Agent-based Modelling in Healthcare Operations: A Systematic Review of its Scope, Quality and Implementation

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ABSTRACT

Introduction Simulation is a common approach in healthcare operations research. In recent years, a new simulation method, Agent-based Modelling (ABM), has gained increasing popularity due to its flexible 'bottom-up' framework. For all the hypes around ABM, it is unclear to what extent it is being used in healthcare operations, if it is being utilised to full potential and whether it provides robust evidence for change. The aim of this review is to systematically evaluate its state of the art.

Research Questions What are the topic addressed by ABM and their associated characteristics? What was the quality of these studies? How were these models implemented?

Methods A comprehensive interdisciplinary search strategy was developed to account for materials not published in traditional journals, and double screening was applied. A data extraction form was developed to enable standardised description of studies across topic areas. An easy-to-use quality assessment tool was developed in line with the academic principles and industry experience.

Results Thirty-one studies met the inclusion criteria. 11 studies are about service efficiency, 9 on nosocomial infection, 4 on care coordination, and the rest are on hospital layout design, patient choice, and payment model. Although ABM is not evidently advantageous in studies on service efficiency, it demonstrated unique properties for studies on other topic areas (e.g. care coordination) where patients and providers enjoy greater autonomy. The quality of these studies was quite low, on average meeting 2 out of 7 quality items. In particular, most studies failed to justify their conceptual model and the time horizon chosen for model execution. Only two studies on hospital layout have been implemented and even the study of highest quality was not.

Conclusion Future studies should improve the quality of conduct and reporting, and find new ways to make an impact on healthcare operations and eventually population health.

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INTRODUCTION

Agent-based modelling (ABM) is an emerging simulation method that enjoys both praise and criticism (Schumann, 2016). While it has been successfully applied in some areas of healthcare such as pandemic modelling, its application in healthcare operations is relatively new. This is also an area where it 'competes' head-to-head with more established simulation methods. In the mist of all the hypes that ABM is the superior approach to tackle complex issues in healthcare organisations, it is critical to systematically review its current state of the art.

What is Simulation?

Simulation is an imitation of the operation of a real-world process or system (Banks, et al., 2014). The act of simulating requires the development of a model to represent key characteristics and behaviours of the real-world process or system. For example, it could be a model of patients, key staff and major tasks of a hospital operating room. Strictly speaking, *model* is an abstraction of the real-world system, *modelling* is the process of producing a model, whereas *simulation* represents the execution of such a model over time (Maria, 1997). For the purpose of evidence review, this distinction is nonsignificant. Therefore, in line with previous review (Brailsford, et al., 2009), this review will treat 'model', 'modelling' and 'simulation' as interchangeable when appropriate.

Accordingly to Professor Sally Brailsford, simulation is very commonly used in operations research, and is regarded by many as the technique of choice in healthcare. There are three main reasons for this. Firstly, healthcare systems are characterized by uncertainty and variability, requiring a stochastic approach. Secondly, healthcare organizations can be hugely complex and therefore require a modelling approach capable of dealing effectively with complexity. Thirdly, the key role played by human beings in healthcare systems requires an approach which allows interaction and communication between modellers and users. These features are all strengths of simulation and help to explain why this approach has been so widely used in healthcare applications (Brailsford, 2007).

What is Agent-based Modelling?

In the last decade, a new simulation method, Agent-based Modelling (ABM), becomes increasingly popular. Here, ‘agents’ simply mean discrete entities. This is a technical term not to be confused with the regular English word (i.e., a person who is authorised to act for another person). In the context of healthcare, ‘agents’ could be human entities such as patient or clinicians, biological entities such as pathogens, inanimate entities such as treatment rooms, and other discrete entities.

Agents are self-contained and uniquely identifiable entities with their own attributes (Macal & North, 2010). For example, historical data shows that on average there are 50 patients admitted into the hospital per day. One can model one hypothetical group which has attributes with the average values of 50 patients, and then calculate how many staff is needed on average. Or, in the ABM approach, one can model each individual patient with his own attributes. During the first run of the model, there are 46 patients, each admitted at different time of the day. In another run of the model, there may be 52 patient admitted. Eventually one can estimate the number of staff corresponding to different patient characteristics at different time of the day across all the model runs.

Agents are usually autonomous, which means that each agent can direct its own decisions and behaviours, and is not controlled by a central process. For example, a model could enable patient agents to make their own decisions on which hospitals they want to go to seek care.

Agents have internal states and external interaction with other agents, which in turn influence their own states. For example, a patient agent in the state of ‘sick’ and physician in the state of ‘free’ can have an interaction ‘treatment’, which will change the patient agent’s state back to ‘healthy’. These behaviours are described by algorithms that are usually simple ‘if-then’ rules, but could also be highly complex stochastic ‘black box’ ones (Brailsford, 2014).

ABM is a 'bottom-up' approach, in the sense that by modelling agent by agent and interaction by interaction, self-organization and system-level effect can often be observed. This is contrast to traditional approaches, which usually configure algorithms on the system level ('top-down' approach). In ABMs, we may be able to observe emerging patterns, structures, and behaviours that were not explicitly programmed into the models, but arise through the agent interactions (Macal & North, 2010).

ABM's modelling assumption is wide open and the model design could be highly flexible, which makes it arguably the most generalised framework to model complex systems (Sayama, 2015). The notion of 'complex systems' was first introduced into healthcare in 2001 by Plsek and Greenhalgh, who argued that a dynamic, emergent, creative, and intuitive view of the world must replace traditional 'reduce and resolve' approaches to clinical care and service organisation. While scholars are still in discussion on what 'complexity' is, one thing they all seem to agree is that ABM is *the* tool for this 'new way to see the world' (Mitchell, 2018) This is because ABM's distinguishing ability to model emerging macro-level phenomena from micro-level activities (Macal & North, 2010), which matches the feature of complex systems.

Simulation and Healthcare Operations

According to a taxonomy on healthcare simulation modelling (Brailsford, 2007), there are three levels of simulation. The first level is on the human body. The second level, which is the target level of this review, 'denotes operational or tactical models at the healthcare unit level'. The third level is on system-wide strategic planning.

Healthcare operations are the activities to support the core function of a healthcare organisation or facility (Henderson, 1995). They consist of certain administrative, financial, legal and quality improvement activities to support the delivery of care (U.S. Department of Health & Human Services, 2017). Since the introduction of 'complexity science', healthcare operations have been the focal point of discussion to challenge the traditional reductionist thinking that healthcare organizations are simple manufacture-like systems. In fact, in Plsek and Greenhalgh's very first paper on complexity, they used a healthcare operation example to substantiate that tension and paradox are natural phenomena in complex systems, and not necessarily to be resolved. The view that healthcare organisations are operated like factories may have cause slow application of ABM in this domain. In other healthcare domains where the complexity is widely recognised, ABM is hardly new. For decades, epidemiologists have been using it to study infectious disease transmission, with around 700 papers published in the last 10 years alone (Willem, et al., 2017). The paradigm of ABM, i.e., focusing on agent interactions, is a natural fit for how infectious diseases spread. Such paradigm is equally applicable to health operations, where human interactions go beyond exchanging pathogens. Patients and clinicians could observe, reason, and act upon other patients' and clinician's status and behaviours. If one looks outside of health, ABM is a simple but powerful way to think about many social phenomena, and is now a standard form of modelling in the field of social simulations (Kehoe, 2017).

Currently, the established method for healthcare operations is Discrete Event Simulation, which will be referred as 'traditional simulation' in this review to reduce the use of jargon. In over 40 years, hundreds, if not thousands of traditional simulation models have been published for clinics, emergency departments (ED), operating theatres, intensive care units and hospital bed capacity management. Modelling queuing systems and patient flow are mainstream of traditional simulation (Brailsford, 2014). After the rise of ABM, researchers had debated for years on which method was superior, and whether traditional simulation was a special case or subset of ABM. Sieber and colleagues' paper (2010) entitled '*Discrete-event simulation is dead, long live agent-based simulation!*' is a provocative example in this debate. Figure 1 Comparison of Traditional Simulation and Agent-based Modelling for an Example of Patients Waiting to See Doctor is a simple example to demonstrate how traditional simulation and ABM approach the same situation (patients waiting to see the doctor) from different directions.

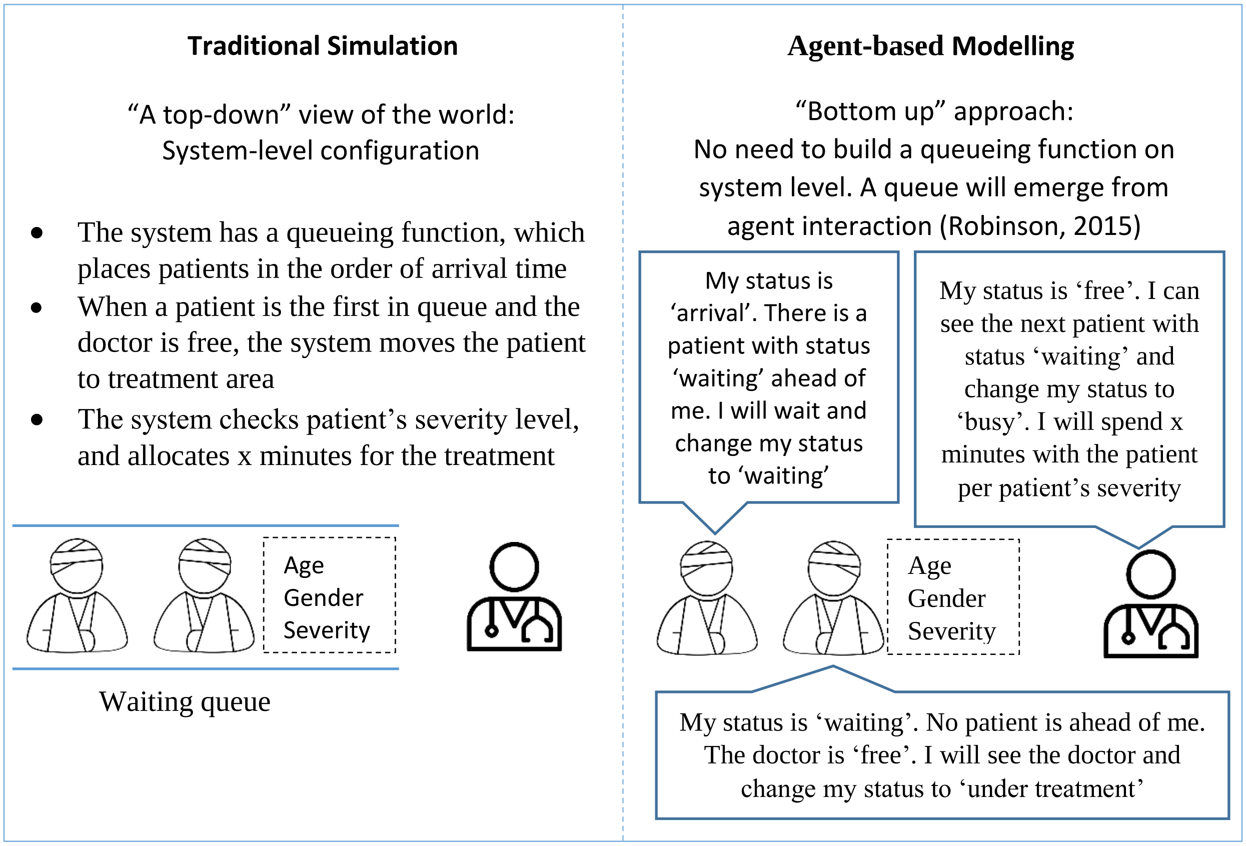

Figure 1 Comparison of Traditional Simulation and Agent-based Modelling for an Example of Patients Waiting to See Doctor

In this example, there is no better or worse method for the simple objective of maintaining the order. Both models could produce similar result. However, ABM will be computationally more expensive because it needs to account for the behaviours of each agent. This difference is probably trivial for most readers of this review. Later in the Results and Discussion sections, advantages and disadvantages in different settings will be discussed more in depth from clinical and operational standpoints.

To switch from traditional simulation to ABM requires evidence to demonstrate its added value. This review will attempt to identify and appraise some of the supporting evidence. Traditional simulation has obtained user acceptance to support daily operation of healthcare facilities (Brailsford, 2014). Switching to a new approach without proven advantages may do more harm than good (Jahangirian, et al., 2015). Compared to real experiment, virtual experiment by simulation is less risky, but is not risk-free. Virtual experiment is less expensive, but is not cost-free. The Evidence-based Medicine thinking requires us to systematically review relevant evidence before adopting a new technology. For all of the hype surrounding ABM, it is unclear to what extent this approach is being used in the care delivery setting, if it is being utilised to its full potential and whether it provides robust evidence that lead to changes in practice. The aim of this study was to systematically review the current state of the art of ABM in health operations, critically appraise the quality of these studies, discuss the challenges and limitations of this approach and suggest where future research in this field could go.

Previous Reviews on Related Topics

Fone and colleagues' paper (2003) was regarded as the first rigorous review of simulation in healthcare (Brailsford, et al., 2009). It reviewed computer simulations in 'population health and health care delivery'. No agent-based model was included in the review due to how the search query was constructed (which is probably because ABM was not a well-known concept at that time). This review is the first to apply a thoughtful quality assessment process on included studies, and it developed its own quality scoring method, although it is not certain how it was developed. This review affirmed the finding from previous review that few papers reported implementation.

In 2009, Brailsford and colleagues conducted a review with a very broad scope of simulation and modelling (including qualitative, mathematical and statistical modelling) in all domains of healthcare. Among the 342 studies that were included, three were agent-based models. It was infeasible for them to conduct critical appraisal on so many studies, but the authors did check the percentage of studies being implemented, which turned out to be 'depressingly low'. Neither did they empirically compare different simulation methods. Such comparison was undertaken later in a review of modelling approaches for emergency department patient flow and crowding (Wiler, et al., 2011). The authors assessed the five approaches for their ability to define crowding, to forecast crowding, to predict process improvement impact, and their ease of model development and ease of use. It was a development from previous discuss, as it used clinical-domain-specific indicators to compare various simulation methods. Thus it was able to present the practical differences clearer to the readers than theoretical papers.

As ABM became popular, reviews exclusively on ABM started to be published. Gill and Paranjape took the first attempt in a book chapter (2010). Although it had ‘review’ in the title, this article was rather a collection of abstracts, and did not present information on search strategy, screening criteria, or any synthesis of studies. Also, as discussed later, it seems that the authors confused ABM with ‘multi-agent system’. This problem of merely collecting papers with no critical appraisal continued into three reviews published later. These include a literature scan article (Friesen & McLeod, 2014), which summarised different thematic areas of ABM in hospital, a review paper on chronic diseases (Li, et al., 2016), which described one or two examples under each of the chronic diseases, and a review paper on Emergency Department (Adleberg, et al., 2017), which reformatted study information in a tabular format. A good exception is a review by Nianogo and colleagues (2015) on non-communicable diseases. This is the first review that distinguishes between observational and experimental models. It paid attention to how the conceptual models were described, how agent interactions were designed, and how the computerised models were validated. Appraising these items from the original paper is very helpful for the reader to understand the purpose, context and reliability of a model. However, the authors pointed out a strong limitation that they only searched public health and clinical research journals, excluding simulation-focused journals and other types of publications. Previous review (Brailsford, et al., 2009) suggested that ‘many references to healthcare modelling exist outside the domain of conventional journal publications’. As shown later in this review, most papers come from simulation- or computation-focused conferences. Even when it is published in journal, it is usually not a healthcare-focused journal.

From the title ‘Applications of Agent-Based Modelling and Simulation to Healthcare Operations Management’, Barnes and colleagues’ review (Barnes, et al., 2013) seems to be right on the topic.

However, it does not present a search strategy and inclusion criteria. Consequently the second half of its content actually covers a wide range of materials, such as national health policy on vaccine, which are not usually considered as health operations. In the first half, it retells the content of one paper on patient flow and another paper on real-time patient location tracking, and reviews four papers on emergency department. When reviewing papers on emergency department, it presents a workflow diagram of patients. This is concerning because the ABM paradigm does not model after workflow or processes. As introduced earlier, it models after the alternation of states within individual agents. In terms of data extract, this review uses five ‘parameters’ to compare across studies on emergency department, and later uses a different set of ‘parameters’ to review articles on nosocomial disease transmission. No comment was provided by the authors on the meaning of getting a ‘yes’ or ‘no’ on these parameters.

In summary, although previous reviews have laid some methodological foundations and provided a list of citations to chase, they present some limitations, including unclear or limited search strategy, confusion over some main concepts, varying way to extract data from studies, and unclear quality assessment methods. The design of this review will try to overcome these limitations.

RATIONAL AND OBJECTIVES

To summarise, much attention has been paid to healthcare operations after people realised the complexity involved in care delivery. Although traditional simulation has been applied to health operations research for decades, a new simulation method – Agent-based Modelling (ABM) – has gained popularity recently. This is because ABM is arguably the most generalised framework to model complex systems. ABM has been widely used in pandemic modelling, but its application in health operations is relatively new. Among all the types around ABM, before we put more resources to advocate, adopt or teach ABM, the evidence-based medicine (EBM) thinking requires us to properly evaluate its properties and impact (World Health Organization, 2012). Previous review on related topics are either dated or suffer from important methodological limitations. Thus it is critical to have a new review to systematically evaluate the state of the art of ABM, in a rigorous and transparent manner.

There are three main questions for this review. In the domain of healthcare operations,

(1) What are the topic areas addressed by ABM and their associated characteristics?

(2) What is the quality of these studies?

(3) How were these models implemented?

There are prerequisite questions around these main questions. To answer main question 1, we need find out what items characterise an ABM. By acquiring information on these characteristics, we could engage in the debate on how unique ABM is when compared to other simulation methods. To answer question 2, we need to have a quality assessment framework for ABM. These issues will be discussed in the Methods section, and the findings for the main questions will be presented in the Results section.

Of note, the research questions of this review do not follow the conventional PICO framework (Population, Intervention, Comparison, Outcome) because 'the PICO framework is primarily centred on therapy questions, and is less suitable for representing other types of clinical information needs' (Huang, et al., 2006). Systematic review, as a knowledge synthesis method, is not restricted to intervention review, and should ask questions that best fit its purpose (Tricco, et al., 2011). It is not characterised by meta-analysis on quantitative outcome measures, but characterised by its process being systematic, explicit, and reproducible (Cooke, et al., 2012), which is the aim of this review.

METHODS

Although the objective and design of this review is different from a conventional systematic reviews, I follow PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) as close as possible to ease locating information in the manuscript. The study protocol was registered in PROSPERO (protocol ID: CRD42018094769), an international database of prospectively registered systematic reviews protocols.

Search Strategy

The comprehensive interdisciplinary search strategy was developed. Compared to conventional search strategy employed in previous review, this review expanded significantly on the coverage of a variety of information sources. Previous review (Brailsford 2009) stated that 'many references to healthcare modelling exist outside the domain of conventional journal publications'. It suggested that commercial and promotional literature, website references and unpublished presentations were much of interest in this field, but the challenge was to find a viable means of accessing and referencing these sources. In this review, I answered this challenge by employing a versatile search strategy that, besides searching conventional databases, consists of searching modelling-focused literature databases, browsing model libraries, browsing conference materials, citation-tracking of related reviews, and contacting researcher.

First, Scopus, Orchestra and DBLP were searched from inception to May 2018 with no restriction on language and publication type. Scopus was selected because of its full coverage of MEDLINE, good coverage of computer science papers (Cavacini, 2015) and inclusion of about 30,000 conference proceedings (Elsevier, 2017). ORchestra is a reference database created by University of Twente on operation research literature in health care (Hulshof, et al., 2011). DBLP is a computer science bibliography website created by the University of Trier, and has indexed the highest number of unique articles (Cavacini, 2015). These three sources provide both comprehensive and specialised coverage of an interdisciplinary subject.

Second, online model libraries of nine open-source ABM tools[1] and two commercial ABM tools[2] were screened, as well as the OpenABM Computational Model Library[3]. Model libraries are repositories for researcher to share their models' computer source codes. Many ABM tools have their model libraries to showcase the tools' capabilities and user bases. As far as I know, this is the first review to consider model libraries as an information source. There is no comprehensive list of all the available ABM tools and their community libraries. This was based on personal knowledge and Internet search, but it did cover all the tools one will usually see from an introductory paper on ABM (for example, see (Chen, 2012)). On the other hand, the OpenABM Computational Model Library is maintained by an international community to share and preserve models across tools, and has been recommended by a journal 'to enable readers to replicate reported simulation experiments' (Journal of Artificial Societies and Social Simulation, 2017). For the purpose and rigour of this review, the source codes themselves were usually not sufficiently detailed. However, they provided hints (such as contributors, affiliations, acronyms of project names) that I used use to chase for additional information.

Third, relevant conference materials (program books, video recordings, etc.) from 2009 to 2018 were browsed or searched when available. These conferences include: Winter Simulation Conference, the AnyLogic Company Conference, International Workshop on Agents Applied in Health Care (A2HC), Conference on Complex Systems, and INFORMS Healthcare Conference. As far as I know, this is the first review to manually screen conference materials. Similar to the list of ABM tools, there is no comprehensive list of conferences at the crux of ABM and healthcare, thus the list in this review was

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[1] The open-source tools were A-globe (agents.felk.cvut.cz/publications), ABLE (researcher.watson.ibm.com/researcher/view_group_pubs.php?grp=979), Ascape (ascape.sourceforge.net), breve (www.spiderland.org/s/), Cormas (cormas.cirad.fr/en/applica/), Mason (cs.gmu.edu/~eclab/projects/mason/), Repast (repast.github.io/papers.html) and NetLogo (ccl.northwestern.edu/netlogo/models/community/). Links were accessed on 2018 September 24.

[2] The commercial vendors were SIMUL8 (www.simul8.com) and AnyLogic (www.anylogic.com/resources/case-studies/#healthcare). Links were accessed on 2018 September 24.

[3] https://www.comses.net/codebases/ (Link was accessed on 2018 September 24).

mainly derived from personal knowledge and Internet search. Due to the high volume of materials usually included in conference proceedings and the relatively short history of ABM in healthcare, only the last 10 years of conferences were screened. When only abstracts were provided, authors of relevant studies were contacted for full paper.

Fourth, citations from related reviews mentioned above were tracked. Lastly, a University of Oxford professor (Kenneth Kahn) who is specialised in ABM and has been organising a regular ABM workshop in Oxford was contacted for additional studies.

Built upon queries from previous reviews, I attempt to enhance the sensitivity and specificity of the search query used in literature database search. The main concept here is obviously 'agent-based model'. Previous reviews, when the search queries were given, have used both 'agent-based model' (ABM) and 'individual-based model' (IBM). I agree with their approach. The relationship between ABM and IBM varies from author to author, from discipline to discipline, with some saying that ABM is a *subset* of IBM in which the individuals must have interactions (Friesen & McLeod, 2014), some saying that ABM is a *superset* of IBM in which agents could be both human and inanimate entities, and some saying that they are interchangeable (Grimm, et al., 2010).

To improve sensitivity, I removed '-based' in the search term to account for scenarios like 'agent-oriented stochastic model'. On the other hand, to enhance specificity, I excluded studies on 'multi-agent system', which is a term used in computerised system. 'Agents' in multi-agent systems typically represent computer software entities, rather than entities in the physical world like patients or physicians (Wikipedia contributors, 2018). This is indeed a difficult concept to master, and a previous review did get confused between ABM and multi-agent system. This review is the first one to explicitly draw down this distinction. This is necessary because, compared with previous reviews, this review's information sources expand greatly to some computer-science-oriented sources, and thus there would be too many false hits without this distinction.

Eligibility Criteria

Studies were included if patients are modelled as interactive individual agents. Interactivity means they sense, communicate with or react to other agents. There is no restriction on patients' medical condition, number of states, ability of adaptation, or awareness of the entire system. There is no restriction on whether patients are modelled after empirical data or theory. Studies will be excluded if there is no patient agents, or if the patient agents are not interactive, i.e. patients are modelled as 'dummy' inert individuals or as a group. This review is agnostic to how an ABM is executed. It could be built as a standalone model, or as part of a hybrid model. It could be programmed by any computer software or language, even by software that is not designed for ABM *per se* as long as the authors justify the choice.

As defined earlier, a study was included if it addresses activities that impacts how healthcare services is delivered. It is not relevant if it is about the service delivery itself, such as different treatment options. I take a broad view on the healthcare settings. It is not only limited to a single healthcare facility with four walls. It could be a group of health organizations closely collaborating with each other, such as alliances of practices, or mobile units under one dispatching control. A study could be explanatory, attempting to explain the mechanism behind certain observed phenomena, or could be experimental, investigating 'what-if' scenarios.

Only completed studies (an actual model is built and results are presented) were included. Since I searched through a variety of information sources, only those materials with sufficient details were included. This has the biggest impact on promotional materials (from simulation consultants or commercial software companies) and industry-sponsored conferences. Attempts were made to use keywords from those brief materials to identify more detailed materials, and some authors were contacted.

Screening

Two reviewers independently assessed the eligibility of articles. Disagreement was resolved through discussion. A third reviewer's opinion was not sought. Because the two reviewers work in the same non-academic organisation and one reviewer is a senior colleague to the other reviewer (an undergraduate intern), a protocol was established at the beginning to avoid the power hierarchy and company politics interfering with the discussion.

Data Extraction

Although this review does not have research questions in PICO format, data extraction form was built upon PICO format to standardise descriptions of studies and ease understanding. This was in response to the non-standardised data extraction in previous reviews. Each of the previous reviews had its own way to describe an ABM, with few items overlapped among them. Such 'ad hoc descriptions of models' was criticised as 'often difficult to follow and incomplete' (Grimm, et al., 2010). PICO alone was not enough, because ABM studies have their own features that randomised controlled trials do not possess. In order to answer the research questions of this review, it is critical to identify the items can could uniquely characterises an ABM.

A search was carried out on reporting guideline related to ABM. This is worth trying because items in a reporting guideline represent essential information for a particular type of study. While a search on the EQUATOR Network (a library of reporting guidelines for health research)[4] returned no result, a broader literature search identified the 'ODD' (Overview, Design concepts, and Details) protocol developed by ecologists (Grimm, et al., 2010), which consists of 17 items to describe ABM. This comprehensive list has been recommended by a journal as the standard format of reporting (Journal of Artificial Societies and Social Simulation, 2017). It was tested in a literature review as a data extraction form (Lemos, 2016).

[4] https://www.equator-network.org/

From his testing, however, the author found the ODD protocol infeasible to use, so most items were not removed. This was because very small portion of studies were actually reported in this format[5], which made extraction of all its items a significant effort: it was essentially re-writing the entire studies. Only two reviews were able to adopt most items of ODD in their data extraction, probably because they only included three articles (Jelassi, et al., 2015; Berger, et al., 2008). As shown later, the number of articles included in this review far exceeds three, thus using the full ODD protocol is likely infeasible.

So, is there a smaller set of items that could characterise an ABM? To answer this question, I turned to case studies (Majid, et al., 2016; Majid, et al., 2016; Zankoul, et al., 2015) that empirically compared ABM and traditional simulation. These are studies that built an ABM and a traditional model for the same researcher questions, and then compared their features or performances. It revealed that, from an implementation perspective, ABM focused on the alternation of states of the agents. As previously discussed in the Introduction section (page 3), 'Pure' ABM did not specify the system-level rules or workflow (Brailsford 2012), which may emerge from the interaction of agents and the corresponding changes of their states. This feature could be translated into the following items in data extraction: the possible states of the patient agents and provider agents (two descriptive items), whether a 'statechart diagram' is provided to show the alternation of states (a binary item), and agent interaction (three descriptive items on patient-and-patient, patient-and-provider, provider-and-provider interactions). Although it may sound unfamiliar, statechart diagram (or state machine diagram) is in fact more oriented to healthcare professionals' mind set of patient's health and treatment status. It is a standard diagram which describes agent behaviours by showing the finite sequence of states during the lifetime of an agent (Richiardi, et al., 2006). For example, a patient agent could have four states: healthy, sick (waiting for treatment), sick (under treatment) and dead, while and a physician agent could have two

[5] For example, as shown later, the only study included in this review that used ODD is Ferrer, et al., 2013.

states: idle and busy. A link between the patient's 'sick (under treatment)' state and the physician's busy state could demonstrate how the interaction (treatment) effects the states of both agents'. Although it is only one of the five recommended agent-oriented diagrams (in contrast to the conventional workflow-oriented diagrams) (Richiardi, et al., 2006), it's simple and closely aligned with healthcare literature on ABM. A 'yes' is assigned to this data extraction item regardless whether a statechart diagram stands alone or is part of a bigger diagram in the manuscript. In terms of agent interaction, there are three possible values: none, direct, or indirect. Direction interaction means agents encounter and effect each other (e.g., a provider offering treatment to a patient), while indirect interaction means agents compete for a mediating resource (e.g., a hospital bed) (Grimm, et al., 2010).

Other frequently mentioned features of ABM are spatial representation (Barnes, et al., 2010; Brailsford, 2014; Nianogo & Arah, 2015) and adaptation. 'Spatial representation' means the model design considers the impact of space and location. Where an agent is located will have an impact on the state of the agent or how this agent interacts with other agents. Moreover, it takes time to move from one location to another. The spatial representation could be very real, mimicking how an actual facility is constructed, or could be hypothetical, describing a 'typical' paediatric clinic, for example. However, I do not consider a model having spatial representation if it is merely symbolic. In symbolic representation of space, different locations usually serve as visual separation of agents from each other, or a visual representation of a workflow. There is no actual topological connection between locations. Agents could move from one location to another instantly. Because whether spatial representation is truly a feature of ABM is yet to conclude in the literature, I will extract relevant data in this review to inform the discussion. The other feature, 'adaptation' refers to the adaptive trait of agents. An agent is adaptive if he has rules for making decisions or changing behaviours in response to changes in himself or his environment (Grimm, et al., 2010). Although adaptation has been promoted and phrased passionately in theoretical papers, previous reviews found that it was seldom reported in studies: in fact, these studies reported most items from the ODD protocol, but intentionally left this one out (Grimm 2010). I verified the result by pilot testing with five studies included in this review, and none of them reported adaptation. My personal observation is that, no matter how much one wants to humanise ‘agents’, all behaviours of an agent eventually need to be programmed by computer codes. If one wants an agent to change behaviour when the environment changes in a certain way, one needs to explicitly program that as a behaviour rule. But once it is programmed, it is hard to distinguish that ‘adaptive’ rule from other ‘regular’ rules. From a programming perspective, it is just one more line of ‘if-then’ codes. Humans, on the other hand, have great plasticity in our genomes, bodies, and minds via million years of evolution. We have many hidden capabilities that could be harnessed when we are in a new environment, a.k.a, we adapt (Massey, 2013). Agents in an agent-based model, however, do not have such inherent plasticity. At least for now, they could only behave to the extent explicitly specified rules. In the future, if we advance to not use simple ‘if-then’ rules but use complex stochastic representation of stimulus-response mappings (Brailsford, 2014), then agents may become more adaptive to every possible input from the environment. In summary, because ‘adaptation’ has been more a concept in theory but seldom an item reported in practice, I will not include it in the data extraction of this review.

The final data extraction form is illustrated in Table 1 Data Extraction Form:

Table 1 Data Extraction Form

Item	Explanation
Country	The residing country of the healthcare organisation(s) that a study simulates after. Modelling studies are usually commissioned for or inspired by real-word problems (Brailsford 2012). If a study models a completely hypothetical issue, the residing country of the first author was extracted.
Publication type	Journal paper, conference paper, book, commercial materials, etc.
Study type	Experimental or explanatory
Topic area	Resource allocation
Healthcare setting	Particular place, facility or type of surroundings where the agents are in.

Spatial Representation	Whether the model environment is designed after a (real or 'hypothetical but realistic') topology
Investigational components	The factors that the investigators deliberately change or test in the model
Patient agents	By what state and attributes, are these patient agents characterized?
Leading provider agents	By what role does the leading provider play? By what state and attributes, are these provider agents characterized?
Other provider agents	By what role do other providers play? By what state and attributes, are these provider agents characterized?
Interaction	What kinds of interactions among agents are assumed? Whether the rules of behaviours are specified within each agent or on a system level?
Outcomes	Indicators measured in the study
Stochasticity	What processes are modelled by assuming they are random or partly random?
Model presentation – Statechart	Is statechart diagram (or similar diagram or text) provided to describe the lifecycle of all important agents?
Model presentation – Other	How is the model presented besides using the statechart diagram (workflow diagram, equations, pseudo-code, source code, etc.)?
Implementation	How is the model implemented?

Data was extracted by me and checked by the other reviewer. Disagreement was resolved by discussion.

Quality Assessment

Simulation is not a study type included in the Evidence-based Medicine's 'level of evidence' pyramid (Oxford Centre for Evidence-based Medicine, 2009) and is in lack of standardised quality assessment tool. Having a reliable tool to assess 'quality' has been at the core of the methodological development of systematic reviews, because 'quality' plays a vital part of interpreting the evidence (Burton, 2017). This is evident in the publication and adoption of tools for other study types, such as the Cochrane risk of bias assessment tool for randomised controlled trials, the Newcastle-Ottawa Scale (NOS) for nonrandomised studies, the Grading of Recommendations Assessment, Development and Evaluation (GRADE) method, and many more.

Literature search found four methodological articles that proposed full assessment frameworks. Two of them (Richiardi, et al., 2006; Abuelezam, et al., 2013) focused on evaluating ABM in social science and HIV transmission, respectively. The other two (Philips, et al., 2006; Dahabreh, et al., 2016) focused on evaluating decision-analytic modelling in heath technology assessment. The literature search also identified two papers that touched just couple quality issues. Also, as mentioned earlier, a previous review (Fone, et al., 2003) developed its own assessment tool. Appendix II. Detailed Synthesis of Quality Assessment Tools is a detailed synthesis of the quality assessment items from all these articles, identifying distinct items and combining similar ones. The final list is very lengthy, containing 33 questions in 6 domains. This is partially because each article's quality items do not overlap significantly with others. A pilot was carried out by me and my supervisor to test the feasibility of using all 33 questions in quality assessment.

The pilot testing reveals serious issues. First of all is its length, which is way longer than any other standardised assessment tools. For example, Cochrane risk of bias (RoB) assessment tool contains 6 questions. Because of its length, it took between 60 to 120 minutes to complete one assessment. As a comparison, Cochrane RoB users reported that taking 10-20 minutes is most common (Savović, et al., 2014). The design of an assessment tool needs to balance between the insights that could be obtained and the time investment. Second is its difficulty to use. Many of the questions require subject matter expertise in the particular setting of a study, such as the nuances of the daily operation of an operating room, which is difficult for non-clinician reviewers to obtain. Also, many questions require substantial judgement call. While judgement is evitable in quality assessment (Higgins, et al., 2011) (Castellini, et al., 2018), the arbitration and low interrater agreement in the pilot testing are concerning.

In industries other than healthcare, 'validation' is a primary process to substantiate and assess the quality of a simulation model (Sargent, 2010). This concept aligns with the original principles of the development of Cochrane RoB, which are to focus on internal validity, results, and empirical considerations (Higgins, et al., 2011). It also aligns with the clinical-practice-oriented principle of other modelling works in healthcare, such as prognostic modelling (Altman & Royston, 2000). Among the many validation frameworks (Richiardi, et al., 2006). One validation framework is from Robert Sargent (2010), which considers the relationship between the problem entity, conceptual model and computerised model. The problem entity is the system, idea, situation, policy, or phenomena to be modelled. The conceptual model is the mathematical/logical/verbal representation (mimic) of the problem entity developed for a particular study and the computerized model is the conceptual model implemented on a computer. A reliable study needs to, at the minimum, validate both of its conceptual model and operational model. Of note, there are more than 11 operational validation techniques against different facets (outcomes of interest, behaviours that generate those outcomes, etc.) of a classical simulation model (Sargent, 2010), and in the last decade even more techniques are under development specifically for ABM (e.g., participatory simulation (Macal, et al., 2014) or Immersive Assessment (Klügl, 2008)). In this review, I will give a 'yes' if a study uses any of the validation techniques to assess how well the study outcomes match the historical or current state of the real-world problem entity. I do not require validation on the predicted study outcomes, although such 'predictive validation' (Sargent, 2010) is highly desirable and will be highlighted in the analysis.

With the goal of having an assessment tool that could be completed objectively in reasonable time by reviewers without in-depth knowledge of the study context, and could identify areas of focus for future research (both primary and meta research) (Savović, et al., 2012), the following tool was synthesised and pilot tested, and will be used in the next section to analyse included studies (Table 2).

Table 2 Quality Assessment Tool

Item	Quality Assessment Question
Conceptual Model	Was the design of the conceptual model validated by appropriate approaches?
Parameters	Were the estimates of parameters obtained from appropriate approaches?

Time horizon	Did the author justify that the time horizon chosen for the model execution is sufficient to reflect important outcomes?
Sensitivity analysis	Was sensitivity analysis of parameters performed and/or was the model's robustness discussed?
Parsimony	Were more simple/complex models explored?
Operational Validation	Was operational validation of model outcomes performed?
Generalisability	Did the authors justify the generalisability of its concept model to other settings?

One item in this table, 'Parsimony', is an easily overlook item in assessing simulation models, only mentioned by one assessment framework in Appendix II. Detailed Synthesis of Quality Assessment Tools. The concept of parsimony is deeply rooted in the philosophy of science and the rational nature of evidence (Forster, 2004). In computer simulation, the discussion by far has also been vivid, from some researchers adopting a minimalist approach that models should be 'as simple as possible while still allowing specific problems to be solved' (Grimm & Railsback, 2005), to others suggesting that a model needs to maintain a certain level of complexity in order to have end-users' acceptance that it is 'real', even it does not outperform a parsimonious one (Grimm, et al., 2010) (Chwif & Paul, 2000). Dahabreh described Parsimony in the model development process in the following way: 'Determine the targeted level of complexity (or parsimony) based on the research question and model scope. It is often preferable to build a simpler model first and progressively increase the degree of complexity' (Dahabreh, et al., 2016). Accordingly, I will give a 'yes' to this item if such a process is evident from a manuscript. Beyond the scope of this review, how to determine the right level of complexity for an agent-based model of a complex adaptive system is an intriguing and paradoxical question which by my knowledge has not been fully examined.

Overall, all questions are carefully phrased to be answerable by quotes in the manuscript. For example, instead of asking 'Could the model be applied to other settings', which requires significant judgement and is arbitrary because 'other settings' could have different meanings for different reviewers in different contexts, this tool asks about whether the authors justified the generalisability of its conceptual model. Of note, comparing to two decades of international collaboration on developing the Cochrane RoB tool (Chandler & Hopewell, 2013), quality assessment in healthcare simulation model (especially ABM) is very early in its development. The tool used in this review warrants further scrutiny and enhancement from the academic community.

Synthesis

Data were narratively and graphically summarised. No statistical analysis was necessary, except for some simple counts.

RESULTS

Electronic database search identified 1193 records. The exact number of records from other sources is not available because they were browsed manually. Authors of four studies were contacted, but only ones study's authors replied with additional materials. After full-text screening, 31 studies (36 articles) were included in analysis (Figure 1).

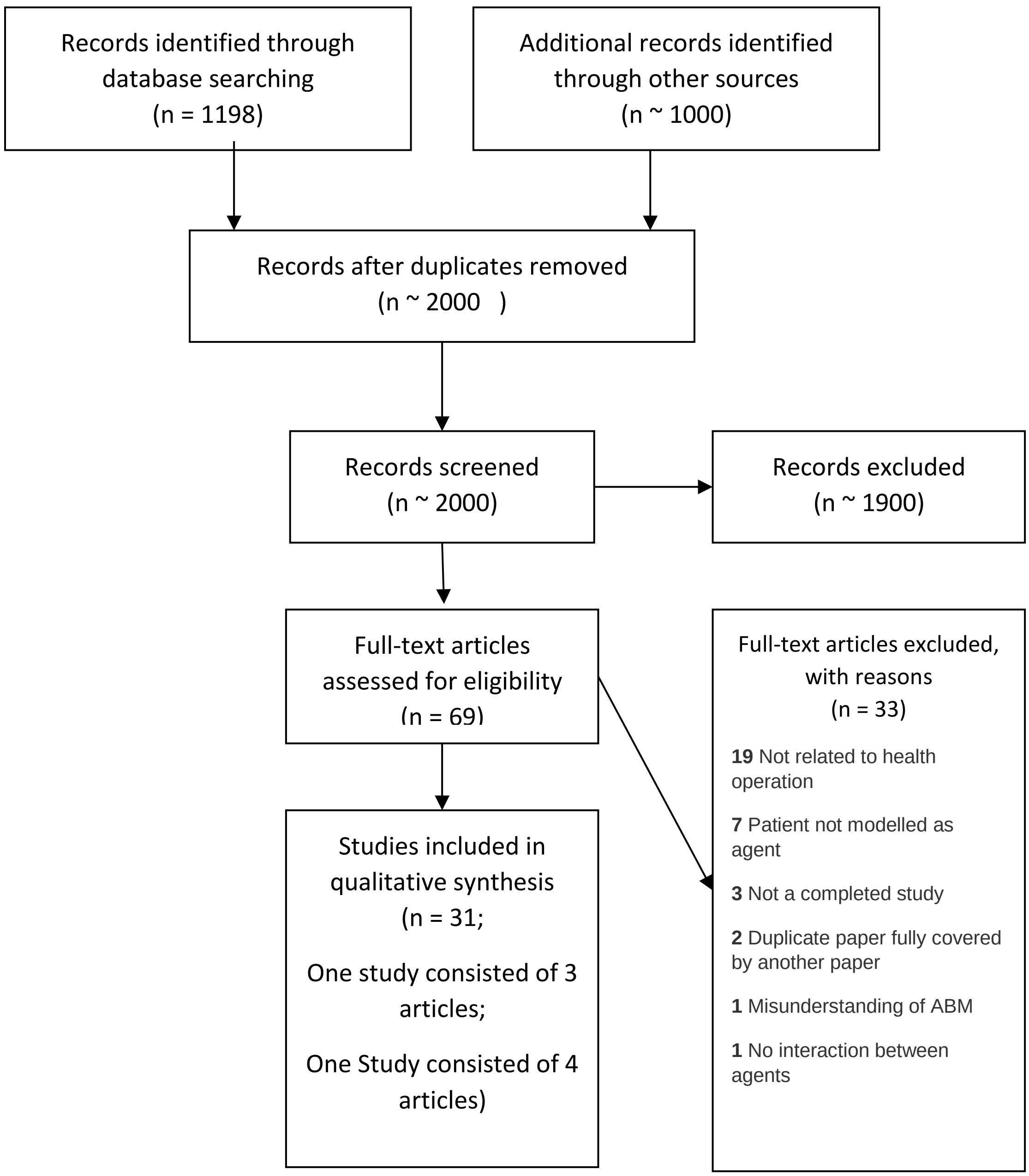

Figure 2 PRISMA Flow Diagram

Most articles were excluded because they were not related to healthcare operations. For example, a study's abstract may suggest that it was about how health facility could operate to meet the care demand of future generation. However, a careful examination of the full text revealed that it only modelled the aging process and disease progression of patients over the years. No healthcare operations were actually modelled.

Most included studies are from North America (14 studies from US, four from Canada) and Europe (three from France, two from UK, one from Spain, the Netherlands and Germany respectively), but there are studies from all continents (one from Algeria, Australia, Brazil, Chile and China, respectively). They were all published in the last 13 years (2005 – 2018). Slightly over half of the studies (17) were published in conferences (conference papers later published in books, lecture notes or journals were still considered conference papers), and the rest were from conventional journals. Only less than half of the studies (14) were published in healthcare-related conferences or journals, even under a broad definition that includes 'e-health', etc. The rest were published in computation- or simulation-related conferences or journals.

Research question 1: What are the topic addressed by ABM and their associated characteristics?

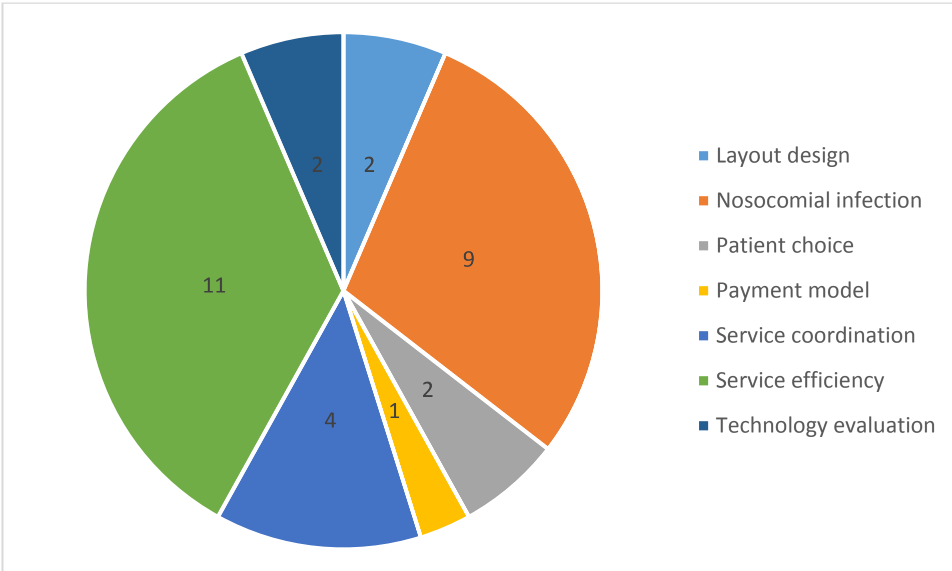

Figure 3 Counts of Studies in Each Topic Area

Previous reviews do not have a standard way to summarising the topic areas within health operations. The areas presented in **Error! Reference source not found.**is my own classification, which is slightly more granular than previous reviews due to the more focused nature of this review.

The 'Service efficiency' category consists of most studies (11 studies; 35% of all studies)[6]. Studies in this category typically investigated the impact of resource allocation (such as adding a certain number of clinicians or treatment rooms) or new operating procedures (such as new way of scheduling appointment or having longer operating hours) on some efficiency indicators such as patient waiting time. Emergency Room (ER) was the main healthcare setting being addressed (8 studies), probably due to its unpredictable arrival of patients and their severity. It is encouraging to see two studies on primary

[6] These studies are Bai, et al., 2016, Garbey, et al., 2017, Greenroyd, et al., 2018, Guclu, et al., 2016, Jones & Evans, 2008, Kanagarajah, et al., 2008, Laskowski, et al., 2009, Liu, et al., 2017, Saoud, et al., 2016, Turkcan, et al., 2014 and Yousefi & Ferreira, 2017.

care practice because primary care's complexity was sometime overlooked (Ellis, 2010). ABMs in these studies were typically designed as provider agents having direct one-way 'interaction' on the patient agents (diagnosis, treatment, etc.), while patient agents interact indirectly with each other (i.e., competing for available bed). For example, Kanagarajah and colleagues (2008) built a model on a hypothetical emergency room (ER) to test the effect of increasing the number of doctors and decreasing the number of treatment rooms on the time patients spent in the ER. Agents included patients, doctors, registration clerks, triage nurses, treatment rooms, and other technicians. The states of patient agents were unknown. Patients were attended according to their criticality. Doctors changed their consultation time with the patients based on the ED waiting room queue. The availability of inpatient beds to admit ER patients was based on a stochastic function. Spatial factors were not considered in this model. The model was not implemented.

The second biggest category is 'Nosocomial infection', or disease transmission within a healthcare facility (n=9; 29%)[7]. This is not surprising since ABM has been successful applied in pandemic modelling. The nine studies in this category applied a wide range of interventions to control nosocomial infection in hospital general wards, intensive care unit and other settings. The most common interventions were changing the number of staff, improving hand hygiene compliance, and restricting visitors. Models were typically designed as provider agents having two-way direct interaction with the patient agents. The provider-to-provider and patient-to-patient interactions, however, were modelled differently in each study. For example, Hotchkiss and colleagues (2007) built a model on a dialysis unit to test the impact of three interventions (spatial segregation, temporal segregation, and both) on the number of contamination events. Agents (patients, technicians, dialysis chairs) had two states: infections or non-infectious. Each patient agents had his own risk of being infectious, which was determined by a

[7] These studies are Barnes, et al., 2010, D'Agata, et al., 2007, Ferrer, et al., 2013, Ferrer, et al., 2014, Greer & Fisman, 2009, Jiménez, et al., 2013, Temime, et al., 2010, Hotchkiss, et al., 2005, and Hotchkiss, et al., 2007.

screening procedure with an error rate. An infectious patient agent could contaminate a non-infectious technician agent or a dialysis chair agent via direct interaction, and vice versa. There was no patient-to-patient interaction or technician-to-technician interaction. Contamination and decontamination were based on probabilities. This model did not have spatial representation, and was not implemented.

The next category is 'Service coordination' (n=4; 13%)[8]. The four studies in this topic area investigated how provider collaboration impacted utilisation and patient outcomes. Compared to studies in other categories where provider-to-provider relationship were not modelled or would not be changed during the studies, studies under this category focused on provider's relationship with each other. Such relationship could be modelled indirectly (one study, where one provider could correct errors of another provider) or directly (three studies). When modelled directly, studies either modelled direct interactions between individual providers, or grouped providers into a team in order to test some collaborative team features. For example, Ramsey (2014) built a model to test the effect to two care coordination policies (continuous care and opportunistic care) on the average glycated haemoglobin, cost and medication errors in diabetes patients. Patient agents each was in the state of high, medium or low glycated haemoglobin, and had an array of attributes on his vitals, lab test results and diagnosis history. Physician agents, whose states were not given in the manuscript, each had certain level of error rate. Physician agents interacted in the opportunistic care setting with the ability to correct each other's mistake in care. There was not spatial considerations, and the model was not implemented.

The next category is 'Patient choice' (n=2; 6%). The two studies (Gao & Chan, 2013; Alibramhim & Wu, 2018) in this category investigate how patient's choice on visiting which providers may have an impact on the growth and performance (clinical and financial) of providers. Due to the small number of studies, characteristics have not emerged yet. Equal number of studies (n=2; 6%) (Zambrano, et al., 2016)

[8] These studies are (Leykum, et al., 2012), (Xu, et al., 2008), (Ramsey, 2014), and (Lim, et al., 2013)

(Rothengatter, et al., 2010) are in the categories of ‘Layout design’ (n=2; 6%). They investigated how the physical layouts of health facilities impact the flow of people (patients, providers and others). Compared to other studies, spatial representation was the key in these studies. Two studies (6%) (Djanatliev, et al., 2014) (Laskowski, et al., 2010) are about ‘technology evaluation’, prospectively modelling the performance of new technologies. Feature of these studies was the focus on interaction between the objects (the new technology) and people. Inanimate agents were modelled in other studies as well, but only in this category that they were the focal point. The last category is ‘Payment model’. There is only one study (3%) so far investigating the impact of different business agreement between payers and providers on providers’ decision to form a health alliance, and the subsequent impact on clinical outcomes of patients and financial outcomes of providers (Liu & Wu, 2016). Compared to other studies, there was one more agent type in this study, the payers.

Among these topic areas, ABM seemed to be a natural fit for ‘Nosocomial infection’, ‘Service coordination’, ‘Payment model’ and ‘Patient choice’. From reading the manuscripts of these studies, ‘Nosocomial infection’ was a noticeably more mature than other topic areas, because of ABM’s successful history in pandemic modelling. Besides, ‘Service coordination’ was an emerging area that ABM was more convenient than traditional simulation. Traditional simulation did not usually model individual providers. Rather, they modelled the care processes or activities. Traditionally, it was hard for to test different care coordination schemes because when there was a need to mix two processes, a new process would need to be created to replace the existing ones (Zeigler, 2014). On the other hand, it was relatively easy in ABM to create or remove interactions among providers. As a result, ABM made it easier to conduct such virtual experiments. The same applied to ‘Payment model’ and ‘Patient choice’, as ABM enabled individual decision making under different payment and service agreements.

On the contrary, for the topic areas of ‘Service efficiency’ and ‘Layout design’, ABM studies appear to be quite similar to traditional simulation in regards to model design and presentation. For example, the concept of ‘queuing’. It was suggested that ABM is the method of choice when there was no centralised process and queue in a study. As shown in Table 3 Number of Studies with the Proposed Features of ABM, this really depends on a study’s topic. The model design of all ‘Service efficiency’ studies could probably be replaced by a traditional queueing model. On the other hand, the concept of ‘queueing’ cannot be applied to ‘Nosocomial infection’ studies.

Table 3 Number of Studies with the Proposed Features of ABM; by Topic Areas

	Service efficiency (n=11)	**Nosocomial infection (n=9)**	**Service coordination, Patient choice, Payment model, and Technology evaluation (n=9)**	**Layout design (n=2)**	**(total n=31)**
Irreplaceable by a queuing model	0 (0%)	9 (100%)	6 (44%)	1 (50%)	16 (51%)
Spatial representation	3 (27%)	4 (44%)	3 (33%)	2 (100%)	12 (39%)
Statechart diagram	4 (36%)	3 (33%)	4 (44%)	0 (0%)	11 (35%)

Note: Rows represent the features of ABM proposed in the literature. Columns represent topic areas, with some topic areas combined due to similarity in model design.

As explained in the Methods section (page 17), spatial representation was proposed as a feature of ABM. However, my analysis shows that this is not the case, as only 12 out of 31 studies had spatial representation (Table 3 Number of Studies with the Proposed Features of ABM). In particular, only three ‘Service efficiency’ studies had spatial representation. While many studies had a graphical or visual user interface, they didn’t truly have spatial representation because the movements of agents were instantaneous and effortless. A model with true spatial consideration would need to account for the time or probability of moving from one place to another for an agent (patient, physician, pathogen, etc.). A good example is Liu and colleagues’ study, which models the time needed for physicians to walk from one treatment room to another.

My analysis also shows that agents’ states were not modelled or reported to a desirable level. As introduced in the Methods section (page 17), in theory, ABM focuses on the alternation of agents’ states as result of agent interactions. In reality, thirteen studies (42%) did not provide any details regarding the possible states of their patient and provider agents. However, at least one can tell these studies took agents' states into consideration, but just did not report them in details. It is more worthwhile to mention that two studies (6%) did not model the states of patient agents at all, and four studies (13%) did not model the states of provider agents' at all. As shown in Table 3 Number of Studies with the Proposed Features of ABM, only 11 studies (35%) provided a statechart diagram. In these diagrams, one's content was actually more like a workflow diagram (Saoud, et al., 2016), indicating potential confusion among researchers. A very interesting case is Liu and colleagues' study (2017). In the 4 papers published for their model, the statechart diagram was only presented in the very first paper when the conceptual model was introduced (Liu, et al., 2014). In the subsequent paper when they executed the model, the workflow diagram was presented instead. I suspect that there might be some barriers to the acceptance of statechart diagram, hence the investigators switched back to a more traditional diagram.

Research question 2: What was the quality of these studies?

An overview of each study's assessment on seven quality items are shown below.

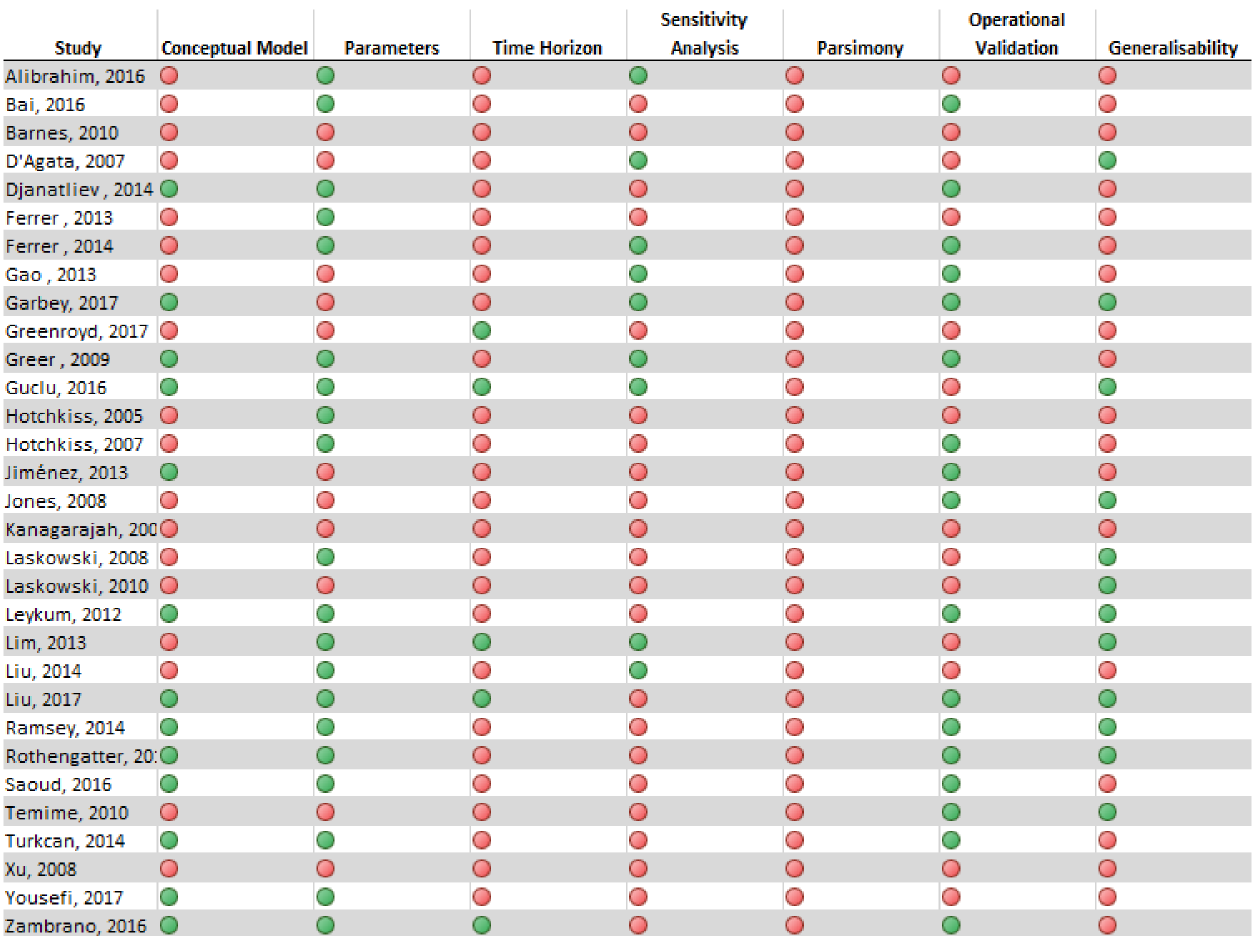

Figure 4 Quality Assessment Result

Note: Green means 'yes' to the quality assessment question, and red means 'no'.

The overall quality of these studies is quite low. Not a single study achieves 'yes' on all items, and median number of 'yes' for a study is only two.

More than half of the studies failed to elaborate why their conceptual models were good representation of the situations or phenomena under investigation (18 studies rate as 'no'; 58%). Many studies started their method sections by going straight into the details on agents and workflows, without supporting information on how they came to know about these. There could be virtually unlimited number of conceptual models for a single healthcare setting. For example, in this review's nine studies on emergency room, the types, attributes and interactions of agents were modelled differently in each study. As the aphorism goes, 'all models are wrong, and some are useful' (Wikipedia contributors, 2018), thus supporting information on how a conceptual model is developed is critical for readers to understand its usefulness. This has not been the case for many studies included in this review. For some studies, such as (Greer & Fisman, 2009), it seems one of the authors was a clinician working in the healthcare unit under investigation, from whom, the conceptual model seemed to be drawn. However, having an 'insider' clinician as a co-author does not automatically warrant a good conceptual model. Due to the 'insider-researcher bias', it actually requires equal if not more caution in the design than using 'outsider' approaches (such as interviews or ethnographic observation) (Costley, et al., 2010). On the other spectrum, a study by Leykum and colleagues (2012), provided extensive information on how they observed and understood the phenomena of team sense making and improvisation. Their paper described the behavioural framework, measurement and the execution of their ethnography.

Two thirds of the studies provided some supporting information about the values used in their parameters, making the quality 'Parameters' the best performer among all quality items (11 studies rated as 'no'; 35%). Most studies were able to draw parameters from real-world data. When real-world data is not available, they were able to identify supporting literature, or in four studies, expert. In one study (Greer & Fisman, 2009), because there is no supporting data on the probability of pertussis transmission, the authors diligently tested a wide range of values.

In terms of 'Time horizon', vast majority of the studies did not justify the length of time horizon and whether they were enough for the research objectives (26 rated as 'no'; 84%). Two contrasting example are Liu, et al., 2017 and Saoud, et al., 2016, both aim at reducing patients' length of stay in Emergency Department. Liu simulated for 365 days and Saoud simulated for 24 hours. While Saoud did not justify simulating for 24 hours, Liu did so by examining a subset of population (those with highest acuity level). It was determined that because there were so few patients in this population, simulating for 365 days was necessary in order to have a good estimate of the study outcomes.

Majority of the studies did not perform sensitivity analysis (22 rated as ‘no’; 71%). Even in those with such analysis, some examples of confusion existed. For instance, in one study (Gao & Chan, 2013), the authors wrongly considered the changes in patient preference and search radius as part of the sensitivity analysis. This was not because those components were under investigation of the research. Sensitivity analysis is about whether the findings of the investigational components still hold true if there are changes in the non-investigational components (i.e., parameters).

Contrast to sensitivity analysis, the awareness of operational validation is higher (14 rated as ‘no’; 45%), with more than half of the studies (17) were validated against real-world data, literature, or, in one case, review from staff members (Rothengatter, et al., 2010). The rest of the studies expressed the need to do so in the future, such as (Yousefi & Ferreira, 2017). Of note, no study compared its result to other models (ABM or otherwise), which is considered an essential practice to link a new model to literature (Richiardi, et al., 2006). For example, even though there are eight studies in this review on the same topic (improving efficiency of emergency department), they neither cross-referenced each other, nor compared their results to other hundreds of non-ABM studies in the literature.

When it comes to generalisability, only 12 studies discussed how their conceptual models could be generalised to other settings (19 rated as ‘no’; 61%). This should be viewed in conjunction with the low percentage of studies that described how their conceptual models were developed. One study (Yousefi & Ferreira, 2017) expressed confidence in the generalisability of its model, although no explanation was given. Two studies (Turkcan, et al., 2014; Greenroyd, et al., 2018) discussed how flexible they were in terms of parameterisation and user interface, without examining the conceptual models first. One could only configure the parameters to the extent that the conceptual model allows. But if the conceptual model is not a good representation of the phenomena (e.g., missing an important agent type), configuring the parameters is not going to help.

Lastly, in terms of 'Parsimony', no study explored a more complex or parsimonious model. My observation is that the ABM studies included in this review are still very simplistic (too simple to be realistic). For example, one study stated that further work needs to apply its learnings in a 'real life environment' (Kanagarajah, et al., 2008). They has not been developed to the stage where we need to balance between realism and parsimony. More discussion will follow in the Discussion section.

Research question 3: How were these models implemented?

This review finds only two studies out of the 28 experimental studies were implemented. Both studies were about hospital layout design. It seems it is relatively straightforward for users to accept visualisations of patient flows and facility layouts. For example, authors from one study (Rothengatter, et al., 2010) 'noticed remarkable enthusiasm after a brief try out' of a five-minute movie clip. For studies in other topic areas, however, the issue is more complicated. As mentioned earlier, many models are very simplistic. They intended to demonstrate that ABM may be useful for those their objectives and usually called for building more realistic models at the end of their manuscripts. Therefore, it is not surprising that they were not implemented. But sometimes, operationally validated models were not implemented either. For example, Bai, et al., 2016. Via email communication with the authors, I learned that the project was terminated before implementation because no funding was secured. Another interesting case a study on emergency department (Liu, et al., 2017). It was rated 'yes' for 5 out of the 7 quality items, the highest number among all studies. A university research team had dedicated to it for many years, and one member of the team devoted his doctorate thesis to it. Even with such amount of effort, it was not implemented in its intended use case to support operation and decision making of this emergency department. Rather, it is being re-used as a synthetic patient generator for other research projects.

DISCUSSION

The clinical motivation of this review is in line with previous review (Fone, et al., 2003) that 'the potential of simulation modelling to inform evidence-based policy development for the provision of health care is clear, but information on the outcomes of model implementation and hence the value of modelling requires further research'. This review focuses on one type of simulation that is popular in recent years: agent-based modelling (ABM). Its flexible and 'bottom-up' approach proposedly yields greater potential to tackle the complex issues healthcare organisations encounter in delivering service to patients.

The clinical significance of ABM on service efficiency is *not* evident from this review when compared to traditional simulation. Although 'service efficiency' is the topic area with the highest number of studies, the advantage of using ABM over traditional simulation is not obvious from analysing the designs and outcomes of these studies. Their model designs appeared to be quite similar to tradition simulation. When there is a difference, it appears that they could be replaced by traditional queueing technique. Moreover, most of them did not have spatial representation, which was featured by ABM advocates because it is harder to do so in traditional simulation. Lastly, no empirical comparison was provided to demonstrate better model performance. Under the current body of evidence, the value of promoting the use of ABM on service efficiency is debatable because traditional simulation have already obtained user acceptance.

On the contrary, clinical significance is higher in emerging topic areas (e.g. care coordination, patient choice), where ABM is a more natural fit than traditional simulation. The ability to model physician and patient behaviours under different team structures, coordination schemes or payment arrangements opens up exciting areas for research. In traditional simulation, there is a limit to how much a modeller can experiment in, for example, a primary care clinic (e.g., changing the number of doctors in different time of the day). In these new topic areas, however, there is more room for innovation. For example, a modeller can test the effect of a variety of payment models to incentivise a primary care clinic to collaborate with a variety of specialists in a variety of ways to streamline the care of a population. Although no model included in this review was developed to a stage that is ready for implementation, they did seem to support that ABM is a useful virtual tool for in areas where it is hard to conduct real-world experiments. International workgroups have recognised that simulation is the method of choice when dealing with complex healthcare systems, because it enables virtual experimentation on the upstream and downstream consequences of changes in healthcare operations (Marshall, et al., 2015). In the last couple years, simulation has been in such rapid development that some announced 'simulation in healthcare comes of age' (Roberts, 2015). Agent-based Modelling, as the most generalised simulation framework, offer even more flexibility and convenience in handling the interdependency of sub-components. It is promising to contribute to the reform of healthcare operations and the transparency of healthcare policy (Cookson, 2005), which may eventually improve population health.

In regards to research significance, there is a long journey ahead before ABM could achieve the aforementioned clinical goal. Most studies in this review have substantial methodological limitations and were too simplistic for practical use. The poor quality of these models plus researchers working in silo may be the reasons why there was no cross-reference between any two studies included in this review. Although the goal of simulation is to explore system dynamics and it is not for different modellers to replicate the same experiments for some unchanged facts, the lack of re-use of other's work is worrying and potentially wasteful. The only study that did not build everything from scratch is (Guclu, et al., 2016), which utilised a publicly-funded open-source pandemic ABM[9] to generate its own patient cohorts. This is inspirational as it provides a standardised synthetic population, which could save

[9] It is called A Framework for Reconstructing Epidemiological Dynamics (FRED), and could be accessed here: https://fred.publichealth.pitt.edu/ (Accessed 2018 September 24).

development time, improve data validity, and enhance study-to-study comparability. There are general-purpose synthetic patient generators available now[10], and they may be useful for generating standardised synthetic populations for future ABM studies. Healthcare modellers have promoted the concept of reusable agents and behaviours for couple years (Mills, 2014). This is an area of potential.

The research significance may also be hindered by lacking alternative measure on the value of models. As mentioned in the answer for Research Question 3 (page 37), only two studies included in this review were implemented, and even the study of highest quality was able to achieve implementation. Previous review stated that the implementation of healthcare simulation models were '*depressively low'* (Brailsford, et al., 2009). While this review confirms the *low* rate of implementation, I would like to challenge the notion that this is *depressing*. To begin with, ABM is being applied in new topic areas that go beyond the physical healthcare facilities. Subsequently ABM is being used by more diverse users other than health administrators. Therefore we need to re-define the value of these models other than implementation alone. There are other ways to uptake (the knowledge of) a model for healthcare operations. Implementing the model, as a support tool for daily operations, is just one way. As Eldabi suggested (2009), implementation should not be the sole measure of success. He gave examples such as providing a tool for debate amongst stakeholders, providing better insights about the nature of interactions within the system, visual representation of the system, or as a reflective tool. All of these were more or less realised in the studies included in this review. Future systematic review should indeed consider alternatives ways to measure the impact of healthcare models. Of note, although there are other ways, they are by no means easier than implementation. For Mills' caesarean delivery model mentioned above, 'it is a game-oriented simulation-based learning environment' (Mills, 2014). Via email exchange, he communicated to me the ending of this work: 'shortly after, physicians in Seattle rebelled

[10] For example, Synthea, which could be accessed here: https://github.com/synthetichealth/synthea (Accessed 2018 September 24).

and shut down the project', because 'they didn't want to relinquish control over pregnancies and they felt that a new model of care could adversely affect physician income'. One study found that modellers believed healthcare professionals were more resistance to change (Tako & Robinson, 2012). This is indeed the case.

This review finds, as opposite to existing propositions, statechart diagram or spatial consideration were not necessarily the features of ABM. Instead, ABM is featured by the health behaviours specified within patient and provider agents. In health settings with stringent care processes, such agent-based specifications do not appear to be advantageous. But in settings where patients and providers enjoy greater freedom, agent-based specifications enable autonomous decision making, which could lead to interesting phenomena (coordination, competition, selfish or irrational behaviours etc.) for research.

This review has made couple methodological advancements. Firstly, a comprehensive interdisciplinary search strategy was developed to account for materials not published in conventional journals or in healthcare domains. A data collection form was developed to capture essential information of an ABM in a standardised way across all topic areas. A quality assessment tool was developed in line with the academic principles of quality assessment for other types of clinical study, and also in line with the rich practice history of simulation validation in the engineering industry. As far as I known, this is the first review that applies a rigorous, transparent and reproducible approach to examine agent-based modelling (ABM) in healthcare operations.

Limitation

Although I did not limit the publication language to English, but the fact that I only used the English terms in searching inevitably limit my results to those studies with at least titles and abstracts in English. The final set of included studies turns out to be published in English exclusively. Language bias is a longstanding issue for systematic review (Higgins & Green, 2011). I conducted a quick search in the

China National Knowledge Infrastructure (CNKI)[11] and found that there were at least three different translations of ABM in Chinese academic journals. How to comprehensively identify studies in non-English languages is worth investigating. The impact of this limitation is unknown. Another limitation is that I did not pay enough attention to inanimate agents in my data extraction. While this may be acceptable if these agents were things like treatment rooms, it is more a problem in studies that prospectively evaluated new technologies, because inanimate agents (the new technology) played active roles in those studies. This limitation may make it a more difficult for readers to get a general sense of these studies when reading the appendix, but should not hinder their interpretation of the main findings of this review. The last limitation is that, I should also assess whether a study executes enough number of model runs. Because of the stochastic nature of ABM, it needs to be ran enough times to get a good estimate of model behaviours. When I designed the quality assessment tool, I was under the wrong impression that there was no good way to determine how many runs are 'enough', thus I cannot include a subjective item in my tool. Further reading afterward suggests that there are rigorous ways to do so. The impact of this limitation is that we have a slightly incomplete picture of all important quality dimensions of ABM, but this should not change the overall assessment of the quality in these studies.

Implication for Future Research

For primary studies on service efficiency or nosocomial infection, there is no need to create additional demonstration models. There are 'enough' number of studies demonstrating the potential usefulness of ABM in these topic areas. For topic areas where patients and providers have high autonomy, ABM seems to be methodologically advantageous to traditional simulation, but more studies are needed to further our understanding. Regardless of topic areas, we need realistic model for practical use, which includes but is not limited to implementation of the model. To make a model realistic, modellers need to

[11] http://www.cnki.net/ (Accessed 2018 September 24).

pay close attention to the design of the conceptual model. Besides utilising appropriate sources (expert opinions, observation, literature, etc.) in the design process, modellers also need to balance between a model's specificity to the question in hand and its generalisability to other settings. When executing the model, modellers need to run it for enough time steps to allow important outcome to emerge. Modellers need to improve reporting quality and provide linkage to source codes.

For systematic reviewers, the search strategy of this review provides a good starting point to identify studies not published in conventional journals, and additional effort may be made to further reduce language bias. The data extraction tool could be re-used in most parts. More attention could be paid to inanimate agents. There is probably no need to fill out whether spatial representation or statechart diagram is presented in a study, since these do not seem to be the features of ABM. The quality assessment tool is concise and informative. One more quality item, 'enough number of runs', could be added in future reviews.

CONCLUSION

This review finds that agent-based modelling (ABM) were applied in a broad range of topic areas in healthcare operations. Its characteristics is not obvious in studies on service efficiency, but more advantageous in other topic areas (e.g., care coordination) where patient and provider agents enjoy greater autonomy on their behaviours. Overall quality of these studies was low, on averaging meeting two out of the seven quality assessment items. Only two studies on facility layout design were implemented, and even the study of highest quality was not. Simulation is the method of choice to explore complex issues in health operations. ABM appears to be a more natural fit to do experiments with different team structures, coordination schemes, payment arranges, etc., than traditional simulation. Future studies should improve the quality of conduct and reporting, and find new ways to make an impact on health operations and eventually population health. This review has made couple methodological advancements that are good starting points for future reviews.

AUTHOR'S CONTRIBUTION

Following the best practice recommended in systematic review handbook (Higgins & Green, 2011), a second reviewer screened article in parallel and double checked data extraction. My supervisor also helped in the testing of quality assessment tool. I was responsible for the conceptualisation, search, primary review, primary data extraction, analysis, and the writing of this manuscript.

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I am indebted to my supervisor Dr Jason Oke, for his mentorship on not only my dissertation, but also on my entire journey of studying at Oxford. Dr Oke equipped me with the skills and calmness to critically analyse evidence in the mist of hypes around new healthcare technologies. I am also indebted to my wife. Her support is the only reason I can do this. I owe her a long vacation, and, frankly, a relaxed dinner somewhere without thinking of need to go back to study at night. Lastly, for my parents in China, I miss you!

REFERENCES

Abuelezam, N., Rough, K. & Seage, G. 3., 2013. Individual-Based Simulation Models of HIV Transmission: Reporting Quality and Recommendations. *PLOS One,* 8(9), p. e75624.

Adleberg, J. M. et al., 2017. Novel applications of agent-based modeling in emergency medicine research – A systematic literature review. *The American Journal of Emergency Medicine,* 35(12), pp. 1971-1973.

Alibramhim, A. & Wu, S., 2018. An agent-based simulation model of patient choice of health care providers in accountable care organizations. *Health Care Manag Sci,* Volume 21, pp. 131-143.

Altman, D. G. & Royston, P., 2000. What do we mean by validating a prognostic model?. *Statist. Med.,* Volume 19, pp. 453-473.

Bai, H. et al., 2016. *Management of emergency departments using complex systems modelling.* Advanced Computing Research Centre, University of Sheffield, Sheffield, United Kingdom, IADIS, pp. 172-176.

Banks, J., Carson, J. S., Nelson, B. L. & Nicol, D. M., 2014. *Discrete-Event System Simulation (5th Edition).* Harlow: Pearson Education.

Barnes, S., Golden, B. & Price, S., 2013. Applications of Agent-Based Modeling and Simulation to Healthcare Operations. In: B. Denton, ed. *Handbook of Healthcare Operations Management: Methods and Applications.* New York: International Series in Operations Research & Management Science, pp. 45-74.

Barnes, S., Golden, B. & Wasil, E., 2010. MRSAT transmission reduction using agent-based modeling and simulation. *INFORMS Journal on Computing,* Volume 22, pp. 635-646.

Berger, U. et al., 2008. Advances and limitations of individual-based models to analyze and predict dynamics of mangrove forests: A review. *Aquatic Botany,* 89(2), pp. 260-274.

Brailsford, S. C., 2007. *Tutorial: Advances and challenges in healthcare simulation modeling.* Washington, DC, IEEE.

Brailsford, S. C., 2014. Discrete-event simulation is alive and kicking. *Journal of Simulation,* 8(1), pp. 1-8.

Brailsford, S. C., Harper, P. R., Patel, B. & Pitt, M., 2009. An analysis of the academic literature on simulation and modelling in health care. *Journal of Simulation,* Volume 3, pp. 130-140.

Burton, J., 2017. *Why assess quality in a systematic review?.* [Online]
Available at: https://www.students4bestevidence.net/quality/
[Accessed 24 September 2018].

Castellini, G. et al., 2018. Assessing imprecision in Cochrane systematic reviews: a comparison of GRADE and Trial Sequential Analysis. *Systematic Reviews,* 7(1), p. 110.

Cavacini, A., 2015. What is the best database for computer science journal articles?. *Scientometrics ,* 102(3), pp. 2059-2071.

Chandler, J. & Hopewell, S., 2013. Cochrane methods - twenty years experience in developing systematic review methods. *Systematic Reviews,* 2(1), p. 76.

Chen, L., 2012. Agent-based modeling in urban and architectural research: A brief literature review. *Frontiers of Architectural Research,* 1(2), pp. 166-177.

Chwif, L. & Paul, R. J., 2000. *On Simulation model Complexity.* Orlando, IEEE.

Cooke, A., Smith, D. & Booth, A., 2012. Beyond PICO: The SPIDER Tool for Qualitative Evidence Synthesis. *Qualitative Health Research,* 22(10), pp. 1435-1443.

Cookson, R., 2005. Evidence-based policy making in health care: what it is and what it isn't. *Journal of Health Services Research & Policy,* 10(2), pp. 118-121.

Costley, C., Elliott, G. & Gibbs, P., 2010. *Doing Work Based Research: Approaches to Enquiry for Insider-Researchers.* London: SAGE Publications Ltd.

D'Agata, E. M. C. et al., 2007. Modeling antibiotic resistance in hospitals: The impact of minimizing treatment duration. *Journal of Theoretical Biology,* Volume 249, pp. 487-499.

Dahabreh, I., Trikalinos, T., Balk, E. & Wong, J., 2016. Recommendations for the Conduct and Reporting of Modeling and Simulation Studies in Health Technology Assessment.. *Ann Intern Med,* 165(8), pp. 575-581.

Djanatliev, A. et al., 2014. *System dynamics and agent-based simulation for prospective health technology assessments*.* Department of Computer Science 7, University of Erlangen-Nuremberg, Germany: Springer Verlag.

Eldabi, T., 2009. *Implementation Issues of Modelling Healthcare Problems: Misconceptions and Lessons.* Austin, The Institute for Operations Research and the Management Sciences.

Ellis, B., 2010. Complexity in practice: understanding primary care as a complex adaptive system.. *Inform Prim Care,* 18(2), pp. 135-140.

Elsevier, 2017. *Stay abreast of the research happening in your area.* [Online]
Available at: https://www.elsevier.com/solutions/scopus/how-scopus-works/content
[Accessed 24 September 2018].

Ferrer, J. et al., 2014. Management of nurse shortage and its impact on pathogen dissemination in the intensive care unit. *Epidemics,* Volume 9, pp. 62-69.

Ferrer, J., Salmon, M. & Temime, L., 2013. *Nosolink: An agent-based approach to link patient flows and staff organization with the circulation of nosocomial pathogens in an intensive care unit.* Conservatoire National des Arts et MÉtiers, Paris 75003, France, Elsevier B.V., pp. 1485-1494.

Fone, D. et al., 2003. Systematic review of the use and value of computer simulation modelling in population health and health care delivery. *Journal of Public Health Medicine,* 25(4), pp. 325-335.

Forster, M. R., 2004. *Occam's Razor and the Relational Nature of Evidence.* [Online]
Available at: http://philosophy.wisc.edu/forster/
[Accessed 24 September 2018].

Friesen, M. R. & McLeod, R. D., 2014. A Survey of Agent-Based Modeling of Hospital Environments. *IEEE Access,* Volume 2, pp. 227-233.

Gao, B. & Chan, W. K. (., 2013. *Sub-Lognormal Size Distribution of hospitals - An Agent-based Approach and Empirical Study.* Washington, DC, IEEE Press.

Garbey, M. et al., 2017. *Multiscale Modeling of Surgical Flow in a Large Operating Room Suite: Understanding the Mechanism of Accumulation of Delays in Clinical Practice.* Houston Methodist Research Institute, Houston, TX, United States, Elsevier B.V., pp. 1863-1872.

Gill, S. & Paranjape, R., 2010. A Review of Recent Contribution in Agent Based Health Care Modeling. In: R. Paranjape & A. Sadanand, eds. *Multi-agent systems for healthcare simulation and modeling : applications for.* Hershey: Medical Information Science Reference, pp. 26-43.

Greenroyd, F. L. et al., 2018. *Modeling and simulating hospital operations in a 3D environment.* School of Civil and Building Engineering, Loughborough University, Loughborough, Leicestershire, United Kingdom, Institute of Electrical and Electronics Engineers Inc., pp. 2952-2963.

Greer, A. L. & Fisman, D. N., 2009. Keeping vulnerable children safe from pertussis: Preventing nosocomial pertussis transmission in the neonatal intensive care unit. *Infection Control and Hospital Epidemiology,* Volume 30, pp. 1084-1089.

Grimm, V. et al., 2010. The ODD protocol: A review and first update. *Ecological Modelling,* pp. 2760-2768.

Grimm, V. & Railsback, S. F., 2005. *Individual-based Modeling and Ecology.* Princeton: Princeton University Press.

Guclu, H. et al., 2016. An Agent-Based Model for Addressing the Impact of a Disaster on Access to Primary Care Services. *Disaster Medicine and Public Health Preparedness,* Volume 10, pp. 386-393.

Guclu, H. et al., 2016. An Agent-Based Model for Addressing the Impact of a Disaster on Access to Primary Care Services. *Disaster Medicine and Public Health Preparedness,* Volume 10, pp. 386-393.

Henderson, M., 1995. Operations management in health care. *J Health Care Finance,* 21(3), pp. 44-47.

Higgins, J. & Green, S., 2011. *Cochrane Handbook for Systematic Reviews of Interventions.* Version 5.1.0 ed. s.l.:The Cochrane Collaboration.

Higgins, J. P. T. et al., 2011. The Cochrane Collaboration's tool for assessing risk of bias in randomised trials. *BMJ,* Volume 343, p. d5928.

Hotchkiss, J. R., Holley, P. & Crooke, P. S., 2007. Analyzing Pathogen Transmission in the Dialysis Unit: Time for a (Schedule) Change?. *Clin J Am Soc Nephrol,* Volume 2, pp. 1176-1185.

Hotchkiss, J. R., Strike, D. G., Simonson, D. A. & Broccard, A. F., 2005. An agent-based and spatially explicit model of pathogen dissemination in the intensive care unit. *Crit Care Med,* 33(1), pp. 168-176.

Huang, X., Lin, J. & Demner-Fushman, D., 2006. *Evaluation of PICO as a knowledge representation for clinical questions..* Washington, DC, AMIA.

Hulshof, P. J. H. et al., 2011. ORchestra: an online reference database of OR/MS literature in health care. *Health Care Manag Sci,* 14(4), pp. 383-384.

Jahangirian, M. et al., 2015. Causal study of low stakeholder engagement in. *Journal of the Operational Research Society,* 66(3), pp. 369-379.

Jelassi, M., Miled, S. B., Saoud, N. B. B. & Demongeot, J., 2015. *Obesity determinants: A systematic review.* Marrakech, Morocco, IEEE.

Jiménez, J. M., Lewis, B. & Eubank, S., 2013. *Hospitals as complex social systems: Agent-based simulations of hospital-acquired infections.* s.l.:Springer Verlag.

Jones, S. S. & Evans, R. S., 2008. An agent based simulation tool for scheduling emergency department physicians.. *AMIA ... Annual Symposium proceedings / AMIA Symposium. AMIA Symposium,* pp. 338-342.

Journal of Artificial Societies and Social Simulation, 2017. *How to submit a paper to JASSS.* [Online]
Available at: http://jasss.soc.surrey.ac.uk/admin/submit.html
[Accessed 24 September 2018].

Kanagarajah, A. K., Lindsay, P., Miller, A. & Parker, D., 2008. *An Exploration into the Uses of Agent-Based Modeling to Improve Quality of Healthcare.* Boston, Springer.

Kehoe, J., 2017. *Replication in agent based models using formal methods and multiple updating strategies.* Dublin: Dublin City University.

Klügl, F., 2008. *A validation methodology for agent-based simulations.* Fortaleza, Ceara, Brazil, ACM.

Laskowski, M., Demianyk, B., Friesen, M. & McLeod, R., 2010. *Uncertainties Inherent in RFID Tracking Systems in an Emergency Department.* Venice, Italy, IEEEE, p. 263.

Laskowski, M. et al., 2009. Models of Emergency Departments for Reducing Patient Waiting Times. *PLoS One,* 4(7), p. e6127.

Lemos, C. M. R. S. d. O. e., 2016. *On Agent-Based Modelling of Large Scale.* Lisbon: ISCTE-IUL.

Leykum, L. et al., 2012. Use of an agent-based model to understand clinical systems. *JASSS,* Volume 15.

Lim, M. E., Worster, A., Goeree, R. & Tarride, J.-E., 2013. Simulating an emergency department: the importance of modeling the interactions between physicians and delegates in a discrete event simulation. *BMC Medical Informatics and Decision Making,* 13(1), p. 59.

Liu, P. & Wu, S., 2016. An agent-based simulation model to study accountable care organizations. *Health Care Management Science,* Volume 19, pp. 89-101.

Liu, Z., Cabrera, E., Rexachs, D. & Luque, E., 2014. *A Generalized Agent-Based Model to Simulate Emergency Departments.* Nice, France, IARIA, pp. 65-70.

Liu, Z., Rexachs, D., Epelde, F. & Luque, E., 2017. An agent-based model for quantitatively analyzing and predicting the complex behavior of emergency departments. *Journal of Computational Science,* Volume 21, pp. 11-23.

Li, Y. et al., 2016. Agent-Based Modeling of Chronic Diseases: A Narrative Review and Future Research Directions. *Prev Chronic Dis,* 13(E69).

Lorek, H. & Sonnenschein, M., 1999. Modelling and simulation software to support individual-based ecological modelling. *Ecological Modelling,* 115(2-3), pp. 199-216.

Macal, C. M. & North, M. J., 2010. Tutorial on agent-based modelling and simulation. *Journal of Simulation,* 4(3), pp. 151-162.

Macal, C. et al., 2014. *Agent-based modeling of electric power markets.* Savannah, Georgia, IEEE Press.

Majid, M. A., Fakhreldin, M. & Zuhairi, K. Z., 2016. *Comparing Discrete Event and Agent Based Simulation in Modelling Human Behaviour at Airport Check-in Counter.* Cham, Springer International Publishing.

Majid, M. A., Fakhreldin, M. & Zuhairi, K. Z., 2016. *Comparing Discrete Event and Agent Based Simulation in Modelling Human Behaviour at Airport Check-in Counter.* Berlin, Heidelberg, Springer-Verlag.

Maria, A., 1997. *Introduction to modeling and simulation.* Atlanta, Georgia, USA, IEEE Computer Society , pp. 7-13.

Marshall, D. A. et al., 2015. Applying Dynamic Simulation Modeling Methods in Health Care Delivery Research—The SIMULATE Checklist: Report of the ISPOR Simulation Modeling Emerging Good Practices Task Force,. *Value in Health,* 18(1), pp. 5-16.

Massey, N., 2013. Humans May Be the Most Adaptive Species. *Scientific American*, 25 September.

Mills, A., 2014. *Cesarean Delivery Model: Meeting the challenge to reduce rates of Cesarean delivery.* [Online]
Available at: https://www.anylogic.com/upload/conference/2014/Alan_Mills-AnyLogicPresentation_v3_Draft1_AnyLogic.pdf
[Accessed 5 January 2018].

Mitchell, M., 2018. *Introduction to Complexity.* [Online]
Available at: https://www.santafe.edu/engage/learn/courses/introduction-complexity
[Accessed 24 September 2018].

Nianogo, R. & Arah, O., 2015. Agent-based modeling of noncommunicable diseases: a systematic review. *Am J Public Health,* pp. e20-31.

Oxford Centre for Evidence-based Medicine, 2009. *Levels of Evidence.* [Online]
Available at: https://www.cebm.net/2009/06/oxford-centre-evidence-based-medicine-levels-evidence-march-2009/
[Accessed 24 September 2018].

Philips, Z. et al., 2006. Good practice guidelines for decision-analytic modelling in health technology assessment: a review and consolidation of quality assessment. *Pharmacoeconomics,* 24(4), pp. 355-371.

Plsek, P. & Greenhalgh, T., 2001. Complexity science: The challenge of complexity in health care. *BMJ,* pp. 625-628.

Ramsey, G. W., 2014. Evaluating policies using agent-based simulations: investigating policies for continuity of care. *Int. J. Simulation and Process Modelling,* 9(4), pp. 255-269.

Richiardi, M., Leombruni, R., Saam, N. & Sonnessa, M., 2006. A Common Protocol for Agent-Based Social Simulation. *Journal of Artificial Societies and Social Simulation,* 9(1).

Roberts, M. S., 2015. Dynamic Simulation in Health Care Comes of Age. *Value in Health,* 18(2), pp. 143-144.

Robinson, S., 2015. Modelling without queues: adapting discrete-event simulation for service operations. *Journal of Simulation,* 9(3), pp. 195-205.

Rothengatter, D., Katsma, C. & Hillegersberg, J. v., 2010. *Simulation As a Method To Support Complex Organizational Transformations in Healthcare.* Lima, Association for Information Systems, p. 554.

Saoud, M. S., Boubetra, A. & Attia, S., 2016. A simulation knowledge extractionbased decision support system for the healthcare emergency department. *International Journal of Healthcare Information Systems and Informatics,* Volume 11, pp. 19-37.

Sargent, R. G., 2010. *Verification and Validation of Simulation Models.* Baltimore, The Institute for Operations Research and the Management Sciences.

Savović, J. et al., 2012. Influence of reported study design characteristics on intervention effect estimates from randomized, controlled trials.. *Ann Intern Med,* 157(6), pp. 429-438.

Savović, J. et al., 2014. Evaluation of the Cochrane Collaboration's tool for assessing the risk of bias in randomized trials: focus groups, online survey, proposed recommendations and their implementation. *Systematic Reviews,* Volume 3, p. 37.

Sayama, H., 2015. *Introduction to the modeling and analysis of complex systems.* Geneseo, New York: Open SUNY Textbooks, Milne Library, State University of New York at Geneseo.

Schruben, L. & Goldsman, D., 1984. *Initiation Effects in Computer Simulation Experiments,* Fort Belvoir, Virginia: U.S. Defense Technical Information Center.

Schumann, B., 2016. *What if the "Big Data Analytics" Hype were About Agent-Based Modelling.* [Online] Available at: https://www.benjamin-schumann.com/blog/2016/6/27/what-if-the-big-data-analytics-hype-were-about-agent-based-modelling
[Accessed 22 September 2018].

Siebers, P. O. et al., 2010. Discrete-event simulation is dead, long live agent-based simulation!. *ournal of Simulation,* 4(3), pp. 204-210.

Tako, A. & Robinson, S., 2012. *Is simulation in health different and is it more difficult?.* Worcestershire, The Operational Research Soceity, pp. 92-101.

Temime, L. et al., 2010. NosoSim: an agent-based model of nosocomial pathogens circulation in hospitals. *Procedia Computer Science,* 1(1), pp. 2245-2252.

Tricco, A. C., Tetzlaff, J. & Moher, D., 2011. The art and science of knowledge synthesis. *Journal of Clinical Epidemiology,* 64(1), pp. 11-20.

Turkcan, A., Toscos, T. & Doebbeling, B. N., 2014. Patient-centered appointment scheduling using agent-based simulation. *AMIA ... Annual Symposium proceedings / AMIA Symposium. AMIA Symposium,* Volume 2014, pp. 1125-1133.

U.S. Department of Health & Human Services, 2017. *Disclosures for Emergency Preparedness - A Decision Tool: Health Care Operations.* [Online]
Available at: https://www.hhs.gov/hipaa/for-professionals/special-topics/emergency-preparedness/health-care-operations/index.html
[Accessed 24 September 2018].

Wikipedia contributors, 2018. *All models are wrong.* [Online]
Available at: https://en.wikipedia.org/w/index.php?title=All_models_are_wrong&oldid=860093639
[Accessed 24 September 2018].

Wikipedia contributors, 2018. *Multi-agent system.* [Online]
Available at: https://en.wikipedia.org/w/index.php?title=Multi-agent_system&oldid=853149320
[Accessed 24 September 2018].

Wiler, J. L., Griffey, R. T. & Olsen, T., 2011. Review of Modeling Approaches for Emergency Department Patient Flow and Crowding Research. *Academic Emergency Medicine,* Volume 18, pp. 1371-1379.

Willem, L. et al., 2017. Lessons from a decade of individual-based models for infectious disease transmission: a systematic review (2006-2015). *BMC Infectious Diseases,* 17(1), p. 612.

World Health Organization, 2012. *Health technology assessment.* [Online]
Available at: http://www.who.int/medical_devices/assessment/en/
[Accessed 24 September 2018].

Xu, X., Li, L. & Wu, H., 2008. *Cooperation policy simulation in urban health care system.* Department of Industrial Engineering, Tsinghua University, Beijing, China, s.n., pp. 447-451.

Yousefi, M. & Ferreira, R. P. M., 2017. An agent-based simulation combined with group decision-making technique for improving the performance of an emergency department. *Brazilian Journal of Medical and Biological Research,* Volume 50.

Zambrano, F. et al., 2016. *Iimproving Patient Access to a Public Hospital Comlex Using Agent Simulation.* Washington DC, IEEE.

Zankoul, E., Khoury, H. & Awwad, R., 2015. *Evaluation of Agent-Based and Discrete-Event Simulation for Modeling Construction Earthmoving Operations.* Oulu, Finland, International Association for Automation & Robotics in Construction.

Zeigler, B. P., 2014. *The Role of Modeling and Simulation in Coordination of Health Care.* Vienna, Austra, SCITEPRESS.

Appendix I. Search Query for Scopus

(ABS (agent PRE/3 simulation) OR ABS (individual PRE/3 simulation) OR ABS (agent PRE/3 model) OR ABS (individual PRE/3 model) OR ABS (agent PRE/3 platform) OR ABS (netlogo))

AND TITLE-ABS-KEY ((health* OR medic* OR clinic* OR nurs* OR hospital OR drug OR disease OR mortality OR treatment OR patient) W/5 (manag* OR {operation} OR {operation} OR {operational} OR administ* OR policy* OR service OR delivery OR provision OR insur* OR reform OR business OR quality OR payment OR cost))

AND NOT TITLE-ABS-KEY (cell) AND NOT TITLE-ABS-KEY (tissue) AND NOT TITLE-ABS-KEY (administ* PRE/0 *therapy) AND NOT TITLE-ABS-KEY (administ* PRE/0 *drug) AND NOT TITLE-ABS-KEY (administ* PRE/0 *treatment) AND NOT TITLE-ABS-KEY (genes) AND NOT TITLE-ABS-KEY (gene) AND NOT TITLE-ABS-KEY (rat) AND NOT TITLE-ABS-KEY (mouse) AND NOT ({individuals that}) AND NOT ({individuals to}) AND NOT ({agents that}) AND NOT ({agents to}) AND NOT (multi-agent) AND NOT (multiagent) AND NOT ({multi agent})

Appendix II. Detailed Synthesis of Quality Assessment Tools

Item	Quality Assessment Questions (Answer "Yes" or "No" for appropriateness. Answer "Unknown" for non-transparency. Answer "Not applicable" for an item not being applicable to a study)	Concordance with Existing Frameworks					
		Fone, 2003	Richiardi, 2006	Philips, 2006	Abuelezam, 2013	Dahabreh, 2016	Other literature
	Overview						
Objective	Were the objectives, aims and questions clearly stated and focused with specific reference to the population, intervention, outcome, setting and time period?	X	X	X	X	X	
Literature Review	Was the study justified by or based on published systematic review or a sufficiently search of literature, including both ABM and non-ABM literature? If not, was sufficient expert knowledge or stakeholder input being sought?	X	X	X	X	X	
Method Justification	Were the need for modelling versus other research methods, and the need for agent-based modelling versus other modelling methods, explained in the context of the objectives by referencing necessary model features? Was there priori preferred modelling perspective (there should not).	X			X	X	
	Design						
Structure	Does the conceptual structure of the model, such as the different types of agents, afford to explore the research question?		X	X	X	X	
Assumptions	Were all structural assumptions and computational approximation appropriate?	X		X	X	X	
Agent attributes and states	Did agents' attributes represent all important factors in the context of the objective? Were the transitions of states of these attributes consistent with biological and clinical process?		X	X	X		
Agent internal rules	Were the agents' internal rules for decision making and behavioural strategies appropriate?		X		X		
Agent interaction	Was the way in which agents sense, communicate with, influence or act upon other agents, appropriate?		X		X		
Other entities	Were entities other than agents, such as spatial units, environment and collectives of agents, appropriate?						Grimm, et al., 2010
Heterogeneity	Was biological and behavioural heterogeneity appropriately implemented in the model structure?			X	X	X	
Time horizon	Was the time horizon of the model sufficient to reflect all important outcomes?			X		X	
Time step	Did the model has an appropriate choice of treating time as a continuous or discrete		X	X	X		

	variable? If discrete, was each time step dictated appropriately by natural history of disease or real-word health behaviours?						
Parameters from external source	Was the data used for parameters obtained by “best evidence approach”? Were the sources’ risks of bias accounted for? Were the statistical distributions of the parameters justified?	X		X	X	X	
Parameters from local source	If parameters are based on the investigator’s local observation, did the investigators use an appropriate sample and method to obtain the data? If they are based on expert opinions, were formal elicitation methods used to quantify expert opinions and its associated uncertainty?	X				X	
Parsimony	Was the model built to the targeted level of complexity / parsimony?					X	
	Execution						
Calibration	Was the process used to calibrate the model dynamics sufficiently described?				X		
Parameter sensitivity	Was sensitivity analysis of main parameters performed, such as different distribution or values?				X	X	
Assumption sensitivity	Was sensitivity analysis of alternative assumptions performed?				X		
Stochastic Sensitivity	Was the impact of stochasticity evaluated?	X	X		X		
Internal Consistency	Was the programmatic / computational logic of the model tested thoroughly before use?			X	X		
Initiation	Were the technique to control initiation bias appropriate? Initiation bias occurs when the selected starting conditions of the model represent unusual system states.						Schruben & Goldsman, 1984
Multiple runs	Were sufficient runs performed for adequate precision? Were the values of parameters in each run described?	X			X		
	Result						
Result relevance	Did the results address the research question?	X					
Consistency with observed data	Were the results compared with observed data? Was any difference explained?	X		X	X		
Consistency with experts review	Were topic experts invited to review the model structure and output? Was any difference explained?					X	
Comparison with other models / studies	Were the results compared with those of previous models? Was any difference explained?	X		X		X	
Result representation	Were the results represented in the way that is oriented to the targeted audience?					X	

Result uncertainty	Were the results reported in a way that communicates uncertainty?	X			X	X	
Dissemination							
Replicability	Were source codes, technical documents, or simulation platform provided to the readers? If not, was the model described clear enough to allow replicability?		X				
Implementation	Has the model been implemented in its targeted use case, such as serving as a decision support tool or having an impact on clinical practice?	X					
Generalizability	Can the model be applied to other similar settings?	X			X		
Model Maintenance	Is the modelling being updated as new data become available, new interventions are added, or our understanding of the investigated phenomenon improves?					X	
Authorship and Funding							
Authorship and Funding	Were the source of funding's influence accounted for? Was each author's conflict of interest accounted for?				X	X	

Appendix III. Study Characteristics

Bai, 2016		
Item	**Content**	**Remark**
Topic area	Service efficiency	
Country	UK	
Publication type	Conference Proceeding	
Study type	Experimental	
Healthcare setting	Hospital - Emergency Department	
Spatial representation	No	
Investigational components	(Details not available)	
Outcomes	Attendees seen > 4 hours	
Patient agents		
States	(Details not available)	
Attributes	(Details not available)	
Leading provider agents		
Role	Physician	
States	(Details not available)	
Attributes	(Details not available)	
Other agents	Receptionist, triage nurse, nurse, nurse practitioner	
Interactions		
Patients with patients	Indirectly	Patient agents interact with receptionist agents for registration, interact with nurses for triage, interact with doctors for assessment, interact with nurses and nurse practitioners for treatment
Providers with patients	Directly	
Providers with providers	Indirectly	
Does the concept of queuing apply?	Yes	
Stochasticity	(Details not available)	
Model presentation		
Statechart	No	
Others	Text and patient flow chart	
Implementation	No	Project terminated

Djanatliev, 2012; 2013; 2014 (main)		
Item	**Content**	**Remark**
Topic area	Technology evaluation	
Country	Germany	
Publication type	Conference Proceeding	
Study type	Experimental	
Healthcare setting	Ambulance	
Spatial representation	Yes	
Investigational components	Launching mobile stroke unit	
Outcomes	Quality of life	
Patient agents		
States	Normal, Symptoms, Affected, Pre-treatment, Dead	
Attributes	(Details not available)	
Leading provider agents		
Role	Mobile Stroke Unit	
States	Free, Busy	
Attributes	timeApprToScene (delay in arrival)	
Other agents	Dispatcher, inpatient staff (Details not available)	
Interactions		
Patients with patients	(Not modelled)	Patient agents interact with emergency call operators, mobile units, and inpatient staff; Mobile units interact with dispatchers and inpatient staff
Providers with patients	Directly	
Providers with providers	Directly	
Does the concept of queuing apply?	No	
Stochasticity	(Details not available)	
Model presentation		
Statechart	Yes	
Others	Text	
Implementation	No	Proof-of-concept

Gao, 2013		
Item	**Content**	**Remark**
Topic area	Patient choice	
Country	US	
Publication type	Conference Proceeding	
Study type	Explanatory	
Healthcare setting	Health system alliance	
Spatial representation	No	
Investigational components	Patient preference and search distance	
Outcomes	Hospital size	
Patient agents		
States	(Details not available)	
Attributes	Search-Radius (only visit the hospitals within a distance threshold)	
Leading provider agents		
Role	Hospital	
States	(Details not available)	
Attributes	Size, patient days (indicator of reputation)	
Other agents	None	
Interactions		
Patients with patients	Indirectly	Patients choose hospitals. Hospitals provide services
Providers with patients	Directly	
Providers with providers	(Not modelled)	
Does the concept of queuing apply?	Yes	
Stochasticity	(1) Patient visits hospital according to a Poisson process; (2) Choosing which hospital is conditionally probalistic	
Model presentation		
Statechart	No	
Others	Pseudo code	
Implementation	NA	

Garbey, 2017		
Item	**Content**	**Remark**
Topic area	Service efficiency	
Country	US	
Publication type	Conference Proceeding	
Study type	Experimental	
Healthcare setting	Hospital - Operating Room	
Spatial representation	Yes	
Investigational components	Time to arrive from the preoperative area, time to put under anaesthesia, time for minimally invasive surgery, time for open surgery, time to wake up from anaesthesia, time to clean and infect the OR, number of anaesthesiologists, number of janitors, awareness delay of anaesthesiologist, average recovery time in the post-operative area	
Outcomes	Turnover time between procedures	
Patient agents		
States	(Not modelled)	
Attributes	Medical condition	
Leading provider agents		
Role	Surgeon	
States	(Details not available)	
Attributes	(Details not available)	
Other agents	Surgeon assistant, anaesthesiologist, certified registered nurse anaesthetist, scrub nurse, cleaning crew	
Interactions		
Patients with patients	Indirectly	Surgical team operates on patients; Direct communication among surgical team members.
Providers with patients	Directly	
Providers with providers	Directly	
Does the concept of queuing apply?	Yes	
Stochasticity	"our model is stochastic and accounts for delays due team members lack of timely availability, poor coordination between tasks, or suboptimal performance of the surgical team"	
Model presentation		
Statechart	Yes, in the form of formula	
Others	Text	
Implementation	No	

Greenroyd, 2017		
Item	**Content**	**Remark**
Topic area	Service efficiency	
Country	UK	
Publication type	Conference Proceeding	
Study type	Experimental	
Healthcare setting	Hospital - Emergency Department	
Spatial representation	Yes	
Investigational components	Adding two walk-in triage rooms, or rapid assess and treat (RAT)	
Outcomes	Maximum and average wait time	
Patient agents		
States	(Details not available)	
Attributes	(Details not available)	
Leading provider agents		
Role	Senior medical practitioner	
States	(Details not available)	
Attributes	(Details not available)	
Other agents	Junior doctors, nurses, registration, specialist consultant	
Interactions		
Patients with patients	Indirectly	In the traditional scenario, patient agents interact with triage staff, and then be seen by doctor. In the "Rapid assess and treat" process, patient agents are seen by junior doctor and if the condition is minor, are treated right away, and if the condition is major, transferred to senior doctor right away.
Providers with patients	Directly	
Providers with providers	(Details not available)	
Does the concept of queuing apply?	Yes	
Stochasticity	(Not modelled)	
Model presentation		
Statechart	No	
Others	Text and flow chart	
Implementation	No	Demonstration

Jones, 2008		
Item	**Content**	**Remark**
Topic area	Service efficiency	
Country	US	
Publication type	Conference Proceeding	
Study type	Experimental	
Healthcare setting	Hospital - Emergency Department	
Spatial representation	No	
Investigational components	Different staffing configuration (not very specific)	
Outcomes	Door-to-Doc time	
Patient agents		
States	(Details not available)	
Attributes	Arrive time, acuity, discharge disposition, and length of service time	
Leading provider agents		
Role	Physician	
States	Free, Busy	
Attributes	Shift	
Other agents	Registration units, triage units	
Interactions		
Patients with patients	Indirectly	Patient agents interact with registration unit and triage units to be registered and triaged, then interact with physician agents for diagnosis and treatment.
Providers with patients	Directly	
Providers with providers	(Details not available)	
Does the concept of queuing apply?	Yes	
Stochasticity	"Patient arrivals follow a heterogeneous Poisson process"; "Each physician agent is assigned a patients per hour capacity at the beginning of their shift, the value assigned is a random variable from a Poisson distribution "	
Model presentation		
Statechart	No	
Others	Text and flow chart	
Implementation	No	

Leykum, 2012		
Item	**Content**	**Remark**
Topic area	Service coordination	
Country	US	
Publication type	Journal paper	
Study type	Explanatory	
Healthcare setting	Hospital - Inpatient	
Spatial representation	No	
Investigational components	Different level of sense making and improvising	
Outcomes	Length of stay, mortality	
Patient agents		
States	Active, Dead	
Attributes	Severity, Infection,	
Leading provider agents		
Role	Physician team	
States	(Details not available)	
Attributes	Attending attitude, improvisation and sense making	
Other agents		
Interactions		
Patients with patients	Indirectly	The physician team is modelled as a single entity. There is only one physician team at a time, and this team treats patient agents.
Providers with patients	Directly	
Providers with providers	(Not modelled)	
Does the concept of queuing apply?	No	
Stochasticity	"number and severity of patients admitted to the team was a random function" "The development of a crisis is also a random function, but will occur more frequently based on the census"	
Model presentation		
Statechart	No	
Others	Executable codes	
Implementation	No	

Liu, 2014, 2015, 2016, 2017 (main)		
Item	**Content**	**Remark**
Topic area	Service efficiency	
Country	US	
Publication type	Conference Proceeding	
Study type	Experimental	
Healthcare setting	Hospital - Emergency Department	
Spatial representation	Yes ("The time it takes for the doctor to move is important to consider as it is not constant and significant for the system efficiency" (2017 paper)	
Investigational components	Two more lab technicians or two more doctors in response to a flu pandemic, and reduced delay in ambulance response(2015 paper)	
Outcomes	Average length of stay	
Patient agents		
States	Receiving treatment, waiting, location	
Attributes	Severity	
Leading provider agents		
Role	Physician	
States	(Details not available)	
Attributes	Experience	
Other agents	Registration and triage staff (modelled together), Nurse, Auxiliary Technician, Imaging team, lab team	
Interactions		
Patients with patients	Indirectly	Provider communicate by information system
Providers with patients	Directly	
Providers with providers	Indirectly	
Does the concept of queuing apply?	Yes	
Stochasticity	"Poisson distribution is used to fit the bed availability pattern in hospital"; "a Gamma distribution was used to fit the length of ambulance response time"; "The probability density function of patient inter-arrival time can be expressed as follows..." (2017 paper)	
Model presentation		
Statechart	Yes (2014 paper)	
Others	Text, flow chart, formula ad Pseudo code	
Implementation	No	(These "implementation" are not the intended use case of the model :) "For

		example, the presented simulator is currently working as a platform to study MRSA transmission in EDs [29, 30] and as an experimental ED platform to provide data under various scenarios for knowledge discovery [31]."

Turkcan, 2014		
Item	**Content**	**Remark**
Topic area	Service efficiency	
Country	US	
Publication type	Conference Proceeding	
Study type	Experimental	
Healthcare setting	Primary Care	
Spatial representation	No	
Investigational components	Traditional scheduling with triage appointments, and open access scheduling	
Outcomes	Wait time for appointments, continuity of care, No-show percentage	
Patient agents		
States	(Details not available)	
Attributes	Age, gender, insurance, chronic condition, pregnant, physician assignment	
Leading provider agents		
Role	Primary Care Physician	
States	Free, Busy	
Attributes	Specialty, Capacity	
Other agents	Scheduler	
Interactions		
Patients with patients	Indirectly	Patient agents schedule appointment with primary care physicians, who later treat them if they show up
Providers with patients	Directly	
Providers with providers	(Not modelled)	
Does the concept of queuing apply?	Yes	
Stochasticity	"demand for healthcare can be expressed in a better way through stochastic modelling of disease progression of each person in a patient population."	
Model presentation		
Statechart	No	
Others	Text and flow chart	
Implementation	No	

Xu, 2008		
Item	**Content**	**Remark**
Topic area	Service coordination	
Country	China	
Publication type	Conference Proceeding	
Study type	Experimental	
Healthcare setting	Health system alliance	
Spatial representation	Yes	
Investigational components	Two coordination policies (share doctors and share beds)	
Outcomes	Access time, bed over use rate in MDS, bed utilisation in CHS	
Patient agents		
States	Healthy, ill, and Go to, Arrive, Queue, Clinic, Seen, In hospital	
Attributes	Travel speed, location, disease type, severity	
Leading provider agents		
Role	Hospital	
States	(Not modelled)	
Attributes	Type (community versus medical)	
Other agents		
Interactions		
Patients with patients	Indirectly	Patient agents choose which hospital to go. The hospital treats the patient. The policies under evaluation promotes cooperation between hospitals.
Providers with patients	Directly	
Providers with providers	Directly	
Does the concept of queuing apply?	Yes	
Stochasticity	"These parameters are randomly generated according to uniform distribution which characterizes the difference among patients"; "So we run each of four situations by three different random variable seeds and the average result are shown as table".	
Model presentation		
Statechart	Yes	
Others	Text and map	
Implementation	No	

Zambrano, 2016		
Item	**Content**	**Remark**
Topic area	Layout design	
Country	Chile	
Publication type	Conference Proceeding	
Study type	Experimental	
Healthcare setting	Hospital	
Spatial representation	Yes	
Investigational components	Layout of the hospital	
Outcomes	Pedestrian flow rate	
Patient agents		
States	(Details not available)	
Attributes	(Details not available)	
Leading provider agents		
Role	Hospital	
States	(Details not available)	
Attributes	(Details not available)	
Other agents		
Interactions		
Patients with patients	Directly	Agents interact directly in terms of walking through traffic
Providers with patients	Directly	
Providers with providers	Directly	
Does the concept of queuing apply?	No	
Stochasticity	(Details not available)	
Model presentation		
Statechart	No	
Others	Text, flow chart and graphical representation	
Implementation	Yes	"After the base simulation model was presented in a first assessment to the project managers of the hospital complex, they agreed to make improvements and changes in both the design layout of the hospital as well as in the pedestrian flows to different service areas."

Laskowski, 2008		
Item	**Content**	**Remark**
Topic area	Service efficiency	
Country	Canada	
Publication type	Conference Proceeding	
Study type	Experimental	
Healthcare setting	Hospital - Emergency Department	
Spatial representation	No	
Investigational components	Two, three, and four doctors;	
Outcomes	Queue length	
Patient agents		
States	(Details not available)	
Attributes	(Details not available)	
Leading provider agents		
Role	Physician	
States	(Details not available)	
Attributes	(Details not available)	
Other agents	(Details not available)	
Interactions		
Patients with patients	(Details not available)	Patient agents receive treatment from physician agents
Providers with patients	Directly	
Providers with providers	(Details not available)	
Does the concept of queuing apply?	Yes	
Stochasticity	Selection of ED: "The second scenario allows redirection based on the RED model, and the destination ED is chosen from a uniform probability. This scenario is labelled Random RED. The third scenario, labelled Guided RED, invokes RED redirection where EDs with lower expected waiting time are probabilistically chosen more often as the destination ED"	
Model presentation		
Statechart	No	
Others	Text and diagram	
Implementation	No	

Laskowski, 2010		
Item	**Content**	**Remark**
Topic area	Technology evaluation	
Country	Canada	
Publication type	Conference Proceeding	
Study type	Experimental	
Healthcare setting	Hospital - Emergency Department	
Spatial representation	Yes	
Investigational components	5, 10, 20 and 40 RFID readers	
Outcomes	Reader errors	
Patient agents		
States	(Details not available)	
Attributes	Triage score, Location	
Leading provider agents		
Role	(Not modelled)	
States	(Not modelled)	
Attributes	(Not modelled)	
Other agents	RFID readers	
Interactions		
Patients with patients	(Not modelled)	Patient agents are identified by RFID readers when within their proximity
Providers with patients	(Not modelled)	
Providers with providers	(Not modelled)	
Does the concept of queuing apply?	No	
Stochasticity	Patient behaviours:" The behaviour of the patient is highly stochastic, governed by a number of random variables."	
Model presentation		
Statechart	NA	
Others	Text and flow chart	
Implementation	No	

Rothengatter, 2010		
Item	**Content**	**Remark**
Topic area	Layout design	
Country	Netherlands	
Publication type	Conference Proceeding	
Study type	Experimental	
Healthcare setting	Hospital - Department of Ophthalmology	
Spatial representation	Yes	
Investigational components	New hospital layout	
Outcomes	Occupation rate of waiting room and examination room, heat map of patient flow in the clinic	
Patient agents		
States	(Details not available)	
Attributes	Location	
Leading provider agents		
Role	Physician	
States	(Details not available)	
Attributes	(Details not available)	
Other agents	Physician assistant	
Interactions		
Patients with patients	Indirectly	(Details not available)
Providers with patients	Directly	
Providers with providers	(Details not available)	
Does the concept of queuing apply?	Yes	
Stochasticity	(Not modelled)	
Model presentation		
Statechart	No	
Others	Text and flow char	
Implementation	Yes	

Kanagarajah, 2008		
Item	**Content**	**Remark**
Topic area	Service efficiency	
Country	Australia	
Publication type	Conference Proceeding	
Study type	Experimental	
Healthcare setting	Hospital - Emergency Department	
Spatial representation	No	
Investigational components	Increase the number of doctors to 9, decrease the number of minor rooms from 8 to 3	
Outcomes	Time patient spent in ED	
Patient agents		
States	(Details not available)	
Attributes	Criticality	
Leading provider agents		
Role	Physician	
States	Busy, On-Call	
Attributes	Time with patient	
Other agents	registration clerk, triage nurse, nurse, lab clerk and technician, discharge clerk, phlebotomist, ECG technician and treatment rooms	
Interactions		
Patients with patients	Indirectly	Patient arrives at hospital, goes through the registration and triage process, and is treated by physician
Providers with patients	Directly	
Providers with providers	(Details not available)	
Does the concept of queuing apply?	Yes	
Stochasticity	"Transfer out to other wards will depend on the availability of appropriate beds in other areas. We demonstrate this by introducing a stochastic function to generate the bed availability for transfer."	
Model presentation		
Statechart	No	
Others	Text	
Implementation	No	

Guclu, 2016		
Item	**Content**	**Remark**
Topic area	Service efficiency	
Country	US	
Publication type	Journal paper	
Study type	Experimental	
Healthcare setting	Primary care	
Spatial representation	No	
Investigational components	50% higher capacity in the immediate aftermath of Sandy	
Outcomes	Number of patients unable to get care	
Patient agents		
States	(Details not available)	
Attributes	Age, sex, race, household location, PCP assignment, distance to PCP, insurance type, chronic condition	
Leading provider agents		
Role	Physician	
States	(Details not available)	
Attributes	Location, specialty, capacity,	
Other agents	Mobile health clinics	
Interactions		
Patients with patients	Indirectly	Patient agents go to assigned primary care physicians or mobile health clinics to be treated
Providers with patients	Directly	
Providers with providers	(Not modelled)	
Does the concept of queuing apply?	Yes	
Stochasticity	(Not modelled)	
Model presentation		
Statechart	No	
Others	Text	
Implementation	No	

Yousefi, 2017		
Item	**Content**	**Remark**
Topic area	Service efficiency	
Country	Brazil	
Publication type	Journal paper	
Study type	Experimental	
Healthcare setting	Hospital - Emergency Department	
Spatial representation	No	
Investigational components	Changing the number of receptionist, doctors, nurses, and triage nurses/doctors	
Outcomes	Left without being seen, length of stay, total wait time, wrongly discharged	
Patient agents		
States	Waiting for a treatment, receiving service, Moving to different sections, Dying	
Attributes	Severity	
Leading provider agents		
Role	Physician	
States	Waiting, giving treatment, moving to different sections, attending in group decision-making, triaging	
Attributes	(Not modelled)	
Other agents	Nurse, laboratory technician	
Interactions		
Patients with patients	Indirectly	Patient arrives at hospital, goes through the registration and triage process, and is treated by physician. Providers participate directly in the group decision-making process
Providers with patients	Directly	
Providers with providers	Directly	
Does the concept of queuing apply?	Yes (Patient will leave if finding long queue)	
Stochasticity	State transition ("the transition will be chosen randomly when an agent reaches the transition time. Each transition has a different possibility, which are given by different weights. For instance, we have an agent with a current state of Sx that receives an input Ia. The agent may stay in the same state as before (Sx)"	
Model presentation		
Statechart	Yes, in the form of formula	
Others	Text and flow chart	

Implementation	No	

Saoud, 2016		
Item	**Content**	**Remark**
Topic area	Service efficiency	
Country	Algeria	
Publication type	Journal paper	
Study type	Experimental	
Healthcare setting	Hospital - Emergency Department	
Spatial representation	No	
Investigational components	Add a doctor in the consultation zone between 11 am and 3 pm, adding a doctor in the observation unit between 6pm and 11pm, or these two scenario combined	
Outcomes	Average length of stay and waiting time stratified by acuity	
Patient agents		
States	(Details not available)	
Attributes	Acuity level	
Leading provider agents		
Role	Physician	
States	Type (consultation, expert, observation)	
Attributes		
Other agents	Nurse, lab technician	
Interactions		
Patients with patients	Indirectly	Patient arrives at hospital, goes through the registration and triage process, and is treated by physician. The observation doctor installed initially in the observation unit monitors and treats serious patients assessed by the consultation physician. If the patient's state needs a specialized opinion, the observation doctor requests an expert doctor who decides whether an outpatient treatment or the patient's hospitalization"
Providers with patients	Directly	
Providers with providers	Directly	

Does the concept of queuing apply?	Yes	
Stochasticity	(Not modelled)	
Model presentation		
Statechart	Yes, although the content is more like a workflow chart	
Others	Text and flow chart	
Implementation	No	

Barnes, 2010		
Item	**Content**	**Remark**
Topic area	Nosocomial infection	
Country	US	
Publication type	Journal paper	
Study type	Experimental	
Healthcare setting	Hospital - General Wards and ICU	
Spatial representation	No	
Investigational components	Nurse-to-physician ratio; Proportion of patient visits from nurses; hand-hygiene compliance	
Outcomes	Colonization from physicians and from nurses	
Patient agents		
States	Susceptible, colonized, infected	
Attributes	Length of stay, required number of visit, risk level	
Leading provider agents		
Role	Nurse	
States	Susceptible, colonized	
Attributes	hand-hygiene compliance	
Other agents	Physician, visitor	
Interactions		
Patients with patients	(Not modelled)	"The only modelled interactions are between patients and HCWs, and patients and their visitors. Interactions between HCWs are not modelled because there is insufficient data to support a significant contribution to transmission from such interactions. "
Providers with patients	Directly	
Providers with providers	(Not modelled)	
Does the concept of queuing apply?	No	
Stochasticity	"A fixed number of visitors are generated each day, each visiting a single patient in the hospital at random"; "These parameters can be constant values for all patients or be randomly generated and vary for each patient."	
Model presentation		

Statechart	Yes	
Others	Text	
Implementation	No	

D'Agata, 2007		
Item	**Content**	**Remark**
Topic area	Nosocomial infection	
Country	US	
Publication type	Journal paper	
Study type	Experimental	
Healthcare setting	Hospital - Inpatient	
Spatial representation	No	
Investigational components	Start day of treatment and the duration of the treatment period	
Outcomes	Basic epidemic reproductive numbers for both the non-resistant strain and the resistant strain.	
Patient agents		
States	Uninfected, infected only by the non-resistant strain, infected by the resistant strain.	
Attributes	(Not modelled)	
Leading provider agents		
Role	Healthcare worker	
States	Uncontaminated (HU), contaminated only with non-resistant, bacteria (HN), contaminated with both non-resistant and resistant bacteria (HNR), and contaminated only with resistant bacteria (HR)	
Attributes	(Not modelled)	
Other agents		
Interactions		
Patients with patients	(Not modelled)	
Providers with patients	Directly	
Providers with providers	(Not modelled)	
Does the concept of queuing apply?	No	
Stochasticity	"each HCW begins the first visit of the shift uncontaminated and subsequent patient visits are randomly chosen; at the end of a visit a HCW becomes contaminated from an infectious patient with probability Pc and a patient becomes infected from a contaminated HCW with probability Pi"	
Model presentation		
Statechart	Yes	
Others	Text and formula	
Implementation	No	

Ferrer, 2014		
Item	**Content**	**Remark**
Topic area	Nosocomial infection	
Country	France	
Publication type	Journal paper	
Study type	Experimental	
Healthcare setting	Hospital - Intensive Care Unit	
Spatial representation	No	
Investigational components	Three strategies to handle nurse shortage: transfer patients, substitute nurses, and reassign patients	
Outcomes	Prevalence of pathogen carriage	
Patient agents		
States	(Details not available)	
Attributes	Simplified Acute Physiology Score, Carriers at admission	
Leading provider agents		
Role	Nurse	
States	(Details not available)	
Attributes	Number of visits per patient	
Other agents		
Interactions		
Patients with patients	(Not modelled)	"We assumed that all pathogen transmissions occurred via nurse–patient interactions, we considered a simplified contact structure with a limited number of patient–HCW contacts, and we ignored direct HCW-to-HCW transmissions"
Providers with patients	Directly	
Providers with providers	(Not modelled)	
Does the concept of queuing apply?	No	
Stochasticity	"In HCWs, we modelled transient contamination with the pathogen, with a duration following an exponential distribution of mean 10 h,"	
Model presentation		
Statechart	No	
Others	Text and diagram	
Implementation	No	

Ferrer, 2013		
Item	**Content**	**Remark**
Topic area	Nosocomial infection	
Country	France	
Publication type	Conference Proceeding	
Study type	Experimental	
Healthcare setting	Hospital - Intensive Care Unit	
Spatial representation	No	
Investigational components	Bed occupancy, Nurse-to-patient ratio, nurse rosters, absenteeism and substitution	
Outcomes	Prevalence of colonisation	
Patient agents		
States	Healthy, colonised	
Attributes	Location, bed occupancy, length of stay and daily list of visits	
Leading provider agents		
Role	Nurse	
States	Healthy, colonised	
Attributes	Fatigue, occupation state	
Other agents	Physician	
Interactions		
Patients with patients	(Not modelled)	"Transmission routes other than patient–HCW–patient are not accounted for"
Providers with patients	Directly	
Providers with providers	(Not modelled)	
Does the concept of queuing apply?	No	
Stochasticity	"The order of action of agents is set at random every time step and individual variables" "the Length of Stay (LoS), which has been drawn from a long-tailed gamma distribution function at patient admission"; "Nosolink allows the daily entry of a pathogen in the ward via a fixed probability of colonization at patient admission"; "Patients are randomly assigned to nurses according to the nurse-to-patient ratio defined at setup"; "Duration of colonization of HCWs is set with an exponential distribution with mean: miu =10 hours"	
Model presentation		
Statechart	No	
Others	Text	
Implementation	No	"It is a first prototype for a decision support

		tool to guide ICU management heeding the control of HAIs"

Greer, 2009		
Item	**Content**	**Remark**
Topic area	Nosocomial infection	
Country	Canada	
Publication type	Journal paper	
Study type	Experimental	
Healthcare setting	Hospital - Neonatal Intensive Care Unit	
Spatial representation	No	
Investigational components	Different vaccination strategies for HCWs (25%, 50%, 75%, and 95%) and 2 different vaccination strategies for family caregivers (0% and 100%).	
Outcomes	Number of patient infected	
Patient agents		
States	Susceptible, infected and contagious, recovered and immune	
Attributes	(Details not available)	
Leading provider agents		
Role	Healthcare worker	
States	Susceptible, infected and contagious, recovered and immune	
Attributes	(Details not available)	
Other agents	Family caregiver	
Interactions		
Patients with patients	(Not modelled)	"Transmission could occur between HCWs during social interactions, between HCWs and patients and/or family caregivers during patient care activities, and between family caregivers and patients during close contact activities."
Providers with patients	Directly	
Providers with providers	Directly	
Does the concept of queuing apply?	No	
Stochasticity	"HCWs were randomly assigned to infants at each time step"; Probability of pertussis transmission during interaction	
Model presentation		
Statechart	No	
Others	Text	
Implementation	No	

Jiménez, 2013		
Item	**Content**	**Remark**
Topic area	Nosocomial infection	
Country	US	
Publication type	Conference Proceeding	
Study type	Experimental	
Healthcare setting	Hospital - one floor (multidisplinary; no ER or OR)	
Spatial representation	Yes	
Investigational components	Vaccine and antimicrobials	
Outcomes	Cumulative cases of infection	
Patient agents		
States	Uninfected, colonized, infected, not colonised, asymptomatic, mild Clostridium difficile-associated disease (CDAD), severe CDAD, death, recovered	
Attributes	(Details not available)	
Leading provider agents		
Role	Nurse	
States	(Details not available)	
Attributes	(Details not available)	
Other agents	Nurse assistant, infection preventionist, infection control physician, janitor, dietician, social worker, etc.	
Interactions		
Patients with patients	Directly	
Providers with patients	Directly	
Providers with providers	Directly	
Does the concept of queuing apply?	No	
Stochasticity	Added in nursing behaviour. Each run had different seed.	
Model presentation		
Statechart	Yes	
Others	Text and graph	
Implementation	No	

Temime, 2010		
Item	**Content**	**Remark**
Topic area	Nosocomial infection	
Country	France	
Publication type	Conference Proceeding	
Study type	Explanatory	
Healthcare setting	Hospital - Intensive Care Unit	
Spatial representation	Yes ("a geographically realistic hospital ward"	
Investigational components	The efficacy and compliance of hand hygiene	
Outcomes	Average number of colonised patients	
Patient agents		
States	Healthy, colonised	
Attributes	Location, length of stay and daily list of visits	
Leading provider agents		
Role	Nurse	
States	Healthy, colonised	
Attributes	Hand hygiene compliance, nurse to patient ratio	
Other agents	Physician, peripatetic healthcare worker, pathogens and antibiotics	
Interactions		
Patients with patients	(Not modelled)	"Only patient/HCW interactions are modelled; in particular, HCW/HCW interactions are not modelled yet"
Providers with patients	Directly	
Providers with providers	(Not modelled)	
Does the concept of queuing apply?	No	
Stochasticity	"probability of patient-to-HCW transmission is the same as that of HCW-to-patient transmission"	
Model presentation		
Statechart	No	
Others	Text	
Implementation	NA	

Hotchkiss, 2005		
Item	**Content**	**Remark**
Topic area	Nosocomial infection	
Country	US	
Publication type	Journal paper	
Study type	Experimental	
Healthcare setting	Hospital - Intensive Care Unit	
Spatial representation	Yes	
Investigational components	Cohorting patients, the lag time of isolation, decrease number of physician visits, restrictive visitation patterns	
Outcomes	Percentage of the total population of patients will become contaminated at the end of 1 wk	
Patient agents		
States	Contaminated or not contaminated	
Attributes		
Leading provider agents		
Role	Nurse	
States	Contaminated or not contaminated	
Attributes		
Other agents	Primary physician and consultant physician	
Interactions		
Patients with patients	(Not modelled)	" Incorporation of direct patient-to-patient and caregiver-to-caregiver transmission… but would not contribute substantively to the message of this communication"
Providers with patients	Directly	
Providers with providers	(Not modelled)	
Does the concept of queuing apply?	No	
Stochasticity	"There is a finite probability specified as the per-encounter acquisition probability"; "random patient contacts may be with patients assigned to the caregiver or other patients within the specified geographic domain “covered” by that caregiver"	
Model presentation		
Statechart	No	
Others	Text and source code (link broken)	
Implementation	No	"The model we present is intended to highlight the potential utility of

		spatially explicit, agent-based simulations in predicting pathogen dissemination dynamics in the ICU"

Hotchkiss, 2007		
Item	**Content**	**Remark**
Topic area	Nosocomial infection	
Country	US	
Publication type	Journal paper	
Study type	Experimental	
Healthcare setting	Hospital - Dialysis Unit	
Spatial representation	Yes	
Investigational components	Spatial segregation, temporal segregation, Spatial + temporal segregation	
Outcomes	Contamination events per 100 patients	
Patient agents		
States	Infectious or noninfectious	
Attributes	Risk of being infectious	
Leading provider agents		
Role	Technician	
States	Infectious or noninfectious	
Attributes		
Other agents	Dialysis chair	
Interactions		
Patients with patients	(Not modelled)	"An infectious patient can contaminate the chair, the caregiver, or both with distinct probabilities."
Providers with patients	Directly	
Providers with providers	Not applicable	
Does the concept of queuing apply?	No	
Stochasticity	"An infectious patient can contaminate the chair, the caregiver, or both with distinct probabilities."	
Model presentation		
Statechart	No	
Others	Text and diagram	
Implementation	No	

Ramsey, 2014		
Item	**Content**	**Remark**
Topic area	Service coordination	
Country	US	
Publication type	Journal paper	
Study type	Experimental	
Healthcare setting	Primary Care	
Spatial representation	No	
Investigational components	Two continuity of care policies	
Outcomes	Average A1c, costs, errors on day 360	
Patient agents		
States	Blood glucose (A1c)	
Attributes	blood pressure, lipids, adherence, weight, height, creatinine, history of depression, stress, medication allergies, and medications in use at the start of treatment.	
Leading provider agents		
Role	Primary care physician	
States	(Details not available)	
Attributes	Errors of commission, errors of omission	
Other agents		
Interactions		
Patients with patients	(Not modelled)	
Providers with patients	Directly	
Providers with providers	(Not modelled)	
Does the concept of queuing apply?	No	
Stochasticity	"For CC, each patient was randomly assigned to a physician model for treatments across all visits. For OC, on each visit a physician model was randomly assigned to treat the patient on that given visit." (CC: continuous care; OC: opportunistic care)	
Model presentation		
Statechart	No	
Others	Text and formula	
Implementation	No	"The primary objective of this paper is to examine the usefulness of multi-agent simulations as a means for evaluating effects of policies/guidelines on organisational

		outcomes. A secondary objective is to provide evidence for specifying conditions where COC is beneficial to patients with T2DM and to help reconcile some noted disparities in research findings on the values of COC."

Liu, 2014		
Item	**Content**	**Remark**
Topic area	Payment model	
Country	US	
Publication type	Journal paper	
Study type	Experimental	
Healthcare setting	Health system alliance	
Spatial representation	No	
Investigational components	Providers forming an Accountable Care Organization (ACO); Payer tries different shared saving rate (SSR) and sharing rate to hospital (SRH).	
Outcomes	CHF-related hospitalization rate and annual mortality rate of CHF patients; Average cost saving per CHF patient (for payer, and for the distribution to hospital)	
Patient agents		
States	CHF Free, CHF onsite, CHF-related hospitalization, Mortality	
Attributes	Age, race, gender, income, disease (diabetes, hypertension, CHF)	
Leading provider agents		
Role	Hospital agent and Primary Care Physician agent	
States	(Not modelled)	
Attributes	Attitude, subjective norm, perceived behaviour control	
Other agents	Payers	
Interactions		
Patients with patients	(Not modelled)	"Based on his/her current attitude toward the CHF intervention, a provider agent will send a supportive message either for the behaviour of implementing the intervention or for the opposite behaviour of not implementing the intervention to a random agent within his/her network. A provider agent can then estimate other provider agents' attitudes based
Providers with patients	Directly	
Providers with providers	Directly	

		on the number of supportive messages received for each behaviour."
Does the concept of queuing apply?	No	
Stochasticity	Poisson process to model outpatient visit; Age-adjusted transition probability from the CHF-diagnosed state to CHF-related hospitalization	
Model presentation		
Statechart	Yes	
Others	Text, diagram and formula	
Implementation	No	

Alibrahim, 2016		
Item	**Content**	**Remark**
Topic area	Patient Choice	
Country	US	
Publication type	Journal paper	
Study type	Experimental	
Healthcare setting	Health system alliance	
Spatial representation	No (there is distance between providers. It is a calculated value and does not translate back to eh real world topology	
Investigational components	Providers forming an Accountable Care Organization (ACO); Patients are allow to bypass providers	
Outcomes	Yearly bypass rates, yearly hospitalization rate, average yearly Medicare payment	
Patient agents		
States	CHF Free, CHF onsite, CHF-related hospitalization, Mortality	
Attributes	Age, race, gender, income, disease (diabetes, hypertension, CHF)	
Leading provider agents		
Role	Provider	
States	(Not modelled)	
Attributes	Mortality rate, hospitalization Rate, disease management program, distance with other providers	
Other agents		
Interactions		
Patients with patients	(Not modelled)	"patients were fully aware of yearly provider performance: mortality rates, hospitalization rates, and disease management programs."
Providers with patients	Indirectly	
Providers with providers	(Not modelled)	
Does the concept of queuing apply?	No	
Stochasticity	Patients assigned to random providers;	
Model presentation		
Statechart	No	
Others	Text, Tables and formula	
Implementation	No	

Lim, 2013		
Item	**Content**	**Remark**
Topic area	Service coordination	
Country	Canada	
Publication type	Journal paper	
Study type	Explanatory	
Healthcare setting	Hospital - Emergency Department	
Spatial representation	No	
Investigational components	Interaction between physicians and their delegates	
Outcomes	Resource utilization, time to disposition	
Patient agents		
States	(Not modelled; Patients are modelled more from the perspective of Discrete Event Simulation, thus no state is modelled)	
Attributes	Severity	
Leading provider agents		
Role	Physician	
States	Waiting, consulting with delegates, treatment patients	
Attributes		
Other agents	Delegate	
Interactions		
Patients with patients	Indirectly	
Providers with patients	Directly	
Providers with providers	Directly	
Does the concept of queuing apply?	Yes	
Stochasticity	"An exponential distribution is used to distribute the arrivals over each hour."	
Model presentation		
Statechart	Yes (for physicians and delegates)	
Others	Text and flow chart	
Implementation	NA	