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A Discrete-Event Simulation Model to Configure Operating Rooms for Robotic Cardiac Surgery

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Abstract

Background. Robotic cardiac surgery (RCS) has emerged as a promising alternative in clinical practice to overcome the limitations of minimally invasive techniques. However, the integration of RCS with surgical process management is key in taking full advantage of its benefits. **Aim.** We assess the performance of RCS interventions as a function of operating room (OR) layout, using a discrete-event simulation (DES) tool, which allows the simulation of different RCS procedures in different layouts. **Methods.** A DES model was developed for 2 types of RCS, atrial fibrillation ablation and mitral valve repair, to analyze them in the presence of different OR layouts. Data on the activities and timings of all operators in the OR, used to feed the DES, were collected on site at Humanitas Gavazzeni Hospital, Bergamo, Italy, through direct recording during RCS procedures. **Results.** The advantages and disadvantages of different OR layouts were highlighted and quantified through a series of key performance indicators and qualitative outcomes, including the overall duration of the entire surgical process, the distance covered by the surgical team, and their utilization. Specifically, the characteristics of a new, larger OR in the considered hospital were assessed prior to the actual transfer of the RCS department in the new OR. **Conclusion.** This work provided valuable insights and recommendations to RCS operators, which were put in practice, specifically tailoring OR configurations to RCS procedural characteristics.

Highlights

- Discrete event simulation (DES) is used for the first time to improve the performance of robotic cardiac surgery (RCS), an application that presents unique challenges.
- The flexible DES model for RCS can parametrize various factors related to both operating rooms and procedures.
- The impact of these factors is evaluated on a set of KPIs.
- New insights into the positioning of equipment and personnel in the OR are provided, allowing to formulate informed recommendations for RCS providers.

Keywords

discrete-event simulation, operating room design, operations management, robotic cardiac surgery

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Robotic surgery represents one of the most advanced technological achievements in the surgical context. This novel approach uses robotic systems to enhance, and in some cases replace, conventional techniques. Unlike other minimally invasive methods, it involves the use of a robotic platform that replaces or reproduces the movements and effects of handheld instruments within body cavities. There are 3 main types of robotic surgical systems: 1) active, 2) semi-active, and 3) master–slave.[1] Active systems operate independently by performing preprogrammed tasks while remaining under the control of the surgeon. Semi-active systems integrate operator-dependent and preprogrammed functions. Master–slave systems rely entirely on the surgeon's activity, transmitting the surgeon's movements to robotic arms operating on the patient. The latter type is currently the most widely used in clinical practice and is the one considered in this study. All these types also allow for remote surgery, in which surgeons control the actuators that perform the surgical activity by interacting with a console that is not close to the robotic arms and surgical instruments.[2] This console is usually located inside the operating room (OR), but it can even be placed in another location to allow for remote collaboration. In this work, we focus on robotic cardiac surgery (RCS), which represents one of the most complex but also most promising use cases of robotic surgery.[3]

In light of RCS complexity, effective integration of the robotic technology into surgical practice is necessary to take full advantage of the benefits it can bring forth, such as improved clinical outcomes for patients, more convenient working conditions for clinicians, and more efficient use of resources. Many factors influence RCS performance: first and foremost, the experience of the surgeon who uses the system, but a crucial role is also played by surgical process management. Thus, the optimization of several factors, including the OR layout, is required, leveraging quantitative methods to improve RCS efficiency.

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However, both in the literature and in clinical practice, no work or guideline analyzes the effect of OR layout on RCS performance, and existing studies on nonrobotic OR setups can be only partially applied to RCS due to its complexity and distinctive features. This work fills this gap by quantitatively assessing the performance of RCS interventions as a function of OR layout, using a discrete-event simulation (DES) model. This model enables a virtual exploration of several configurations and strategies without actually implementing them into clinical practice. In particular, DES allows the simulation of different RCS procedures under different OR layouts, to perform what-if analyses that assess the strengths and weaknesses of the different layouts and enable informed recommendations. The evaluation focuses on time and space efficiency through a set of key performance indicators (KPIs) extracted from each simulation run for comparative analyses.

This study is practically rooted in the case of the RCS division of Humanitas Gavazzeni Hospital (Bergamo, Italy), which is responsible for approximately 15% of all cardiac surgeries performed in the hospital in the year 2025.[i] This division was established in 2019[4] and is currently using a small dedicated OR equipped with the Da Vinci X Surgical System.[5] The division is considering moving to a larger OR in a new pavilion of the hospital, which was built in 2020 to accommodate COVID-19 patients and will be reconfigured to house several hospital departments. Therefore, our analyses will be of practical value in supporting the configuration of the new OR for RCS. More specifically, our aim is to quantify any variations in performance metrics between candidate OR layouts, including compared with the current OR, thus providing valuable insights for optimizing RCS performance. The surgical procedures themselves will not be investigated, on the assumption that the same procedure is performed regardless of the OR layout.

The considered division mainly performs 2 types of RCS: robotic atrial fibrillation ablation (AFA) and robotic mitral valve repair (MVR). Both types of surgery are analyzed here under different OR layouts to identify the most suitable one to implement. Data to feed the DES model were collected on site at Humanitas Gavazzeni Hospital through direct recording during some RCS interventions of the 2 types considered. Indeed, data on activities and timings of all operators in the OR, as well as their interactions, were extracted from video recordings, formalized, and included as activities within DES. AFA targets atrial fibrillation using conventional catheter ablation techniques facilitated by the Da Vinci Robotic System. Atrial fibrillation is a condition in which the atria of the heart beat irregularly and rapidly, which poses risks of complications, such as stroke and heart failure.[6] Catheter ablation consists of inserting a catheter equipped with electrodes into the heart to create focal lesions in the faulty electrical pathways, disrupting nonphysiological signals.[7] Ablation procedures are usually classified according to the energy source that creates the focal lesion; these include radiofrequency, laser, and cryoablation. Choosing one method over another depends on individual characteristics and often follows a failed attempt at treating the condition with drugs after evaluation by a cardiac electrophysiologist.[8] MVR addresses valvular insufficiency.[9] This condition, characterized by a progression toward valve failure, can lead to various complications, including death.[10] MVR restores the functionality of the faulty valve using a series of techniques, such as annuloplasty and flap resection. Advanced methods, including the lateral endoscopic robotic approach, offer enhanced precision and better outcomes. Preoperative imaging guides surgical planning, while robotic arms facilitate precise repairs during the procedure, resulting in a minimally invasive approach and quicker recovery for patients.[11]

Among the recognized guidelines for high-quality reporting of models in health care decision making,[12,13] we reference the ISPOR-SMDM[ii] good research practices,[14] which include specific guidelines on model conceptualization,[15] model parameter estimation and uncertainty,[16] and transparency and validation.[17] In particular, we use the condensed 18-item checklist by Zhang et al.,[18] the ISPOR-SMDM DES-specific guidelines,[19] and the STRESS[iii]-DES 20-item checklist.[20] This gives our results generalizability beyond the real case considered and guarantees the possibility of applying the same DES model to other RCS centers.

The remainder of this article is structured as follows. The "Literature Review" section covers literature related to both RCS ("Robotic Cardiac Surgery" section) and the use of DES in health care ("DES in Health Care" section). The methodology used is presented in the third section. We first specify how data from real surgeries were collected by means of cameras activated during the surgery ("Data Collection" section). Then, we show how the DES model was implemented for both surgery types based on the recorded data ("DES Model" section), first to simulate the existing layout and then to perform what-if analyses ("Design of Experiments and KPIs" section). The performance of each layout is reported in the "Results" section and then discussed in the "Discussion" section. Finally, conclusions are drawn in the last section.

Literature Review

We first overview the literature on RCS and related OR setups. Next, we address the use of DES in health care, with a focus on OR planning and performance analysis.

Robotic Cardiac Surgery

Some works have already demonstrated the advantages of using robots for cardiac surgery over open surgical approaches[21] and also over minimally invasive techniques,[3,22,23] of which RCS in some sense represents an evolution. RCS dates back to 1988, when the first procedure was performed.[1] However, the proliferation of this approach has not been very rapid because of still-immature technology, high costs, and steep learning curves for surgeons, especially in comparison with traditional approaches. For the successful adoption of a robotic surgery program, one of the most crucial steps is the management of its early stages, when the team needs to be trained.[4,24] In Europe, interest in RCS was renewed around 2011, especially in the context of MVR,[25–29] with a 112% registered increase in annual RCS surgery volumes from 2016 (435 reported cases) to 2019 (923 reported cases). This increment has been directly associated with improved robotic technology.[30] Today, robotic surgical systems are equipped with magnified, 3-dimensional visualization tools and articulated instrumental arms with up to 7 degrees of freedom, greatly improving surgeons' dexterity above their physiological limits. However, the complexity of the machinery and surgery requires an optimal OR environment to take full advantage of the potential benefits.

One of the most advanced robotic surgical systems is the Da Vinci Surgical System (Intuitive Surgical Inc., Sunnyvale, CA, USA). The version of this platform that is the most widely used in clinical practice is the Da Vinci X Surgical System. It consists of 3 main elements: the console, from where the surgeon controls the endoscopic system and the instruments; the patient-side cart, which is the operating component of the system and contains mechanical arms that actively operate on the patient; and, finally, the vision cart, which contains the central image processing unit.[31] This system is most frequently applied in urologic, gynecologic, and gastrointestinal surgery. Although robotic options are available for surgical treatments in other specialties, including general, cardiothoracic, oncologic, and pediatric surgery, their use is less frequent.[2] Policies to improve the cost-effectiveness of robotic surgery have been tested for some procedures, such as hysterectomies.[32] This work explored how patients should be triaged for robotic surgery based on the severity of their conditions, what the optimal size of the pool of surgeons using the same robot should be to facilitate learning, and what the minimum experience required for surgeons to be included in the robotic surgery pool should be. As for RCS, the Da Vinci system has a set of specific requirements for both OR configuration and the composition of the surgical team. Malik[33] provides a useful tool for setting up a robotic OR from a clinical perspective, while Agnino et al.[34] provide some guidelines on how to establish an RCS program for MVR and AFA.

DES in Health Care

Several studies have shown how simulations, both DES and other tools as virtual reality, are beneficial as part of the training and optimization process in robotic surgery.[35]

DES has been used since the 1950s in a variety of fields, such as manufacturing, supply chain management, military operations, information technology, network design, and even voting systems.[36] As computer processing power has continued to improve, the ability to model complex systems has become accessible for an increasingly wide range of applications. One of these is health care, which involves complex interactions among various entities and is characterized by high levels of variability and uncertainty, making it difficult to understand situations, plan for contingencies and predict outcomes.[37] Many works have applied DES to medical decision making and the analysis of processes within hospitals (e.g., for what-if analyses).[38] Most works are mainly concerned with patient flow optimization under different layouts.[39–41] However, more specific topics, such as resource management, OR planning, and waiting time reduction, are also addressed in the literature.[42–44] Concerning ORs, 2 streams of work can be found in the literature. On one hand, DES can be used to manage patient and resource flows according to the available ORs and to integrate their management with other hospital facilities, such as beds. On the other hand, it can be used to define the layout of the OR itself, detailing the positioning of instruments and personnel.

In the first stream, Stahl et al.[45] conducted a cost-effectiveness analysis using DES to reorganize the system of care surrounding laparoscopic surgery. Ferreira et al.[46] used DES to analyze the impact of an increased number of postanesthetic beds, of changes in OR scheduling strategies, and of an increased number of surgeries. Fei et al.[47] developed a DES model to evaluate alternative OR planning strategies in a medium-sized hospital. Allen et al.[48] used DES to analyze OR rescheduling when the current schedule is subjected to disruptions on the day of surgery. Hassanzadeh et al.[49] studied the allocation of surgical procedures to ORs as a function of patients admitted to inpatient beds and sent for surgery. Based on 6 scenarios, they evaluated the impact of OR case mix, opening and closing times, turnaround, and rearrangement based on efficiency parameters such as OR utilization, preoperative length of stay, and recovery. Pu et al.[50] built a DES model for thoracic, gastrointestinal, and orthopedic surgeries, including preoperative preparation, OR occupation, and OR preparation. They then conducted scenario analyses to assess the impact of improving different aspects, such as the use of new equipment to reduce surgical duration. In the second stream, specifically dealing with OR layout, Berg et al.[51] developed a DES model for a colonoscopy suite, comparing operational configurations by varying the number of endoscopists, procedure ORs, patient arrival times, and room-turnaround times. Indexed performance parameters included the number of patients served daily and resource utilization. Taaffe et al.[52] divided the OR into zones, analyzed movements between zones, and studied how OR size and equipment layout affected surgical staff movements and contacts during a procedure. Then, they developed a linear regression to model surgical team contacts and identified the variables that significantly influenced them.

However, to the best of our knowledge, there is no literature on how simulation and DES in particular can be used to plan an OR layout for RCS. This is a significant gap, considering the greater degree of complexity of RCS, to be managed appropriately, introduced by the presence of the robotic system on top of all the other equipment normally present in a cardiac OR (e.g., the cardiopulmonary bypass [CPB] machine and anesthesia instruments), along with their encumbrances and attendants, such as cables and reservoirs.

Methodology

We focused on MVR and AFA, which are the 2 main procedures performed in the considered division, with the goal of analyzing the current layout and improving it as well as in the light of the possibility of moving to a new, larger OR. These 2 procedures represent $\sim 90\%$ of all robotic procedures of the output of the RCS department at Gavazzeni Hospital.

Data Collection

The recorded RCS interventions included a total of 6 cases, 3 MVR and 3 AFA procedures, performed between June 2023 and July 2023. RCS procedures were recorded to obtain the sequence of tasks performed by each operator during the procedures, along with times, locations, and movements within the OR.

Three cameras were positioned to provide a complete view of the OR and capture all operators while excluding a direct view of the patient to avoid privacy issues. This way, the ability to record the operators' times and movements was not compromised, but informed consent was not required from the patients, as no data about them were recorded. Furthermore, because no patient data (e.g., age, gender, and diagnosis) were recorded, the Legal Affairs Office of Gavazzeni hospital granted an exemption from obtaining approval from an ethics committee or equivalent board. On the contrary, all operators voluntarily signed informed consent to participate in the study and to be recorded during their work activities, with the approval of their labor union representatives. The task and movement sequences were then extracted by the authorized researchers involved in the study.

Even if the staff varied among surgeries, operators belonged to one of the following staff classes, which were used in the study to model the surgeries without using the real identity of the personnel involved:

1. *Lead surgeon:* surgeon positioned at the console of the robot, who is ultimately responsible for coordinating and overseeing the surgical procedure, as well as monitoring the quality and safety of the RCS program.
2. *Assistant surgeon:* surgeon positioned at the patient's side, responsible for positioning and removing the robotic arms from the patient and for introducing and removing instruments in the arms. They coordinate with the lead surgeon so that the required tools are placed on the arms and other accessories (e.g., prostheses, stitches, gauze) are available next to the tools.
3. *Anesthesiologist:* physician responsible for monitoring anesthesia and vital functions during the entire procedure, as well as for medically inducing loss of consciousness and emergence. They may work independently or as part of an anesthesia care team.
4. *Anesthesia resident:* medical student acting as an assistant to the anesthesiologist. Even if their presence was not strictly required, they were present in every procedure and played a central role in helping the primary anesthetist in each intervention.
5. *Nurse anesthetist:* nurse in charge of assisting the anesthesiologist and the anesthesia resident.
6. *Scrub nurse:* operator with a specialized technical role in preparing and positioning movable equipment within the OR according to the different types of operations. Moreover, the scrub nurse assists the surgeon during procedures by managing sterile surgical instruments, equipment, and supplies.
7. *Nursing assistant:* operator in charge of managing the 3 elements of the robot, connecting them with auxiliary devices, ensuring that the robotic platform is in the right position, and supporting the scrub nurse during the draping of the robotic arms. They are also in charge of (re)supplying all the stocks in the OR and of providing assistance to all other operators.

In addition to these operators, who participated in both intervention types (MVR and AFA), an electrophysiologist and a perfusionist participated in only one type each. The electrophysiologist is present in the OR during only AFA procedures; their input is needed to interpret the electrical potential of the heart muscle and to check the effectiveness of the robotic ablation. The perfusionist is instead essential in MVR procedures and is responsible for the CPB machine, which provides oxygenated blood flow to the patient's systemic circulation while the heart is stopped. Additional operators engaged in marginal tasks or present in the OR but without performing any activity (such as medical students) were excluded from the analyses, as they did not help nor obstruct the surgical team.

Once all data were collected, each operator's activity was analyzed in both recorded procedures to standardize tasks and movements and define a reference scheme for each RCS type. For each operator, only the activities performed in all observed procedures of an RCS type were codified, with the aim of making the process robust and consistent. However, many of these tasks were brief and did not interfere with those of the other operators, for instance, when one of the staff members moved around the OR perimeter to retrieve or supply materials. Therefore, and for the sake of simplicity, it was decided to condense some activities in specific OR zones into single macro-activities, which can incorporate minor movements in the zone. The nursing assistant was the agent who performed the largest number of these kinds of minor tasks and movements and the one operator for which the condensation in macro-tasks was more pronounced. A complete list of the codified activities with observed durations can be found in the Supplementary Materials of this work.

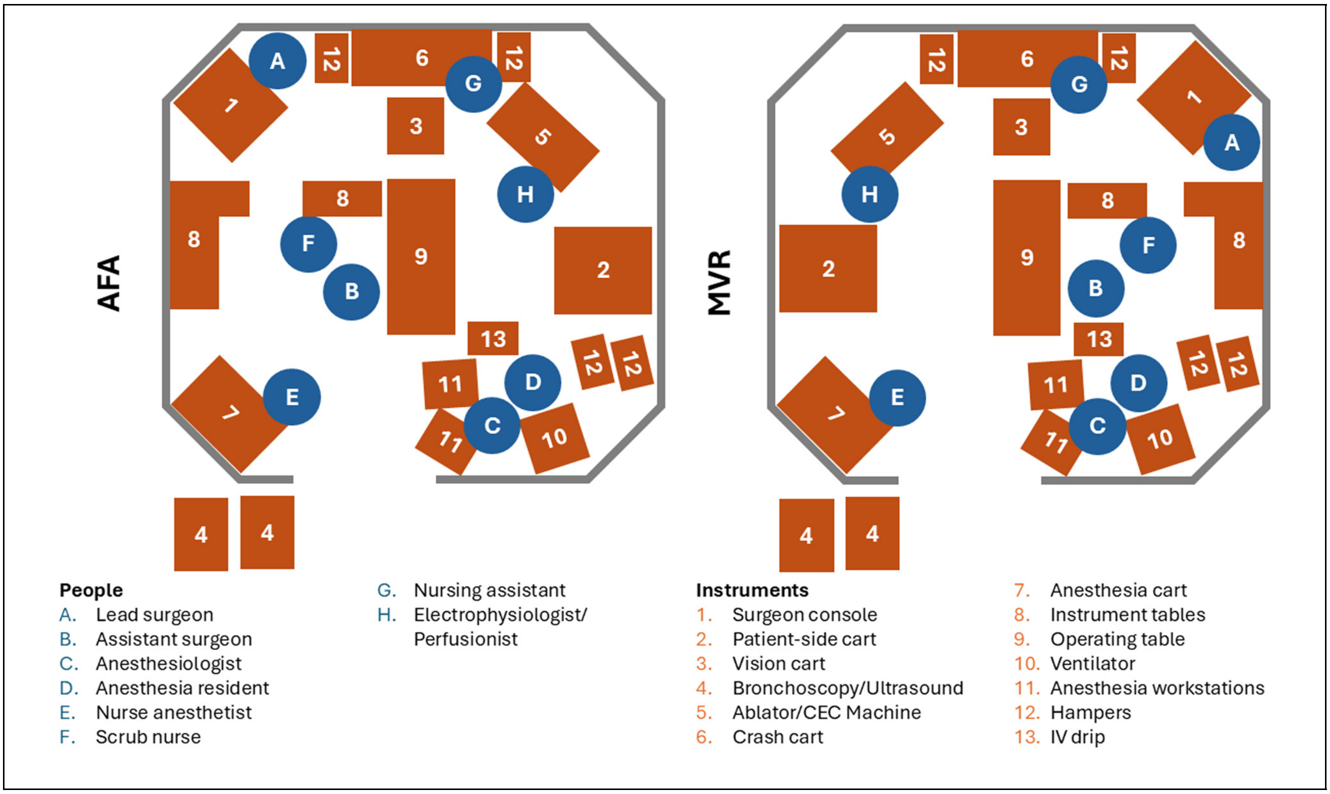

Figure 1 Current configuration of the operating room for atrial fibrillation ablation (AFA; left) and mitral valve repair (MVR; right) procedures, with main elements highlighted. Operators are shown using blue circles, and equipment is indicated by orange rectangles.

In addition to recording and processing operator tasks, the OR layout was also acquired, along with the dimensions and positioning of all surgical instruments and machines.

DES Model

The role of each entity in the DES model is defined following the description provided in the "Data Collection" section. In addition, we assumed that each staff member has at any given time a state attribute, which defines their usage at a more general level, among the following: *providing care*, *performing task*, *in transit*, or *idle*. Any activity they perform can change their state attribute to one of the first tree, while being unused sets their state attribute to the last one. Similarly, the entity representing that patient has a state attribute that can be either *receiving care* or *idle*. The simulation (along with the creation of all entities) begins when the patient is generated outside the OR and accompanied inside by the nursing assistant and ends when the last surgical activity is performed on the patient. Therefore, the time horizon of the simulation is variable and depends on the simulated process itself. The permanence of each entity in each state is calculated cumulatively at the end of the simulation.

The initial step in the development of the DES was to replicate the layout of the current OR based on both direct observations within the OR and the videos captured by the 3 cameras. The layout of the current OR is reported in Figure 1 for both MVR and AFA. This OR is almost square, measuring 6.10 by 6.54 m, with truncated corners (as it is customary to do in the OR to improve hygiene and cleanability by eliminating right angles), giving it an octagonal shape. Its area is of approximately 38.6 m^2.

The current OR layout is shown in Figure 1, where the size of the objects is approximate but provides a visual cue of how many pieces of equipment are needed and how cluttered the space is, especially due to the large amount of space occupied by the robot, its console, and the vision cart. It presents different zones where each operator moves and spends time while working during the surgery. Observed from a top-down perspective, these main areas are the patient bed in the middle of the OR, the anesthesia cart to the left of the door, the anesthesia workstations to its right, another cart at the top of the OR, and the vision cart placed at the patient's feet. For the AFA procedure, the surgeon console is placed at the top left corner of the OR, and the patient-side cart is positioned at the patient's left-hand side (the right side of the OR), with the scrub nurse tables on to the right of that. For the MVR procedure, the surgeon console is positioned in the top right corner, with the patient-side cart positioned on the patient's right-hand side (the left side of the OR). The scrub nurse tables are to the left of the patient bed. For AFA, an ablator machine is placed ipsilaterally with respect to the patient-side cart, while for MVR, the CPB machine is placed contralaterally with respect to it. Both stand close to the vision cart. Outside the OR, some lighter equipment that is needed in only certain phases is stored. In various parts of the surgery, a bronchoscopy machine, an ultrasound station, and additional chairs are stationed. This equipment is on wheels and can be moved easily even during the surgery.

The next step was to create a digital twin of the new OR. The new OR is rectangular, again with truncated corners, and measures 6.26 by 10.34 m, for an area of approximately 64.7 m^2. To determine an initial positioning of the equipment in the new OR, to be further changed in the what-if analysis, we assumed that 1) equipment placed against the wall in the old OR remains similarly positioned in the new OR and that 2) items located near the patient's bed in the center of the OR retain a similar placement. In addition, the layout was manually tweaked following guidance from the surgical team to ensure adequate spacing. Finally, since in the new, larger, OR there is enough space to internally store all the aforementioned equipment on wheels, in the DES model we eliminated all activities related to retrieving and moving equipment outside the OR.

Once ORs were digitally reconstructed, the following step was to build the whole process flow replicating the activities acquired in the collection phase. Some assumptions were made. First, to allow the DES to investigate the variability of RCS performance, stochastic durations of operators' tasks were considered using lognormal distributions. These distributions are suitable for a limited amount of positive real-valued data, as they correctly represent the underlying variability of the process and allow for wide dispersion in the simulated outcomes. Therefore, the behavior of the system can be better evaluated over a wider range of plausible conditions derived from the observed data, particularly in the right tail, where rare but high-impact events can occur. Triangular distributions that bound the minimum and maximum values were excluded because they would have generated less variability and dispersion of data. More complex distributions were also excluded due to the limited amount of data. Moreover, no comparable detailed data on AFA and MVR procedures exist in the literature, preventing benchmarking against other models. In any case, the fitted distributions were face validated by the surgical staff, who deemed them realistic. Further, the displacement of each operator was assumed to follow the shortest path available path, using the A* algorithm, a well-established heuristic that systematically evaluates nodes in the direction of travel, determining the most efficient route.[53] In this relatively small-scale context, in which all agents have perfect knowledge of the space they need to navigate, this choice makes the process flow as realistic as possible. Lastly, to coordinate different elements or processes within the simulation, it was necessary to understand whether they needed to occur simultaneously or in succession. This feature was embedded in the model, allowing for certain actions to start only when specific conditions were met, typically when operators involved in an activity complete their previous tasks.

Detailed flowcharts, following the logic of BPMN 2.0[54] standards, are reported in the Supplementary Materials.

The DES model was implemented using the simulation software FlexSim™, version 2025.1.3 (Orem, UT, USA), which provides a health care environment that enables customized visualization of health care environments and operators. FlexSim was chosen over general programming languages because it provides a 3-dimensional visualization of the process in a realistic environment, which is recognized to improve stakeholder engagement,[55] without compromising in execution speed and transparency.[19] All alternative scenarios were implemented within a single DES model file to ensure consistent workflows.

Design of Experiments and KPIs

The scenarios considered were developed following discussions with system experts and process managers at Gavazzeni Hospital. First, we considered that the same space has to be shared for 2 types of procedures: AFA and MVR. Therefore, the first factor considered in our experiments is the surgery type (*A*FA or *M*VR). Next, as mentioned in the introduction, the RCS team plans to move to a new OR of a different size; consequently, the

Table 1 Scenarios Considered in the Analyses

ID	Type	Operating Room	Layout
ACuRL	AFA	Current	RL
ACuLR	AFA	Current	LR
ACuRR	AFA	Current	RR
ACuLL	AFA	Current	LL
ACaRL	AFA	Candidate	RL
ACaLR	AFA	Candidate	LR
ACaRR	AFA	Candidate	RR
ACaLL	AFA	Candidate	LL
MCuRL	MVR	Current	RL
MCuLR	MVR	Current	LR
MCuRR	MVR	Current	RR
MCuLL	MVR	Current	LL
MCaRL	MVR	Candidate	RL
MCaLR	MVR	Candidate	LR
MCaRR	MVR	Candidate	RR
MCaLL	MVR	Candidate	LL

second factor is the OR itself, which also has 2 possible values (*Cu*rrent OR *Ca*ndidate). Last but foremost, we explored whether varying the positioning of the 2 focal elements of the Da Vinci System—the surgeon console and the patient-side cart—would determine improvements or setbacks in the overall performance of the surgeries. Malik[33] provides some guidelines on how to position these elements based on the location of the anatomical target of the surgery; however, as long as the robotic arms do not interfere with other equipment, other configurations are theoretically possible and worth exploring. The possible layouts are as follows: surgeon console on the right side of the OR, patient-side cart on the left (*RL* layout); console on the left, side cart on the right (*LR*); console and side cart on the right (*RR*); console and side cart on the left (*LL*).

Table 1 lists all tested scenarios, along with the synthetic and explanatory ID assigned to them. Since all the parameters are categorical, it was not possible to conduct a sensitivity analysis on them.

After a discussion with the surgical team, we identified 3 main quantitative KPIs to assess the effectiveness of a layout:

- *Total Process Time* (*TPT*): the overall length of the entire surgical procedure, which provides an overview of the utilization of the OR as a whole and is a paramount measure of efficiency.
- *Distance Covered* (*DC*): the distance covered by each operator during the entire surgical procedure, an indication of the efficiency of the layout.
- *Utilization* (*U*): the utilization of each operator during the entirety of the surgery. It is calculated in proportion to *TPT*, because, even if resources are not actively performing surgery-related tasks, they are required to remain available for the entire duration of the surgery for safety and legal reasons, preventing them from performing other tasks. This KPI provides a clear and concise assessment of the efficiency and productivity of an individual in the OR environment. It helps evaluate how effectively an operator performs their assigned tasks and contributes to the overall flow and success of surgical procedures.

We conducted a set of analyses of variance (ANOVAs) on these KPIs to establish if (some of) the experimental factors influence the outcome.

Metrics directly related to health were not included among the set of KPIs because this study focused more on management rather than medical aspects; that is, we did not analyze how to reorganize the medical activities performed in the OR; we did not collect patient-specific data and health outcomes of the procedures. Moreover, unlike scenarios in which prolonged waiting times can negatively affect patients, surgery is a standalone procedure without an internal queuing process. Nevertheless, in our experiments, we measured the following durations of surgical phases, which have a proven impact on the success of a procedure and the health outcomes:

- skin-to-skin time (t_{S2S}), that is, the duration of the surgery from the first incision to the last suture;
- duration of the robotic part of the surgery (t_R) from the insertion of the robotic arms to their removal; and
- total CPB time (t_{CPB}) from when the heart is stopped to when it is restarted (for only MVR procedures).

Results

Simulations were run on a local Microsoft Windows 11 machine equipped with an Intel® Core™ i7-11390 @ 3.40 GHz processor and 16 GB of RAM. They were run in a single batch stemming from a single parametrized model file. The results were exported from the native sql format to csv using the internal FlexSim converter and processed using Python 3.13. The KPIs of the 16 identified experimental setups were calculated over 500 independent repetitions with random seeds. This number of repetitions was sufficient to limit the variance around all KPIs and to ensure that their output distributions reached a stable

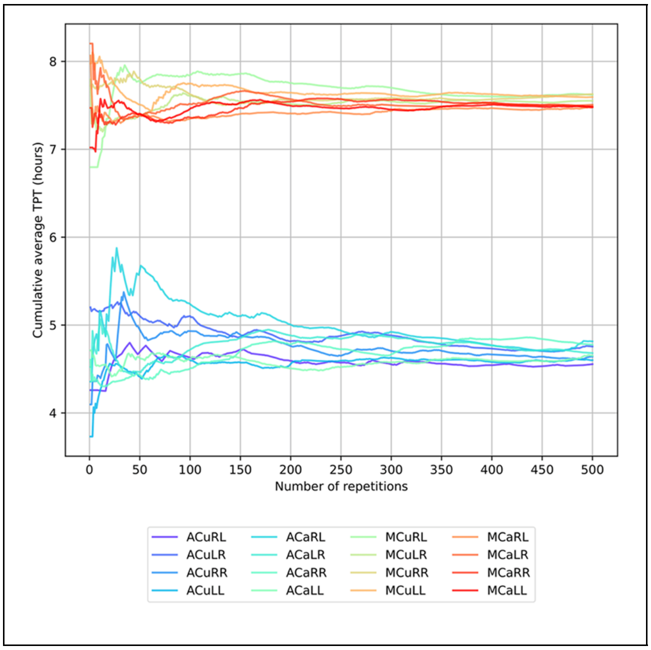

Figure 2 Cumulative average *total process time* (*TPT*) in each scenario as a function of the number of repetitions (values in hours).

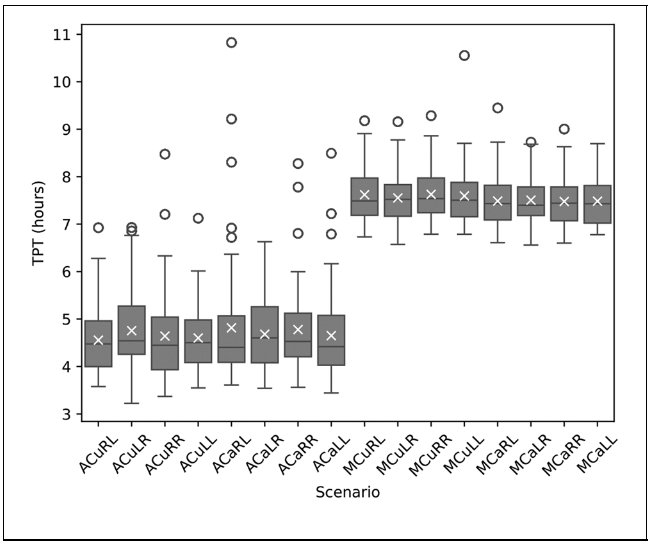

Figure 3 Box plots of *total process time* (*TPT*) over the simulated scenarios (values in hours).

asymptotic value. Figure 2 shows the convergence of the cumulative average for *TPT*; similar plots were obtained for the others KPIs.

The behavior of the system in the currently used configurations (i.e., ACuLR for AFA and MCuRL for

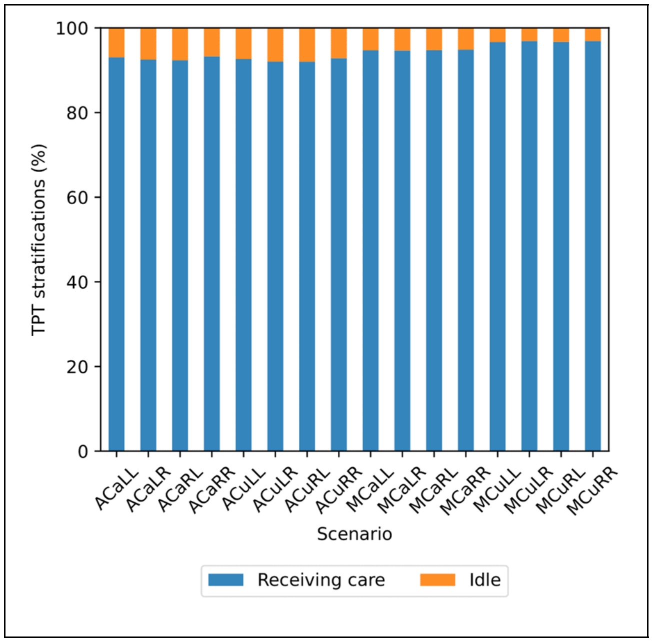

Figure 4 Percentage bar plots of the average value-added time from the patient's perspective.

MVR) was empirically compared against the surgical team's experience and was deemed as a good fit for reality. Moreover, the ratio between the standard deviation and the average value of the KPIs in the scenarios was compatible with what reported in the literature.[56]

Figure 3 reports the results for *TPT*. It is immediately observable that the 2 different procedures have significantly different durations, as expected given their different nature and purpose. It also appears that the OR plays an effect, albeit on a smaller scale. For AFA, the *TPT* values of the simulations performed in the new OR are on average 5.56 min higher than in the current OR. An inverse effect is observed for MVR: in the new OR, the *TPT* values are on average 6.61 min lower. The standard deviation from the current to the new OR increases for AFA (+ 10.99 min) and decreases for MVR and (−3.85 min). For what concerns the impact of the layout, *LR* results in the the highest average *TPT* for AFA (283.1 min), while *RL* in the highest for MVR (453.2 min).

We also investigated how much the duration of surgery in each scenario is spent in activities that add value from the patient's perspective (value-added time). Figure 4 shows high value-added times, with the percentage of time patients receive care during surgery averaging 94.2% of the *TPT* over the scenarios.

The average values obtained for U are reported in Table 2, along with their values at the first (q_1) and third

Table 2 Summary Statistics for U in Each Experimental Setting (Values [%] Reported as $q_2[q_1, q_3]$)

Staff	Lead Surgeon	Assistant Surgeon	Scrub Nurse	Anesthesiologist	Anesthesia Resident	Nurse Anesthetist	Nursing Assistant		
ACuRL	41.3 [35.3, 45.3]	45.4 [41.0, 48.5]	49.7 [44.3, 55.1]	84.5 [81.6, 88.6]	68.0 [63.9, 72.7]	72.5 [69.3, 77.0]	58.7 [51.7, 65.0]	Electrophysiologist	18.0 [13.4, 20.3]
ACuLR	42.1 [35.0, 46.6]	46.9 [42.5, 50.9]	49.4 [43.9, 54.1]	83.9 [82.4, 89.0]	68.8 [64.8, 75.2]	72.8 [70.2, 78.2]	59.5 [54.1, 67.9]		17.2 [14.0, 19.9]
ACuRR	44.2 [38.0, 48.0]	48.5 [43.6, 51.3]	52.7 [48.3, 58.8]	86.0 [83.6, 88.7]	69.5 [64.9, 73.2]	74.6 [70.5, 78.3]	61.1 [54.4, 68.3]		17.6 [13.7, 21.0]
ACuLL	42.9 [37.7, 47.3]	46.5 [43.7, 49.4]	52.3 [46.4, 56.0]	86.5 [84.3, 88.7]	70.0 [66.3, 73.5]	74.6 [70.6, 78.5]	58.7 [52.1, 65.6]		17.6 [14.4, 19.7]
ACaRL	41.7 [36.6, 46.6]	45.7 [41.9, 50.4]	50.1 [44.9, 55.9]	86.8 [84.8, 89.7]	68.0 [63.9, 72.2]	72.6 [68.4, 77.1]	57.7 [50.6, 64.0]		17.6 [13.4, 22.3]
ACaLR	43.4 [38.5, 47.6]	47.6 [42.6, 51.7]	51.3 [46.9, 55.7]	85.9 [83.8, 89.3]	66.2 [63.0, 69.4]	72.5 [69.1, 76.4]	60.0 [55.0, 67.4]		16.8 [12.6, 19.3]
ACaRR	43.0 [37.3, 47.8]	46.5 [43.0, 49.9]	49.1 [43.7, 53.2]	85.3 [82.6, 89.1]	65.9 [61.1, 71.4]	71.6 [66.4, 75.9]	57.7 [52.3, 60.9]		16.8 [13.3, 18.4]
ACaLL	42.2 [37.1, 46.4]	46.4 [42.0, 50.6]	49.2 [45.7, 54.4]	84.9 [81.5, 89.6]	65.2 [60.2, 68.1]	71.2 [66.7, 76.4]	58.4 [53.9, 63.7]		17.9 [13.9, 19.9]
MCuRL	42.1 [40.4, 43.8]	64.3 [61.9, 67.1]	56.9 [54.8, 59.6]	74.8 [71.5, 77.8]	62.8 [60.1, 64.5]	72.7 [70.6, 74.9]	54.5 [51.7, 56.6]	Perfusionist	11.1 [7.1, 8.9]
MCuLR	42.1 [40.6, 44.0]	64.6 [63.1, 67.4]	56.8 [54.4, 59.7]	75.0 [72.7, 77.0]	63.3 [61.1, 65.0]	72.8 [70.2, 75.1]	53.9 [51.8, 55.5]		9.6 [6.9, 9.1]
MCuRR	42.0 [39.6, 44.2]	65.0 [63.0, 67.0]	56.9 [54.7, 59.5]	73.9 [71.6, 76.7]	62.4 [60.4, 65.2]	71.7 [69.6, 75.0]	54.1 [51.3, 56.8]		7.9 [6.8, 8.7]
MCuLL	42.0 [39.3, 44.4]	65.5 [64.0, 68.3]	57.0 [54.5, 60.1]	73.6 [71.6, 77.3]	62.0 [59.8, 64.6]	71.4 [69.6, 74.4]	54.1 [50.8, 56.9]		8.0 [7.0, 8.9]
MCaRL	42.3 [40.1, 44.0]	65.2 [63.0, 67.4]	56.8 [54.8, 59.4]	75.5 [74.0, 78.1]	63.8 [62.3, 66.2]	71.2 [69.7, 73.2]	54.8 [51.7, 57.5]		7.9 [6.8, 8.4]
MCaLR	43.1 [41.1, 44.8]	65.8 [64.0, 67.9]	57.2 [55.6, 59.0]	76.0 [73.9, 79.3]	64.0 [62.1, 66.5]	71.4 [70.1, 72.8]	55.2 [51.7, 57.4]		8.2 [7.3, 8.8]
MCaRR	42.7 [40.5, 44.7]	65.5 [63.8, 68.2]	57.4 [55.4, 60.1]	74.9 [71.9, 77.1]	63.6 [60.9, 65.7]	71.4 [69.4, 73.7]	54.9 [51.7, 57.4]		8.3 [6.9, 9.1]
MCaLL	42.8 [40.9, 44.1]	65.1 [63.7, 67.5]	58.1 [55.7, 60.5]	74.9 [72.2, 77.7]	63.3 [61.7, 65.4]	71.0 [69.0, 73.1]	56.3 [52.4, 58.5]		7.9 [6.9, 8.7]

(q_2) quartiles. They are also reported in the form of box plots in Figure 5. Clearly, the main element affecting the utilization of resources is the type of procedure. For most operators, except for the assistant surgeon and the scrub nurse, the U value increases for the AFA procedures and decreases for the MVR ones. In the new OR, there is a slight decrease in global utilization for the AFA procedures (−0.74%) and a minor increase for MVR procedures (+ 0.33%). Concerning the layout, for AFA the best result was obtained with the *RR* configuration, and the worst with the *LR* one, but with an extremely small difference (0.31%). For MVR, the best result was obtained with *LR* and the worst with *RR* but with an even smaller difference equal to 0.08%. In summary, the OR layout does not appear to significantly affect this KPI.

Moreover, we decided to observe how each staff member's utilization is reflected in terms of hours, thus eliminating its proportion with respect to the KPI *TPT*. Figure 6 reports the bar plot of the average amount of hours spent in each state by each staff member, identifying how many hours each staff member spends providing care (i.e., working directly or indirectly on the patient), performing an ancillary task, walking, or being idle. Immediately, it is possible to notice that transit times (in green) are negligible, being almost unreadable for all staff members but for the nursing assistant. Second, it is interesting to notice that idle times appear to be very high for each staff member. However, these idle times are not necessarily wasted time, as per the insights obtained from the data presented in Figure 4. Both surgeries require extensive coordination among actors, and most of that idle time is time spent waiting for another member of the surgical team to finish an activity before being able to start the following one or for phases in which the staff member is conducting monitoring activities. It is especially evident for the lead surgeon, who has to wait for many tasks to be completed before being able to start the robotic surgery proper. A similar consideration can be done for the electrophysiologist. The perfusionist presents the largest share of idle time: this is because once they have connected the CPB, they have only to monitor it, without actively being engaged if there are no complications or problems during the surgery: hence, we decided to set their state to idle during the monitoring phase in the FlexSim model. Lastly, the largest share of time spent performing ancillary tasks (in orange in Figure 4) is unsurprisingly found among the nursing personnel (scrub nurse, nurse anesthetist, and nursing assistant), but some nonidle time not dedicated to directly providing care to the patient is found also in the medical personnel.

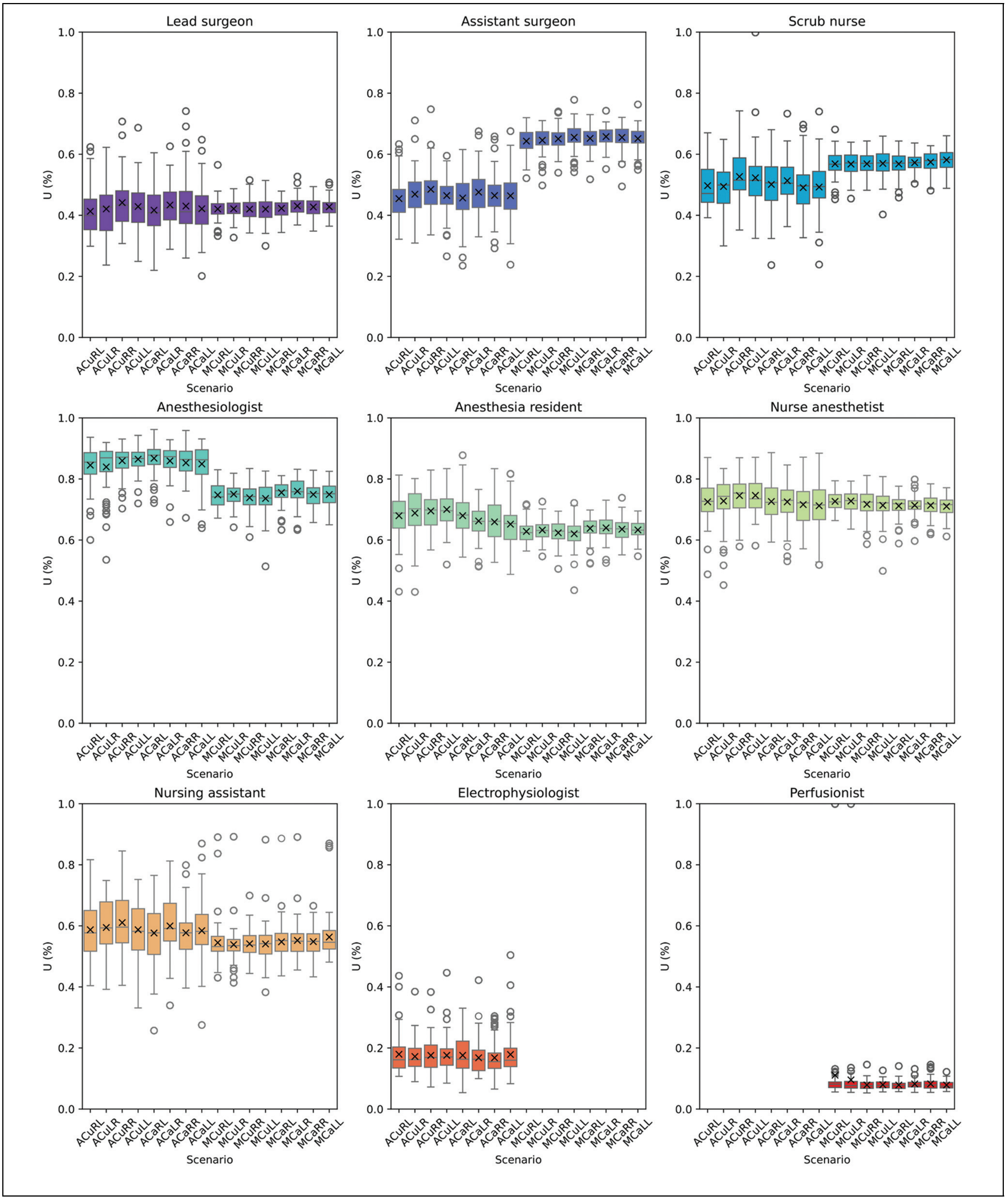

Figure 5 Box plots of U for each staff member.

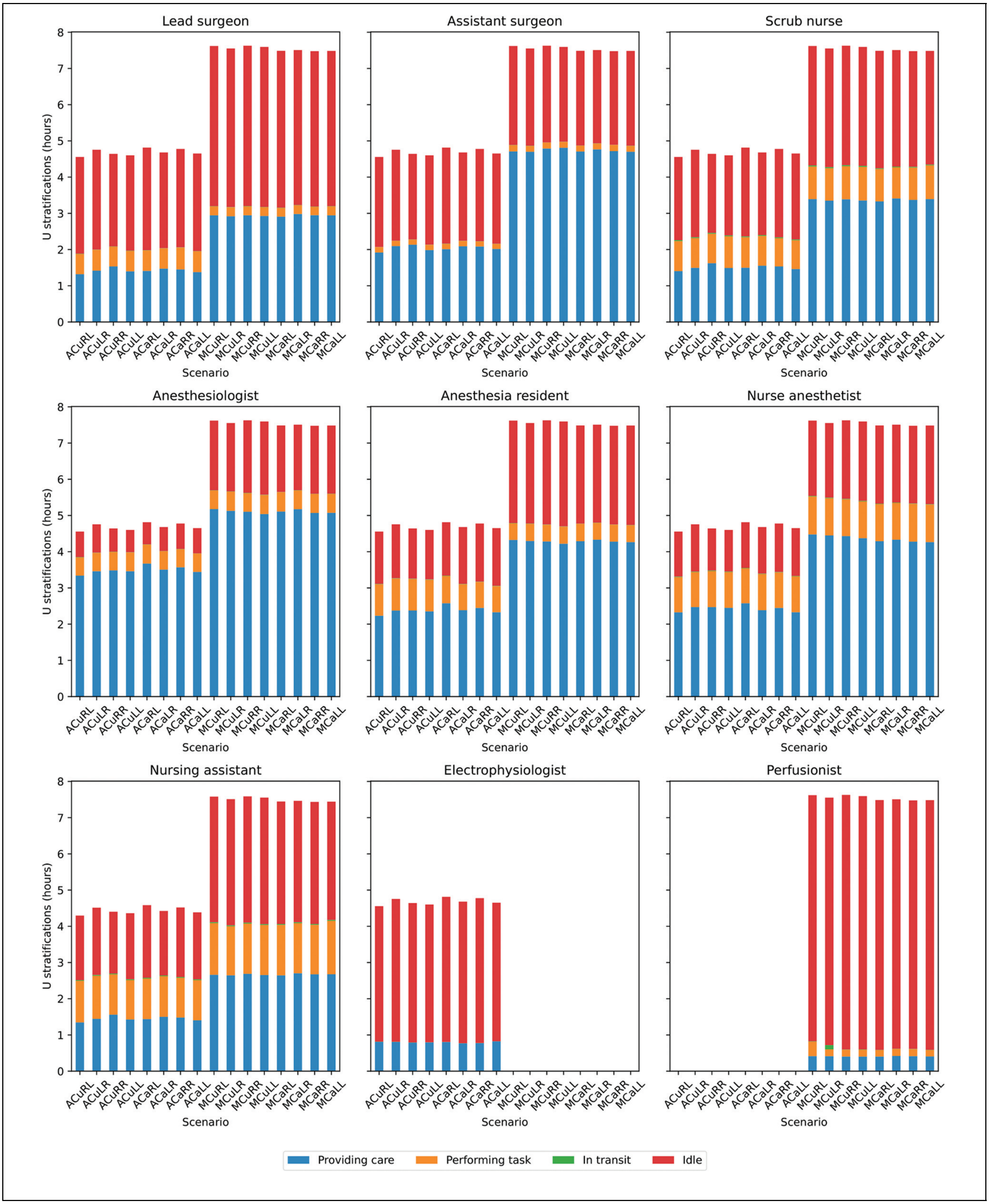

Figure 6 Bar plots of the average time spent in each state by each staff member (values in hours).

Table 3 Summary Statistics for DC in Each Experimental Setting (Values Reported as $q_2[q_1, q_3]$)

Staff	Lead Surgeon	Assistant Surgeon	Scrub Nurse	Anesthesiologist	Anesthesia Resident	Nurse Anesthetist	Nursing Assistant		
ACuRL	23.0 [23.0, 23.0]	13.5 [12.2, 14.5]	88.4 [88.1, 88.1]	23.6 [22.9, 22.9]	31.0 [31.5, 31.5]	51.4 [51.7, 51.7]	83.6 [84.1, 84.1]	Electrophysiologist	15.8 [15.8, 15.8]
ACuLR	23.0 [23.0, 23.0]	13.6 [12.2, 14.5]	87.7 [88.1, 88.1]	23.7 [22.9, 22.9]	30.9 [31.5, 31.5]	51.8 [51.7, 51.7]	83.3 [84.1, 84.1]		15.8 [15.8, 15.8]
ACuRR	23.0 [23.0, 23.0]	13.3 [12.2, 14.5]	88.2 [88.1, 88.1]	23.5 [22.9, 22.9]	31.1 [31.5, 31.5]	51.4 [51.7, 51.7]	83.3 [84.1, 84.1]		15.8 [15.8, 15.8]
ACuLL	23.0 [23.0, 23.0]	13.9 [12.2, 14.5]	87.6 [88.1, 88.1]	23.3 [22.9, 22.9]	31.2 [31.5, 31.5]	52.0 [51.7, 51.7]	83.5 [84.1, 84.1]		15.8 [15.8, 15.8]
ACaRL	19.3 [19.3, 19.3]	13.4 [11.8, 14.5]	81.7 [79.0, 87.6]	15.0 [15.0, 15.0]	30.3 [30.3, 30.3]	39.8 [36.5, 41.3]	78.1 [79.1, 79.1]		15.8 [15.8, 15.8]
ACaLR	19.3 [19.3, 19.3]	13.2 [11.8, 14.5]	81.5 [79.0, 87.6]	15.4 [15.0, 15.0]	29.8 [30.3, 30.3]	39.7 [36.5, 41.3]	78.0 [79.1, 79.1]		15.8 [15.8, 15.8]
ACaRR	19.3 [19.3, 19.3]	13.0 [11.8, 14.5]	80.6 [79.0, 79.0]	15.2 [15.0, 15.0]	30.1 [30.3, 30.3]	40.3 [41.3, 41.3]	78.4 [79.1, 79.1]		15.8 [15.8, 15.8]
ACaLL	19.3 [19.3, 19.3]	12.9 [11.8, 14.5]	81.5 [79.0, 87.6]	15.3 [15.0, 15.0]	29.9 [30.3, 30.3]	39.9 [36.5, 41.3]	78.3 [79.1, 79.1]		15.8 [15.8, 15.8]
MCuRL	23.0 [23.0, 23.0]	12.3 [12.3, 12.3]	100.1 [100.1, 100.1]	21.6 [22.1, 22.1]	24.3 [23.6, 26.5]	51.3 [50.5, 50.5]	92.9 [90.4, 95.0]	Perfusionist	50.6 [41.8, 57.9]
MCuLR	23.0 [23.0, 23.0]	12.3 [12.3, 12.3]	100.1 [100.1, 100.1]	21.9 [22.1, 22.1]	24.7 [23.6, 26.5]	50.9 [50.5, 50.5]	92.0 [90.4, 93.6]		50.0 [41.8, 57.9]
MCuRR	23.0 [23.0, 23.0]	12.5 [12.3, 12.3]	99.9 [100.1, 100.1]	21.6 [22.1, 22.1]	24.5 [23.6, 26.5]	51.1 [50.5, 50.5]	93.1 [90.4, 95.0]		49.5 [41.8, 57.9]
MCuLL	23.0 [23.0, 23.0]	12.5 [12.3, 12.3]	99.9 [100.1, 100.1]	21.9 [22.1, 22.1]	24.7 [23.6, 26.5]	50.8 [50.5, 50.5]	92.9 [90.4, 95.0]		50.1 [41.8, 57.9]
MCaRL	19.3 [19.3, 19.3]	12.3 [11.9, 11.9]	73.1 [73.7, 73.7]	19.6 [20.4, 20.4]	16.3 [16.6, 16.6]	35.9 [35.1, 35.1]	90.0 [90.2, 90.2]		41.8 [41.8, 41.8]
MCaLR	19.3 [19.3, 19.3]	12.1 [11.9, 11.9]	73.5 [73.7, 73.7]	19.0 [20.4, 20.4]	16.0 [16.6, 16.6]	36.6 [35.1, 35.1]	90.0 [90.2, 90.2]		41.8 [41.8, 41.8]
MCaRR	19.3 [19.3, 19.3]	12.0 [11.9, 11.9]	73.5 [73.7, 73.7]	20.2 [20.4, 20.4]	16.5 [16.6, 16.6]	35.3 [35.1, 35.1]	90.0 [90.2, 90.2]		41.8 [41.8, 41.8]
MCaLL	19.3 [19.3, 19.3]	12.2 [11.9, 11.9]	73.4 [73.7, 73.7]	19.6 [20.4, 20.4]	16.3 [16.6, 16.6]	35.9 [35.1, 35.1]	89.8 [90.2, 90.2]		41.8 [41.8, 41.8]

Table 3 and Figure 7 report the mean value of DC, stratified for each operator involved in the procedures. This KPI was internally stable in each scenario, as derivable by the small or nonexistent interquartile range computable using the q_1 and q_3 values reported in Table 3, so the analysis focused only on its average. Results show that operators do not cover a bigger distance in the new OR. This is not expected, given the bigger OR size, but can be explained by 2 factors: 1) given that there is less crowding, the A* algorithm enables operators to walk the shortest path to where they need to go, and 2) as all the equipment can fit into the OR, there is no need to go and retrieve it from outside, as it happens in the current OR. On average, DC actually decreases by an average of 3.5 m for AFA and 7.0 m for MVR. The electrophysiologist (who is present for only AFA) fares equally in the new OR, while the perfusionist (who is present for only MVR) reduces DC by -8.3 m. In absolute terms, the worst-faring staff member for this KPI is the scrub nurse, who walks between 73.1 and 100.1 m per surgery, followed by the nursing assistant, who walks between 78.0 and 92.9 m. Intuitively, the staff member who walks the least is the assistant surgeon, who is constantly at the patient's side, with an average across all scenarios of only 12.8 m, followed by the electrophysiologist, who is actively engaged in the surgery for a brief period by providing assistance and monitoring (the average DC across all AFA scenarios of 15.8 m).

Lastly, we report in Figure 8 some box plots showing the values of t_{S2S}, t_R, and t_{CPB} across all scenarios. As mentioned, these values are related to the health outcomes of the patient and do not provide extensive managerial guidance. t_{S2S} is obviously the highest of the three, followed by t_{CPB} and t_R.

To quantitatively determine whether a factor influenced 1 or more KPIs, we conducted a multifactorial ANOVA analysis. This is particularly suitable for our experimental design, as all the factors are categorical: the use of ANOVA can overcome the limitations stemming from not being able to perform a sensitivity analysis nor using a response surface methodology tool. The resulting P values are reported in Table 4. As noted in the previous analyses, the main factor influencing all KPIs is the type of surgery. This is to be expected, as they are 2 entirely different processes, even if they share many aspects. The OR factor also affects the utilization KPI of some operators, with the notable exceptions of the assistant surgeon, the scrub nurse, the nursing assistant, and the electrophysiologist, along with its interactions with the surgery type. The layout is also affecting, albeit with a generally lower degree of confidence. Considering the perfusionist, it is

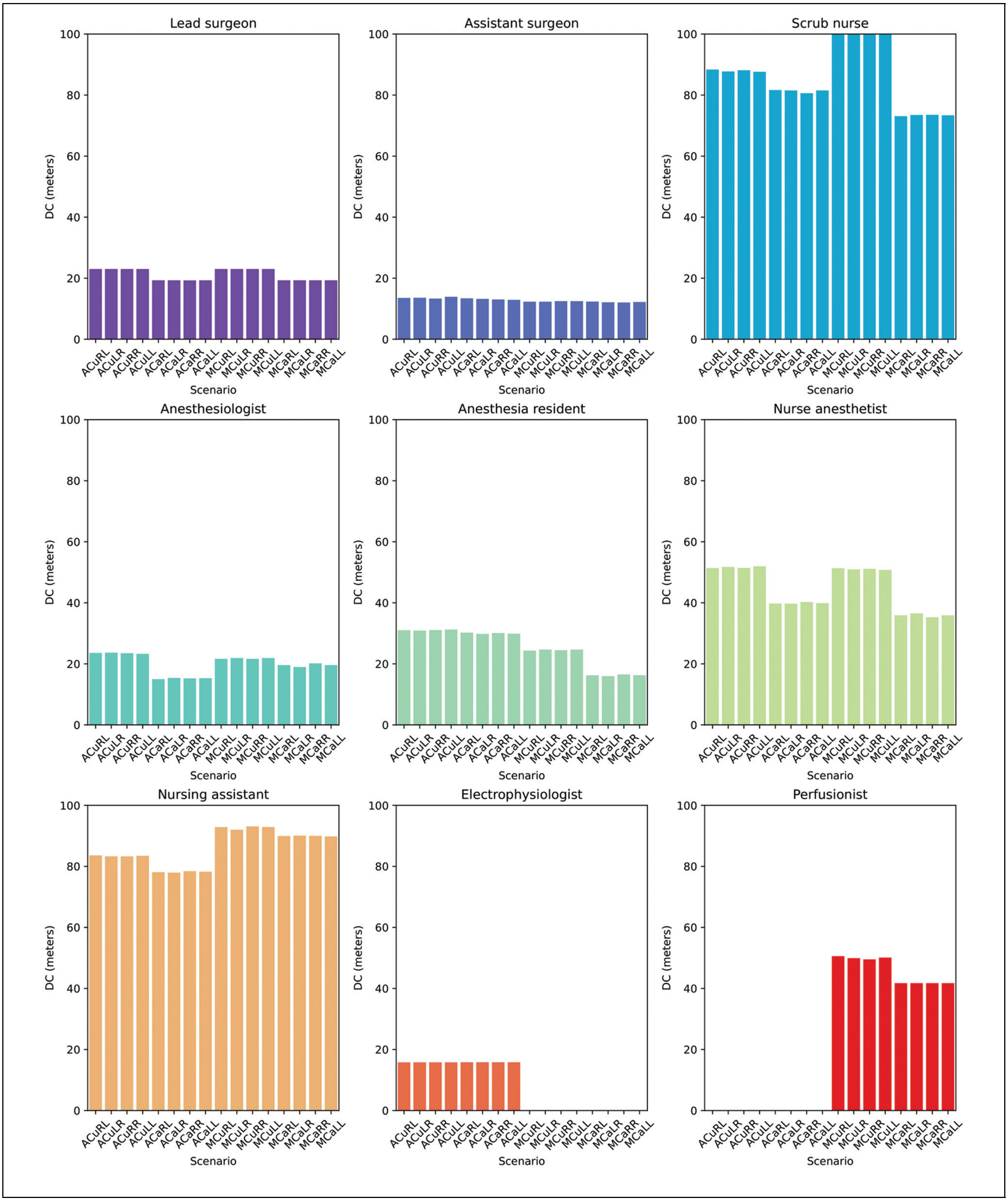

Figure 7 Bar plots of the average *DC* metric for each staff member (values are reported in meters, all on the same scale).

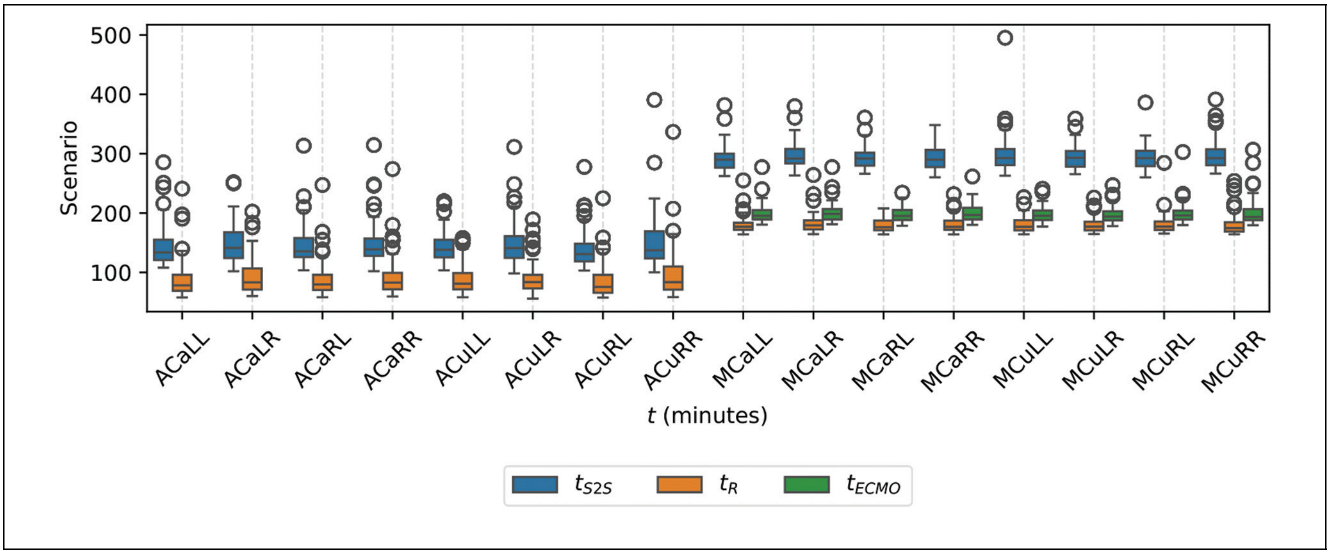

Figure 8 Box plots of t_{S2S}, t_R, and t_{CPB} values among scenarios (values in minutes).

Table 4 *P* Values <0.01 of the *n*-Way Analysis of Variance.[a]

		Type	OR	Layout	Type x OR	Type x Layout	OR x Layout	Type x OR x Layout
Total processing time		*0.000*			*0.000*			*0.000*
Utilization	Lead surgeon			*0.000*	0.001	*0.000*	0.003	0.004
	Assistant surgeon	*0.000*		*0.000*	0.001	*0.000*	*0.000*	0.001
	Scrub nurse	*0.000*		*0.000*	*0.000*		*0.000*	*0.000*
	Anesthesiologist	*0.000*	*0.000*			*0.000*	*0.000*	*0.000*
	Anesthesia resident	*0.000*	*0.000*		*0.000*		*0.000*	*0.000*
	Nurse anesthetist	*0.000*	*0.000*		0.002	*0.000*	0.001	*0.000*
	Nursing assistant	*0.000*			*0.000*	*0.000*	*0.000*	
	Electrophysiologist	/		0.005	/	/		/
	Perfusionist	/	*0.000*	*0.000*	/	/	*0.000*	/
Distance covered	Lead surgeon	*0.000*	*0.000*	*0.000*		*0.000*	*0.000*	*0.000*
	Assistant surgeon	*0.000*	*0.000*	0.003	*0.000*		*0.000*	*0.000*
	Scrub nurse	*0.000*	*0.000*	0.005	*0.000*	*0.000*	0.001	*0.000*
	Anesthesiologist	*0.000*	*0.000*	0.001	*0.000*	*0.000*	*0.000*	*0.000*
	Anesthesia resident	*0.000*	*0.000*	*0.000*	*0.000*	0.004	*0.000*	0.002
	Nurse anesthetist	*0.000*	*0.000*	0.006	*0.000*	0.001		*0.000*
	Nursing assistant	*0.000*	*0.000*	*0.000*	*0.000*		0.001	*0.000*
	Electrophysiologist	/	*0.000*	*0.000*	/	/	*0.000*	/
	Perfusionist	/	*0.000*		/	/		/

OR, operating room.
[a]*P* values <0.001 are presented in italics. Values ≥ 0.01 are not reported.

possible to ascertain that the OR appears to have an impact on their utilization, while the layout is with high probability affecting both them and the electrophysiologist. The layout is also affecting for the lead surgeon, the assistant surgeon, and, most importantly, the scrub nurse. Because scrub nurses move more equipment around the OR, different configurations determine different utilization, for instance, because they have to maneuver around other encumbrances or personnel. For what concerns *DC*, it is possible to make similar considerations. Moreover, moving to a different OR indeed strongly affects the distance covered as does the layout for all staff members.

Discussion

Optimizing operational efficiency in surgical procedures requires a relevant consideration of individual process times and the overall process duration. Each team member's unique tasks contribute to the procedural timeline, and analyzing these individual times provides crucial insights into the overall workflow. Exploring potential alterations in the OR size gives an assessment of how spatial design changes may affect individual process times and, consequently, the overall duration of the surgical procedure.

The DES model represents a suitable tool for this analysis, in accordance with the guidelines of Karnon et al.,[19] according to which this technique "should be used when the problem ... involves constrained or limited resources ... when time-to-event is best described stochastically ...; and when recording individual entity experience is desirable." Our results showed that intervention times remained mostly unaltered when simulating surgeries in the new OR, with a decrease for MVR and a negligible increase of a few minutes for AFA. This outcome suggests that, although some operators have to cover more distance during surgery, the impact on the overall process time is negligible, and there is no counterindication to housing the RCS division in the new OR. This outcome can be attributed to the fact that, even though one operator may need more time to cover larger distances during the procedure, this takes only seconds, an imperceptible increase at the scale of the overall process time. The time spent on task execution, encompassing both individual and total process time, absorbs the few seconds operators take to relocate when changing workstations. Moreover, keeping all necessary movable equipment (including bronchoscopy and ultrasound machines) in the OR eliminates some movements, further streamlining the process. This also benefits hygiene, as fewer components are stored outside the controlled environment of the OR.

The outcomes of the analyses reveal that the impact of the larger candidate OR on the distance traveled by surgical staff does not necessarily align with what might be expected (i.e., an overall increase in travel times). In fact, despite the increment in OR size, some operators end up covering a shorter distance, which signals enhanced efficiency. This is especially true for the nursing staff. In the new OR, despite the increased size, the distance between the door and the opposite wall is shorter than in the current OR. In light of this, some operators face a reduction in the total distance covered. For example, the lead surgeon, who mainly has to walk from the entry door to their workstation positioned at at the patient's side, would travel an average of 19.3 m for AFA and 19.3 m for MVR procedures versus a current average of 23.0 m for both. This reduction, although minimal, indicates a potential efficiency gain in the new larger OR. However, it should be noted that larger ORs may take longer to clean due to the increased volume, which may offset any efficiencies gained from reduced travel times. A similar trend is observed for the scrub nurse and the nurse anesthetist, whose travel distances are reduced in the new OR. The rationale behind this result may be related to a more streamlined path in the larger OR. In the current OR, walking to the patient's bed involves numerous directional changes. In contrast, the new OR provides a more open and linear pathway, optimizing efficiency. Regarding operator utilization, as already mentioned, the U value of some operators (lead and assistant surgeon, anesthesia resident, scrub nurse, and nursing assistant) increases slightly for the MVR procedures performed in the new OR and remains essentially unaffected in the other cases.

On one hand, several of the results we obtained were predictable, but in any case, this study allowed us quantify them. On the other hand, some evidence could not have been predicted without our DES model.

As mentioned, one of the major obstacles in adopting RCS is its steep learning curve.[4] In our case study, as the team has already learned to perform the procedures using a certain layout and no layout is theoretically superior to the others, the conclusion is that the team can choose to keep the layout they have been accustomed to in the current OR. Also, it is important to report that, prior to this study, some empiric optimization approaches had already been carried out in the layout of the current OR, such as the repositioning of various elements within the surgical suite. The overarching goal of these modifications was to enhance operational efficiency and minimize intervention times, albeit without a formal exploration. The configurations chosen for the analysis in this work capture the one developed with the experience of the surgical team. Stemming from the obtained results, 2 logical suggestions for improvement in the new OR, given its larger footprint, would be to either 1) create a second entrance to facilitate the flow of people and materials in and out (if structurally possible) or 2) use the extra space toward the 2 lateral ends of the OR to store all necessary equipment within the OR, as it was tested in our experiments. This last point, along with reducing congestion, improves the DC metric for most operators, as they would no longer need to fetch equipment outside.

Finally, further considerations could be made regarding recoverability in the event of device failure or complications that may arise during the procedure. If it is necessary to switch from robotic to traditional surgery, all obstructions must be removed as quickly as possible to allow the surgeon immediate visibility of the surgical field. In this case, positioning the side cart on the opposite side to the surgeon ensures faster OR reconfiguration on the fly. This also applies to device malfunctions that occur during surgery, as a result of which the devices must be removed from the patient. For scheduled maintenance, the layout is not important, as all equipment is on wheels and can be moved as desired.

Limitations

The most relevant limitation encountered during this work was the limited amount of data available. Obviously, a larger dataset would have enhanced the robustness of the analysis, but the inherent complexity of data acquisition required a careful balance between the quantity of data and the practical challenges of its collection. It was not possible to widely extend the data acquisition phase. This issue has been partially solved by using stochastic models rather than deterministic ones, to provide a more differentiated amount of data as inputs. The limited standard deviations of the acquired times also suggested that a low number of acquired interventions was sufficient. In the literature, there are no usable estimates for activity durations, other than the overall surgery duration and t_{S2S}, t_R, and t_{CPB}, which are outputs and not inputs of the DES model. Similarly, we could not find any comparable models to cross-validate our results.

From the application viewpoint, at the time of writing, the RCS division has not been transferred to the new OR, but a future effort would be to compare how closely the results obtained by the DES model in all the scenarios match with new data that will be collected in the future.

Conclusion

Understanding and analyzing the individual activities that constitute a surgery can provide valuable insights into the overall workflow. The configuration of the OR can affect these activities, influencing the efficiency of the entire surgical process. When exploring potential changes in OR size or layout, it becomes important to assess how alterations in spatial design may affect individual team members and, consequently, the overall surgical procedure.

This work began with a critical exploration of efficiency within the ORs employed for RCS interventions due to the lack of scientific literature on the topic, with a link to a real-world application, the case of Humanitas Gavazzeni Hospital. Therefore, this work was not just a theoretical activity but had real-world implications for the partner provider. The presented tool was built to serve the purpose of exploring whether the Gavazzeni RCS team could move to another OR, as planned, without losing or even gaining efficiency. The DES methodology was chosen because it is a powerful and rather inexpensive tool for conducting scenario analyses in a virtual environment, eliminating the need for costly real-world analyses. In contrast to traditional analyses that require direct observation or practical implementation of changes, DES allows for the virtual exploration of different configurations and strategies without affecting actual operations.

Various efficiency metrics have been evaluated, capturing the intricate dynamics of the surgical environment. To feed realistic inputs to the DES tool, data were collected on the field, in collaboration with the RCS team. Regarding *TPT*, comparing the 2 ORs for both the MVR and AFA procedures showed that changing the OR would not damage the efficiency of the operations. This result is particularly interesting because it suggests that the current OR, which is the result of several changes over time, is already arranged in a rather efficient way.

Summing up, this work presents 2 main contributions. First, the broader significance of this work lies in its contribution to addressing the existing gap in the literature related to the application of DES in the field of RCS. The insights gained from this study can serve as a support for future research activities, providing a basis for more comprehensive analyses and investigations into the dynamics of OR design and workflow optimization in the context of RCS procedures. In this direction, in the future we will analyze whether operational constraints, such as OR layout, have an effect on clinical outcomes. Second, this work provided valuable insights and recommendations for RCS providers, specifically tailoring the configurations to their procedural characteristics. It is also a base on which further what-if analyses can be conducted. In this direction, we will follow step by step the movement of the studied RCS division in the new OR.

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Data Availability Statement

Data of the instances and the developed model can be made available upon motivated request by contacting the corresponding author. Please note that the model was implemented with commercial software (FlexSim) and requires a valid license to be executed.

Notes

i. According to internal data.
ii. Joint task force from the International Society for Pharmacoeconomics and Outcomes Research (ISPOR) and the Society for Medical Decision Making (SMDM).
iii. Strengthening the Reporting of Empirical Simulation Studies.

References

1. Morrell ALG, Morrell-Junior AC, Morrell AG, et al. The history of robotic surgery and its evolution: when illusion becomes reality. *Rev Col Bras Cir*. 2021;48:e20202798.
2. Leung T, Vyas D. Robotic surgery: applications. *Am J Robot Surg*. 2014;1(1):38–41.
3. Giroletti L, Salvi D, Peluso L, et al. Impact of COVID-19 in the age of computer-assisted surgery: cost and effectiveness comparison between robotic and minimally invasive mitral valve surgery in a single-center experience. *J Card Surg*. 2024;2024:2453937.
4. Giroletti L, Brembilla V, Graniero A, et al. Learning curve analysis of robotic-assisted mitral valve repair with COVID-19 exogenous factor: a single center experience. *Medicina*. 2023;59(9):1568.
5. Douissard J, Hagen ME, Morel P.The Da Vinci surgical system. In: Domene CE, Kim KC, Puy RV, Volpe P, eds. *Bariatric Robotic Surgery: A Comprehensive Guide*. New York: Springer; 2019. p 13–27.
6. Nattel S. New ideas about atrial fibrillation 50 years on. *Nature*. 2002;415(6868):219–26.
7. Pappone C, Vicedomini G, Manguso F, et al. Robotic magnetic navigation for atrial fibrillation ablation. *J Am Coll Cardiol*. 2006;47(7):1390–400.
8. Agnino A, Giroletti L, Graniero A, et al. Robotic-assisted epicardial hybrid ablation and left appendage closure in persistent atrial fibrillation: first European experience. *J Clin Med*. 2024;13(6):1563.
9. Madesis A, Tsakiridis K, Zarogoulidis P, et al. Review of mitral valve insufficiency: repair or replacement. *J Thorac Dis*. 2014;6(suppl 1):S39.
10. Fedak PW, McCarthy PM, Bonow RO. Evolving concepts and technologies in mitral valve repair. *Circulation*. 2008; 117(7):963–74.
11. Kypson AP, Nifong LW, Chitwood WR, Jr. Robotic mitral valve surgery. *Semin Thorac Cardiovasc Surg*. 2003;15:121–9.
12. Law A. *Simulation Modeling and Analysis*. 6th ed. Columbus (OH): McGraw-Hill Education; 2024.
13. Robinson S. *Simulation*. 2nd ed. London: Red Globe Press; 2014.
14. Caro JJ, Briggs AH, Siebert U, Kuntz KM, ISPOR-SMDM Modeling Good Research Practices Task Force. Modeling good research practices—overview: a report of the ISPOR-SMDM modeling good research practices task force-1. *Value Health*. 2012;15(6):796–803. DOI:10.1016/j.jval.2012.06.012
15. Roberts M, Russell LB, Paltiel AD, et al. Conceptualizing a model: a report of the ISPOR-SMDM modeling good research practices task force-2. *Value Health*. 2012;15(6): 804–11. DOI:10.1016/j.jval.2012.06.016
16. Briggs AH, Weinstein MC, Fenwick EA, et al. Model parameter estimation and uncertainty: a report of the ISPOR-SMDM modeling good research practices task force-6. *Value Health*. 2012;15(6):835–42. DOI:10.1016/j.jval.2012.04.014
17. Eddy DM, Hollingworth W, Caro JJ, et al. Model transparency and validation: a report of the ISPOR-SMDM Modeling Good Research Practices Task Force-7. *Value Health*. 2012;15(6):843–50. DOI: 10.1016/j.jval.2012.04.012
18. Zhang X, Lhachimi SK, Rogowski WH. Reporting quality of discrete event simulations in healthcare—results from a generic reporting checklist. *Value Health*. 2020;23(4): 506–14. DOI:10.1016/j.jval.2020.01.005
19. Karnon J, Stahl J, Brennan A, et al. Modeling using discrete event simulation: a report of the ISPOR-SMDM Modeling Good Research Practices Task Force-4. *Value Health*. 2012;15(6):821–7. DOI:10.1016/j.jval.2012.04.013
20. Monks T, Currie CSM, Onggo BS, Robinson S, Kunc M, Taylor SJE. Strengthening the reporting of empirical simulation studies: introducing the stress guidelines. *J Simul*. 2018;13(1):55–67. DOI:10.1080/17477778.2018.1442155
21. Kam JK, Cooray SD, Kam JK, Smith JA, Almeida AA. A cost-analysis study of robotic versus conventional mitral valve repair. *Heart Lung Circ*. 2010;19(7):413–8.
22. Hassan M, Miao Y, Lincoln J, Ricci M. Cost-benefit analysis of robotic versus nonrobotic minimally invasive mitral valve surgery. *Innovations*. 2015;10(2):90–5.
23. Husen TF, Kohar K, Angelica R, Saputro BIL. Robotic vs other surgery techniques for mitral valve repair and/or replacement: a systematic review and meta-analysis. *Hellenic J Cardiol*. 2023;71:16–25.
24. Palmen M, Navarra E, Bonatti J, et al. Current state of the art and recommendations in robotic mitral valve surgery. *Interact Cardiovasc Thorac Surg*. 2022;35(6):ivac160.
25. Mihaljevic T, Koprivanac M, Kelava M, et al. Value of robotically assisted surgery for mitral valve disease. *JAMA Surg*. 2014;149(7):679–86.
26. Suri RM, Dearani JA, Mihaljevic T, et al. Mitral valve repair using robotic technology: safe, effective, and durable. *J Thorac Cardiovasc Surg*. 2016;151(6):1450–4.

27. Pettinari M, Navarra E, Noirhomme P, Gutermann H. The state of robotic cardiac surgery in Europe. *Ann Cardiothorac Surg*. 2017;6(1):1.
28. Gillinov AM, Mihaljevic T, Javadikasgari H, et al. Early results of robotically assisted mitral valve surgery: analysis of the first 1000 cases. *J Thorac Cardiovasc Surg*. 2018; 155(1):82–91.
29. Agnino A, Graniero A, Villari N, et al. Evaluation of robotic-assisted mitral surgery in a contemporary experience. *J Cardiovasc Med*. 2022;23(6):399–405.
30. Cerny S, Oosterlinck W, Onan B, et al. Robotic cardiac surgery in Europe: status 2020. *Front Cardiovasc Med*. 2022;8:827515.
31. Azizian M, Liu M, Khalaji I, DiMaio S. The Da Vinci surgical system. In: Nasab MHA, ed. *Handbook of Robotic and Image-Guided Surgery*. Amsterdam: Elsevier; 2020. p 39–55.
32. Mukherjee UK, Sinha KK. Robot-assisted surgical care delivery at a hospital: policies for maximizing clinical outcome benefits and minimizing costs. *J Oper Manag*. 2019;66(1–2):227–56. DOI:10.1002/joom.1058
33. Malik S.Robotic surgery: operating room setup and docking. In: Lomanto D, Chen WT-L, Fuentes MB, eds. *Mastering Endo-Laparoscopic and Thoracoscopic Surgery: ELSA Manual*. New York: Springer; 2022. p 555–63.
34. Agnino A, Graniero A, Albano G, et al. Towards the age of computer-assisted surgery: how to establish a robotic-assisted mitral surgery program with a last-generation platform. *G Ital Cardiol*. 2021;22(8):648–56.
35. Abboudi H, Khan MS, Aboumarzouk O, et al. Current status of validation for robotic surgery simulators—a systematic review. *BJU Int*. 2013;111(2):194–205. DOI: 10.1111/j.1464-410X.2012.11270.x
36. Allen TT. *Introduction to Discrete Event Simulation and Agent-Based Modeling: Voting Systems, Health Care, Military, and Manufacturing*. London: Springer Science & Business Media; 2011.
37. Günal MM, Pidd M. Discrete event simulation for performance modelling in health care: a review of the literature. *J Simul*. 2010;4:42–51.
38. Klein RW, Dittus RS, Roberts SD, Wilson JR. Simulation modeling and health-care decision making. *Med Decis Making*. 1993;13(4):347–54.
39. Hung GR, Whitehouse SR, O'Neill C, Gray AP, Kissoon N. Computer modeling of patient flow in a pediatric emergency department using discrete event simulation. *Pediatr Emerg Care*. 2007;23(1):5–10.
40. Sepúlveda JA, Thompson WJ, Baesler FF, Alvarez MI.The use of simulation for process improvement in a cancer treatment center. In: *Proceedings of the 31st Winter Simulation Conference: Simulation — A Bridge to the Future*. Vol 2. New York: Association for Computing Machinery; 1999. p 1541–8.
41. Vázquez-Serrano JI, Peimbert-García RE, Cárdenas-Barrón LE. Discrete-event simulation modeling in healthcare: a comprehensive review. *Int J Environ Res Public Health*. 2021;18(22):12262.
42. Jun JB, Jacobson SH, Swisher JR. Application of discrete-event simulation in health care clinics: a survey. *J Oper Res Soc*. 1999;50:109–23.
43. Doneda M, Yalçındağ S, Marques I, Lanzarone E. A discrete-event simulation model for analysing and improving operations in a blood donation centre. *Vox Sang*. 2021;116(10):1060–75.
44. Forbus JJ, Berleant D. Discrete-event simulation in healthcare settings: a review. *Modelling*. 2022;3(4):417–33.
45. Stahl JE, Rattner D, Wiklund R, Lester J, Beinfeld M, Gazelle GS. Reorganizing the system of care surrounding laparoscopic surgery: a cost-effectiveness analysis using discrete-event simulation. *Med Decis Making*. 2004;24(5): 461–71.
46. Ferreira RB, Coelli FC, Pereira WC, Almeida RM. Optimizing patient flow in a large hospital surgical centre by means of discrete-event computer simulation models. *J Eval Clin Pract*. 2008;14(6):1031–7.
47. Fei H, Meskens N, El-Darzi E.Evaluating alternative surgery plans with discrete-event simulation model. In: *2010 IEEE Workshop on Health Care Management (WHCM)*, Venice, Italy. IEEE. p 1–6.
48. Allen RW, Taaffe KM, Ritchie G.Surgery rescheduling using discrete event simulation: a case study. In: *Proceedings of the Winter Simulation Conference 2014*, Savannah, Georgia. IEEE. p 1365–76.
49. Hassanzadeh H, Boyle J, Khanna S, et al. A discrete event simulation for improving operating theatre efficiency. *Int J Health Plann Manage*. 2023;38(2):360–79.
50. Pu Z, Wu S, Han Y. A discrete-event simulation model for assessing operating room efficiency of thoracic, gastrointestinal, and orthopedic surgeries. *World J Surg*. 2024; 48(5):1102–10.
51. Berg B, Denton B, Nelson H, et al. A discrete event simulation model to evaluate operational performance of a colonoscopy suite. *Med Decis Making*. 2010;30(3):380–7.
52. Taaffe K, Ferrand YB, Khoshkenar A, et al. Operating room design using agent-based simulation to reduce room obstructions. *Health Care Manag Sci*. 2023;26(2):261–78.
53. Hart PE, Nilsson NJ, Raphael B. A formal basis for the heuristic determination of minimum cost paths. *IEEE Trans Syst Sci Cyber*. 1968;4(2):100–7.
54. Geiger M, Harrer S, Lenhard J, Wirtz G. BPMN 2.0: the state of support and implementation. *Future Gener Comput Syst*. 2018;80:250–62.
55. Jones LM, Hirst AJ. Visual simulation in hospitals: a managerial or a political tool? *Eur J Opl Res*. 1987;29(2): 167–77. DOI:10.1016/0377-2217(87)90106-8
56. Leeftink G, Hans EW. Case mix classification and a benchmark set for surgery scheduling. *J Sched*. 2017;21: 17–33. DOI:10.1007/s10951-017-0539-8