is essential.

In recognition of inadequate access to epilepsy care, the Ontario Health Technology Advisory Committee (OHTAC), a provincial body that makes recommendations on the uptake and diffusion of health interventions in Ontario [15], requested the creation of a Provincial Epilepsy Strategy Working Group (further referred to as the Working Group) to address the problem. With representation from all of the centres in the province providing specialized care for epilepsy for both children and adults, the Working Group set out to identify barriers and recommend strategies to improve access to diagnostic and surgical services [2,11,13]. They proposed a provincial strategy to increase capacity and re-organize services into epilepsy specific care centres (ESCC) whereby a regional epilepsy centre offering full services including surgery would act as a hub and district epilepsy centres would feed into the hub and offer only diagnostic services and medical management. Following a review of the evidence, OHTAC has endorsed the implementation of this strategy to the Ministry of Health and Long-Term Care in Ontario [11] where the recommendation is currently under consideration.

Under the proposed strategy, the Hospital for Sick Children (SickKids) in Toronto, the primary paediatric epilepsy surgery referral center for the province, would become a regional hub for children, dramatically affecting referral rates for surgical evaluation and surgery for this institution and the province. Children are already waiting between 5 and 8 months between decision for surgery and surgery, with a total time from surgical evaluation to surgery of over 1.5 years [13]. Demand is currently greater than capacity and so any changes in healthcare delivery will impact time to treatment. Modeling the surgical evaluation process would provide useful information to decision makers about current system resource capacity constraints and potential solutions to reduce waiting times.

Discrete event simulation (DES) is a systems analysis tool that integrates patient flow with resource utilization and capacity constraints (e.g. number of beds) in order to identify the magnitude of system changes on waiting times and resource utilization. Compared with traditional decision analytic models used to evaluate healthcare interventions (e.g. Markov model), a DES model can estimate unintended consequences due to feedback and waiting times due to the use of queuing theory and the way time is treated (moving forward versus cycles). However, the true advantage lies in the ability to vary resources to determine effects on system performance (i.e. waiting times).

Addressing the issue of waiting times and resource capacity involves multiple levels of the healthcare system (i.e. micro, meso, macro). The goals of the patient, institution and province need to be considered in order to develop policy that optimizes the goals of all those affected. DES is a tool that can link these goals using data from all health system levels to inform the model. The objective of this article is to outline the methods used to develop and validate a DES model as an aid to decision making. The purpose of the DES is to model the current system for determination of epilepsy surgery candidacy in children with MRE at SickKids and to evaluate the effect of alternative resource capacities on waiting times and meet system benchmarks proposed by SickKids.

METHODS

A DES model was developed and validated using data collected through a field evaluation previously conducted at the paediatric hospital [2]. Development of the simulation model began with building a conceptual model of the surgical evaluation process at SickKids. Following description of the conceptual model, the methods of data collection and analysis are presented, as is the development of the simulation model including its validation and analysis.

Conceptual Model

The simulation model is based on the process at SickKids to evaluate MRE children (<18 years old) for surgical candidacy. The conceptual model is organized in four modules (Figure 1): 1) epilepsy monitoring unit (EMU), 2) diagnostic imaging and neuropsychological assessment, 3) multidisciplinary seizure conference, and 4) surgery.

Epilepsy monitoring unit: Patients enter the evaluation process through referral to the EMU for video electroencepholgraphy (vEEG). The vEEG is a monitoring device involving electrode placement on the scalp to record electrical activity of the brain, the electroencephalogram (EEG). Patients are videotaped to monitor any seizure associated behaviours and the video is time locked to the EEG so that any EEG correlate with behaviour can document seizure. For the purposes of the model, the duration of the vEEG can vary from overnight (16 hours) to 5 days. The EMU is open on weekdays and can maximally accommodate 3 prolonged (> 8 hours) vEEG patients and 1 overnight vEEG a week on the 3 bed unit (at the time of the evaluation). Following completion of vEEG monitoring three potential outcomes are possible. First, patients may be considered ineligible for surgery based on the EEG or clinical characteristics (semiology of the seizure). If this is the case, a medical treatment plan is prescribed and care is transferred back to the referring physician. Second, based on the EEG and semiology, the case may be sent directly to seizure conference. Finally, the EEG and semiological data may be suggestive of surgical candidacy, but further diagnostic testing is undertaken prior to presentation at seizure conference.

Diagnostic Imaging: When required, further diagnostic evaluation consists of one or more of the following: magnetoencephalography (MEG), 3 Tesla magnetic resonance imaging (MRI), functional MRI (fMRI), positron emission tomography (PET), evoked potentials (EP), and neuropsychological assessment (NPA).

Seizure conference: Once all ordered diagnostic tests needed to make a surgical decision are complete the patient's case is scheduled for seizure conference review. The seizure conference is a multidisciplinary meeting amongst epileptologists, neurosurgeons, neuropsychologists, psychometrists, radiologists, nurses, nurse practitioners, social workers, pharmacists, EEG technologists, and others to determine the patient's surgical candidacy [16]. Seizure conferences occur once a week for 50 weeks of the year where 4 patient cases are reviewed at each meeting. There are three possible patient outcomes of a seizure conference: 1) patient is a surgical candidate and is scheduled for surgery, 2) patient is not a surgical candidate, and 3) surgical candidacy remains uncertain and the patient is sent for further diagnostic testing. In the latter case, once diagnostics are completed, the patient returns to seizure conference for surgical candidacy re-evaluation. For the purpose of the model we assume a patient will have no more than three seizure conferences as further multidisciplinary assessment is seldom required [13].

Surgery: For patients determined to be surgical candidates, a meeting is scheduled with the family to discuss whether they would like to proceed with surgery. Once the decision is made to proceed, patients are scheduled for surgery. As a component of the diagnostic assessment, it is determined a priori whether a patient will require an intracranial EEG grid (iEEG) at time of surgery to determine the precise localization of the epileptogenic focus and the location of eloquent cortex, i.e. motor, sensory, and language before resection. iEEG entails the surgical placement of electrodes on and in the brain with subsequent monitoring of the EEG directly from the surface of the brain for several days 24/7 in order to capture and accurately map seizures. A brain map is then created and the data analyzed in order to make a decision as to whether to proceed to epilepsy surgery. In the model, scheduling differs depending on whether the patient requires iEEG as extra resources are required for grid placement and monitoring. Current monthly surgical capacity consists of one surgery a month requiring iEEG, whereas up to two non-iEEG surgeries can be scheduled each month. Surgeries are generally completed during week days (5 days per week). If required, an iEEG grid (electrodes to monitor electrical activity) is inserted on the Monday. In this case, a CT scan to assess grid placement, VEEG from the grid, analysis of data, grid removal and surgical resection of the epileptic focus as mapped out by the grid recording can occur in the following 4 days. Before resection the family is presented with the data and the recommendations for or against epilepsy surgery and a parental decision is reached. The child then returns to surgery and the grid and electrodes are removed and, if indicated, surgical resection of the epileptic focus is done. Following surgery and the associated inpatient stay, the patient is discharged and she/he returns for follow-up every three months for a year. If a neurological deficit occurs as a result of the surgery, the patient undergoes either inpatient or outpatient neuro rehabilitation, depending upon the severity of the deficit. As shown by the data, included in the DES is a 1% chance of surgical mortality.

Data Collection and Input Analysis

Data from a field evaluation was used to populate the model. It was collected through a retrospective chart review between April 1, 2004 and March 31, 2006 of all patients referred to the EMU at SickKids. Details on EMU admission, seizure and medical history, seizure conferences, surgery and follow-up were collected as part of the field evaluation. For more information on data collection methods the reader is referred to the study report [2] and publication [13].

Within the data collection period, 349 patients were referred to the EMU for overnight or prolonged vEEG over the two year period. Based on this data a new patient referral was made every 2.5 days with an exponentially distributed inter-arrival rate. The following parameters were also estimated: probability of referral for certain diagnostics (MEG, MRI, fMRI, NPA, other diagnostics (PET, EEG and EP)), probability of proceeding to seizure conference and number of seizure conferences, probability of becoming a surgical candidate (yes, no, further diagnostics needed) and probability of receiving iEEG prior to surgical resection. The following durations were also estimated: vEEG and time from diagnostic referral to completion for each test. Based on the time of data collection, the following resources were assumed: 3 beds in the EMU, 1 seizure conference team and 1 surgical team. Table 1 presents the model parameters and distributions.

We performed data tabulation and statistical analyses using STATA Intercool 12.0 and derived distributions using Arena®'s Input Analyzer, which fits probability distribution functions based on a set of data. We assessed goodness-of-fit using the Chi-square test and a corresponding p-value of 0.05.

Simulation Model Development and Validation

The conceptual model was used to inform development of a DES model using Arena® 13.9. Both the conceptual and simulation models were developed in collaboration with members of the Working Group. Including these individuals in the process built trust and understanding of the model which was essential for it to be used as a decision support tool. As a result, the model was developed through an iterative process of constant feedback from the members.

We pre-loaded initial waiting times based on the empirical data from SickKids for the EMU and surgery to reflect the current state of the system [17]. Patients arrive in the model based on a daily referral rate to the EMU and are assigned as needing either an overnight or prolonged vEEG. Arrivals are based on a Poisson process and are exponentially distributed. A patient schedule for the EMU is generated based on a first in first out (FIFO) priority and an occupancy rate of 3 prolonged and 1 overnight vEEGs a week. The EMU is closed for three weeks of the year due to conferences, equipment maintenance and weeks when a surgery requiring iEEG is scheduled. Patients wait until their scheduled EMU appointment before proceeding. Following the EMU, the patient may be sent for multiple diagnostic tests (up to 5) or proceed directly to the seizure conference queue. If sent for diagnostic tests, they must wait until results from all tests have been received before proceeding to seizure conference. This process is repeated each time the patient is sent for diagnostic testing. The seizure conference queue is prioritized based on FIFO. Following seizure conference, patients can proceed through one of five transitions (Table 1, Figure 1): 1) considered a surgical candidate proceed directly to surgical queue, 2) considered a surgical candidate proceed for more diagnostic tests, 3) not considered a surgical candidate at this time proceed for more diagnostic tests, 4) no decision at this time and exits the evaluation process and 5) not a surgical candidate and exits the evaluation process. If the patient is sent for further diagnostic testing they must wait for all results before re-entering the seizure conference queue for surgical candidacy re-assessment. If the patient is determined to be a surgical candidate a decision is also made as to whether the patient requires iEEG at surgery to determine resection location. Following this decision the family decides whether they want to proceed with surgery. If no, the patient exits the model. If yes, they are then scheduled for surgery. Two separate surgical schedules (one for iEEG and one for non-iEEG patients) are generated based on FIFO. While waiting for their surgery date, all patients requiring iEEG are scheduled for a grid fitting in the EMU and are considered overnight patients. The patient must re-enter the EMU queue for scheduling. After surgery, patients have follow-up and then leave exit the model.

Following the Schellenberger framework [18], we implemented a number of validation steps to ensure the simulation model accurately represented the surgical evaluation process. The conceptual model and subsequently the simulation model were first presented and verified with members of the working group to certify assumptions aligned with their perceptions of the process. Additionally, the process ensured the correct level of detail was included for decision making purposes. Logical validity of the simulation model was assessed by running sub-cohorts through the model under specific conditions and ensuring the model outcome matched with the logical outcome (e.g. if probability of receiving an MRI is 1 then the model should predict all patients receive MRI). Predictive validity was assessed by comparing 95% confidence intervals (CI) of model outputs for key metrics with observed data. For validation the simulation was run using 350 patients to reflect the number of patients in the observed data over the 2 year period. The simulation was run over 1000 replications and initialized with alternative random seeds between each replication to account for stochasticity. This number of replications created 95% CIs within 5% of the mean for all outputs. This provides enough precision to be confident that the mean across replications is a reflection of the mean output for the simulation model. Lastly, a final presentation of the simulation model and outputs was made to members of the working group to ensure the degree of differences between predicted and observed outcomes were acceptable from a clinical and operational perspective. Acceptance of the model and outputs by the users also shows face validity.

Simulation Analysis

Analyses were performed on the base case to draw insights into the effects of changing resource capacity on waiting times associated with stages in the surgical evaluation process. Current resource capacities cause EMU referrals to wait 103 days for EMU admission, surgical patients receiving iEEG to wait approximately 1.64 years (95% CI 1.3-1.9) between EMU referral and surgery and surgical patients not receiving iEEG to wait approximately 1.11 years (95% CI 0.75-1.47) [13]. Waiting times of 30 days to proceed from EMU referral to admission and 1.5 years (with iEEG) and 1 year (without iEEG) to proceed from EMU referral to surgery have been suggested as benchmarks. To achieve these benchmarks analyses were conducted by investigating system effects of increasing EMU (additional prolonged and overnight vEEG capacity), number of patients processed at seizure conference, and surgical capacity. When including additional surgeries with iEEG, the EMU was also shut down for that week to re-allocate resources to observe the patient. Based on the results of these analyses, alternative resource configurations to increase access to surgery were proposed and tested against the simulation estimates (i.e. base case).

In order to compare with the base case, each scenario was evaluated as a terminating system with a five year time horizon over 1000 independent replications to ensure tight 95% CIs over relevant output measures. Q-Q plots were used to test for normality of the output measures of the base case and alternate resource configurations before determining statistical differences using a two sample t-test.

RESULTS

Simulation Model Validation

Table 2 presents a comparison based on important decision making operational outcomes. The 95% CIs between the observed data and the predicted outputs from the simulation overlap considerably, suggesting the model predicts accurately. Overall, the mean differences ranged from 2 to 32 percent between observed and predicted values, deemed acceptable by the Working Group. Total time in system for surgical patients not requiring iEEG differed the most by 32%, however, the simulation mean still fell within the 95% CI of the observed data. Additional outputs were generated and compared with the observed data: number of patients proceeding to seizure conference, number of seizure conferences each patient receives, number of surgical patients, number of dropouts, and number of diagnostic imaging tests received. Differences between the observed data were less than 10% for all outputs. The validated results are considered the base case and use for subsequent analyses.

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Simulation Analysis

Following validation, resource capacities were varied individually to assess effect on waiting times and to determine alternative resource configurations to meet proposed benchmarks. The analysis indicated that increasing the number of cases assessed each week at seizure conference did not affect waiting times, therefore further analyses focused on EMU and surgical capacity. Increasing EMU capacity to include one additional prolonged vEEG and one additional overnight vEEG on a weekly basis resulted in an average waiting time of 30 days from EMU referral to admission compared to 118 days in the base case. The increase in throughput from the EMU did not affect time to seizure conference but led to a longer queue for surgery. Increasing the number of annual surgeries with iEEG by two decreased the waiting time for surgery resulting in a total time of 1.4 years (523 days) from EMU referral to surgery compared to 1.7 years in the base case. Scheduling two additional surgeries with iEEG did not have a significant feedback effect on time from EMU referral to admission as the EMU would have to close for two extra weeks a year to allocate the resources for surgery. Annual capacity for surgery without iEEG was increased until only marginal gains were observed between 6 and 9 additional surgeries. The decrease in waiting time for surgery without iEEG tapered off as the average number waiting in queue for surgery without iEEG decreased from 1.3 to <1 suggesting that no more benefits were to be gained from increasing capacity. These results are illustrated in Figure 2.

Based on results from the simulation analyses, two alternative resource configurations were proposed and compared with the base case. The first configuration includes the following increases in capacity: 1 prolonged vEEG (weekly), 1 overnight vEEG (weekly), 2 surgeries with iEEG (annual) and 6 surgeries without iEEG (annual). The second configuration builds on the first increases in capacity but limits the number of seizure conferences to 2 as opposed to 3. Results comparing the base case with the two alternative configurations are presented in Table 3. Alternative configuration one is able to process surgical patients requiring iEEG within the acceptable 1.5 years, however, it does not process surgical patients not requiring iEEG within 1 year. By eliminating the need for a third seizure conference, proposed configuration 2 results in both types of surgical patients being processed under the proposed benchmarks but at the expensive of increased surgical waiting times. Additionally, it bypasses any additional diagnostic tests that may occur between seizure conferences, leading to reduced time to treatment.

DISCUSSION

This paper presents a simulation study of the epilepsy surgical assessment process at SickKids and may be used to help support decision making to increase access to surgical evaluation and surgery for children with MRE in Ontario. Aligned with the Provincial Epilepsy Strategy Working Group recommendations, a DES model was developed and validated. Simulation model results indicated that the number of cases presented weekly at seizure conference does not contribute to the current system’s waiting times and that an increase in EMU capacity and surgical capacity is necessary to provide surgical assessment and treatment within suggested benchmarks. Two alternative resource configurations were proposed to increase access where the main difference between them is in the number of seizure conferences.

In the base case system, patients may return for up to three seizure conferences. Multiple seizure conferences secondary to staged diagnostic imaging can result in the diagnostic findings becoming outdated or a need for different diagnostic imaging tests to determine surgical candidacy. Streamlining diagnostic imaging and standardizing provincial diagnostic imaging regimens may prevent the need to send patients for multiple seizure conferences and therefore decreasing their time to determining surgical candidacy. As shown in the analyses, the issue with increasing seizure conference throughput is that patients will queue longer for surgery. In terms of funding, decision makers will have to decide whether decreasing the total time patients spend in the system from EMU referral to surgery is more pertinent than the waiting time for surgery. This application illustrates the use of these types of models as decision support tools when implementing national, regional or local policies aimed at improving access to care. As discrete event simulation models allow for the integration of capacity constraints, mathematical or simulation models provide greater insight than other types of modeling methods typically used to evaluate healthcare programmes. When simulation studies are conducted in collaboration with the end users it engages key stakeholders in the development process and produces a more unified and comprehensive view of the system. It provides a mechanism for stakeholders to examine their clinical and resource pathways promoting a more meaningful identification of how any change in clinical/surgical management might affect operations.

Despite the strengths associated with this study, there are a few limitations. Firstly, diagnostic imaging tests are not modelled as a resource, only as a delay with an associated distribution based on observed data. Modeling diagnostic imaging tests as a resource would require collecting data on competing patients. Secondly, it was assumed that all patients scheduled for the EMU and surgery did not miss their appointments. However, this should not affect results as the objective was not to optimize the schedule. Thirdly, multiple EMU visits were not implemented in the model, which might have impacted EMU capacity. We assumed the effect to be small as a minimal number of patients (13%) had multiple visits. Fourthly, we estimated a surgical mortality rate of 1%, which may be a slight overestimate as the death in the data was due to sudden unexpected death of epilepsy (i.e. unknown cause). Lastly, due to large variation in the observed data, total time in the system for surgical patients not requiring iEEG produced by the simulation model may be overestimated.

Despite these limitations, our results indicate that in order to provide more timely access to surgical evaluation and surgery, capacity should be expanded. Our simulation study was able to identify the specific resources that needed to be increased. Any re-organization of services through a provincial epilepsy strategy could also require an increase in capacity and a thorough investigation to identify which types of resources should be expanded. For example, our data showed that increasing the number of cases evaluated weekly at seizure conference has a small impact on time to surgery compared to increasing surgical capacity. Although our study provides valuable information, future steps include extending this model in a number of directions: 1) to reflect streamlining diagnostic imaging in order to decrease the number of seizure conferences, 2) incorporate costs and conduct a budget impact analysis, and 3) model the inter-relationship between ESCCs under the proposed provincial strategy to determine the optimal resource configuration. This population is already under serviced and under referred. Increasing the referral rate without increasing capacity will dramatically increase a patient's time in the system. Under the proposed provincial epilepsy strategy, patient referrals would increase as a result of greater awareness in the medical community. Capacity would need to be greatly increased to handle not only the prevalent but also the incident MRE cases if patients are to receive timely service.

CONCLUSION

This study examined issues related to resource capacity at a primary paediatric referral centre related to the surgical evaluation process and surgery for paediatric MRE. It presented the development and validation of a discrete event simulation model that can be used for operational planning. Specifically, it identified bottlenecks and proposed the most efficient resource configuration to reach the goal of improving access by decreasing waiting times. The next step is to determine efficient allocation of resources for the implementation of a provincial strategy in order for those with epilepsy, not just MRE, to receive timely access to care.

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References

1. Epilepsy Canada. Epilepsy Facts. *Epilepsy Canada* 2013. Available: http://www.epilepsy.ca/en-CA/Facts/Epilepsy-Facts.html (accessed 2013 Mar 23).

2. Bowen JM, Snead OC, Hopkins RB, Elliott I, Burke N, Atkin J, et al. Diagnostic evaluation of infants, children and adolescents with epilepsy for surgery candidacy and the role of magnetoencephalography (MEG) [Report No. FEEAP-HTA013a-2011.REP]. Hamilton (ON): Programs for Assessment of Technology in Health, St. Joseph's Healthcare Hamilton/McMaster University; 2011. Available: http://www.path-hta.ca/Libraries/Reports/MEG_OHTAC_report.sflb.ashx

3. Kwan P, Brodie MJ. Early identification of refractory epilepsy. *N Engl J Med* .2000;342(5):314-9.

4. Drewel EH, Bell DJ, Austin JK. Peer difficulties in children with epilepsy: association with seizure, neuropsychological, academic, and behavioral variables. *Child Neuropsychol* .2009;15(4):305-20.

5. Elliott I, Kadis DS, Lach L, Olds J, McCleary L, Whiting S, et al. Quality of life in young adults who underwent resective surgery for epilepsy in childhood. *Epilepsia* .2012;53(9):1577-86.

6. Jones JE, Austin JK, Caplan R, Dunn D, Plioplys S, Salpekar JA. Psychiatric disorders in children and adolescents who have epilepsy. *Pediatr Rev* .2008;29(2):e9-14.

7. Jacoby A, Buck D, Baker G, McNamee P, Graham-Jones S - Chadwick. Uptake and costs of care for epilepsy: findings from a U.K. regional study. *Epilepsia* .1998;39(7):776-86.

8. D'Argenzio L, Colonnelli MC, Harrison S, Jacques TS, Harkness W, Scott RC, et al. Seizure outcome after extratemporal epilepsy surgery in childhood. *Dev Med Child Neurol* .2012;54(11):995-1000.

9. Hauptman JS, Pedram K, Sison CA, Sankar R, Salamon N, Vinters HV, et al. Pediatric Epilepsy Surgery: Long-term 5-Year Seizure Remission and Medication Use. *Neurosurgery* .2012;71(5):985-93.

10. Tellez-Zenteno JF, Dhar R, Wiebe S. Long-term seizure outcomes following epilepsy surgery: a systematic review and meta-analysis. *Brain* .2005;128(Pt 5):1188-98.

11. Ontario Health Technology Assessment Committee. OHTAC Recommendation: Care for Drug-Refractory Epilepsy in Ontario. Toronto: Ontario Ministry of Health Technology Advisory Committee: Health Quality Ontario; 2012. Available: http://www.hqontario.ca/fr/mas/pdfs/EpilepsyOHTACRec20120605ac.pdf

12. Bowen JM, Snead OC, Chandra K, Blackhouse G, Goeree R. Epilepsy care in Ontario: an economic analysis of increasing access to epilepsy surgery. *Ont Health Technol Assess Ser* .2012;12(18):1-41.

13. Lim ME, Bowen JM, Snead III OC, Elliott I, Donner E, Weiss SK, et al. Access to Surgery for Paediatric Patients with Medically Refractory Epilepsy: A Systems Analysis. *Epilepsy Research* .2013;In submission.

14. Ibrahim GM, Barry BW, Fallah A, Snead OC 3rd, Drake JM, Rutka JT, et al. Inequities in access to pediatric epilepsy surgery: a bioethical framework. *Neurosurg Focus* .2012;32(3):E2.

15. Health Quality Ontario. About the Ontario Health Technology Advisory Committee. *Health Quality Ontario* 2012. Available: http://www.hqontario.ca/evidence/evidence-process/about-the-ontario-health-technology-advisory-committee (accessed 2013 May 16).

16. Go C, Snead OC 3rd. Pharmacologically intractable epilepsy in children: diagnosis and preoperative evaluation. *Neurosurg Focus* .2008;25(3):E2.

17. Karnon J, Stahl J, Brennan A, Caro JJ, Mar J, Möller J, et al. Modeling using discrete event simulation: a report of the ISPOR-SMDM Modeling Good Research Practices Task Force--4. *Value in Health* .2012;15(6):821-7.

18. Schellenberger R. Criteria for Assessing Model Validity for Managerial Purposes. *Decision Sciences* .1974;5(4):644-53.

Table 1: Model inputs

Parameter	**Value**			
Initial Values (days)				
Initial wait time EMU	90			
Initial wait time seizure conference	90			
Initial wait times surgery	365			
Epilepsy Monitoring Unit				
Patient referral rate (inter-arrival rate)	Exponential (2.45)			
Probability of proceeding to seizure conference from EMU	0.46			
Probability of proceeding to diagnostic imaging before seizure conference	0.30			
	Probability			
Diagnostic Imaging Tests	**Seizure conference 1**	**Seizure conference 2**	**Seizure conference 3**	**Time ordered to completion (days)**
MEG	0.77	0.55	0.23	Exponential (103) + 3
MRI	0.63	0.27	0.09	Triangular (14, 90, 370)
fMRI	0.28	0.25	0.32	Triangular (36,120,456)
NPA	0.28	0.32	0.14	Weibull (149,1.18) + 14
Other diagnostics	0.07	0.43	0.72	Exponential (109) - 0.001

EMU-epilepsy monitoring unit, vEEG-video electroencephalography, MEG-magnetoencephalography, MRI-magnetic resonance imaging, fMRI-functional MRI, NPA-neuropsychological assessment, iEEG-intracranial EEG

Table 1 continued: Model inputs

Parameter	Value		
	Probability		
Seizure Conference Decisions	**Seizure conference 1**	**Seizure conference 2**	**Seizure conference 3**
1: Surgical candidate go directly to surgery queue	0.12	0.42	0.64
2: Surgical candidate proceed for more diagnostics	0.12	0.17	0.18
3: Not at this time, dropout	0.14	0.1	0.05
4: Not at this time proceed for more diagnostics	0.28	0.2	0.09
5: Not a surgical candidate, dropout	0.34	0.12	0.05
Surgery			
Probability of dropout due to family decision	0.04		
Time for family decision (days)	63		
Probability of needing an iEEG	0.46		

iEEG-intracranial EEG

Table 2: Simulation output compared to observed data from SickKids for primary operational outcomes

Operational outcomes	Observed (days)	Simulation (days)	Difference
Waiting time from EMU referral to EMU admission	116.3 (107.7-124.9)	118.4 (116.84-119.93)	2%
Time from EMU admission to 1st seizure conference*	80.1 (67.1-93.1)	81.9 (81.4-82.4)	2%
Waiting time for surgery with iEEG	221.8 (141.9-301.7)	273.1 (268.2-278.0)	23%
Waiting time for surgery without iEEG	148.9 (100.4-197.5)	152.2 (149.8-154.6)	2%
Total time in system - seizure conference, non-surgical	272.5 (231.9-313.2)	250.8 (248.9-252.6)	-8%
Total time in system - surgical (with iEEG)	598.7 (473.2-724.1)	660.9 (655.9-665.9)	10%
Total time in system - surgical (without iEEG)	405.3 (272.3-538.28)	535.6 (532.6-538.7)	32%

*Includes time for diagnostic imaging and waiting time for seizure conference

(95% confidence interval)

Table 3: Performance differences between base case and proposed alternatives

Performance measurement	Base Case	Alternative 1	Alternative 2
Epilepsy Monitoring Unit			
Patients waiting for EMU admission (n)	19.6	4.9	4.95
Waiting time from EMU referral to EMU admission (days)	118.4	30.59	30.61
Seizure Conference			
Patients waiting for seizure conference (n)	0.7	0.95	0.91
Time from EMU admission to 1st seizure conference (days)*	81.9	84.4	84.56
Surgery			
Patients waiting for iEEG (n)	2.37	2.02	2.66
Patients waiting for non iEEG (n)	1.25	0.44	0.73
Waiting time for surgery with iEEG (days)	273.1	214.74	260.85
Waiting time for surgery without iEEG (days)	152.2	94.54	112.16
Total time in system			
Patients with no seizure conference (days)	120.4	32.51	32.52
Patients with seizure conference, non surgical (days)	250.8	166.02	151.58
Patients with surgery with iEEG (days)	660.9	517.09	511.89
Patients with surgery without iEEG (days)	535.6	395.83	364.68

*Includes time for diagnostic imaging and waiting time for seizure conference

Output magnitude differences with the base case are all statistically significant ($p<0.05$)

Alternative 1: Addition of 1 prolonged vEEG, 1 overnight vEEG, 2 surgeries with iEEG, 2 surgeries without iEEG

Alternative 2: Alternative 1 and maximum of only 2 seizure conferences

Figure 1: Patient flow once referred to epilepsy monitoring unit

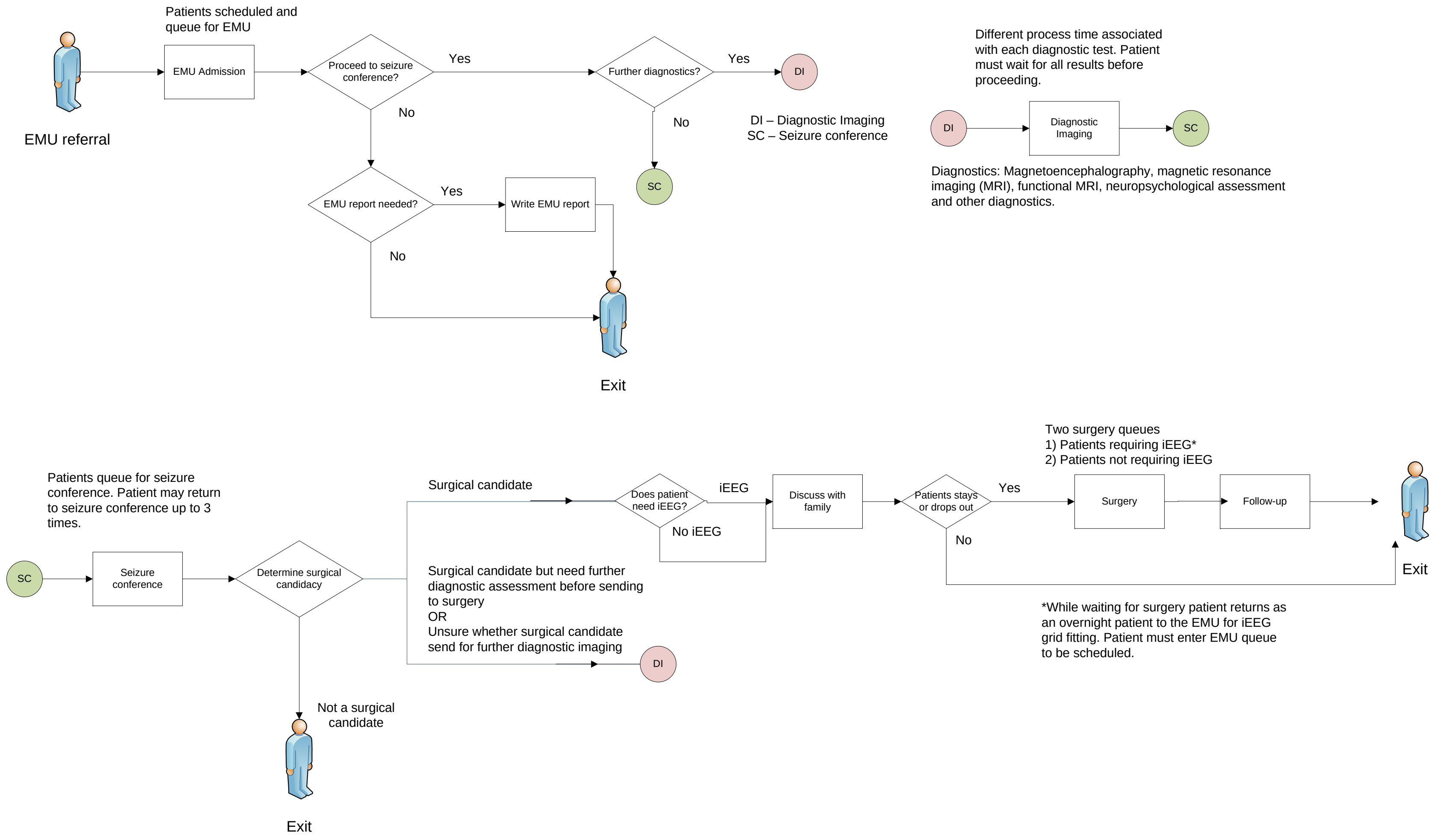
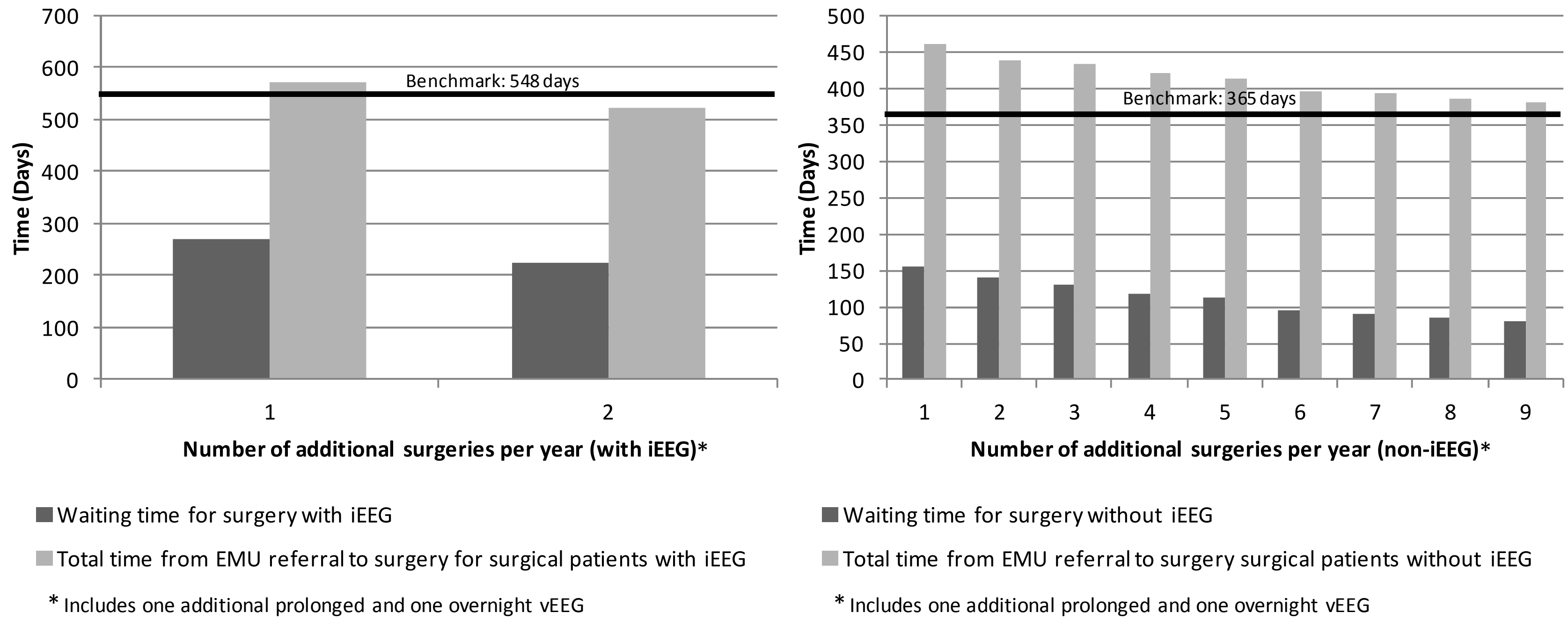


Figure 2: Simulation analysis for epilepsy monitoring unit and surgical capacity



CHAPTER 5

Conclusions of the thesis

Currently, there exists a gap between the care we provide and the care we *could* provide [1]. It is the responsibility of clinicians, administrators, academics, and policy makers to work towards a common goal of ensuring quality care for patients that not only meet their needs but is also evidence-based. Inadequate quality care stems from a number of factors including but not limited to the growing complexity of interventions and poorly organized service delivery[1]. These challenges are multifaceted and as such require the use of more sophisticated tools and better designed care processes [1] which can be achieved through the use of systems analysis.

Systems analysis is an approach we can use to develop policies that integrate the priorities and are generalizable to multiple levels of healthcare and governance (i.e. micro, meso, macro). For instance, large funding policy decisions are often made at the macro (e.g. provincial) level despite the fact that the organization of services is at the meso (e.g. institutional) and micro (e.g. practitioner) levels, particularly in Canada [2]. We can apply systems analysis to examine a patient's entire continuum of care (e.g. primary care and hospital care) in order to inform policy decisions that maximize health outcomes and organize service delivery in an efficient and equitable manner.

This thesis has addressed the use of the systems analysis tool discrete event simulation (DES) to inform policy decision making by conducting research that bridges the multiple levels of healthcare. We developed two separate DES models in collaboration with stakeholders that integrate qualitative and quantitative information to model complex healthcare problems. This final chapter offers a summary of the thesis findings accompanied by a discussion of the implications, contributions and areas for future research.

Among systems analysis tools, DES is frequently used to assist management when evaluating different operational alternatives in order to improve healthcare performance. Literature shows that a number of DES models have been developed to evaluate healthcare clinic system performance by modeling, for example a hospital emergency department (ED), and running simulations to determine the best way to minimize waiting times [3]. However, few successful implementations of recommendations derived from simulation findings have been reported in the academic literature [3-6]. This may have resulted from lack of involvement by the stakeholders or end users in model development or lack of confidence in the validity of the outputs produced by a DES model.

To improve upon previous modeling approaches, we addressed a methodological issue associated with DES that may lead to overestimation of staff resource utilization in a hospital ED setting (Chapter 2). When modeling the ED using DES, healthcare staff is typically modelled as homogeneous resources that only interact with the patient, which may limit the generalizability of the findings. Tackling this issue is important for a number of reasons: 1) physicians and their delegates, i.e. residents, medical students and other trainees, attend to indirect patient related tasks such as charting that are not typically accounted for in DES modelling, 2) physicians often spend time interacting with their delegates through teaching activities, and 3) producing inaccurate resource utilization outputs may lead to mismanagement of resources. To address this methodological gap, this research presents the development and application of an alternative approach where physicians and their delegates are modeled as interacting pseudo-agents in a DES model. They are considered pseudo-agents because they are not fully autonomous agents but rather modeled as separate entities with embedded decision logic and interaction between each other including the patient.

This research is the first time that an ED agent-based modeling (ABM) model has been implemented in terms of a DES [7]. This is significant because full ABM models are more time consuming to develop and are typically based on theories and subjective data. There is also a greater level of distrust associated with ABM as it is less well known in the management and modeling communities [8]. Our results indicate that staff resource availability is overestimated and patient length of stay and queue length for physical resources are underestimated if the interaction between physician and their delegates is ignored. This is particularly important if the DES model is being used to inform optimal staff scheduling in which case previous ED simulations that did not consider interactions may have been biased.

In order to provide timely and efficient access to care it is important for institutions to work towards allocating resources to meet patient demand. This is a particular challenge in the hospital ED where patient arrivals and needs may vary significantly over time. Developing a DES model that can incorporate the complexity of ED patient demand and staff scheduling is a significant step in delivering quality care at the institutional level. This research presents an example of how DES can be used to integrate the micro with the meso level of healthcare by modeling the patient and staff flows with the goals of the institution (i.e. waiting times, length of stay and resource utilization). It provides a means to focus not only on re-allocating resources according to performance measures but also by focusing on patient-centred outcomes (i.e. access to care).

In Chapter 3, we conducted a systems analysis study of the surgical evaluation process for children with medically refractory epilepsy (MRE) at the Hospital for Sick Children (SickKids) in Toronto, Ontario, Canada. SickKids is the primary referral centre for children in Ontario for diagnosis and surgical intervention of MRE. The purpose of this study was to identify rate limiting steps that may lead to delayed surgical candidacy decision and surgery in children by examining referral patterns, healthcare utilization and time intervals. Through the use of data from a retrospective chart review of a cohort of children referred over a two-year period, we found that only 5.7% of the eligible population was referred annually for surgical evaluation and that time between first seizure and referral for surgical evaluation was almost 5 years. This means children are unnecessarily living years with a potentially treatable disorder that could lead to developmental problems [9] and that does not even account for the remaining 94.3% of the eligible population who continue to live with uncontrolled seizures. We also found that children identified as surgical candidates had to wait on average 1-2 years for surgery. This is compounded by the misconception that occasional seizures while on medication is considered an acceptable response [10]. The goal of treatment should be seizure freedom which is what epilepsy surgery can provide for approximately 75% of individuals. These findings may indicate a lack of awareness or education among family practitioners and neurologists about the potential benefits of epilepsy surgery [11].

Through mapping of patient flow and resource utilization we were able to identify multiple barriers to surgery. Selected patients were returning to seizure conference up to 4 times as a result of being sent for further or repeat diagnostic testing (primarily MRI). In addition, further testing could have been reduced by standardizing the testing sequence (i.e. MEG before first seizure conference) and that repeat diagnostics could be reduced by standardizing and coordinating diagnostic test protocols across institutions. By taking a systems analysis approach to examine the entire process from referral for surgical evaluation to surgery we were able to identify rate limiting steps and data on referral patterns that can be used by institutional administrators and practitioners to inform allocation of resources and organization of care. These findings can also be used to help make funding decisions and recommendations on the organization of epilepsy services at the provincial level since SickKids is the primary paediatric referral and surgical center in the province.

To provide guidance on epilepsy care in Ontario a Provincial Epilepsy Strategy Working Group was formed. The Working Group has recommended the integration, coordination and standardization of delivery of care, decision support and clinical information systems through the organization of currently existing epilepsy specific care centres (ESCC) into district and regional services. Under the proposed strategy, the identification of regional centres offering full services including surgery (which includes SickKids for paediatrics) which act as a hub for district centres, is felt to be necessary. Before a widespread re-organization of services it would be useful information to decision-makers to understand the current system resource capacity constraints at the primary referral centre in the province (SickKids).

In response, we built on the analysis conducted in Chapter 3 by using the data and findings to develop a simulation model to inform policy. Chapter 4 outlines the development and validation of a DES model that can be used as a decision making aid by SickKids and the province on how to increase access to care for children with MRE. The model incorporates the goals of the patient (access to care), institution (waiting times and resource allocation) and province (funding decisions and organization of services across the province). We use the model to evaluate the effect of alternative resource capacities on waiting times for surgical evaluation and surgery at this paediatric centre. Using the validated model as the base case, we investigate changing resource capacities to decrease waiting times to meet suggested benchmarks (30 days to proceed from EMU referral to admission and 1-1.5 years to proceed from EMU referral to surgery).

Simulation results indicate that increasing the number of cases assessed each week at seizure conference did not affect waiting times. Therefore, further analyses focused on EMU and surgical capacity. To meet the suggested benchmarks we found that the most efficient alternative resource configuration to decrease total time from referral to surgery was to eliminate the need for a third seizure conference. However, this would in turn increase the waiting time for surgery because children would be evaluated for surgical candidacy faster. This finding has multiple policy implications in terms of guidelines/protocols (micro), organizing services (meso) and funding (macro). In order to eliminate the possibility of a third seizure conference, institutions would need to streamline diagnostic imaging services to prevent the need to send patients for multiple seizure conferences. Streamlining services would involve standardizing protocols and equipment across the province specifically for epilepsy patients, aligned with the primary referral centre, to minimize repetition of diagnostic evaluations. Although the institution is responsible for their organization of services, accountability for other institutions protocols requires coordination at the provincial level and associated incremental funding (macro).

This analysis supports the recommendations to the province made by OHTAC through the Working Group by directing requested funds. The findings suggest that funding should be directed to surgical capacity and standardizing and streamlining diagnostic technologies to reduce waiting times. It supports the need for completion of all diagnostic testing prior to referral for surgical evaluation which requires all centres to have standardized diagnostic technologies in order to transfer results. However, if the province decides to direct funding towards streamlining diagnostic imaging services it could also increase waiting time for surgery (i.e the time between decision for surgery and actual surgery) because surgical candidates are being identified at a faster rate. Although the net effect is a decrease in time to surgical decision and time to treatment, waiting times are associated with negative public perceptions in a publicly funded healthcare system.

This study highlights how a systems analysis tool such as DES can be used to inform the organization of services and funding decisions. It also shows how stakeholders can be engaged in the process. The DES model was built in collaboration with the stakeholders to validate patient flow and to ensure that we were providing useful, actionable and clinically relevant performance outcomes in addition to developing confidence in model predictions. The collaborative process had an added effect of enhancing the stakeholders' own understandings of the patient clinical pathways. Chapter 4 provides an excellent example of how DES, as a systems analysis tool, can be used to bridge together the goals of the patient (access to services), the institution (waiting times, resource utilization) and the province (where to allocate funds and effects of a province wide strategy).

Future Research

The research in this thesis can be furthered in a number of directions. Related to Chapter 2, we could increase the complexity of our hospital ED model by collecting more data to include re-assessments and multiple diagnostics or by incorporating breaks and shift lengths. The research in this chapter focuses on the relationship between physician and resident. However, it would be useful to extend the model to include other types of delegates such as nurse practitioners and medical students. Although an ED setting was used, the approach of using pseudo-agents can be implemented when modeling other clinical settings such as a general practitioner's clinic.

The link between the micro and meso levels can be broadened to include emergency medical services (EMS). Patients who arrive by ambulance are escorted by paramedics into the ED. If a bed is unavailable, the paramedic must wait with the patient until they are admitted. This is means the paramedic is unavailable to service other emergencies. This is an important interaction to include because it may show that paramedics are spending a significant portion of their time waiting in the ED when they could be attending to other emergencies within the health system (macro).

The natural progression of our research on access to epilepsy care would be to extend the model to examine the inter-relationships between ESCCs under the proposed provincial strategy to determine optimal resource configurations. For example, referral rates to SickKids for the EMU would decrease as district centres would be region specific. Consequently, more children would be assessed at the EMU through district centres which could potentially put more pressure on diagnostic resources such as MEG and create a backlog on the region specific services such as seizure conference and surgical capacity. Conducting a systems analysis of the regional and district centres would provide information to properly understand the feedback associated with re-organizing care into ESCCs. This could be achieved by creating a network of DES models based on the SickKids model.

The SickKids model is divided into four modules: epilepsy monitoring unit (EMU), diagnostic imaging, seizure conference, and surgery. The frontend of the model (i.e. EMU and diagnostic imaging) could be used to represent the district centres which would eventually feed (via referrals) into the seizure conference portion of the regional model (i.e. SickKids). This would provide a more comprehensive understanding of the effects on waiting times, queues, and resources necessary for a dramatic re-organization of services. It is also possible to extend this analysis to the adult population as the surgical evaluation and surgical processes are identical to those for children. Transferring the model to the adult population would require collecting similar data from the adult regional and district centres and inputting it into the model to determine the number of resources necessary to increase access to care. An adult model could be linked with the children's model, as at a provincial level they would be competing for the same resources (i.e. EMU and diagnostic imaging) which would provide decision makers with a complete picture of the province.

In order to bridge the clinical, economic, patient-centered and organizational domains, surgical outcomes, utilities and costs can be integrated into the model. Any re-organization of services would impact institutional costs (sometimes the bottom line) and therefore it is important to consider them in the decision making process. Costs can be incorporated into the DES model to inform decisions around capital purchases and staffing. It is also possible to estimate patient costs based on their resource utilization (e.g. number of diagnostics and surgery). The ability to combine costs and performance measures such as waiting times with the re-organization of services presents a strong case for the use of systems analysis tools.

DES is a flexible systems analysis tool that can be used to generate useful information for policy decision-makers. Although the use of computer simulation to model care processes has increased dramatically in the academic literature after the 1990s, the implementation of recommendations is minimal at only 5.3% of identified studies [6]. Parallels can be drawn between the slow uptake of computer simulation and the slow uptake and acceptance of Markov modeling in the economic evaluation of health technologies. A simple search for Markov models in PubMed showed a 2-fold increase in publications every 5 years since 1995. Adoption of Markov modelling may be the result of increased training in decision analytic modelling through academia, workshops and conferences and increased credibility through the development of guidelines and best modeling practices [12]. As healthcare modeling moves toward resource constrained systems analyses there is a need for more training and guidelines in the development and implementation of individual-level simulations such as DES. The International Society for Pharmacoeconomics and Outcomes Research (ISPOR) Task Force on Good Research Practices in Modeling Studies has recognized this gap for DES [13]. Although these guidelines mostly focus on the use of DES for the evaluation of health technologies it is a promising start. Consequently, the development of guidelines and increased training will have little effect on the uptake of system analysis tools if healthcare institutions do not invest in collecting better health data. One of the key aspects to quality improvement is measurement. Without valid data (e.g. waiting times) it is impossible to evaluate the delivery of care. The systematic collection of data would be another step in facilitating the adoption of systems analysis tools such as DES.

Fundamental changes are needed in the organization and delivery of healthcare in order to improve the quality of care. This means focusing on healthcare that is safe, effective, efficient, equitable, patient-centered and timely [1]. To achieve these goals we need to change the policy framework by making decisions that are generalizable to all levels of healthcare. For instance, the meso level is often sandwiched between the micro and macro where it is constrained by macro policy (e.g. funding) but must be reflexive to micro policy (e.g. patient demand) [2]. Siloed decisions may result in unintended negative feedback, for example, shutting down a hospital ED might have the effect of increasing demand at other EDs. Systems analysis tools can be used to identify and present solutions for poorly designed care processes through the characterization of system waste (e.g. empty beds, long delays and the unnecessary duplication or overuse of services). By adopting the use of these tools we can increase the uptake of evidence in decision making and provide useful information to develop policies for improved healthcare.

References

1. Institute of Medicine. Crossing the Quality Chasm: A New Health System for the 21st Century. Washington, D.C.: National Academy Press; 2001

2. Battista R. Expanding the scientific basis of health technology assessment: A research agenda for the next decade. *International Journal of Technology Assessment in Health Care* .2006;22(3):275-82.

3. Lim M, Nye T, Bowen J, Hurley J, Goeree R, Tarride JE. Mathematical Modeling: The Case of Emergency Department Waiting Times. *International Journal of Teachnology Assessment in Health Care* .2012;28(2):93-109.

4. Jun JB, Jacobson SH, Swisher J. Application of discrete-event simulation in health care clinics: A survey. *Journal of the Operational Research Society* .1999;50:109-23.

5. Fone D, Hollinghurst S, Temple M, Round A, Lester N, Weightman A, et al. Systematic review of the use and value of computer simulation modelling in population health and health care delivery. *Journal of Public Health Medicine* .2003;25(4):325-35.

6. Brailsford S, Harper P, Patel B, Pitt M. An analysis of the academic literature on simulation and modelling in health care. *Journal of Simulation* .2009;3(3):130-40.

7. Lim M, Nye T, Bowen J, Hurley J, Goeree R, Tarride JE. Mathematical Modeling: The Case of Emergency Department Waiting Times. *International Journal of Teachnology Assessment in Health Care* .2012;28(2):93-109.

8. Siebers PO, Macal CM, Garnett J, Buxton D, Pidd M. Discrete-event simulation is dead, long live agent-based simulation! *Journal of Simulation* .2010;4:204-10.

9. Ibrahim GM, Fallah A, Albert GW, Withers T, Otsubo H, Ochi A, et al. Occipital lobe epilepsy in children: characterization, evaluation and surgical outcomes. *Epilepsy Res* .2012;99(3):335-45.

10. Lowenstein DH. Interview: the National Institute of Neurological Diseases and Stroke/American Epilepsy Society benchmarks and research priorities for epilepsy research. *Biomark Med* .2011;5(5):531-5.

11. Ontario Health Technology Advisory Committee. OHTAC Recommendation: Care for Drug-Refractory Epilepsy in Ontario. Toronto: Ontario Ministry of

Health Technology Advisory Committee: Health Quality Ontario; 2012. Available: http://www.hqontario.ca/fr/mas/pdfs/EpilepsyOHTACRec20120605ac.pdf

12. Caro J, Briggs A, Siebert U, Kuntz K. Modeling Good Research Practises - Overview: A Report of the ISPOR-SMDM Modeling Good Research Task Force. *Medical Decision Making* .2012;32:667-77.

13. Karnon J, Stahl J, Brennan A, Caro J, Mar J, Moller J. Modeling using Discrete Event Simulation: A Report of the ISPOR-SMDM Modeling Good Research Practices Task Force - 4. *Value in Health* .2012;15:821-7.