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REVIEW OF MODELLING APPROACHES FOR HEALTHCARE SIMULATION

The goal of this paper is to present a summary of various simulation methods applied to health services and to discuss several internal and external determinants for selecting a particular simulation method to study a given managerial problem within the healthcare system. The analysis presented is based on a literature survey and considers four primary simulation techniques: Monte Carlo, discrete-event simulation, agent-based simulation and system dynamics. A range of internal and external factors are reviewed and characterised to determine the most suitable simulation technique for addressing a particular healthcare decision problem.

Keywords: *simulation, healthcare, decision support, management*

1. Introduction

The healthcare domain has been successfully analysed using operations research (OR) methods for more than 40 years. The role of simulation modelling in healthcare services has been widely recognized and is now one of the commonly used OR approaches to studying healthcare management problems. Although many quantitative and qualitative methods can be used to study healthcare systems, simulation is perceived as one of the more promising avenues and is playing an increasingly important role in the processes that support healthcare managerial decisions [15].

The advantages of the simulation approach stem from its flexibility, as well as its ability to handle the variability, uncertainty and complexity of dynamic systems. Simulation is particularly useful when a problem exhibits significant uncertainties, which require stochastic analysis. It is also an ideal tool for performing "what-if" analysis. Simulation is usually used to analyse a system's performance in routine and extreme

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conditions, to compare alternative strategies to find the optimal solution, and to forecast a system's behaviour, either in the future or under significantly different circumstances.

Simulation plays an important role in healthcare decision making. It is widely used in research studies but it is also a popular educational tool and a decision support technique that allows stakeholders to implement long-term planning processes. Simulation modelling offers the opportunity to gain a deeper understanding of mass events, like the spread of an infectious disease [23, 34] but it is also used to analyse the current performance of a particular healthcare unit (e.g., hospitals, operating theatres, outpatient departments, and diagnostic centres) [9, 27] or forecast the future behaviour of the system under study [33].

Simulation methods are categorized in various ways but most commonly they are classified [6, 24, 31] into four categories: Monte Carlo (MC), discrete-event simulation (DES), system dynamics (SD) and agent-based simulation (ABS). The selection of the method depends mainly on the area of the problem. For example, when modelling emergency medical systems, DES is definitely the preferred technique. In contrast, models of epidemics and disease prevention are usually built using the SD approach. However, the general area of a problem should not be the only determinant of the choice of the method. Simulations can describe a wide range of healthcare units, different goals can be formulated, research can be performed for a short- or long-term horizon, and input data can have a low or high level of aggregation. These and other factors make the process of selecting the most appropriate simulation method difficult.

Although it does not seem possible to elaborate a universal, conclusive procedure for matching the most suitable simulation technique to a specific problem, it is still possible to define the most important factors to be considered before a decision is made. The goal of this paper is to discuss some internal and external determinants for selecting a particular simulation method to study a given managerial problem within the healthcare system. It will be demonstrated that the analytic, diagnostic and predictive capabilities of the main simulation approaches, i.e., DES, MC, SD, and ABS, are not identical. Therefore, the potential of each of these methods, in relation to cause-and-effect analysis and the ability to predict the consequences of decisions, also varies. However, it is possible to distinguish the most important internal and external determinants for selecting a simulation method to study healthcare problems at various managerial levels. Arguments in support of the thesis that there is a strong dependence between the appropriateness of a simulation technique and the decision problem to be studied will be given. Thus, it is possible to highlight important requirements that should be considered before the final selection of a method is made. The paper ends with a conclusion summarizing the specific features of each approach to simulation and explaining the notably diverse range of applications of each method in various areas of healthcare decision making.

2. Simulation methods

2.1. Monte Carlo methods

Monte Carlo is a statistical technique that is primarily applied in physics and mathematics. Fishman [13] defines MC simulation as a sampling experiment carried out via computer, the purpose of which is to estimate the distributions of output variables. This definition means that any sampling experiment with the goal of estimating the distribution of an outcome variable that depends on several probabilistic input variables is called a MC experiment, and in fact, every type of stochastic simulation requires MC techniques to be performed internally. However, one specific class of models, MC simulations, is often used to evaluate the expected impact of policy changes and the risks involved in a decision process. This type of simulation, often referred to as spreadsheet simulation, is a popular technique among healthcare researchers.

MC simulation is performed on one or more typical individuals who are intended to describe the experience of a larger group within a population. A number of assumptions relating to the indicated group of patients are formulated, and the conclusions are only valid for the pre-defined individuals. The advantage of an MC simulation is its flexibility to test any modification necessary to understand the whole context of an issue and its ability to estimate the variability involved in the decision process. Simulations are based on probabilistic distributions that are, in most cases, derived from historical data sets. A model simulates hundreds or thousands of potential scenarios and produces forecasts as outputs, usually in the form of relevant means, probabilities and the dispersion of results around an expected value. For example, the MC model in [12] considers the randomly changing demand for immunization sessions. The goal of the simulation is to determine the optimal size of a vial and the stock level at which to reorder, in order to ensure adequate vaccine supply. The random arrival of patients and the randomly changing necessity to prolong a hospital stay are important determinants when examining the required bed capacity [2].

2.2. Discrete-event simulation

According to many surveys [22, 29], DES is the most often used technique in the field of healthcare management. Discrete-event models simulate processes over time and follow individual, dynamic objects (entities) that interact with the system's resources. In healthcare modelling, these entities are usually equivalent to individual patients, although there are models that simulate the flow of receipts or medicines. Entities move in the time dimension, and they occupy and release the system's resources such as doctors, nurses, beds, operating theatres and diagnostic equipment. They are described by attributes that may differ from person to person and can reflect risk factors, such as age, gender, disease history and previous treatments. The routes of entities and the times between activities are described by random values sampled from parametric and empirical distributions. Patients move, stop, queue, wait for access to resources, generate costs, and influence other entities and the sequence and timing of activities. The history of patients' stays in the system is described by discrete events that initialize and finalize the activities. The main advantage of discrete event simulation is its ability to relate risks, activities and interventions with patients who are guided by their own will, have their own individual traits and may behave unpredictably.

Discrete simulation falls under the umbrella of stochastic approaches and is used to model systems for which a significant share of random factors are observable. In DES healthcare modelling, probabilistic distributions are used to describe the arrival processes, service times, likelihood of intervention and other random factors (c.f. [3, 4]).

2.3. System dynamics approach

This method focuses on the dynamic analysis of complex phenomena. It uses a holistic perspective to study a system by means of a set of stocks and flows, specific theoretical constructions that make the system dynamic approach significantly different from other simulation methods. The stocks accumulate dynamic objects that move through the system. At each moment of passing simulation time, the stocks report the present quantitative status of the objects considered (for example, the number of infected people as registered on the 1st January). The flows are used to model the movement of objects over a specified period of time (for example, the number of people infected during a given time unit, i.e., in January). The dynamics of the system are caused by feedback loops (i.e., balancing and reinforcing loops) and delays. The basic concept of SD modelling assumes that the smallest change occurring anywhere in the system starts a chain reaction, and – through a set of balancing/reinforcing loops and the internal relations between the components – secondary changes are observable in other parts of the system. For complex systems, the changes in the output cannot be forecast by a visual inspection of graphical models because one element sometimes belongs to different sets of components that simultaneously stabilize and strengthen the system's behaviour.

The SD approach is particularly helpful when attempting to formalize a mental model of a given problem. It is also useful when analysing the relations between a system's structure and its behaviour after some changes have been initialized. Typically, SD models are not designed to yield exact numerical predictions regarding a healthcare issue but rather are intended to explore different policy options (cf. e.g., [1, 7, 10]).

2.4. Agent-based simulation

ABS has gained increased interest over the past several years. The key elements of this approach are agents who usually represent individual people or groups of people. Relationships between agents [26] are simulated to model social interactions between individuals to more precisely understand, for example, the transmission patterns arising from contacting infected persons. ABS is a bottom-up technique: the modelling process starts from agents, and then their relationships and environment are defined. An agent is an autonomous, self-directed object capable of making independent decisions. Agents can assess the current situation and, based on pre-defined rules, make decisions that affect other objects (agents). Each agent has a state that varies over time, and the state of the model is defined by the collective states of all the agents and the state of the environment.

There are two types of agents: passive and active. The active agents are usually used to model such individuals as patients and personnel (e.g., doctors, nurses, and technicians). The passive agents can represent medical and diagnostic services and infrastructure (e.g., wards, medical facilities, and operating theatres). An agent may have explicit goals that drive its behaviour. An agent is also capable of learning and adapting its behaviour based on previous experiences. When building an ABS model, the modeller's attention is focused on the behaviour of the agent rather than simulating the process as a whole. The changes observed in the system are the result of decisions made by the agents [23]. ABS is used to study systems for which consequences at the collective level are not predictable, despite the fact that the modeller has detailed knowledge describing the behaviour of individuals.

3. Method of research

A number of reviews have been published on the application of simulation in healthcare management (cf. e.g., [14, 24]). However, the purpose of this paper is not to survey the academic literature pertaining to the use of computer simulation in health services, but to discuss the range of external and internal determinants that drive the selection of a simulation method. The literature is surveyed and discussed elsewhere (namely, in [28]). A detailed list of the papers reviewed is attached there and is also available from the Author on request. Below, the profiling process is briefly recapitulated.

The papers selected for review were found in databases such as ACM Digital Library, EBSCO, Elsevier, ProQuest, Springer, Cambridge and SAGE. The study period covered the period of 1999–2012. The methodology for literature profiling consisted of three stages. During the first stage, the search engines of all the databases were used with the following criteria: the inclusion of the word simulation in the title OR keywords of the article AND one of the following words: health, healthcare, hospital, patient, emergency, ER, outpatient, surgery in the article's abstract. The second stage involved the screening of these papers and a heuristic search through the bibliographies of these papers. The basic pool of papers was enriched with a large group of additional models. During the third stage, decisions about the inclusion of papers were made based on the following criteria: (1) the paper described a computer simulation technique, (2) the topic or the setting referred to the delivery of health services or to public health, and (3) a clear relation with issues of health care management existed. The third criterion enabled us to separate and reject from the pool papers dealing with medical decision making and educational/training papers related to physical simulations. This filtering resulted in 232 papers published in scientific journals and included in conference proceedings indexed in the Web of Science® database.

4. Taxonomy

The taxonomy developed concentrates on these 232 papers and classifies the models according to two dimensions (Fig. 1). In the field perspective (horizontal dimension), the main areas in healthcare management are categorised as: health policy, healthcare system operations and improvements, forecasting and healthcare system design, medical decision making and healthcare planning involving extreme events. The method perspective (vertical dimension) reflects the main simulation methods: MC, DES, SD and ABS. The horizontal dimension employs the classification proposed by Lagergen [25] and modified by Mielczarek and Uziałko-Mydlikowska [29].

4.1. Area 1. Health policy

Simulation is of particular benefit to health policy makers who use such tools to support their decisions when shaping global health policy, examining the short- and long-term effects of prevention, screening and vaccination programs and elaborating strategies to address addictions. The information obtained as the result of simulations enables these policy makers to determine the implications of prevention and treatment procedures at regional and national levels. Models for simulating epidemics are designed to predict the dynamic rate and spread of infectious diseases and analyse the direct and indirect causes of the intensification of civilizational diseases (e.g., dementia, diabetes, cardiovascular diseases).

4.2. Area 2. Healthcare system operation

The field of healthcare system operations and improvements has generated particularly strong interest among modellers. Models from this domain are used to support decisions that aim to improve the performance of a healthcare system.

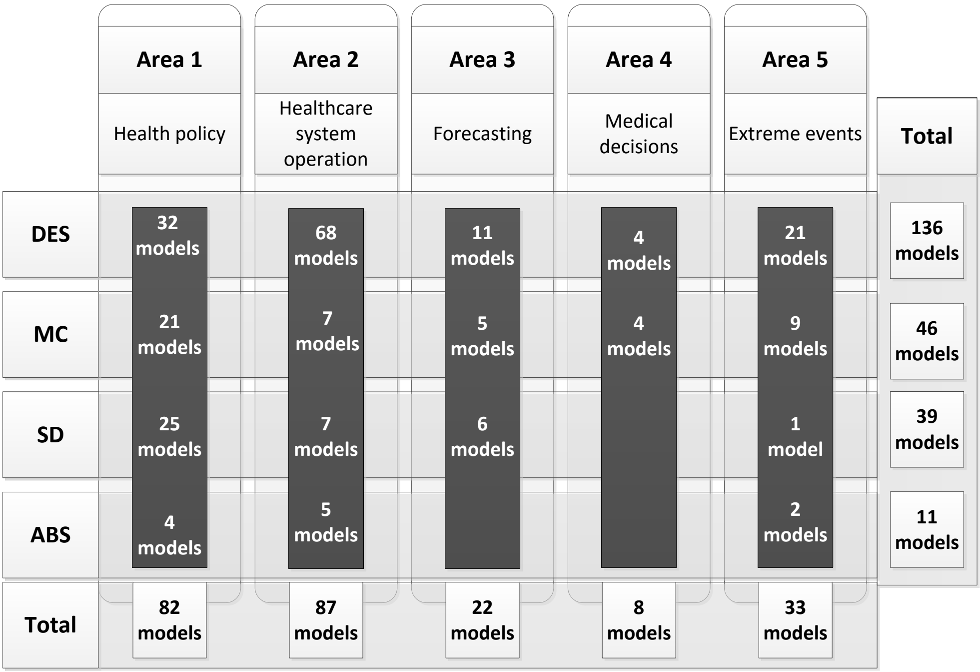

Fig. 1. Healthcare simulation techniques in five domains of healthcare management. DES: discrete-event simulation, MC: Monte Carlo, SD: system dynamics, ABS: agent-based simulation. Source [28]

The object under study is usually a single unit or a complex of mutually related clinics. Such models help to determine more effective ways to utilize existing resources. These models concern such issues as staff scheduling, the optimization of appointment systems, resource allocation and planning of auxiliary services. Such studies are conducted according to a quantitative criterion (e.g., the optimization of hospital beds) or qualitative criterion (e.g., the balancing of ambulance coverage for a region).

4.3. Area 3. Forecasting

Simulations are used to forecast long-term population needs and determine the resources needed to cover the expected demand. This approach is particularly advantageous in predicting the future health of the population of a given region, assessing the relationships between planned organizational solutions and analysing access to health services, considering various environmental factors.

4.4. Area 4. Medical decisions

Simulations are used to evaluate the cost effectiveness of different medical intervention programs, monitor the progress of a disease and conduct comparative analysis of alternative treatment strategies at the clinical level and for individual patients. The results obtained from a simulation may serve as the basis for evaluating the expected efficiency of a type of surgery or drug therapy.

This promising direction of utilizing simulations is also known as clinical pathways, defined by de Blaser et al. as *a method for the patient-care management of a well-defined groups of patients during a well-defined period of time. The aim of a clinical pathway is to improve the quality of care, reduce risks, increase patient satisfaction and increase the efficiency in the use of resources* [11].

4.5. Area 5. Extreme events

Simulation is helpful when evaluating the plans of rescue activities in extreme situations such as natural disasters, traffic problems, industrial incidents, and terrorist or bioterrorist attacks. Such models help to predict staffing needs in a variety of epidemic scenarios, evaluate the response of healthcare systems and optimize resource allocation in the event of an urgent situation. Special attention is given to natural disasters. Simulation methods are used to assess how a regional healthcare system responds to an earthquake or hurricane, making it possible to evaluate alternative strategies to mitigate the threat. Hospital evacuation plans are also analysed, and improvement strategies are tested.

5. Internal determinants

5.1. Main areas of application

The analysis of these 232 papers showed that DES is definitely the preferred modelling technique used to support healthcare decision problems. Based on the conducted review, it was found that 69% of the models were built using the DES approach, and 14,7% of the models were constructed using the MC method. The SD approach was used in approximately 12% of the cases and ABS was identified in approximately 4,3% of all the surveyed papers (Fig. 2).

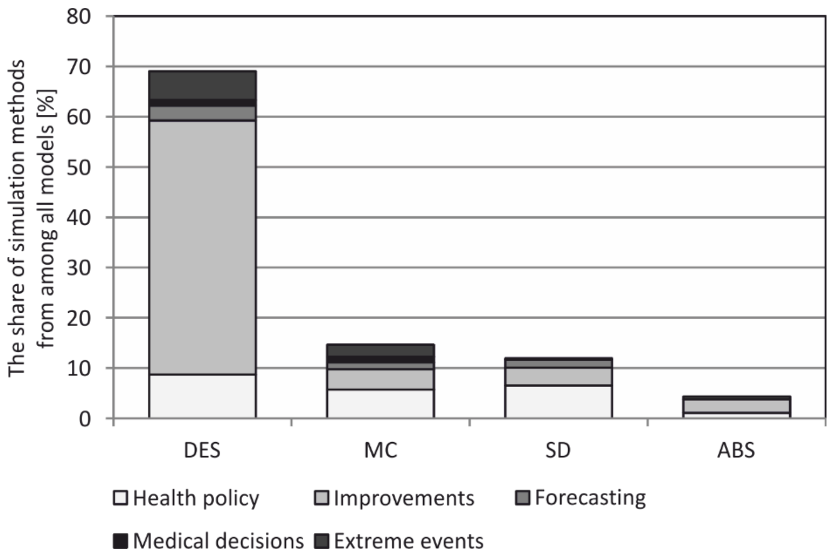

Fig. 2. The choice of simulation method in the main areas of application. Source: [28]

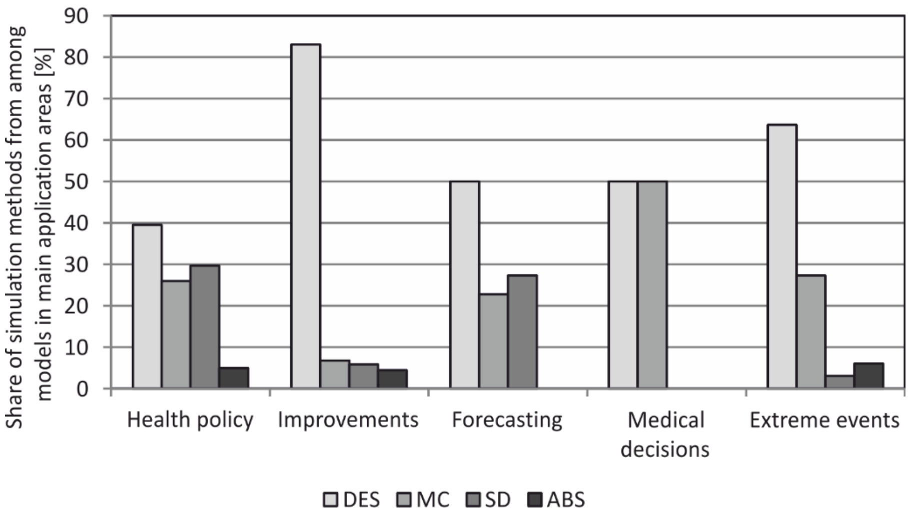

Fig. 3. The distribution of simulation techniques in the different application areas Source: [28]

The distribution of simulation methods among the five main groups of applications (Fig. 3 and Table 1) confirms that DES is the most often applied method in applications to improvements [5], forecasting [17] and extreme events [32]. This dominant position of the DES models is particularly justified when studying system performance, testing various alternatives of system operations, and suggesting system improvements. The

MC method is applied across all of the areas, usually as a support technique. However, it is a preferred modelling approach for analysing health policy and medical decision issues [20]. SD is selected mainly to tackle problems in epidemiology and disease prevention within the areas of health policy and forecasting [19, 23]. Finally, the ABS approach is not yet very popular among healthcare researchers, and very few examples of agent models can be found in the literature [8].

Table 1. The choice of the simulation method[a]

Problem area	DES	MC	SD	ABS
Health policy	■■□	■■□	■■□	■□□
Improvements	■■■	■□□	■□□	■□□
Forecasting	■■■	■■□	■■□	
Medical decisions	■■□	■■□		
Extreme events	■■■	■■□	■□□	■□□

[a]The method used: ■■■ – very frequently, ■■□ – frequently, and ■□□ – rarely. Source: [28].

5.2. Secondary area of application

The basic determinant of the choice of the simulation method is the main area of application. In the case of two main areas (Table 2), improvements and extreme events, there is one clearly preferred approach: DES. However, the three other areas of application are more diverse in regard to the application of simulation methods. The deeper analysis illustrated in Table 2 shows that the specific goal of analysis influences the choice of simulation method.

The preferred method in the area of health policy is discrete simulation (39.5% of the models). However, when a study aims to focus on evaluation and planning to be made at a high level, the SD approach is selected (29.6%). Epidemiological issues are equally commonly addressed by discrete simulation and the MC method. When simulating the progress of a disease, DES is as frequently used as the SD approach (38.1% of the models).

The forecasting domain is most commonly modelled by discrete simulation (50% of the models). However, when the objective of the study is making long-term predictions of the total level of demand for health services, the SD approach is the most dominant (50.2% of the models). The evaluation of national or regional economic and clinical indicators is in turn commonly carried out using the spreadsheet MC method (75% of the models).

The area of medical decisions is equally commonly explored by two main stochastic methods, DES and MC simulation.

Table 2. The choice of simulation methods within the main and secondary areas (all values in %)

Area of application	DES	MC	SD	ABS
Health policy	**39.5**	**25.9**	**29.6**	**4.9**
Evaluation and planning	31.0	27.6	37.9	3.4
Prevention and screening programs	56.3	25.0	12.5	6.3
Epidemiology	40.0	40.0	20.0	0.0
Spread of infectious diseases	38.1	14.3	38.1	9.5
Improvements	**83.0**	**6.7**	**5.8**	**4.5**
Ambulatory care	85.7	7.1	7.1	0.0
Emergency care	80.8	0.0	7.7	11.5
Surgery	90.0	0.0	5.0	5.0
Hospital treatment	77.3	18.2	0.0	4.5
Long-term care	50.0	25.0	25.0	0.0
Forecasting	**50.0**	**22.7**	**27.3**	**0.0**
System design	87.5	0.0	12.5	0.0
Predicting demand	29.8	20.0	50.2	0.0
Economic and clinical indicators	25.0	75.0	0.0	0.0
Medical decisions	**50.0**	**50.0**	**0.0**	**0.0**
Extreme events	**63.6**	**27.3**	**3.0**	**6.1**
Epidemics	63.6	27.3	0.0	9.1
Natural disasters	50.0	50.0	0.0	0.0
Catastrophes	50.0	25.0	0.0	25.0
Hospital evacuation plans	57.1	28.6	14.3	0.0
Logistics	85.7	14.3	0.0	0.0

Source: [28].

6. External determinants

Even when the differences between the above-mentioned simulation approaches are understood, additionally a range of external determinants has been suggested for deciding which modelling method best suits users' needs and the context. Table 3 presents a summary description of the main determinants of this choice and suggests simulation modelling techniques which are appropriate for given areas. All the highlighted determinants and key suggestions are briefly discussed in the following sections.

6.1. A project's life cycle

According to [21], the modelling methods applied in health services management, including simulation, can be placed in various stages of the eight stages of a project's life cycle (Table 4).

Table 3. External determinants influencing
the selection of a simulation method

	DES	MC	SD	ABS
Project life cycle (phases 1–8, cf. Table 4)	4–5	4–5	1–3	4–5
Management levels				
Strategic			√	
Tactical		√		
Operational		√		√
Uncertainty	√	√		√
Time horizon of the experiment				
Long-term			√	
Medium-term	√	√		√
Degree of aggregation of data and formulas				
Patient level	√			√
Sub-group level		√		
Population level			√	
Input data				
Detailed	√	√		√
Aggregated			√	

Source: [28].

Table 4. Simulation methods and stages of a project's life cycle

No.	Stages of a project's life cycle	DES	MC	SD	ABS
1	Identifying consumers' needs for health services			√	
2	Developing a new service to meet those needs			√	
3	Forecasting the demand for services			√	
4	Allocating resources for delivering services	√	√		√
5	Developing plans that will use these resources in delivering services	√	√		√
6	Developing criteria for assessing performance				
7	Managing performance				
8	Evaluating the results of health care delivery				

Source: [21].

For each of these stages, the authors identified the simulation methods that are the most suitable at this point of a project. These methods can be defined as first choice techniques. The authors suggest that during the first stages of a project, the SD approach seems to be the most useful method (stages from 1 to 3). In contrast, the later phases of the project cycle (stages 4 and 5) are more suited to stochastic techniques. The last stages (from 6 to 8) only sometimes use the simulation approach, and other modelling options are preferred.

6.2. Management levels

The operational level of healthcare management is supported mainly by discrete-event and agent-based models. The main goal of discrete simulation is usually to estimate quantitative parameters and develop indicators to assess system effectiveness. ABS models are used to enhance knowledge about a system's behaviour. The strategic level requires a wider and more general perspective and is more appropriate for macro decision processes. Therefore, models built using the SD approach are more often applied here. The tactical level of healthcare management is dominated by MC models, more appropriate for managing risks, i.e., identifying and analysing potential hazards and adverse occurrences, symptoms strongly associated with the outcomes of treatment and preventive programs.

However, this classification is not rigorous, because the objectives of one simulation study usually address overlapping management levels.

6.3. Uncertainty

The majority of processes taking place in a healthcare system are driven strongly by random factors. Generally, uncertainty is related to two main aspects of the healthcare system's performance: the arrival of new entities (e.g., the number of patients registered in a healthcare unit, medical events occurring during the progress of treatment, and the preparedness of a surgical team before any medical procedure) and the length of activities that make up a medical service (e.g., the duration of a medical examination, the travel time of an ambulance from its base to the site of an emergency call, and the length of stay in a hospital ward). Uncertainty also appears when the problem of the availability of resources is considered, for example when an ambulance is dispatched to an emergency call, or when the accessibility of members of a surgical team determines the start time of a procedure. In reality, only a small number of the activities run by a healthcare system may be described by fully predictable and precisely defined parameters. This situation provides a strong premise for the use of stochastic methods in modelling a healthcare system. However, such a decision is not always justified. Halpern et al. [16] argue that, in the case of stochastic approaches, the extra time needed to run simulations, the relatively high cost of collecting and analysing input data and the increased complexity of such models are not always balanced by the better accuracy of predictions or enhanced analysis of the output data. However, because of the widespread presence of random processes in the healthcare environment, the selection of a simulation method to study healthcare decision problems should always be preceded by robust analysis of the potential bias of the results obtained when applying a deterministic approach, which is inevitable when naturally random processes are described by averaged values.

6.4. Time horizon of the experiments

When selecting a simulation method to study a specific healthcare problem, it is advisable to determine in advance the time range of the planned analysis. Discrete-event and agent-based models, because of the necessity to replicate simulations, are usually used for experiments with short- and medium-range time horizons. Deterministic models built using the SD paradigm require only one replication. Therefore, this approach may be applied to studies with a long-term horizon. Before a decision to use MC simulation is made, the expected number of objects to be included in the study and the total number of possible states should be assessed. The observed number of phase transitions of an object (e.g., patient) from one state to another is analogous to the time horizon in a dynamic simulation performed using a discrete-event or agent-based approach. The MC approach, based on random sampling, usually requires a very large number of replications. Therefore, the total number of objects cannot exceed a critical threshold.

6.5. Degree of aggregation of data and formulas

Discrete-event or ABS is the best choice when the problem to be solved requires that mutual relations between particular objects (i.e., patients) be mapped in the model. These methods make it possible to simulate and register the detailed history of an object. Moreover, the number and range of the details considered in the simulation process can be freely defined by the modeller. The simulation of the system's dynamics is run using aggregated data that relate to the whole population and to particular objects. It is possible to define the form of interactions between individuals (e.g., when modelling the interpersonal relations that influence the spread of an infectious disease) but these assumptions can be introduced in the SD model only to a certain (limited) extent. MC models are usually applied in so-called cohort studies, which places MC simulation between the highly detailed DES and ABS methods and the holistic SD approach.

6.6. Input data

Stochastic models (DES, ABS, MC) require a large amount of input data to be collected, processed and included, usually in the form of probabilistic distributions. In the healthcare sector, access to data may be difficult (e.g., in the case of hospital data bases) or even impossible (e.g., in the case of personal and sensitive data protected by legal regulations). SD models are much less demanding on that front. However, the appropriate calibration of key parameters driving the dynamics of internal flows is crucial and has a significant impact on the results. For example, even a slight inaccuracy in the estimation of age-related morbidity factors may lead to a completely different description of the rate of spread of an infectious disease.

7. Comments and conclusions

Simulation techniques have been extensively employed to analyse and design healthcare systems. The literature on healthcare simulation is vast and rapidly expanding. Therefore, there is great value in developing a framework that would serve as a potential basis for selecting the most appropriate simulation approach for studying a specific healthcare management problem. This paper may assist healthcare researchers in understanding the advantages and disadvantages of different simulation methods, so they can select the approach that is the most appropriate to their needs.

DES is commonly used in all the highlighted areas of study, reflecting the large popularity and universality of this approach. However, one domain, healthcare system operations and improvements, is visibly dominated by DES modelling. The literature survey revealed that the majority of publications in this category use discrete simulation and a relatively small proportion of articles use alternative simulation techniques.

MC simulation is more often applied to the categories of health policy and medical decisions. It is also the preferred approach in the sub-category of the forecasting domain of economic and clinical indicators. The common feature of all of these three areas is the necessity to evaluate the economic effectiveness of a project. The goal of such a study may concern preventive or screening programs, strategies to fight the transmission of infectious diseases, the expected efficiency of medical therapy or economic evaluations of long-term interventions designed to cover future needs of the population.

SD is usually applied in the domains of health policy and forecasting because it is traditionally used at a higher, more aggregated and strategic level. The fundamental principle of SD is that structure determines behaviour [7]. The relations between the separate components of an object or a process determine the behaviour of the system as a whole. It is not uncommon that the final reaction of the system defies predictions and is counterintuitive. Healthcare systems are usually large and complex, and their boundaries overlap with other organizations. Multiple stakeholders have conflicting objectives and different levels of ownership. The ability of SD modelling to include qualitative aspects in addition to quantitative aspects is very helpful for fostering a better understanding of the problem analysed. For example, when studying the issue of long waiting lists, the cause-effect relationships between the number of referrals from GPs and the number of patients registering with a specialist maybe defined. However, it could be equally important to consider the influence of local groups lobbying to increase the budget for contracting a specific type of healthcare service. Additionally, when formulating long-term strategies for healthcare systems, dynamic complexity [18] will cause extended delays between the appearance of risk factors and changes in demand, and the SD approach seems to be well adapted for such issues.

Finally, there is considerable scope for the use of ABSs in healthcare modelling, although there are very few reports documenting this. ABS models may be placed somewhere between more detailed DES and the broader treatment of models of SD. Agent models are noticeably represented in two sub-categories: spread of infectious diseases from health policy and epidemics from extreme events. In both areas, the need to model contact and interaction between individuals suggests the importance of considering human behaviour. Agents are decision-making components in a complex system. They are proactive, social and responsive, and characteristics such as adaptation, goal-orientation and heterogeneity are useful when incorporating human behaviour in healthcare modelling [30].

The goal of this paper was to discuss the most important internal and external determinants for selecting a particular simulation method to study a given managerial problem within the healthcare system. Various simulation approaches are used when simulating healthcare systems. However, their analytic, diagnostic and predictive capabilities are not identical. Making the most of these methods is not straightforward. Therefore, it is important to assist healthcare modellers in understanding the advantages and disadvantages of various simulation techniques, so that they can select the method that is most appropriate to their needs.

Considering the findings of this study, it is recommended that before a simulation approach is selected, not only the main area of the study, but also the range of external factors that may contribute to a better match should be considered. Our findings may serve as a user guide that suggests, for a given type of healthcare problem and a given set of user needs, the most suitable simulation method to apply.

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