



Review

Discrete-Event Simulation Modeling in Healthcare: A Comprehensive Review

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Abstract: Discrete-event simulation (DES) is a stochastic modeling approach widely used to address dynamic and complex systems, such as healthcare. In this review, academic databases were systematically searched to identify 231 papers focused on DES modeling in healthcare. These studies were sorted by year, approach, healthcare setting, outcome, provenance, and software use. Among the surveys, conceptual/theoretical studies, reviews, and case studies, it was found that almost two-thirds of the theoretical articles discuss models that include DES along with other analytical techniques, such as optimization and lean/six sigma, and one-third of the applications were carried out in more than one healthcare setting, with emergency departments being the most popular. Moreover, half of the applications seek to improve time- and efficiency-related metrics, and one-third of all papers use hybrid models. Finally, the most popular DES software is Arena and Simul8. Overall, there is an increasing trend towards using DES in healthcare to address issues at an operational level, yet less than 10% of DES applications present actual implementations following the modeling stage. Thus, future research should focus on the implementation of the models to assess their impact on healthcare processes, patients, and, possibly, their clinical value. Other areas are DES studies that emphasize their methodological formulation, as well as the development of frameworks for hybrid models.

Keywords: discrete-event; simulation; modeling; healthcare; hospital; review; literature



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1. Introduction

Healthcare systems are largely adaptive human-based systems that involve both the utilization of limited physical facilities and resources, and complex interactions among different healthcare groups [1–3]. Since these healthcare systems are characterized by a high level of variability and uncertainty, they are not naturally easy to understand, design, and predict [4–7].

As healthcare systems continually evolve, achieving better quality of care while reducing costs is a global concern [7,8]. Thus, strategic, tactical, and operational decisions are made daily to evaluate and improve the efficiency and effectiveness of different healthcare processes and services [3,7]. To foresee the impact of these decisions on the system performance, healthcare providers need proper tools, such as simulation, so they can effectively explore the alternative scenarios [1,9].

A simulation is an imitation of how the real-world system operates over time. This can be used to identify critical points and system bottlenecks, and to answer “what-if” questions about real-world scenarios without any practical and/or financial implications [10–12]. Simulations can estimate the consequences of different interventions in healthcare, allowing for the incorporation of behavioral aspects and personalized decisions [7], as well as for identifying the optimal scenario according to some output criteria [13].

A simulation study requires the definition of a conceptual model; a representation of a problem within a system that is derived from theory or observations [11,14,15]. This concep-

tual representation should integrate different components, such as objectives, inputs, outputs, content, boundaries, assumptions, and simplifications [16,17]. Later, the conceptual model is transferred into computer software that helps healthcare professionals to comprehend the relationship between the input and output variables of the real-world system [1,18].

Discrete-event simulation (DES), also referred to as a time-to-event model, is ideal for complex problems, such as healthcare ones [9,19]. DES is a computer-based operation research technique that models different systems as networks of queues and activities [18] in order to assess, predict, and optimize a proposed or existing system, where changes occur at discrete epochs over time [8,20–22]. DES emerged from the manufacturing world, wherein Tocher developed the first language in the late 1950s for constructing a model to simulate a steel plant in the UK [7,23]. DES is often used to represent systems at an operational level, where transactions, processes, and the flow of individual entities, as well as the variability, are important factors [4,24]. Hence, DES models use events and typical quantities to imitate the observed behavior of the system by generating deterministic quantities or stochastic distributions [3]. DES can capture a system's behavior and interconnection effects, which result from the combinations of many random processes, coupled with the system structure [25]. Conversely, developing a DES model can be time consumingly (and costly), and it is heavily dependent on good quality data to inform the system behavior [24]. Users should, thus, balance the benefits and challenges of using the simulation approach.

The key concepts in DES are events, entities, attributes, and resources. An event is something that happens in the environment at a certain point in time. In the healthcare context, entities are self-contained objects that have attributes and consume resources while experiencing events, e.g., patients, organs for transplant, medical records, etc. [13,26]. Attributes are features or characteristics that are unique to an entity and can change over time, such as age and disease history, which influence their route through the simulation and the length of time between events [26]. Finally, resources are objects or facilities that provide a service to a dynamic entity, for example, doctors, nurses, hospital beds, operating rooms, physicians, etc. In addition, queues represent another important concept in DES, as they occur when several entities compete for a specific constrained resource, and they might have to wait until the resource is available. Each queue has its own logic and rules, commonly called a “queue discipline” [7,13,17].

Building a DES model requires large amounts of quantitative numerical data [18]. It also needs a set of logical statements that are expressed in a computable form to describe how the entities change their state [27]. DES has been used in healthcare as a preferable modeling technique, given its flexibility in responding to scale changes, the level of detail, individual patient focus, stochastic factors affecting the system, the ease in changing the model's components, waiting for the time-related performance, the existence of queues, and the visual representation of patient flows [17]. Although big data analysis is emerging as a technique for data modeling and simulation, it presents more challenges in processes subject to changing conditions and unexpected events [28].

Table 1 summarizes the characteristics of discrete-event simulation. While DES outputs can be point estimates, as well as ranges of values, the experimental results can be measured in terms of performance metrics, such as resource utilization, waiting times, the number of entities in queues, and the throughput of services or products, among others [29].

As healthcare systems become more complex, in combination with stricter quality demands, there is also a growing interest in the use of DES modeling in these settings, exemplified by the increasing number of articles published in the literature every year (period 1994–2021). Since more than 200 research articles are found in the literature, this study conducts a comprehensive literature review to provide a wider perspective of the DES capabilities presented in healthcare until 2021. This paper provides a deep and detailed categorization of the DES articles in healthcare that will help researchers to identify the DES trends (areas of application, outcomes, software used, contribution of articles by country, and popular journals and publishers), and to identify opportunities for future

research through four elements: the key elements to formulating models, frameworks for hybrid models, barriers for implementation, and measuring satisfaction and clinical value. The remainder of the article is presented as follows: Section 2 presents the methodology, including the search strategy, inclusion criteria, and review methodology. Section 3 presents the results and classification by year, approach, healthcare setting, outcome, provenance, and software use. Section 4 discusses these results, and Section 5 provides the conclusions.

Table 1. Characteristics of discrete event simulation.

Scope:	Operational, tactical
Purpose:	Decisions: Optimizations, predictions, and comparisons
Perspective:	Analytic, emphasis on detail complexity
Importance of variability:	High
Importance of tracking individuals:	High
Number of entities:	Large
Control:	Waiting (queues)
Relative timescale:	Short
Resolution of models:	Individual entities, attributes, decisions, and events
Data sources:	Numeric with some critical elements
Lower boundary of technical preparation:	Qualitative workflow
Model elements:	Physical, tangible, information
Model outputs:	Prediction points, performance measurements
Tools:	Arena, Simul8, FlexSim/FlexSim Healthcare, ProModel/MedModel, Simio, AnyLogic, TreeAge, ExtendSim

2. Methods

2.1. Search Strategy

The databases Springer, BioMed Central, ScienceDirect, Web of Science, Research Gate, Wolters Kluwer, MDPI, Taylor & Francis, ProQuest, Wiley Online Library, Mary Ann Liebert, IEEE, Scopus, Emerald, Sage, BMJ, and PubMed Central were systematically searched to retrieve existing articles on DES applications in healthcare, until August 2021 when the last search was conducted. The key terms used to search included: “discrete event”, “DES”, “simulation”, “hospital”, and “healthcare”, in the title, abstract, and/or keywords. No restrictions related to year, approach, healthcare setting, outcome, country of provenance, or software use were considered.

2.2. Paper Inclusion Criteria

The inclusion criteria in this review were narrowed down to research articles that focus on DES in healthcare, including a range of studies from the exploration of theoretical aspects up to practical applications. Publications regarding other operational research techniques were excluded, but studies on hybrid DES models were included in this research. Non-English-language literature, and other English-language articles published outside peer-reviewed journals, such as conference papers, books, editor notes, etc., were discarded. Following the retrieval of publications, 231 papers were considered in this study. A total of 51.8% of the papers were retrieved from healthcare-related journals, while the rest were retrieved from industrial-engineering-related journals. Figure 1 shows the three-stage searching and sorting process that led to the research articles included in this study.

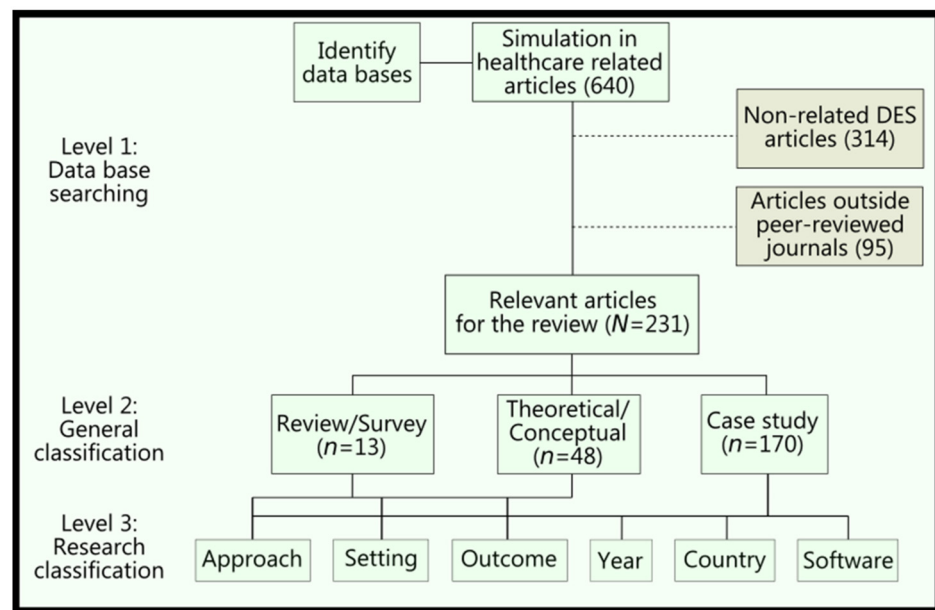


Figure 1. Inclusion and classification process of the review.

2.3. Review Methodology

The articles included in this review are divided into three taxonomy sections: (1) DES application articles that report original research; (2) Theoretical/conceptual articles that provide directions to explore problems or represent relations within DES models; and (3) Review articles that structure and classify the existing literature on the topic. Survey papers were analyzed alongside review papers as they were very few, and they focused on specific DES applications. Specific to the review papers included, only five studies focus entirely on DES as a unique review topic, and the rest aim to analyze healthcare improvements through diverse operations research techniques, DES being one of the approaches mentioned [21,30–33].

The search identified a total of 170 DES applications in healthcare, followed by 48 theoretical/conceptual articles, and 13 review/survey studies. Further classification within these main categories includes the approach, healthcare setting, outcome, country of provenance, and software use. While healthcare setting, country, and software use were directly extracted from the papers, the approach and outcome required deeper analysis. The review process also showed that approaches can vary, from unique DES applications up to models combining DES along with Markov models, Monte Carlo simulation (MCS), system dynamics (SD), agent-based simulation (ABS), optimization (Opt), mathematical models (Math models), and lean/six sigma. Specific to the review and theoretical/conceptual papers, the empirical outcomes, defined after the analysis of the papers, are the descriptions of the operational research techniques, the descriptions of the healthcare backgrounds, and the frameworks. Likewise, possible outcomes for DES application papers are:

- Time and efficiency;
- Financial and cost savings;
- Allocation of resources/schedule;
- Quality and defects;
- Patient health/safety.

3. Results

This section is presented through the three taxonomies mentioned before: (1) Review papers; (2) Theoretical/conceptual papers; and (3) DES application papers. Figure 2 presents the distribution of publications over the years.

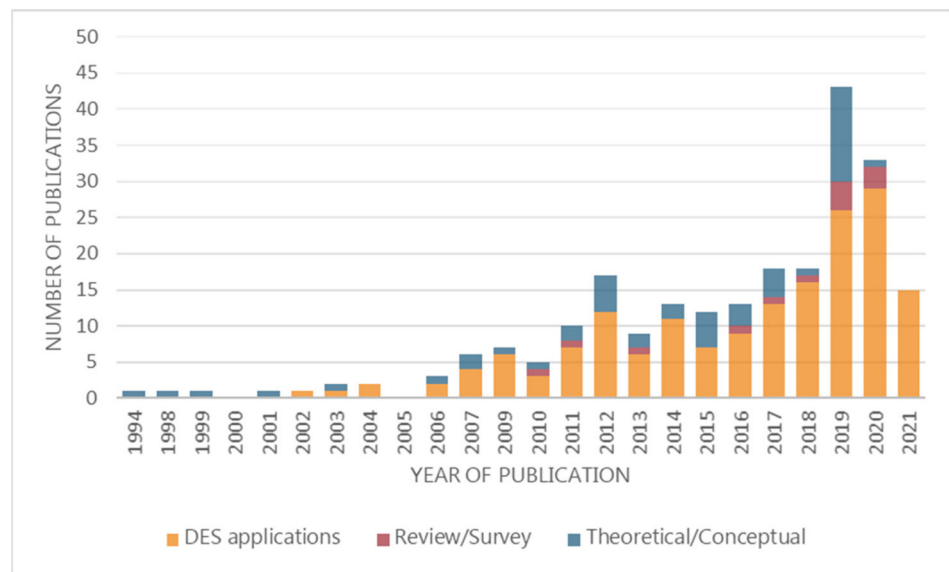


Figure 2. Number of publications per year.

3.1. Review and Survey Papers

Review papers are characterized by the exploration and classification of DES developments in healthcare, and commonly utilize descriptive statistics and frequency counting. DES-related reviews generally analyzed the general healthcare domain (80%), while the rest analyzed applications on a specific area or application. Moreover, half of the paper-reviewed studies consider DES in combination with several other techniques. Table 2 presents the complete set/approach classification and percentages of the review papers considered.

Table 2. Discrete-event simulation review papers in the literature.

Setting/Approach	DES	DES + Markov	DES + SD or ABS	DES + Others	Total
General Healthcare	[30–35]	[36]	[37]	[38,39]	10
Emergency Unit				[40]	1
Medical Center	[21]		[41]		2
Total	7	1	2	3	13

Survey papers: [34–41]

The main limitation of previous DES-related reviews in healthcare is the narrow scope and contribution; some of them focus only on a specific taxonomy or study type, while others do not consider hybrid models, or they divide a shallow classification into fewer categories. Finally, the current directions for future research are very limited since the research was conducted some time ago.

3.2. Theoretical/Conceptual Papers

The aim of the theoretical/conceptual papers is mainly to provide support for performing practical DES applications in healthcare. Developing DES theory and the concepts within healthcare are focused on emergency departments in 13% of the cases, and on the general healthcare domain in 36% of the cases, as per Table 3. Frameworks for the DES applications are provided in 44% of the studies, and the use of DES hybrid models is discussed in 63% of these.

Table 3. Discrete-event simulation theoretical and conceptual papers in the literature.

Setting/Approach	DES	DES + Optimization or Math Model	DES + Lean or Six Sigma	DES + SD or ABS or Monte Carlo	DES + Others	Total	%
General Healthcare	[42–45]	[20]		[3,15,18,43,46–49]	[26,50–52]	17	36
Emergency Unit	[53–56]	[57]		[9]		6	13
Intensive Unit					[58]	1	2
Operating Room			[22]			1	2
Pediatric	[13]					1	2
Therapy				[24,59]		2	4
Psychiatry				[60]		1	2
Patient State	[61–64]			[65]		5	10
Medical Center	[66–70]	[2,71,72]	[73]	[7,17,74–76]		14	29
Total	18	5	2	18	5	48	
%	38	10	4	38	10		100

3.3. DES Applications Papers

3.3.1. Approach

All 170 DES models were validated, and different “what-if” scenarios have been tested with each model. However, less than 10% have carried out implementation to improve the system’s performance (it was considered that a study had an actual implementation if that is stated in the paper, or if evidence of implementation is shown). On the other hand, one-third of the DES applications are complemented with another technique, such as operations research, so they can provide a wider range of characteristics to solve operational healthcare problems. Other hybrid models combine DES with different simulation approaches, such as system dynamics (SD), agent-based simulation (ABS), and Monte Carlo simulation (MCS), in order to complement and enlarge the scope, purpose, and perspective of the simulation. Inferential statistics are also considered and used to infer and make concise predictions about the indicators used in the simulation. Moreover, the soft systems methodology (SSM) is also incorporated to justify changes and/or improvements in organizational systems. Other approaches include optimization models to mathematically describe those factors that are not explained only with probability distributions, and lean/six sigma, and/or mapping techniques to improve the system under study. Figure 3 shows the percentages of the approaches used in the studies.

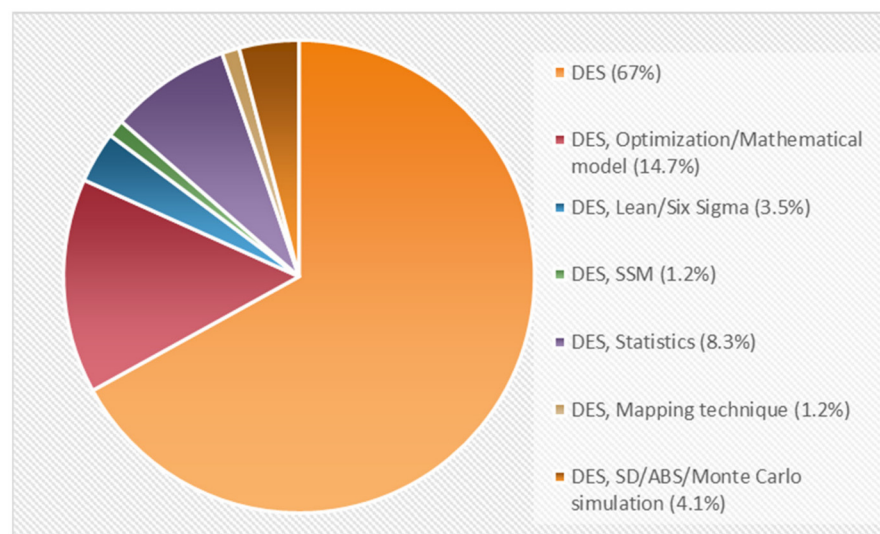


Figure 3. Approaches of applied research papers.

3.3.2. Setting and Outcomes

A total of 38.9% of the DES application studies were conducted in hospital and medical centers, while 21.8% specifically focused on emergency departments, and 13% on the patient clinical conditions. Moreover, half of the outcomes reported in these studies are related to time and efficiency, 21.2% to the allocation of resources/schedules, and 12.3% on financial and cost savings. Table 4 presents the classification of papers based on the healthcare setting under study and the corresponding outcomes.

Table 4. Discrete-event simulation publications classified by setting and outcome.

Setting/Outcome	Time and Efficiency	Financial and Cost Savings	Allocation of Resources/Schedule	Public Health	Others	Total	%
Clinic		[77,78]		[79,80]		4	2.3
Emergency Unit	[10,11,81–104]		[105–113]		[1,114]	37	21.8
Intensive Unit	[115–117]		[118]			4	2.4
Laboratory	[16]					1	0.5
Nursing				[119]	[8]	2	1.2
Oncology	[120,121]	[122,123]				4	2.4
Operating Room	[124–126]		[127,128]			5	3
Orthopedic	[129–131]	[132]	[6,133]			6	3.6
Pathology			[134]			1	0.5
Pediatric			[135]			1	0.5
Therapy	[136,137]					2	1.2
Pharmacy	[138,139]					2	1.2
Radiology	[140–144]					5	3
Support Areas	[145]		[146–148]		[149]	5	3
Dental Area	[150]					1	0.5
Mammography	[151]					1	0.5
Patient State	[152]	[19,153–163]		[164–172]		22	13
Medical Device				[173]		1	0.5
Medical Center	[12,14,22,27,174–202]	[203–206]	[207–223]	[25,224–228]	[229–234]	66	38.9
Total	84	21	36	19	10	170	
%	49.4	12.3	21.2	11.2	5.9		100

3.3.3. Journals, Publishers, and Countries

The journals with the most DES publications in healthcare are *Health Care Management Science* (6% of papers. Rank 2020: SJR 0.9, Q1; CiteScore Scopus 4.6), the *Journal of the Operational Research Society* (5% of papers. Rank 2020: SJR 0.753, Q2; CiteScore Scopus 4.1), and the *Journal of Simulation* (4%. Rank 2020: SJR 0.294, Q3; CiteScore Scopus 3.5). Meanwhile, the top publishers are Elsevier (20%), Springer (20%), and Taylor & Francis (10%). Table 5 presents the top ten publications by the number of citations, as retrieved from Scopus in October 2021.

Concerning countries where these DES-related studies were carried out, 26% of the publications proceeded from authors with affiliations in the US, 19% from the UK, and 12% from Canada. In contrast, the top developing countries, such as Brazil, Egypt, and Malaysia, have each contributed to 4% of the literature. Table 6 shows the main publishers and countries in the literature. Before 2012, almost 50% of the studies were published by institutions affiliated with the U.S. and the U.K. As of 2012, the application of DES in the health sector has become widespread throughout the world.

Table 5. Top DES publications by number of citations.

Article	Journal	Publisher	Number of Citations	Publication Year	Average Citations per Year (until 2021)
[182]	<i>Health Care Management Science</i>	Springer	117	2006	7.8
[131]	<i>Health Care Management Science</i>	Springer	113	2011	11.3
[204]	<i>Health Economics</i>	Wiley	100	2003	5.6
[233]	<i>Health Care Management Science</i>	Springer	69	2002	3.6
[25]	<i>European Journal of Operational Research</i>	Elsevier	67	2014	9.6
[149]	<i>Health Care Management Science</i>	Springer	66	2007	4.7
[184]	<i>Production and Operations Management</i>	Wiley	57	2011	5.7
[125]	<i>Health Care Management Science</i>	Springer	55	2010	5.0
[87]	<i>Simulation Modelling Practice and Theory</i>	Elsevier	50	2015	8.3
[121]	<i>European Journal of Operational Research</i>	Elsevier	49	2016	9.8

Table 6. DES publications classified by main publishers and countries.

Country/Publisher	Springer	Elsevier	Taylor & Francis	Palgrave	Others	Total	%
US	11	8	5	0	20	44	25.9
UK	5	4	4	9	11	33	19.4
Canada	4	4	3	1	9	21	12.4
Others	14	18	6	3	31	72	42.3
Total	34	34	18	13	71	170	
%	20	20	10.5	7.7	41.8		100

3.3.4. Software Use

Specialized DES software is used in 88% of the articles, whereas the complementary 12% utilized low-level simulation scripting languages, such as Python, or intermediate-level simulation tools that incorporated low-level scripting with enhanced graphic interfaces, such as MATLAB (MathWorks, Natick, MA, USA) and Visual Object Net++ (Dr. Reiner Drath, Illemlau, Germany) [235]. The reason why specialized DES software is used the most is that it provides the modeler with an environment that, in comparison to scripting languages, allows for the creation of models in less time and with less complexity. The most common software is Arena (Rockwell Automation, Milwaukee, WI, USA) (35%) and Simul8 (Simul8 Corporation, Boston, MA, USA) (21%). Within articles presenting hybrid models, around half use a specialized DES software, while Arena remains the most used software (22%). However, 32% of the publications do not mention the software utilized.

4. Discussion

The popularity of DES in healthcare is notably increasing, as almost 40% of the papers were published in the last three years. This is due to its ability to include high levels of detail and the ease-of-modeling medical processes using stochastic factors. Lately, DES is being applied in emergency departments, where short lead times and the efficient use of resources are key to operating. Similarly, the clinical analysis of entities (patient clinical condition) is emerging as a broader perspective from which to apply DES from a strictly medical perspective (13% of the application papers). The simulation of the clinical condition of patients plays a critical role in reducing treatment costs, improving the efficiency in the use of medicines, and analyzing the medical evolution of patients out of acute care.

Even though three countries concentrate 57.7% of the publications addressing DES in healthcare (the US, the UK, and Canada), the fundamental tools for engaging the stakeholders in healthcare systems worldwide in the development and application of DES are the virtual interaction elements, such as user interfaces. In addition, the software used to carry out simulations plays an essential role in the DES involvement in healthcare. A specific and flexible DES software has a higher probability of adapting to the healthcare stakeholders' needs. This is the reason why only 12% of the papers utilize low-level simulation scripting languages.

Several elements have caused the impact of DES on healthcare improvement to be questioned, such as the limited scope of the studies found in the literature, and the contextual factors that make healthcare improvement complex. Thus, this discussion is presented through four main areas that present opportunities for further research: key elements to formulate models, frameworks for hybrid models, barriers for implementation, and measuring satisfaction and clinical value. Figure 4 presents the perspective of DES in healthcare considering these elements.

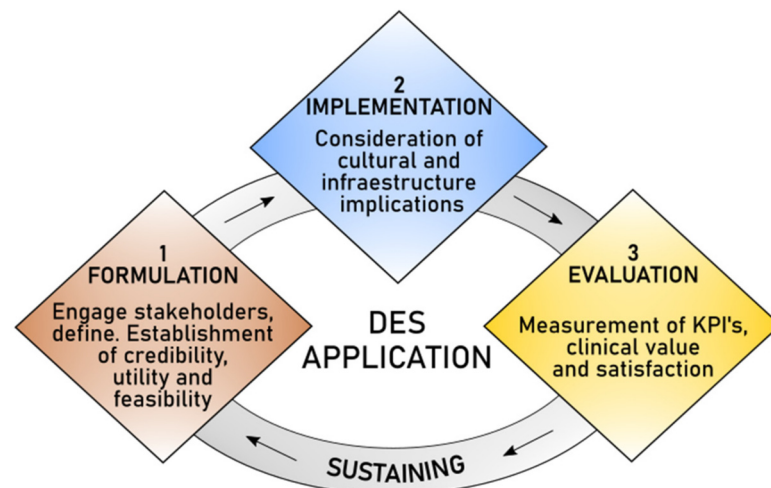


Figure 4. Holistic perspective for DES applications in healthcare.

4.1. Key Elements to Formulate Models

The formulation of a model plays a critical role in simulation research, as it ensures that the modeler depicts the right theoretical state and focuses the impact on the root causes of the problem. A good formulation should consider five key elements: stakeholder engagement, definition, credibility, utility, and feasibility [8,53,65,114]. When theory and applications are supported by a proper formulation, publications tend to be beneficial for both researchers and system stakeholders.

Despite some theoretical publications addressing stakeholder engagement, this is not usually considered in DES applications. Engaging all stakeholders is key to formulating a simulation project [53], particularly in the healthcare context, where there is a plurality of stakeholder opinions, objectives, and power distributions [114]. In conjunction with stakeholders, modelers should define the causes of the problem, the main goal sought, and the internal and external influences that intervene in defining that goal [8]. In alliance with the system's stakeholders, it should be defined whether the conceptual model is sufficiently accurate for the purpose at hand (credibility), if it assists decisionmakers in the problem situation (utility), and if any project limitations, such as time, resources, and/or data availability, are considered (feasibility) [65]. Then, conducting more studies built over these formulation elements are required.

4.2. Frameworks for Hybrid Models

Given that healthcare systems are complex, there are a plethora of problems that cannot be analyzed using a single method. Hybrid approaches provide a more realistic picture of complex systems with fewer assumptions and less complexity [9], which, in turn, allows for addressing a larger range of modeling questions [74]. There is specialized software, such as Simul8, AnyLogic, and Arena that allow the modeler to develop hybrid simulation models in the same interface/environment, as developed in the research presented in [236,237]. However, in the healthcare context, combining simulation techniques is not enough; even when this review has shown that hybrid DES models (mathematical models, statistics, improvement methodologies, or mapping techniques) have been broadly applied over the last years, there are no frameworks available that can serve as the foundation for successful

modeling and implementation. It is important to have this kind of structure that can guide the modeler in developing more robust hybrid models. Additionally, a framework should provide support for identifying the object or system (What), the purpose (Why), and the methodology (How) [74]. Moreover, it should allow for the recognition of the correct approach/technique for collecting data and evaluating the long-term effects and outcomes [9].

4.3. Barriers for Implementation

A proper formulation does not guarantee that DES models will be implemented. Furthermore, transformation efforts never come without challenges [197]. Although simulation is widely reported upon in healthcare, it is not clear whether there is an actual implementation and impact in the real health system [23,238]. It was found that less than 10% of studies showed evidence of implementation. Most of the DES models applied to healthcare settings are led by academics, mainly for research purposes, and they have a limited impact on the potential performance of the systems [23]. Two major barriers to implementation have been identified in this study. First, there is the cultural side, as healthcare professionals (e.g., doctors and nurses) respond to pressure and system modifications by changing their performance and behavior [9]. In conjunction with changes, diversity across entities causes a lack of acceptance and fear regarding information and confidentiality [229]. Second, infrastructure plays a critical role. Difficulty in accessing enough quality data, system failures, and changes in work processes, security, and privacy, all are critical barriers to implementing models [229]. In addition, other financial constraints could undermine research.

Because of the diversity of health systems, no panacea for implementation exists. However, future research should reach to the models' implementations and follow through after the intervention [29] in order to evaluate the long-term effects. This would convince service providers and clinicians that simulation can make a critical contribution [46].

4.4. Measuring Satisfaction and Clinical Value

Most DES applications in healthcare focus on improving direct metrics, such as volume, efficiency, and occupancy rates, whereas after-implementation metrics related to patient satisfaction and value are more difficult and less common. High levels of value and patient satisfaction are associated with better outcomes, given that satisfied patients are more likely to adhere to treatment. Conversely, low patient satisfaction affects treatment compliance, including return visit rates [22]. Thus, measuring these levels is a challenging task [132], and developing methods/techniques alongside surveys and questionnaires to measure them represents a gap in the advances of DES applications in healthcare [230].

5. Conclusions

DES is a stochastic approach that is becoming more popular. This is reflected in the growing number of research articles that are focused on DES in healthcare. A descriptive analysis of DES publications in healthcare was conducted in this study to identify both current trends in research and directions for future research. The findings show a tendency to use this approach within emergency departments, patient clinical conditions, and medical centers seeking to allocate resources and improve times and efficiency. The results also indicate that the main issues addressed through DES are related to operations, where there is a need for high levels of efficiency and financial savings. The US, the UK, and Canada are the top countries that continually look towards improving their healthcare systems, as per Table 5. It was also found that the most popular DES software for the studies is Arena.

The large number of papers considered for this review (231) have shown the versatility of the DES approach, as well as the broad adoption of operational research techniques within some healthcare systems. Even though 231 papers is a large number, it represents a small proportion of the papers presenting analytical studies in healthcare. Healthcare is an area where researchers focus on the application of operations research techniques; however,

DES is not being applied as much as lean/six sigma and other optimization techniques. Specific to hybrid approaches, the combination of several techniques can create a solid analytical approach that addresses the weaknesses of DES, such as strategic alignment and stakeholder behavior, as well as integrated levels.

DES models formulated in future research need to tackle two elements: proper and correct formulation, and the incorporation of the behavior of healthcare staff, in order to defeat cultural obstacles. Furthermore, researchers and professionals should define key infrastructural and financial capacities. Finally, the evaluation of the long-term effects, along with the publication of successful implementations following DES modeling, are key opportunities that need to be addressed in future DES-related research in healthcare.

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