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A Review on the Contribution of Emergency Department Simulation Studies in Reducing Wait Time

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ABSTRACT

Background: Because of the important role of hospital emergency departments (EDs) in providing urgent care, EDs face a constantly large demand that often results in long wait times. Objective: To review and analyze the existing literature in ED simulation modeling and its contribution in reducing patient wait time. Methods: A literature review was conducted on simulation modeling in EDs. Results: A total of 41 articles have met the inclusion criteria. The papers were categorized based on their motivations, modeling techniques, data collection processes, patient classification, recommendations, and implementation statuses. Real impact is seldom measured; only four papers (~10%) have reported the implementation of their recommended changes in the real world. Conclusion: The reported implementations contributed significantly to wait time reduction, but the proportion of simulation studies that are implemented is too low to conclude causality. Researchers should budget resources to implement their simulation recommendations in order to measure their impact on patient wait time.

KEYWORDS

Emergency Department, Literature Review, Modeling, Simulation, Wait Time

INTRODUCTION

An emergency department (ED) is considered the most important part of any hospital. It is responsible for providing care to patients who need immediate but unscheduled healthcare services, 24 hours a day, 7 days a week. However, because of an ED's important role in providing urgent care for ill or injured patients, EDs face a constantly large demand that often results in long wait time. Due to many factors, such as insufficient staffing, budget constraints, poor inpatient bed turnover, unscheduled arrivals, and growing and aging populations, ED services are seriously affected and patient wait time has reached a critical level in many hospitals, which in turn causes serious health consequences and adds an economic cost for both patients and societies. In this context, many healthcare organizations and research centers are wondering whether the analysis results of ED simulation models can help reduce patient wait time.

Background on Patient Wait Time

Wait time is usually known as the difference between the time of arrival in the ED and the time the patient has contact with a physician for the first time. Others define it as the time a patient has spent waiting for diagnostic tests (e.g., X-ray or blood test) or waiting after returning from external testing

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to get therapy (Chin & Fleisher, 1998). According to the Canadian Institute for Health Information (2012), four relevant measures can contribute to patient wait time in the ED:

- **ED Length of Stay:** Time from patient registration to discharge or admission;
- **Time Waiting for Initial Physician Assessment:** Time from patient registration to the moment a physician first assesses the patient;
- **Time to Disposition:** Time from patient registration to the moment the decision is taken to either discharge or admit the patient to a hospital bed; and
- **Time Waiting for Inpatient Bed:** Time from patient admission to the moment the patient leaves the ED to go to the inpatient unit (inside the hospital).

Different organizations have defined targets that give a maximum time a patient should spend in the ED. For instance, in Ontario (Canada), provincial targets for the ED length of stay are eight and four hours for the high acuity and low acuity patients, respectively (Ontario Ministry of Health and Long-Term Care, 2015). In Québec (Canada), the targeted provincial average wait time for ED length of stay is 12 hours (Ministère de la Santé et des Services Sociaux du Québec, 2011). In the UK, the target wait time is set to four hours from arrival to admission, transfer, or discharge (NHS Choices, 2015).

Unfortunately, in many cases, hospitals cannot meet their targets and patients wait longer than expected. Such long time causes negative effects on the patients and the service quality. Patients may experience delays in the treatment of pain or suffering, higher dissatisfaction, and higher risks of stronger or more permanent damage. Some patients even decide to leave without receiving treatment. On the other hand, the efficiency and stress level of physicians and nurses can also be affected negatively by such long waits (Waldrop, 2009).

Since long patient wait time is one of the most important issues in ED, and due to its direct impact on the quality of healthcare services and the satisfaction level of patients, it has attracted much attention lately. A variety of solutions have been considered toward shortening ED wait time, such as better resource allocation strategies (Day, Al-Roubaie, & Goldlust, 2013; Xu, Roger, Rohleder, & Cooke, 2008), improved staff working systems (Kuo, 2014; Kuo, Leung, & Graham, 2015; Wang, McKay, Jewer, & Sharma, 2013), and separate care programs for minor injuries (Khadem, Bashir, Al-Lawati, & Al-Azri, 2008; Maulla, Smarta, Harrisb, & Karasnehc, 2009; Rasheed, Lee, Kim, & Park, 2012). However, because ED is a dynamic system with complex interactions among different components and processes, the challenge with most of the suggested solutions is that, in addition to the possibility of failure, such solutions cost much money and time to be implemented. In this context, hospital decision makers need effective techniques to help them test proposed scenarios and predict results before the actual implementation. Simulation, which is used to imitate in an abstract way the operation of a real-world process or system over time, is a candidate technique that can likely help here.

ED Simulation Overview

Simulation is nowadays perceived as an effective technique for assessing organizations' efficiency, searching for more efficient processes, and testing recommended changes and improvements in a rapid, accurate, low cost, and low risk means. Simulation modeling approaches have been adapted to ED because of their ability to analyze patients flow, predict demand for services, address current problems in ED, and evaluate various interventions. They also help hospital administrators and practitioners examine many "what if" scenarios with an ED complex system by making changes in the system within a user-friendly graphical interface, without jeopardizing patient care (Friesen, McLeod, Strome, & Mukhi, 2011).

Simulation models are used in ED to either support strategic (long-term) decision making or to support operational (day-to-day) decision making. The former type includes improving the process by hiring additional physicians or nurses, or changing the ED layout or processes, whereas the latter type focuses on near real-time decisions such as calling for additional staff or diverting ambulances towards other hospitals (Bahrani, Tchemeube, Mouttham, & Amyot, 2013).

A number of simulation approaches have been used to model EDs such as system dynamics (SD), discrete event simulation (DES), or agent-based simulation (ABS).

The general simulation methodology, for every ED, contains five main steps:

1. Collecting the required data including arrival rates and different service times
2. Analyzing the data to develop statistical distributions and then feeding them to a simulation model of the ED
3. Running the model using the current state of the modeled ED
4. Verifying and validating the simulation model
5. Evaluating different alternatives/scenarios to mitigate patient wait time

The typical patient flow throughout an ED is presented in Figure 1. This flow starts with the patient's arrival to the ED entrance either by ambulance or by walking in and ends when the patient is either discharged from the ED or admitted into the hospital for further treatment. In between these endpoints, three stages are involved. First, in the triage station, patient acuity is decided by a nurse and higher priority for treatment is given for patients with acute conditions. Second, the patient is moved to the waiting area or examination room until seen by a physician. Finally, the patient is seen by a physician, who decides whether to discharge or admit the patient.

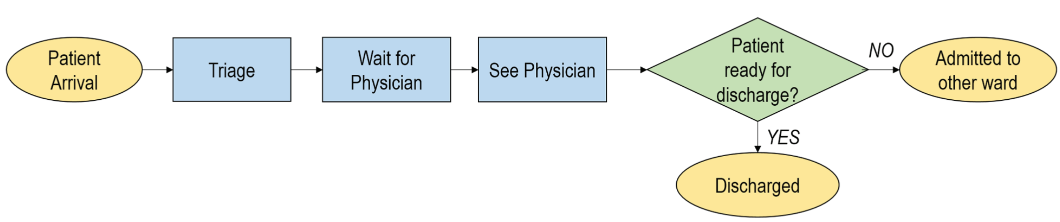
Literature Review Objective

The objective of this review is to study and analyze the existing literature on ED simulation modeling and its contribution in reducing patient wait time to answer the following research question: How well has the simulation approach succeeded in achieving wait time reduction in emergency departments?

The review raises awareness about the gap that exists between the use of simulations for optimizing EDs and the implementation of the simulation recommendations in real environments to measure the concrete impact of these recommendations on wait time. This review is important as most hospitals around the globe that have an ED suffer from wait time issues and are continuously trying to minimize patient wait time. The review is also timely as there now exists a body of ED simulation work that can be analyzed. In addition, Scerbo (2016) reports on the increasing interest in the use of simulation in healthcare, be it for education, research, or operational optimization, as well as on major investments in specialized simulation centers.

The paper is organized as follows. The literature review section provides details on the methodology used to conduct the review and then reports on the findings. Next, the discussion section uses the findings to answer the research question and highlight important limitations of current studies. Threats to the validity of the review itself are then discussed. Finally, conclusions bring final thoughts and directions for future research.

Figure 1. Typical patient flow in an ED



LITERATURE REVIEW METHODOLOGY

To achieve the review objective and answer the research question, a systematized literature review, inspired by Kitchenham's systematic literature review approach (Kitchenham, 2004), is conducted. Kitchenham's popular approach has proven its value in guiding the rigorous collection, selection, and evaluation of research papers related to information technologies. Systematized reviews are done in three stages:

1. Searching as much relevant published (peer-reviewed) evidence as possible through a search query
2. Evaluating the retrieved publications against inclusion and exclusion criteria to only keep the most relevant studies
3. Synthesizing knowledge and conclusions by aggregating and interpreting the findings from individual studies

The specific details of our review protocol are presented next according to these three stages. These details are important for the readers to understand how the papers were selected and how knowledge was synthesized from them. Such details also enable the reproducibility of the review.

Searching Stage

In this first stage, three complementary databases were used to identify relevant papers:

- Scopus® in order to cover both the technology and health literature about simulations. Scopus also covers the journals from IEEE and those included in PubMed/Medline and Embase since 1996. Scopus claims to be the "world's largest abstract and citation database", with more than 60 million citations.
- IEEE Xplore® Digital Library to cover the technical literature related to ED simulation not already covered by Scopus (e.g., conference papers). Xplore includes over 4 million citations.
- PubMed to cover the biomedical/health literature about ED simulations not already covered by Scopus (e.g., conference papers). PubMed comprises over 26 million citations.

Groups of keywords were used to locate potentially relevant papers. In Scopus and IEEE Xplore, the following query was used *simulation AND model*ing AND "wait* time" AND "emergency department" AND healthcare*. In PubMed, Medical Subject Headings (MeSH) were used to search for *"computer simulation[MeSH Terms] AND emergency care[MeSH Terms] AND waiting list[MeSH Terms]"*.

Scopus was the main source for most of the retrieved papers. Then, IEEE Xplore came next (must of the returned papers were already founded by Scopus). Finally, PubMed was used but was not so effective in locating additional papers.

Evaluating Stage

In the second stage, the results were evaluated against inclusion criteria to only include papers with the following conditions:

- **Source Type**: Conference papers and scholarly journals
- **Language**: English

Additionally, the titles and abstracts of the retrieved papers were read to only include papers that satisfy the following selection criteria:

- The paper discusses an application of simulation models in emergency departments;
- The simulation model considers general ED and not only specific departments; and
- A reduction in the patient wait time is one of the simulation goals or results.

Synthesizing Stage

After evaluating the papers, the full text of each selected paper was retrieved and analyzed to extract the required data. The extracted data includes details about each study's reference, location (country and hospital), objectives, simulation tool, and implementation status.

RESULTS

The literature review, conducted in the spring of 2016, has resulted in 41 papers. They have been analyzed with respect to 1) project motivations, 2) modeling techniques, 3) data collection processes, 4) patients' classifications and flows, 5) recommendations, and 6) implementations. Table 3 in the Appendix presents a general summary of the selected papers. For each paper, Table 3 provides details on the target hospital and its country, the objectives of the ED simulation, the simulation tool used, and whether or not there was an actual implementation of the system following the simulation-based analysis.

Project Motivations

The motivations of reviewed papers can be broadly categorized as to 1) increase patient satisfaction, 2) increase service quality, 3) improve ED processes, or 4) improve resources management. Table 3 includes the objectives of every project.

To increase patient satisfaction and increase service quality, many projects worked towards reducing wait time as their main goal (Al-Ajeel et al., 2015; Day et al., 2013; Duguay & Chetouane, 2007; Eskandari, Riyahifard, Khosravi, & Geiger, 2011; Weng et al., 2011), and towards alleviating bottlenecks (Eskandari et al., 2011; MacDonald et al., 2005; Venugopal, Daniel Otero, Otero, & Centeno, 2013). A number of projects examined patient flows and introduced different tracks for different patients' acuity levels (Chonde, Parra, & Chang, 2013; Friesen et al., 2011; Konrad et al., 2013; Zeinali, Mahootchi, & Sepehri, 2015).

Different projects evaluated different procedural changes to improve ED processes. For instance, changes included introducing several discharging plans (Crawford, Parikh, Kong, & Thakar, 2014), reducing lab turn-around time (Storrow et al., 2008) and adding a separate track for pediatric and low acuity patients (Kim, Delbridge, & Kendrick, 2014; Chonde et al., 2013).

One of the primary motivations of some projects is to improve the management of resources such as staff. Several projects considered changing staff sizing (Al-Ajeel et al., 2015; Cabrera, Luque, Taboada, Epelde, & Iglesias, 2012; Cocke et al., 2016; Day et al., 2013; Eskandari et al., 2011; Komashie & Mousavi, 2005; Zeinali et al., 2015) and evaluating different staff schedules (Holm & Dahl, 2009; Kuo, 2014; Venugopal et al., 2013; Weng et al., 2011; Xu et al., 2008; Yeh & Lin, 2007). Other projects examined physician behaviors (Lim, Worster, Goeree, & Tarride, 2013; Wang et al., 2013) and heterogeneity (Y.H. Kuo et al., 2015). The effects of ED layout were also examined in (Khadem et al., 2008).

Modeling Techniques

Discrete event simulation (DES) is the main modeling approach that has been used in almost all reviewed papers, either alone or combined with other approaches, except for one paper that used an agent-based simulation (Cabrera et al., 2012). The high penetration level of DES in ED simulations is due to its ability to model complex non-linear systems while taking into account patient history, staff scheduling, and multiple resource constraints (Duguay & Chetouane, 2007). The DES approach has been used to explain patient flows through a series of queues and activities in discrete time intervals and to represent the relationships between different entities in the ED system.

Some papers integrated different techniques with DES to get a better representation of the actual ED system. For instance, Kuo (2014) introduced the use of simulated annealing (SA). Kuo proposed a simulation-optimization method, in which simulation is integrated as a subroutine to create realizations for evaluating system performances, and at the same time used a simulated annealing algorithm to search for a good solution to develop.

Ahmad et al. (2014) used hybrid simulation models that combine DES and system dynamics (SD) in order to get a better representation of the actual system than by using either modeling paradigm solely.

Another modeling possibility is the use of a Colored Petri Net model (Salimifard, Hosseini, & Moradi, 2013), which is first developed to analyze the performance of ED, and then employed in a DES model to capture patients flow and care processes.

In addition, Zeinali et al. (2015) combined both simulation and metamodels to design a decision support system. They used a metamodel-based optimization to obtain a configuration of resources to reduce the total average wait time of patients with consideration of budget and capacity constraints. Their main idea is to use DES to evaluate the ED performance, and then use a metamodel to allocate resources.

Weng et al. (2011) mixed DES and Data Envelopment Analysis (DEA) to evaluate potential bottlenecks, maximize throughput flows, and reduce wait time. The DEA model is developed to calculate the efficiency of different ED operation alternatives that have been generated by the DES model subject to the available budget.

In Yeh and Lin's work (2007), a genetic algorithm (GA) is utilized in combination with simulation to adjust nurses' schedules without hiring additional staff. They first developed a simulation model to simulate the patients flow through the ED. Then, they applied GA to find a near-optimal nurse schedule minimizes the patients' queue time.

Eskandari et al. (2011) proposed a new framework that integrates the simulation model of a patients' flow process with the group AHP (Analytic Hierarchy Process) and TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) decision models to first identify bottlenecks of the ED and then to evaluate improving scenarios with the lowest possible expenditure developed for overcoming these bottlenecks. TOPSIS decision models take the weights of performance measures from the group AHP and the values of performance measures from the simulation model, and ranks the improvement scenarios.

As mentioned before, a large number of reviewed papers have used DES models in ED studies. In contrast, Cabrera et al. (2012) believed that using ABS to model EDs is more appropriate than DES because of the nature of healthcare systems, which are centered on human actions and interactions.

A wide variety of commercial simulation tools have been used to build the models, including Arena (the most popular tool), AnyLogic, CPN Tools, eM-Plant, Flexsim Healthcare, FORTRAN, MedModel, NetLogo, ProModel, Simio, SIMISCRIPT, and SIMUL8. Table 1 gives a reference for each tool.

Data Collection Processes

Data collection is one of the most challenging issues in many simulation projects. The quality and availability of the data play an important role in providing accurate simulation results. To conduct a valid simulation for an emergency department, several datasets are required. For example, the required data includes but is not limited to i) patterns of patient arrivals, ii) time stamped events such as arrival, registration, discharge, and transfer location, iii) the capacity of each workstation, iv) the number of healthcare providers available at each workstation, v) staff work schedules, and vi) acuity levels. The number and type of collected data are different from one model to the other based on each ED' settings and the model goals. The nature of the required data also depends on the simulation

Table 1. Simulation tools references

Tool	Reference
Arena	Arena Simulation Software. https://www.arenasimulation.com/
AnyLogic	AnyLogic Multimethod Simulation Software. http://www.anylogic.com/
CPN Tools	Colored Petri Nets Tools. http://cpntools.org/
eM-Plant	Plant Simulation (formerly eM-Plant). https://www.simplan.de/en/software/tools/plant-simulation.html
Flexsim Healthcare	Flexsim HealthCare. https://healthcare.flexsim.com/
FORTRAN	Fortan Programming Language. http://fortranwiki.org/fortran/show/Fortran
MedModel	MedModel Patient Flow and Process Improvement. https://www.promodel.com/Products/MedModel
NetLogo	NetLogo. https://ccl.northwestern.edu/netlogo/
ProModel	ProModel Better Decision Faster. https://www.promodel.com/
Simio	Simio Forward Thinking. http://www.simio.com/index.php
SIMISCRIPT	SIMSCRIPT Modeling and Simulation Tools. http://www.simscript.com/partners/partners.html
SIMUL8	SIMUL8 Process Simulation Software. http://www.simul8.com/

goals. For example, if the model is built to evaluate different staff schedules, then the focus will be on collecting all the data related to the staff size, salaries, and schedules.

The reviewed papers used different sources to obtain the required data. Historic patient records are the most popular source (Cocke et al., 2016; Coughlan et al., 2011; Eskandari et al., 2011; Friesen et al., 2011; Holm & Dahl, 2009; Khadem et al., 2008; Konrad et al., 2013; Kuo, 2014; Kuo et al., 2015; Rasheed et al., 2012; Shim & Kumar, 2010; Wang et al., 2013; Weng, Cheng, et al., 2011; Xu et al., 2008). Open interviews with physicians, nurses, and other staff take the second place (Ahmad et al., 2014; Al-Ajeel et al., 2015; Duguay & Chetouane, 2007; Kang et al., 2014; Komashie & Mousavi, 2005; Konrad et al., 2013; Kuo, 2014; MacDonald et al., 2005; Salimifard et al., 2013; Shim & Kumar, 2010; Xu et al., 2008; Yeh & Lin, 2007). The third place is occupied by observation and monitoring data (Duguay & Chetouane, 2007; Khadem et al., 2008; Khurma et al., 2008; Komashie & Mousavi, 2005; Konrad et al., 2013; Maulla et al., 2009). Additionally, other sources were used such as surveys (Al-Ajeel et al., 2015; Holm & Dahl, 2009; Khadem et al., 2008), time-motion studies (Kang et al., 2014; MacDonald et al., 2005; Rasheed et al., 2012), and hospital administrative databases (Lim et al., 2013). In addition to hospital registers data, some papers collected and used data about special events to evaluate how to reduce wait time during those events. For instance, Malavisi et al. (2015) used data collected during the 1994 Northridge earthquake to simulate the seismic event in ED, and Al-Ajeel et al. (2015) collected data during both normal days and during sandstorm days to simulate the ED during a sandstorm.

Patients Classification

The reviewed papers stated that the patients' degree of acuity affects their wait time. For instance, patients who are classified as urgent but not critical, the largest group of patients, have the longest wait time in some ED (Day et al., 2013; Duguay & Chetouane, 2007; Friesen et al., 2011; Khurma et al., 2008; Konrad et al., 2013; Kuo, 2014; Kuo et al., 2015; Lim et al., 2013; MacDonald et al., 2005; Rasheed et al., 2012; Salimifard et al., 2013; Zeinali et al., 2015). The reason is that critical patients preempt all other patients whereas non-urgent patients are treated and discharged immediately. With this issue in mind, different projects categorized patients along different dimensions. The most popular dimension is based on the patients' level of acuity/urgency. In most cases, patients are classified into one of five categories: level 1 (critical), level 2 (emergency), level 3 (urgent), level 4 (less urgent) and level 5 (non-urgent) (Cocke et al., 2016; Day et al., 2013; Eskandari et al., 2011; Weng et al., 2011). Based on these categories, some papers reclassified the patients into other groups, for example, admitted and discharged patients (Chonde et al., 2013; Kang et al., 2014), or high (levels 1 and 2) and low (levels 3, 4 and 5) acuity (Komashie & Mousavi, 2005; Lim et al., 2013). Other projects put category 5 patients into category 4 because they have the same flow and priority in real practice, and there is only a small proportion of category 5 patients (Kuo, 2014; Kuo et al., 2015). In addition, other models consider different categories for the level of acuity: acute, sub-acute, and minor (Wang et al., 2013), or simply red, yellow, and green (Khadem et al., 2008).

Moreover, dimensions of categorization may include age (either adult or pediatric with a cutoff age of 18) (Ahmad et al., 2014; Coughlan et al., 2011), the mode of arrival (arriving by ambulance or arriving by walking in) (Ahmed & Alkhamis, 2009; Coughlan et al., 2011), or a combination of a mode of arrival with a level of acuity (Al-Ajeel et al., 2015; MacDonald et al., 2005).

Recommendations

Simulation models are built either to diagnose process issues or to test performance improvement ideas. The reviewed papers have tested different scenarios to improve the ED process and then presented their recommendations to reduce patient wait time. Most of the recommendations either suggest changing levels and allocation of resources (resources allocation) or suggest changing the ED processes themselves (process improvement). Not all recommendations are feasible; some of them are costly and cannot be implemented due to budget constraints in some EDs.

Processes Improvement

One of the most common recommendations is to introduce different queues for different patient classifications such as acuity level, or admitted or discharged statuses (see the typical patient flow in Figure 1).

Chonde et al. (2013) suggested using two patient flow models: Virtual Streaming (VS), which introduces two virtual queues for admitted and for discharged patients (see Figure 2), and Physician Directed Queuing (PDQ), which introduces a fast track PQD area for low acuity patients. Figure 3 summarizes the PDQ procedure.

Most of the patient redirections are recommended for low acuity patients to save time and resources for high acuity patients. A "fast-track" strategy (Figure 4) allows for the rapid assessment and treatment of less serious injuries and illnesses (Khadem et al., 2008; Maulla et al., 2009; Rasheed et al., 2012).

Figure 2. Flowchart for virtual streaming (VS). Adapted from Chonde et al. (2013).

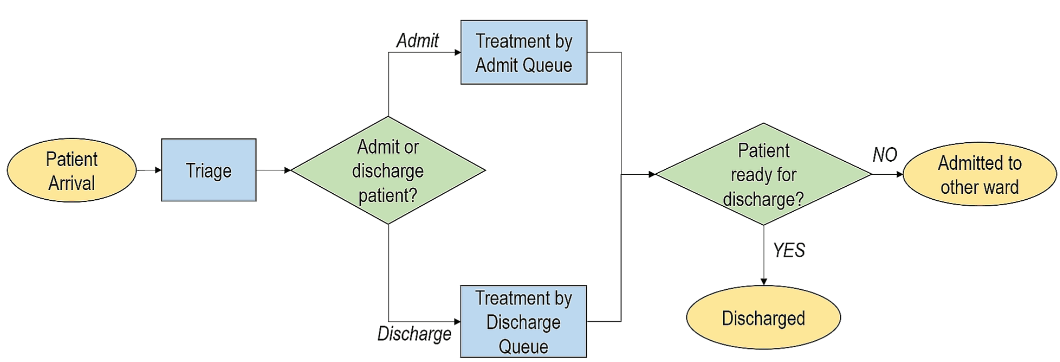


Figure 3. Flowchart for physician directed queuing (PDQ). Adapted from Chonde et al. (2013).

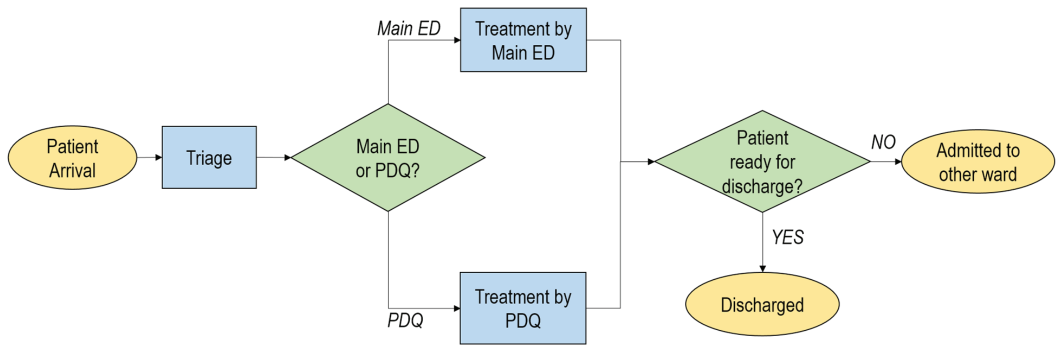
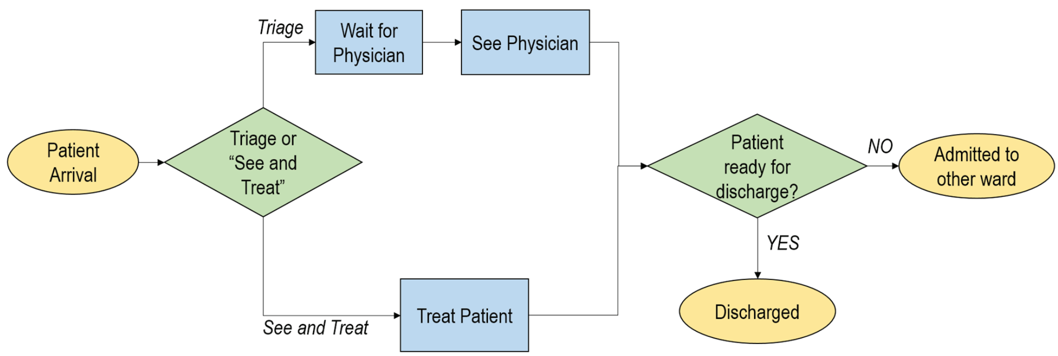


Figure 4. Example of "See and Treat" Model. Adapted from Maulla et al. (2009).



Kim et al. (2014), suggested dividing patients into two groups, adults and pediatric patients with a cutoff age of 18, and using a separate pediatric ED with its own patient flow management and medical resources in order to provide better quality emergency care to the target group.

Friesen et al. (2011) also recommended changing patient flows. They suggested redirecting the patients towards other EDs in order to balance ED loads using "crowdinforming", in which patients with non-urgent conditions consult a website or a smartphone-based service that provides insight into the "busyness" of an ED before deciding which one to attend.

The split-flow process of Konrad et al. (2013) is another example of patient redirection. Less sick patients are split off from the traditional ED process flow, which is then reserved for higher acuity patients, and redirected to a continuous care area.

Another process-related recommendation is presented by Crawford et al. (2014). The authors suggested using two proactive inpatient discharge strategies to reduce ED waiting and boarding times. The two strategies differ in how they estimate the occurrence of ED crowding to start discharging inpatients based on their estimated readmission risk. The proactive strategy-waiting (PS-W) considers the number of patients waiting for an ED bed post triage, whereas proactive strategy-boarding (PS-B) considers the number of patients in an ED who are waiting for an inpatient unit bed after completion of treatment in the ED.

In addition, Storrow (2008) showed that decreasing lab turnaround time resulted in a reduction in the total number of diversion days, average diversion hours per day, percentage of days with diversion, and average ED LOS.

Giving priority to ED patients in need of limited/expensive medical equipment such as advanced scanners over non-ED patients was recommended by Eskandari et al. (2011) to reduce patient wait time.

Resources Allocation

Many papers suggested adding one or more physicians in order to reduce wait time and increase the number of treated patients (Duguay & Chetouane, 2007; Khadem et al., 2008; Konrad et al., 2013; Salimifard et al., 2013). Adding a physician to the split-flow area can reduce the length of stay for lower acuity patients (Konrad et al., 2013). The same result is obtained when adding a physician and mid-level provider in triage, absorbing fast-track patients into triage, and discharging low-acuity patients directly from triage whenever possible (Day et al., 2013). Doan et al. (2014) recommended the addition of physician assistants (PAs) to reduce time without increasing costs. Hung et al. (2007) recommended the addition of a hospital volunteer and a second triage nurse to reduce pre-triage wait time and the proportion of patients waiting longer than 30 to 60 minutes for pre-triage to manage the increase in patient arrival rates in the winter season. Cocke et al. (2016) found that increasing staff by 25% of the current schedule is the feasible solution to handle the upcoming yearly demand in their new ED facility. In contrast, Holm & Dahl (2009) found that no significant change in patient wait time results from replacing the nurse triage with a physician triage during busy hours.

Varying the layout of the ED by adding or removing rooms was also recommended in some papers. Examples include adding an additional triage room and combining reception with triage (Khadem et al., 2008), setting up a new short-stay ward for patients who need to be further observed and monitored for less than a day (Shim & Kumar, 2010), adding a separate load relief area for low acuity patients (Rasheed et al., 2012), adding five mobile beds in the inpatient ward (Eskandari et al., 2011), and establishing a Rapid Assessment and Treatment (RAT) area (MacDonald et al., 2005).

Other recommendations suggested considering physician behavior to reduce wait time, for example:

- Variation in physician service rates can help reducing wait time because employing more efficient physicians can speed up the overall consultation time (Kuo et al., 2015).
- Based on the idea that the speed of physician assessment varies considerably at the beginning and end of a shift, eight-hour shifts should start every four hours, so the shift beginning and shift ending periods overlap (Wang et al., 2013).

In addition, the simulation results of Kuo (2014) suggested that:

- The best staffing level has a similar profile to the patient arrival rate, but shifted 1.5 – 2 hours behind; and
- Staggered shifts are also helpful to match physicians with patient demand.

Other Recommendations

A few papers considered real-time decisions and near-future forecasting. For example, Hoot et al. (2008) developed a ForecastED simulation to predict near-future operating conditions in order to manage the problem of ED crowding proactively.

Furthermore, the work done by Tan et al. (2013) recommended the use of real-time information to manage demand surges or to release doctors to the backroom operations during low peak period. The authors proposed an intelligent model to adjust the number of doctors based on current and historical information about the patient arrival in the ED.

Implementations

Most of the papers' recommendations to improve ED processes and reduce wait time are only theoretically proposed by modelers and have not been implemented in the real world. To examine the impact of the changes recommended by the modeler, recommendations must be implemented and evaluated. From the 41 reviewed papers in Table 3, only four (i.e., less than 10%) have reported the implementation of their suggested changes Table 2.

To analyze the impact on the ED wait time of moving from a "triage and treat" strategy, where patients are treated in the triage area and discharged without reaching the main ED area, to a "see and treat" strategy, Maulla et al. (2009) constructed and implemented a DES model. The research was structured into three phases. Phase 1 was the model creation and validation based on ED data to represent the current processes. Phase 2 involved using the model to assess the impact of a "see and treat" strategy on wait time. Three scenarios have been tested in this phase. Lastly, Phase 3 compared pre- and post-implementation performances with the predicted results of the model. The comparison was conducted by analyzing three data sets: the actual pre-implementation performance, pre- and post-implementation predictions derived from the simulation model, and the actual results obtained from a post-implementation analysis. The results of the comparison show a significant reduction in patient wait time, from 13.2% of the population waiting longer than 4 h before the implementation to 1.4% after the implementation. The authors unfortunately have not mentioned the hospital's name.

Day et al. (2013) had a different objective when implementing their simulation model. Their aim was to assess the accuracy of the simulation in predicting the magnitude of the proposed changes. They suggested adding a physician and a mid-level provider in triage, and consolidating the Fast Track into triage to reduce the average length of stay (LOS) and the proportion of patients with over 6 hours of LOS. The assessment was done by comparing the two simulations (*before* and *after* models) with the real-world data before and after the implementation. The result showed no significant difference between the post-intervention states in the simulated and real-world ED.

Konrad et al. (2013) introduced the idea of using the split-flow concept to manage ED processes by splitting the flow of patients according to patient acuity. They compared seventeen scenarios, regarding Door-to-Doctor time and length-of-stay for different patient acuity levels, to estimate the likely impact of a split-flow process redesign, including staffing level changes and patient volume changes. Finally, they recommended adding a physician to the split-flow area. The hospital management added additional physician assistants based on this recommendation. The implementation resulted in significant improvements in Door-to-Doctor time, total length-of-stay, arrival to bed time, and the number of patients left without being seen. The success of the implementation was evaluated by comparing the performance metrics from three different sources: 1) Saint Vincent hospital data prior to split-flow implementation, 2) Saint Vincent hospital data after split-flow implementation, and 3) benchmark metrics.

A simulation-based metamodeling approach was used as a novel decision support system to improve the patients flow and minimize the average wait time in the Modarres Hospital, in Iran (Zeinali et al., 2015). The idea was to find the optimal number of ED resources within the ED's budget and capacity constraints and then implement the changes through three steps: first, develop a simulation of the ED in order to evaluate the measure (total average wait time of patients) for each configuration of resources; second, use different metamodel techniques and choose the one with the maximum efficiency through a cross-validation technique to replace the computationally expensive DES model, and finally, use the proposed model to minimize the total average wait time of patients. The paper declared that the proposed model has been implemented and has resulted in a 48% decrease in the total average wait time without any further details.

DISCUSSION AND LIMITATION

Discussion

Simulation models were introduced in the reviewed papers as a decision technique to help ED management explore options to improve patient wait time without the typical financial or physical risks that may result from implementing those options in a real ED. A few hospitals have implemented the proposed solutions and achieved not only a significant improvement in terms of reducing patient wait time, but also good predictability of the simulation models.

As explained in the introduction, many metrics are used in the different models to measure wait time. In many cases, the hospitals' historical records do not include data about the start and end of

Table 2. Hospitals names and locations where simulation recommendations have been implemented

Reference	Country	Hospital Name
(Maulla et al., 2009)	UK	N/A
(Day et al., 2013)	USA	St. Louis Veterans Affairs Medical Center
(Konrad et al., 2013)	USA	Saint Vincent Hospital in Worcester
(Zeinali et al., 2015)	Iran	Modarres Hospital

activities. Moreover, the rapid change in demands and the variety in acuity levels affect the accuracy of measured wait time. Almost all the papers consider the average wait time as a measure of ED capacity and quality of service provided except Chin & Fleischer (1998), who proposed the use of the maximum wait time because, in some cases, the maximum time can be much greater than the average.

The trend among the reviewed papers is to model the ED in isolation from other departments. They focus on internal factors that cause the long wait time while in reality there are other external contributing factors. For example, common factors include the delay in transferring admitted patients to other areas of the hospital, and labs turn-around time. On the other hand, the focus on the ED alone can affect other departments by pushing the bottleneck to other hospital units.

ED overcrowding, in which the number of patients in the waiting area exceeds the available resources, has been introduced as a main reason for long patient wait time (Friesen et al., 2011; Konrad et al., 2013; Kuo et al., 2015; Rasheed et al., 2012; Salimifard et al., 2013). Alleviating overcrowding in ED has a high impact on improving patient flow and reducing wait time. Several papers have produced solutions that improve wait time indirectly by solving the overcrowding problem. For example, Friesen et al. (2011) suggest the use of “crowedinforming” to divert incoming patients to an ED during busy periods. In a similar manner, Kuo et al. (2015) found that physician heterogeneity has a great impact in ED overcrowding. Variation in physician service rates can help relieve the ED overcrowding, which in turn reduces wait time.

The “see and treat” strategy provides a promising solution to long wait time. Many papers have evaluated the idea of “see and treat” and the results suggest the implementation of the strategy (Day et al., 2013; Duguay & Chetouane, 2007; Khadem et al., 2008; Konrad et al., 2013; MacDonald et al., 2005; Maulla et al., 2009; Rasheed et al., 2012; Salimifard et al., 2013). Since low acuity patients represent a large proportion of ED patients, the main goal is to discharge low acuity patients directly from triage whenever possible. Adding a physician to the triage succeeded in reducing wait time and in increasing the number of treated patients (Day et al., 2013; Duguay & Chetouane, 2007; MacDonald et al., 2005). One possible threat of using a “see and treat” strategy is that its focus on low-acuity patients may affect patients with higher acuity.

Some papers showed concerns about possible trade-offs when applying certain changes. The discharge strategy suggested by Crawford et al. (2014) may result in an increase in the number of patient readmissions because its main focus is on reducing the crowding by discharging inpatients early.

Papers Limitations

The reviewed simulation projects highlighted a number of useful solutions to reduce patient wait time. However, they have some limitations that could reduce their effectiveness.

First, ED settings vary from one hospital to the other. All the reviewed models were built to represent a specific ED with specific settings that may not be generalizable to other EDs.

Another limitation is that most of the simulation models have represented the ED in isolation from other departments. ED, in reality, is part of a wider system where different services are interacting together in order to achieve their goals. The simulation models need to represent the relationships between the ED and other units of the hospital to capture the big picture and include all the possible factors, internal or external, that may lead to long wait time.

The third limitation is related to the data collection. Acquiring the required data is costly and time consuming. Sometimes, it may be impossible to obtain certain data such as the service time or the data related to the patients or physicians' behavior variation. In that case, modelers tend to make assumptions to close the gap or use a small sample of patients to draw conclusions on system performance, which has an impact on the final results. Other concerns related to the data collection are that the data are collected during a short period. In this case, some useful data such as seasonal peak variations will be overlooked.

Other limitations are related to some common assumptions such as considering equal qualifications and efficiency for all healthcare providers and modeling EDs in stable situations without considering external factors such as different seasons and catastrophes. Also, few papers actually discussed the high cost of some solutions such as adding physicians or nurses.

THREATS TO VALIDITY

Validity refers to the degree of which correct conclusions can be interpreted accurately and confidently from the results of research. The validity of this review is subject to many external and internal threats. The following subsections address those threats and the extent to which they were mitigated.

Internal Validity

Internal validity reflects the extent to which a resulted conclusion is justified. In this review, not all papers that consider the wait time problem in ED may have been retrieved due to:

- Limiting the search to only English-language
- Limiting the search to only three databases
- Not considering referenced papers
- Including only papers that consider the general ED and excluded other papers that studied specific (sub-)departments within the ED

That being said, a sample of 41 relevant papers is large enough to make interesting observations and reach acceptable conclusions. The three databases selected are also quite general, complementary, and comprehensive (and actually Scopus itself also covers many other databases).

Internal validity also considers bias factors such as the number of reviewers. In this review, the retrieved papers were reviewed by a single researcher (the first author); this increases the risk of bias in selecting papers and extracting data. Having more than one reviewer for each paper would have helped but was impossible due to resource limitations. To mitigate this threat, previous related reviews have been considered to verify the research strategy.

External Validity

External validity reflects the ability to generalize the results confidently. From the conducted research, it is concluded that the proportion of implemented simulations is low. A possible reason is that the reviewed papers are limited to journals and conferences in which the focus is on the technical simulation design and not contributions to EDs. Considering the gray literature (magazines, government/hospital reports) may produce different results. Also, the conclusions here are limited to EDs; the ways simulations are used in other hospital departments might be different.

CONCLUSION

From the literature reviewed, a number of important conclusions can be drawn about simulation modeling in ED and its impact on wait time.

First, simulation models, especially DES, have attracted many researchers in ED because: 1) simulations enable researchers to model the uncertainties and variability that are involved in ED systems, 2) they facilitate the representation of the complexity of ED systems, and 3) they assist the communication between modelers and stakeholders.

Second, the use of separate flows for patients based on their acuity level has been proposed, evaluated and applied in real EDs. This recommendation has shown a significant contribution to reducing wait time for less critical patients. The addition of physicians to the triage area to treat and discharge patients has also shown a good result in reducing the waiting in most cases. However, it is still not clear if those approaches have had a negative impact on the wait time of critical patients.

Third, resource allocation has been examined extensively. In human resources, the interesting idea of employing other staff like hospital volunteers and physician assistance to help physicians in treating low acuity patients' needs more investigation to verify its validity and evaluate if this will affect patient readmission rates. Conversely, the expansion of the ED and the addition of more rooms did not lead to wait time reduction unless accompanied by additional staff.

Fourth, the number of reported implementations of the proposed recommendations is low. Without an implementation, some of the recommendations are just theories, and there is no evidence of their actual impact on real systems. It was expected that not all ED simulation papers would contain an implementation, but a mere 10% of implementations is somewhat disappointing. There are many factors that affect the decision to implement recommended changes to an ED. One obvious factor is that not all changes can be applied because of their cost; some changes require hiring an additional physician or adding a new room to the ED. Salimifard et al. (2013) have stated that although the results of the alternatives were promising, ED management may not implement them for unknown reasons: "Also ED staff reaction to our work was positive, and they helped us through the work but due to the reluctance of ED managers, we failed to implement the proposed changes in reality".

Back to the research question "How well has the simulation approach succeeded in achieving wait time reduction in emergency departments?", with the limited number of implemented simulation models, it may be difficult to assess the actual contribution of simulation in reducing patients wait time. One good news is that the implementations reported actually led to positive contributions on reducing patient wait time in EDs. However, as researchers and journals have a tendency to publish more positive results than negative ones, there might exist implemented recommendations that did not lead to positive impacts on wait time, but such results would not be published easily.

In the future, to improve the literature on simulations in EDs, researchers should budget appropriate resources (time, money, and access to data, EDs, and experts) in order to implement the recommendations resulting from the analysis of simulation models and to assess whether there is evidence of improvement. The time and effort spent on such research are huge and should not be wasted with incomplete validation. There is an opportunity to study what factors actually cause the gap between the number of modeled simulations and the number of implemented ones.

In terms of research directions, future ED simulation applications should focus on:

- Modeling ED as part of a larger view of a hospital system by incorporating the interactions between ED and other units. Although ED wait time can be affected by external factors such as labs wait time or inpatient admission processes, most current studies have modeled ED as an isolated unit.
- Modeling real-time decision making. Several studies have considered strategic decisions but only a few have considered real-time, operational decisions (at the patient level rather than at the process level). Forecasting the number of expected patients and dynamically adjusting the number of ED staff based on real-time (e.g., hourly) demand is a promising approach to improve wait time without much economic burden on hospitals.

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APPENDIX

Table 3. Summary of the 41 selected papers

Reference	Country	Hospital Name	Objectives	Simulation tool	Imple-mented?
(Chin & Fleisher, 1998)	USA	An urban, university affiliated pediatric teaching hospital	To quantify the effect of patient arrival time and physician practices on physician idle time and patient wait time	FORTRAN	NO
(Komashie & Mousavi, 2005)	UK	Hospital in London, no name.	(1) To model the system for better understanding of operations, (2) To determine the impact of critical resources on Key Performance Indicators (KPIs), and (3) To provide a cost-effective means of testing various scenarios for possible system improvement.	Arena	NO
(MacDonald et al., 2005)	USA	The University Medical Center in Tucson, Arizona	To propose recommendations that would alleviate bottlenecks in the patient flow process of the ED.	Arena	NO
(Duguay & Chetouane, 2007)	Canada	Dr. Georges-L. Dumont Hospital in Moncton	To reduce patient wait time and to improve overall service delivery and system throughput.	Arena	NO
(Hung, Whitehouse, O'Neill, Gray, & Kissoon, 2007)	Canada	British Columbia Children's Hospital (BCCH)	To determine what aspects of PED (Pediatric ED) activity could be modified to improve patient flow, reduce patient wait time, and increase staff efficiency and morale.	Arena	NO
(Yeh & Lin, 2007)	Taiwan	Show-Chwan Memorial Hospital	To appropriately adjust nurses' schedules without hiring additional staff.	eM-Plant	NO
(Hoot et al., 2008)	N/A	No name.	To forecast near-future operating conditions, and to validate the forecasts using several measures of ED crowding.	Standard C programming language	NO
(Khadem et al., 2008)	Oman	A public hospital, no name.	(1) Improving patient satisfaction through minimizing patient wait time, and (2) Expanding the capacity of the ED.	MedModel	NO
(Khurma, Bacioiu, & Pasek, 2008)	Canada	No name.	To increase the flow throughout the ED by introducing Lean and process improvement methodologies.	ProModel	NO
(Storrow et al., 2008)	USA	No name.	To determine the effect of decreasing turnaround times on emergency medical services (EMS) diversion, ED patient throughput, and total ED length of stay.	N/A	NO
(Xu et al., 2008)	Canada	The Foothills Medical Centre in the Calgary	To test different ED physician management strategies, work practices, and alternative shift schedules to determine their impact on patient wait time in the ED.	Arena	NO
(Ahmed & Alkhamis, 2009)	Kuwait	A government hospital, no name.	To evaluate the impact of various staffing levels on service efficiency	SIMISCRIPT	NO
(Holm & Dahl, 2009)	Norway	Akershus University Hospital	To estimate the effect replacing nurse triage with a physician on patient wait time.	Flexsim Healthcare	NO
(Maulla et al., 2009)	UK	No name.	To evaluate the impact that a fast-track strategy in ED has on patient wait time.	N/A	YES
(Shim & Kumar, 2010)	Singapore	Tan Tock Seng Hospital	Reengineering emergency care process to improve patient wait time.	SIMUL8	NO
(Coughlan, Eatock, & Patel, 2011)	UK	A district general hospital in West London	To determine the impact a re-prioritization strategy has on the 4-hour target.	SIMUL8	NO
(Eskandari et al., 2011)	Iran	A government hospital, no name.	To identify and overcome bottlenecks that lead to long wait times of different patient types.	Arena	NO
(Friesen et al., 2011)	Canada	Different hospitals.	To investigate the application of existing available data and emerging data feeds towards developing an auxiliary ED process control strategy.	N/A	NO

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Table 3. Continued

Reference	Country	Hospital Name	Objectives	Simulation tool	Imple-mented?
(Weng, Tsai, et al., 2011)	Taiwan	Large teaching hospital center, no name.	To develop and deploy a mixed method incorporating DES and DEA to evaluate potential bottlenecks, maximize throughput flows, and identify solutions in reducing patient time in the ED while also increasing patient satisfaction.	Arena	NO
(Weng, Cheng, et al., 2011)	Taiwan	A medical center in Taiwan, no name.	To improve the flow of the ED by increasing the quality of treatment.	SIMUL8	NO
(Cabrera et al., 2012)	Spain	The Hospital of Sabadell	To identify the combination numbers of staff members of ED that optimize its performance.	NetLogo	NO
(Rasheed et al., 2012)	Korea	Hospital located in Seoul.	To assess the effects of an ED load relief area creation on ED effectiveness and service quality.	Arena	NO
(Chonde et al., 2013)	USA	No name.	To improve resource management strategies to combat the increasing costs of healthcare and overutilization of EDs.	Simio	NO
(Day et al., 2013)	USA	St. Louis Veterans Affairs Medical Center	(1) To determine the effects of adding a provider in triage on the average length of stay (LOS) and proportion of patients with >6 h LOS, and (2) To assess the accuracy of computer simulation in predicting the magnitude of such effects on these metrics.	AnyLogic Professional	YES
(Konrad et al., 2013)	USA	Saint Vincent Hospital in Worcester	To evaluate the impact on patient throughput arising from different split-flow configurations.	Arena	YES
(Lim et al., 2013)	Canada	No name.	To present an alternative approach where physicians and their delegates in the ED are modeled as interacting pseudo-agents in a discrete event simulation and to compare it with the traditional approach ignoring such interactions.	Arena	NO
(Salimifard et al., 2013)	Iran	A general hospital in the city of Yazd, no name.	To improve ED processes, in order to solve the crowding problem.	Colored Petri Nets	NO
(Tan, Tan, & Lau, 2013)	Singapore	Local Hospital, no name.	To intelligently adjust the number of doctors based on current and historical information about the patient arrival.	N/A	NO
(Wang et al., 2013)	Canada	St. Mary's General Hospital	To study the impact of physician behaviors on the ED wait time performances.	Arena	NO
(Venugopal et al., 2013)	USA	A major emergency department in Melbourne, Florida.	To understand the ED system's behavior under different alternative staffing solutions.	Arena	NO
(Ahmad et al., 2014)	Malaysia	A government Hospital, no name.	To study patient flows and the complex interactions among hospital resources for ED operations	AnyLogic	NO
(Crawford et al., 2014)	USA	Generic model of an acute care hospital	To analyze the effect of discharge timing on several ED related measures and the number of readmissions.	Arena	NO
(Doan et al., 2014)	Canada	British Columbia Children's Hospital (BCCH)	To compare the effect on key pediatric ED efficiency indicators of extending physician coverage versus adding Physician Assistants with equivalent incremental costs.	Arena	NO
(Kang, Nembhard, Rafferty, & Deflitch, 2014)	USA	Hershey Medical Center.	To investigate the effect of admission process policies on patient flow in the ED.	Simio	NO
(Kim et al., 2014)	USA	No name.	To explore different characteristics between ED pediatric and adult patient groups regarding process flow times and acuities, and to investigate developing pediatric EDs	Arena	NO
(Kuo, 2014)	Hong Kong	The Prince of Wales Hospital (PWH)	To explore different physician schedules iteratively to look for a good solution.	Arena	NO
(Al-Ajeel et al., 2015)	Kuwait	A government hospital, no name.	To determine the minimum number of staff needed to reduce the wait time during sandstorms without affecting the efficiency of the ED and its processes.	Arena	NO

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Table 3. Continued

Reference	Country	Hospital Name	Objectives	Simulation tool	Imple-mented?
(Kuo et al., 2015)	Hong Kong	The Prince of Wales Hospital (PWH)	To examine the effect of physician heterogeneity on the ED performance.	Arena	NO
(Malavisi, Cimellaro, Terzic, & Mahin, 2015)	Italy	Umberto I Mauriziano Hospital	To develop a simplified model in order to describe ED behavior during emergencies	ProModel	NO
(Zeinali et al., 2015)	Iran	Modarres Hospital	To improve the patient flow and relieve congestion by changing the number of ED resources (i.e., the number of receptionists, nurses, residents, and beds).	Arena	YES
(Cocke et al., 2016)	USA	University of Virginia (UVA) Medical Center	To examine whether the future ED facility would be able to handle the upcoming yearly demand and how different resource schedules would affect the average length of stay and average arrival to provider times.	Arena	NO

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