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A Survey of Agent-Based Modeling of Hospital Environments

MARCIA R. FRIESEN AND ROBERT D. MCLEOD, (Member, IEEE)
Department of Electrical and Computer Engineering, University of Manitoba, Winnipeg, MB, Canada
Corresponding author: R. D. McLeod (mcleod@ee.umanitoba.ca)

ABSTRACT Agent-based modeling has become a viable alternative and complement-to-traditional analysis methods for studying complex social environments. In this paper, we survey the role of agent-based modeling within hospital settings, where agent-based models investigate patient flow and other operational issues as well as the dynamics of infection spread within hospitals or hospital units. While there is a rich history of simulation and modeling of hospitals and hospital units, relatively little work exists, which applies agent-based models to this context.

INDEX TERMS Agent based modeling, emergency departments, institutional environments.

I. INTRODUCTION

This paper surveys the application of agent based modeling (ABM) and simulation of complex social dynamics within the institutional scale of a hospital. Hospitals are a promising area of continued ABM research with the concomitant potential for substantive outcomes. Healthcare around the world deals with a perennial pressure to find cost efficiencies, and target areas include the optimization of healthcare processes and flow, reducing emergency department (ED) wait times and length of stay, and reduce admission times. Within these areas, hospitals rely on the experience of practitioners for improvements in triage procedures, diverting low-acuity patients, reconfiguring the healthcare staffing model, and reorganizing operational units both physically and procedurally.

Simulation offers a potential to identify improvements and new understandings in how a facility operates. Simulation has the potential to models real-world variability, lessens testing and implementation costs of planned changes, and helps to minimizes the risk of errors in implementing changes. Patient tracking through their stay in the hospital by using technologies such as radio frequency identification (RFID) and improved electronic reporting and dashboards are one example of initiatives that can be integrated with simulation studies to generate valuable information on social dynamics within the institution.

In general agent based modeling is 'bottom-up' systems modeling from the perspective of constituent parts. Systems studied are modelled as a collection of agents (in social systems, most often people) imbued with properties: characteristics, behaviours (actions), and interactions that attempt to capture actual properties of individuals with a high degree of diversity and fidelity. In the most general context, agents are both adaptive and autonomous entities who are able to assess their situation, make decisions, compete or cooperate with one another on the basis of a set of rules, and adapt future behaviours on the basis of past interactions. Agent properties are determined by the modeler and are ideally derived from actual data that reasonably describe agents' behaviours – i.e. their movements and their interactions with other agents. The emergence of a data culture, also called 'big data' and associated 'big data analytics', offers new opportunities to use real world data, even in near real time, as inputs into ABMs. The modeler's task is to determine which data sources best govern agent profiles in a given ABM institutional simulation.

The foundational premise and the conceptual depth of ABM is that simple rules of individual behaviour will aggregate to illuminate complex and/or emergent group-level phenomena that are not specifically encoded by the modeler and that cannot be predicted or explained by the agent-level rules. In essence, ABM has the potential to reveal a whole that is greater than the sum of its parts [1], [2].

ABMs provide a natural description of a system that can be calibrated and validated by representative expert agents, and is flexible enough to be tuned to high degrees of sensitivity in agent behaviours and interactions. As such, they play a vital role as an information translation vehicle. The lexicon used to develop an ABM is the lexicon of area experts and of the institution under consideration (e.g. a hospital), reflecting the world in a real and specific a manner as possible. In essence, one builds a laboratory where the behaviours of individuals are similar to those in the real-world emergency department and the one observes what happens when the rules of behaviour and interactions are changed. The underlying ABM engine may be quite complex and utilize the most advanced processing and hardware techniques available, but this level of detail is not required in developing the model or in the analysis of its output.

Although simulation and modeling in healthcare facilities is not new, agent based modeling within these settings is a relative newcomer. This survey paper focusses on hospital ABMs, which is an agent centric approach as opposed to more established areas of simulation which tend to the process oriented. The key differences between modeling techniques such as discrete event, system dynamics, network analysis, and ABM are well-documented and to date, the majority of research in healthcare simulation has utilized Monte Carlo, discrete event simulation (DES), and system dynamics rather than ABMs [3]–[5].

Yet, ABMs are considered to be a very promising and complementary technique by which to simulate hospital dynamics, with arguments for their more widespread use within healthcare will depend on more widely adopted and more effective conceptualization and implementation tools [6]. Some researchers claim that the "signature" success of ABMs in public health is in the study of epidemics and infectious disease dynamics [5], [7], where the successes of ABMs have demonstrated the importance of the role of social networks, human movement patterns, transportation systems, and the disease dynamic itself. This overwhelming amount of research in applying ABMs to the study of large scale infectious disease spread (e.g. influenza, STIs) is not addressed here. ABMs applied to institution-scale environments (rather than regional scales) are nonetheless emerging as an excellent vehicle for modeling hospitals due to their inherent ability to leverage social network analysis in a similar manner to social interactions of a large scale infectious disease.

The remainder of this paper is organized as follows. Section II surveys the application of ABMs to hospital and similar institutional settings. Section III discusses data sources that may be useful in extending the models more fully. Section IV provides reference examples that encompasses many of the phenotypes of a typical hospital centric ABM. Section V provides a summary.

II. ABMS WITHIN HOSPITALS

Agent Based Modeling has seen a tremendous growth in many areas over the past 15 years and more recently one of these areas being hospital and healthcare settings. The primary application of ABMs to hospital environments examine patient flow (e.g. emergency departments) [8] and other hospital operational issues, and using ABM to examine the dynamics of infection spread within a hospital (e.g. the hospital's role in an influenza epidemic [9] and the dynamics of nosocomial infection spread [10]). ABMs in healthcare have also examined economic models of healthcare, removed from scale of the patient itself; these models are not surveyed here.

A. SYSTEM ATTRIBUTES

When designing an ABM for hospital applications, there are choices in system attributes that become design decisions unique to the context and objectives of the model. An ABM is inherently agent-centric, and the model arises from the consideration and definition of the agent's *environment,* the agent's *characteristics*, and the agent's *interactions* with other agents.

- Commercial / Homegrown: At present a large number of ABMs are developed as one-offs or custom models, dedicated to the objective at hand. These offer advantages associated with data fusion, accelerators through multicore, cluster, high performance computing (HPC) optimization as well as general purpose computation on graphics processing units (GP-GPU). Disadvantages are the considerable overhead in developing one's own code, inclusive of code verification. The benefits of a commercial platform are a proven code base and user community. Just as with many other areas where simulation plays a crucial role in product development, eventually the benefits of a commercial product usually outweighs the advantages of a homegrown solution. There are however intermediary code bases that are typically open and community supported. These are usually verified to some degree but usually not to the degree of a commercial offering. All forms of ABM development have associated learning curves. The largest and most popular commercial ABM offering is that within AnyLogic (anylogic.com). Opensource ABM frameworks include Repast (http://repast.sourceforge.net/), NetLogo (http://ccl.northwestern.edu/netlogo/), and Swarm (swarm.org).
- Environment:
  - The *topography or layout* upon which agents operate is an initial decision in ABM development. Environments can be real-world, synthesized, or abstracted. Real-world environment can be captured from hospital floor plans, while synthesized environments can be generated by the modeler with simplifications or assumptions compared to real floor plans. The environment can also be abstracted entirely as a data point in the overall model and assigning the agent to discrete non-physical locations within the computer code. However, the strong benefit of ABM is to allow for real-world environments to enhance the validity and credibility of the model, to ease the interpretation of simulation results, and to assist in knowledge transfer.
  - Most ABM simulation suites include some means of *visualization* of the agent within the environment, and this benefit of ABM over other

modeling techniques has been accentuated with the affordability and accessibility of high performance desktop computing and graphical processing. Visualization of specific instances of the process allows verification of the model setup, simulation in progress, and simulation results. Where a simulation requires a very large number of iterations to generate meaningful findings, the visualization methods are halted while data accumulated.

- Agents:
  - The *selection of agents* is a foundational task of the ABM developer. In most hospital ABMs, the logical selection of agents includes patients and hospital staff members. Basic ABMs for hospital EDs may only include patients, nurses, and physicians [6], while more detailed ABMs include allied healthcare providers who also consult within a hospital, and potentially reaching as far as including visitors and facility personnel not directly involved in healthcare delivery (e.g. maintenance staff). Furthermore, an explicit decision should be made to include or exclude inanimate objects as agents within a hospital ABM. Where the ABM is developed to model infection spread (vs. patient flow), researchers have considered the role of equipment and hospital fixtures as vectors for infection [11], including medical instruments, bed capacity, allied areas relevant to the main ABM focus (e.g. diagnostic services within an ED ABM). Inanimate agents are modeled without explicit agency or any decision making capability. Besides their role as vectors in infection spread, the availability and utilization strategies of inanimate agents (e.g. bed capacity, equipment availability) can also be illuminated via ABM.
  - The assignment of *characteristics or profiles* to the agents is another foundational task of the developer. The relevant factors for agent profiles are determined by the objective of the ABM and may include distributions of sex, age and other demographic factors, physical origin and destination within the topography and beyond the topography, and risk factors associated with, for example, infection spread. The power of ABM is accentuated within today's emerging big data culture, where the sources of real data for agent characteristics are numerous and varied. Data sets may or may not have been generated for the purpose at hand. Data sources may include hospital information systems, census data, government databases in the case of publicly-funded health systems (e.g. Canadian Institute for Health Information), cellular service records that can be used to approximate physical trajectories of Smartphone users upon a topography, and even Smartphone apps that are GPS-enabled. The developer must be aware of limitations and gaps within the data and how those limitations impact the veracity of the dataset for the ABM's objective. Pre-processing is generally required for a single dataset as well as the consolidation of varied datasets. While data is often technically available, political barriers may exist to access the data. The area of real data is likely the area where ABMs within healthcare facilities will more fully evolve as they install in-house systems to capture the data (e.g. patient flows) themselves, which will support the ability to fine-tune ABMs. Such systems may include electronic records, dashboards, as well as technologies such as RFID. In the case of RFID, both inanimate and animate agents can be tracked.
  - The assignment of *rules that govern the interactions* between agents is the other foundational task of the ABM developer, in order to capture the processes within the ABM, i.e. the process within the hospital. Here, the ABM's impact is evident in the natural inclusion of expert guidance to establish valid and reliable agent interaction rules, formulated directly in the lexicon of the hospital environment and in the real-world topography of the practitioners (e.g. nurses and physicians in the hospital). The role of real data in the assignment of agent behavioral rules is just as significant as in the assignment of agent characteristics or profiles.
- *Interventions:* Whether the hospital ABM was developed to examine patient flow, infection spread dynamics, or another purpose, the key objective in developing an ABM is to introduce policy changes or interventions (agent profile changes, agent behavioral changes, topography changes, or others) in order to investigate "what if" scenarios. In patient flow ABMs, interventions may include topography re-configurations of the ED or procedural reorganization such as low-priority patient diversions within and between hospitals. In an infection spread ABM, interventions may include agent hygiene behaviours and rules of contact.
- *Validation & Verification*: There are emerging guidelines addressing the importance and techniques to validate ABMs [12], including micro-face validation, macro-face validation, output validation, backcasting to known data, and comparison of output to other modeling methods.

B. EARLY HOSPITAL ABMs

Some early simulation models within healthcare settings were not specifically denoted as ABM but carry all the characteristics of ABM. In 2006, researchers discussed a simulation model of an ED, recognizing the strengths of ABM as a means of communication across disciplines, indicating that part of their validation process was consultation with area experts (doctors and nurses). The model provided a means evaluating "what if scenarios", specifically, alternative triage methods. Their work was also one of the first to recognize the importance of visualization as a strong element of ABM and the requirement of using as real data as possible of available [13].

Earlier in 2001, others argued for the use and requirements of ABM for hospital management, although they do not appear to have built a working model [13]. Another early paper investigated the role of an ABM within an ED, deriving it from a more traditional intelligent software agent perspective or multi agent system (MAS) perspective [14]. That work introduces processes, treatments, individual agents and protocols for their interaction.

C. AGENT BASED MODELS FOR PATIENT FLOWS

An evolving literature exists with respect to applying ABMs, alone or in complement to other techniques, to the operations of EDs. In general, this literature addresses system-level performance dynamics, quantified in terms of patient safety [15], economic indicators [15], [16], staff workload and scheduling [8], [17], [19], and patient flows. While much of the literature addresses system-level operational concerns during periods of typical operation or stasis, there is also a literature on modeling of healthcare operations during critical incidents like disease outbreaks and terrorist attacks [20].

More recently, others have modeled improvements to patient flow using an ABM running on a High Performance Compute resource [21]. The ABM was built with NetLogo and representative of the role for which an ABM is well suited. The objective of the study was to provide impact values of alternative policies for patient diversion. Not unexpectantly, the results indicated that patients that do not require urgent attention and are fast tracked or diverted improves the capacity of the ED and reduces the Length of Stay of patients that remain in the ED. More extensive consideration of ABMs for patient flow in EDs are developed by the same researchers [22], [23], including the utilization of an ABM within a decision support system for EDs [24]. A contrasting technique to model patient flows would be DES [17]. In similar work, the role of re-triage in improving ED patient flow is examined [25]. The results are not unexpected and lend additional credibility to the use of ABMs in healthcare modeling by facilitating and modeling "what if" scenarios. In other work, a pseudo-agent based approach is introduced into a DES in an attempt to capture the representative strengths of each modeling approach for simulating an emergency department [26]. In that work, the importance of interaction at the agent level is illustrated, not typically captured with DES.

D. AGENT BASED MODELS FOR NOSOCOMIAL INFECTIONS

Fig. 1 illustrates where modeling nosocomial infections, or hospital-acquired infections (HAIs) would be characterized within the range of healthcare models.

In general, the modeling of HAI or nosocomial infections is perhaps the best suited area for ABMs within healthcare institutions. This is largely a consequence of being able to address all of the model components included in Fig. 1 relative to topography and agents. HAI ABMs may be useful in assessing the effectiveness of different infection control protocols or policies, intervention costs, as well as shedding light on potential confinement failures which would accompany widespread infection dynamics [10], [27].

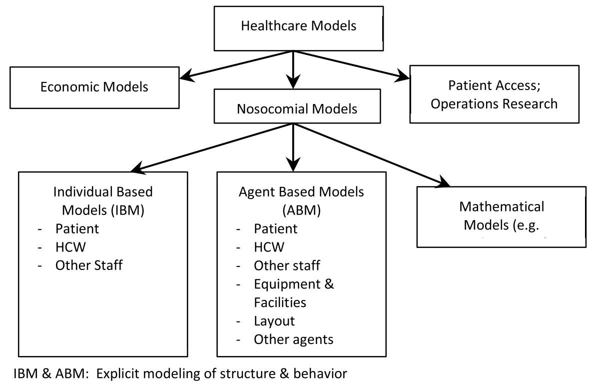

FIGURE 1. An agent based nosocomial model within healthcare models.

Several of the models oriented to nosocomial infections are known as '*individual* based models', in which agents are limited by definition to individuals (persons). One such example is a mathematical individual based model for studying infection spread in a nursing home [28]. By contrast, the notion of an *agent* based model expands the definition of agent beyond an individual person, to include inanimate objects that can act as vectors of transmission for nosocomial infections. This concept is supported by a significant body of evidence that non-person agents play a significant role as infection transmission vectors [29], [30], including the CDC's overview of SARS related information [31], which states "the virus also can spread when a person touches a surface or object contaminated with infectious droplets and then touches his or her mouth, nose, or eye(s). In addition, it is possible that the SARS virus might spread more broadly through the air (airborne spread) or by other ways that are not now known" (pp. 1).

Nosocomial agent based modeling initiatives focus upon explicit modeling of structure and behaviour extending the agent based model to include individuals, inanimate objects, and locations, in order to investigate an organization's policies and practices in the event of a serious nosocomial infection outbreak. Much of the current efforts in nosocomial ABMs set the framework for potential future efforts in modeling and evaluation of organization's documented infection control plans (policies and practices). For example, best practices [32] are available for healthcare practitioners and policy makers dealing with health care-associated infections in patient and resident populations. This may be a useful reference to model, as a means of identifying and evaluating their effectiveness. At this time, best practice documents typically reflect "consensus positions on what the committee deems prudent practice and are made available as a resource to the public health and healthcare provider" (p. ii). Clearly this is also an opportunity for ABM models to contribute to a collaborative, multi-stakeholder effort.

Despite nosocomial modeling's natural fit with the ABM approach, it is a fairly recent area of exploration for health-care ABMs [33]–[35]. One of the earlier simulation efforts modeled antibiotic resistance in hospitals, contrasting and an individual based model with that of a differential equation based model, including consideration of where they can be used in conjunction with one another [36]. Another study investigated the spread of a nosocomial pathogen in a dialysis unit using a Monte Carlo individual based model [10]. The dialysis unit is a very good example of where agent based models may be particularly useful as ''the frequency of patient visits and intimate, prolonged physical contact with the inanimate environment during dialysis treatments make these facilities potentially efficient venues for nosocomial pathogen transmission'' (pp. 1176). In related paper [27], the same authors developed a fairly abstracted nosocomial ABM within an intensive care unit, advocating for a ''conceptually simple discrete element (agent-based or cellular automata) models [that] can explicitly address 'geographic' considerations and probabilistic transmission dynamics germane to the spatially intricate environments and small population sizes characteristic of ICUs'' (pp. 174). In another nosocomial ABM of an intensive care unit, operational and epidemiological features are considered in an attempt to estimate the effect of understaffing and overcrowding on infection spread [37]. The ABM simulated contact-mediated pathogen transmission, which should allow one to establish quantitative relations between patient flow, staffing conditions and pathogen colonization in patients. Another individual based approach investigated the role of cohorting, with the aim of minimizing the possible interactions between individuals within a ward [38]. In a relatively recent nosocomial ABM, a combination of differential equation models and probabilistic models are used for each agent in order to simulate changes, over time, in the bacteria sub-populations within the agent's body [39]. As with many ABM efforts, work is ongoing in terms of validation and verification. In order to construct biologically plausible transmission risk models that can guide cross infection control, researchers have developed an RFID tracking system in an ED by which to extract agent contact data on the understanding of the critical role that contact patterns play in cross-infection control [40]. This type of high-fidelity individual data, topography, as well as contact patterns is ideally suited for an ABM as well.

E. MISCELLANY

Other scenarios that have been investigated using ABMs within healthcare settings include optimization of computer terminals [41], serving as another illustration of incorporating inanimate objects as agents within the ABM. The use of electronic devices including stationary workstations, mobile workstations, tablets, and Smartphones in healthcare delivery is evolving very rapidly, and will likely develop momentum that will outpace the insights of ABMs in this area. Other ABMs are oriented to interactions between hospitals where patient diversion on response to load was modeled [42].

III. VISUALIZATIONS

Agent based models are well suited to visualization and animation as means of informally verifying and validating the model, as well as communicating with practitioners and policy-makers, in that visualization renders potentially complex dynamics more intelligible to the recipient of the information. YouTube is an excellent platform for presenting a model's or project's progress. Fig. 2 illustrates a prototype emergency department. A large waiting area is depicted, where one person is identified at a higher acuity level than the others. Detailed modeling allows for modeling of social distancing within a waiting area, as well as obtaining estimates of ED length of stay, influenced by policy or staffing interventions modeled via ABM. Two videos illustrating the potential use of visualization with ABMs within healthcare facilities are appended to this paper as on-line videos. One video illustrates patient flow through an ED, and the other the use of an ABM in evaluating the efficacy of an RFID/RTLS.

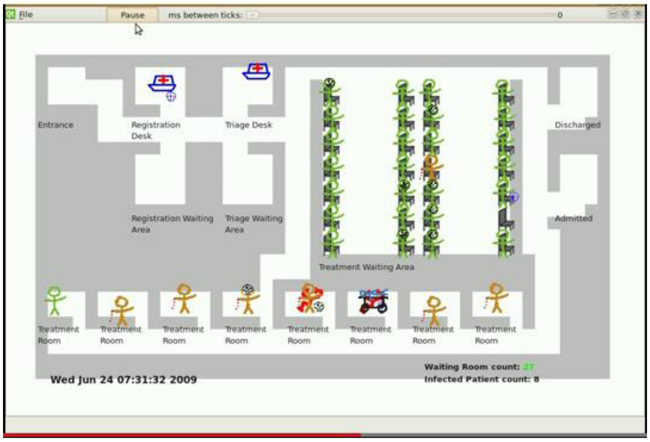

FIGURE 2. **Agent based model of an emergency department.**

AnyLogic, a commercial simulation suite of tools has also been fairly widely deployed for emergency department simulation, with an example at http://www.youtube.com/watch?v=LaHdn3GBIWM (Fig. 3).

It is very likely that hospital simulations and their visualizations will continue to improve, driven largely by initiatives in 'serious games' and the gamification of models and simulations. An example of the level of detail one can envision can be found at http://www.youtube.com/watch?v=7CwoMsVyo2Y. The animation utilized Flexsim, which is a discrete event simulator, but similar high quality animations can be extracted from ABMs as well (Fig. 4).

IV. ENHANCEMENTS TO HOSPITAL ABMs

ABMs tend to be labour intensive and are often deployed for specific experiments or studies. Although time consuming, they generate vast quantities of data for each run. Typically, the many runs are used to extract statistics that can be used to demonstrate the impact of the policy or intervention being simulated. This massive data generator also offers the potential to be mined and used in machine learning

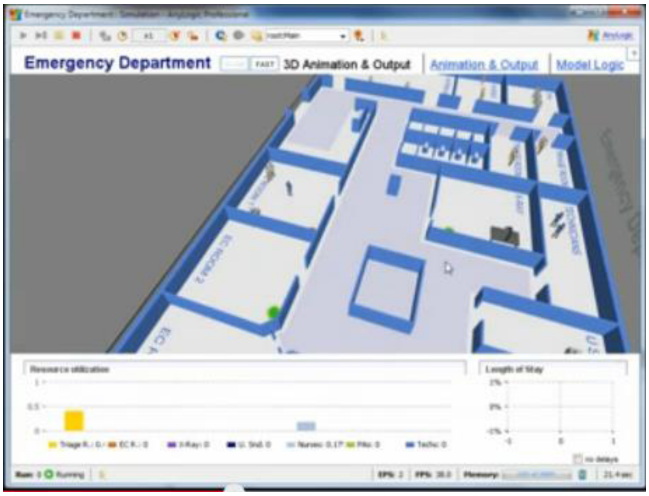

FIGURE 3. Agent based model of an emergency department using AnyLogic.

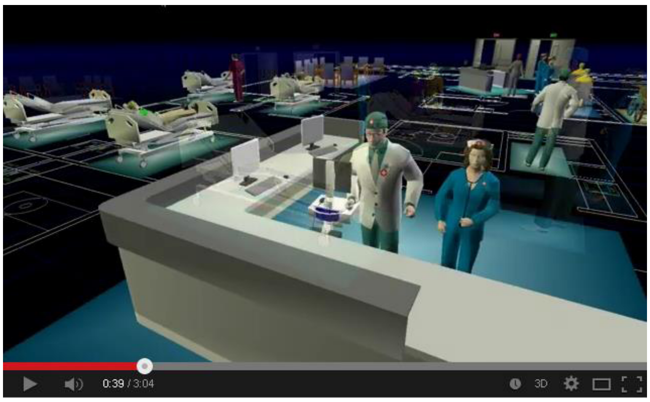

FIGURE 4. "Gamified" simulation visualization using Flexsim.

or pattern classification algorithms. For example, instead of having emergency physicians travel through the ED to see patients in individual treatment rooms, the patients would travel through the ED to visit the (stationary) physician, with this policy generated via a genetic program combined with an ED ABM [43].

Another enhancement to ABMs and to simulation in general arises when data analysis augments the simulation. For example, researchers have analyzed data to identify best scenarios extracted from discrete event simulation of an ED [44]. Although scenarios were extracted from a DES as compared to an ABM, the same type of enhanced data analysis are beginning to emerge in ABM, borrowing heavily from non-parametric methods in operations research. Although ABMs are a useful paradigm for aiding to the understanding of a complex system on their own, this significant existing contribution will be augmented with the integration of data analytics.

ABMs may also be useful in hospital facility design where additional importance may concern the role of the HVAC system within various departments. This would imply a hybrid of simulation techniques, likely encompassing an ABM and computational fluid dynamics model. In another instance, a hybrid ABM-DES model for emergency medical services in a city is conjectured, although an actual model or simulation has not been reported [45]. In a more pedestrian optimization, resource planning for placement of RFID readers in an RFID system may be integrated into the ABM as a means of estimating errors associated with the tracking system [46].

V. SUMMARY

This paper reviews the current status of and advocates for the increased use of ABMs within healthcare settings, particularly within hospitals. In this context, ABMs of nosocomial infection spread are among the most advanced and numerous at this time, with an emerging body of work associated with ABMs investigating patient flow and other operational processes in hospitals. However, ABMs are not without their disadvantages as well. Some of these disadvantages are related to developing robust validation and verification techniques which the ABM research community agrees upon; this is a difficulty faced by many simulation modalities. Other difficulties arise from the challenge of generating accurate models of agent behaviours and interactions, as well as data extracted from the systems being modeled. The emergence of ABMs will likely be within a more integrated simulation and analysis suite, often combined with other established techniques as demonstrated within the more recent literature. The role of ABMs as useful simulation vehicles within healthcare facilities is still in its infancy, but offers tremendous potential for the better understanding and optimization of these complex systems.

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MARCIA R. FRIESEN received the Ph.D. degree in biosystems engineering from the University of Manitoba, Winnipeg, MB, Canada, in 2009. She is a multidisciplinary Design Engineering Researcher with active research in engineering education, and computer modeling and simulation. She is currently an Associate Professor of Design Engineering with the University of Manitoba. She is also serving as the President of the Association of Professional Engineers and Geoscientists of Manitoba.

ROBERT D. MCLEOD received the B.Sc. and M.Sc. degrees in electrical engineering and the Ph.D. degree from the University of Manitoba in 1981, 1983, and 1985, respectively, where he is a Professor of Electrical and Computer Engineering. His research interests include agent-based modeling in diverse application areas with emphasis on leveraging auxiliary data sources originally intended for alternate purposes.