Successful implementation of discrete event simulation: integrating design thinking and simulation approach in an emergency department

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We address the overcrowding problem in an emergency department (ED) by designing and developing a hybrid methodology that combines design thinking with discrete event simulation. The case study shows how the tested methodology led to a successful implementation of the proposed organisational change in less than 18 months, improving system KPIs (such as patients' waiting time) and ED professionals' quality of work. The results confirm a successful combination of the two approaches in practice, by showing i) how to combine design thinking tools and simulation tools in different design phases (comprehension, abstraction, ideation, and testing), and ii) how the two tools nurture each other reciprocally. The paper concludes with some final considerations regarding the use of simulation in organisational processes design.

Keywords: Emergency department; Simulation modelling; Healthcare; Design thinking

1. Introduction

Overcrowding is a common problem faced by many ED facilities, and as such, has received significant attention from the medical, engineering, and design communities (Hoot and Aronsky 2008). Scholars have proposed a variety of solutions and approaches/methodologies in order to minimise the overcrowding problem. From a design perspective, interventions span from space design (e.g., Abdelsamad et al. 2018) to innovation design (e.g., Hayden et al. 2014); from an intervention perspective, solutions leverage lean techniques (e.g., Chan et al. 2014) as well as organisational development techniques (e.g., Song et al. 2013); from a technological perspective, studies span from the use of RFID technologies (e.g., Tapa et al. 2018) to artificial intelligence (e.g., Grant et al. 2020).

A recent review from Ortíz-Barrios and Alfaro-Saíz (2020) concluded that computer simulation and lean manufacturing are the most prominent approaches for

addressing the leading operational problems in EDs. Indeed, in the last 50 years, the research community has often addressed the overcrowding issue through simulation modelling tools, albeit with different objectives and techniques (e.g., Paul, Reddy, and DeFlitch 2010; Gul and Guneri 2015; Salmon et al. 2018). At present, there is a new paradigm in the design and management of healthcare processes, which has spurred greater interest in managing ED systems while considering the needs of all the involved stakeholders. Design competences are recognised as fundamental for delivering value innovation in healthcare (e.g., Koomans and Hilders 2016). The use of design techniques in healthcare multidisciplinary innovation teams is growing (e.g., Dosi, Mattarelli, and Vignoli 2020) and medical professional journals now recognise that "healthcare providers need to understand that successfully implemented design thinking can enhance patient outcomes, clinical practice, and care quality" (Rahemi et al. 2018).

Despite the large number of studies addressing overcrowding and other related problems in ED, and despite the acceptance of simulation techniques and design thinking as relevant instruments for tackling these problems, there are still barriers to implementing these studies' results in practice (e.g., Mohiuddin et al. 2017; Long and Meadows 2018; Long, McDermott, and Meadows 2019). For this reason, Ortíz-Barrios and Alfaro-Saíz (2020) have advised ED administrators and researchers to combine operational research methods with quality-based techniques and data-driven approaches in order to upgrade EDs' performance.

In this work, we investigate a major ED located in the north of Italy. We study the integration of a discrete event simulation (DES) model with a design thinking process aimed at improving some ED key performance indicators (KPI) alongside professionals' quality of work.

The preliminary results of our case study have been presented at international conferences as Dosi et al. (2019, 2020). The former focused on an early implementation of our simulation approach, while the latter discussed methodological elements related to the use of simulation in healthcare. This paper concludes our research by presenting the full results, as well as the feedback obtained by the ED and the final decisions that were implemented to reduce overcrowding.

2. Literature review

2.1. *Simulation tools and implementation limits*

In the last 50 years, several studies have approached the ED overcrowding topic by adopting simulation tools. The literature is awash in surveys on this topic, confirming the community's high interest in applying simulation techniques to overcrowding and improving the efficiency of healthcare units (e.g., Paul, Reddy, and DeFlitch 2010; Gul and Guneri 2015; Salmon et al. 2018).

In the systematic literature review by Paul, Reddy, and DeFlitch (2010), the authors reviewed works that dealt with the problem of ED overcrowding through simulation tools from 1970 to 2006. They identified three different categories of ED overcrowding simulation studies: (i) descriptive studies focused on defining overcrowding and looking for causes and effects; (ii) predictive studies focused on measures to predict when an ED would become overcrowded so as to implement a temporary solution using extra resources; (iii) intervention-oriented studies that aim at optimising available resources and processes. Our study occupies category (iii). Our work follows in the footsteps of several other studies that have applied simulation to the healthcare context, addressing themes of resource allocation (e.g., Visintin et al. 2017),

resource utilization (e.g., Santibáñez et al. 2009), ambulance location (e.g., Unlüyurt and Tunçer 2016), and layout optimisation (e.g., Sepúlveda et al. 1999), just to name a few.

Despite the large number of papers that seek to improve ED efficiency through simulation techniques, there are known implementation issues that have to be overcome in practice. Back in the 1980s, Wilson (1981) found that out of the 200 computer-simulation projects he reviewed, only 16 reported successful implementations. Twenty years later, Fone et al. (2003) systematically reviewed the use of healthcare simulation models and *'were unable to reach any conclusions on the value of modelling in health care because the evidence of implementation was so scant. [...] Further research to assess model implementation is required to assess the value of modelling*'. Brailsford (2007) suggests that nobody has cracked the problem yet, perhaps because the problem is more social, cultural, and educational than it is technical. The author evidenced that '*countless projects are carried out by academics and published in academic journals, but these models are not widely taken up by other health providers*'. In this same sense, Günal and Pidd (2010) stated that '*Even after 25 years of this [Wilson's] review, all these barriers to the successful implementation of simulation still exist to some degree in all domains, including health care*'. In this vein, it is quite remarkable that, by integrating simulation with design thinking, our study led to a real implementation project supported by the ED only 18 months after the project kick-off.

2.2.*Design thinking to maximise the chance of implementation*

Nowadays, the organisational community is increasingly interested in the design thinking process (Kolko 2015; Elsbach and Stigliani 2018). Design thinking is based on the idea that the central focus of innovation projects should be human needs, building on users' emotions, fears and necessities (Carlgreen et al. 2016). Designing around the people involved in the process reduces the risk of innovation and increases the chance of

practically implementing the proposed solutions (Cocchi, Dosi, and Vignoli 2021). This approach also limits the designer's cognitive biases (Liedtka 2015). There are several design-thinking elements that help to identify implementable solutions, such as iteration and experimentation, tolerance of ambiguity and failure, and interdisciplinary collaboration (Micheli et al. 2019).

In a study of Design thinking for a healthcare audience, Roberts et al. (2016) *"show how design thinking can foster new approaches to complex and persistent healthcare problems through human-centred research, collective and diverse teamwork and rapid prototyping"*. The main point is that innovation arises through the involvement of patients, doctors, nurses, and process engineers in a shared process based on learning rather than applying best practices (Dosi et al. 2020). In this context in particular, Design thinking is configured as a model of co-creation where all stakeholders are involved in the design (Sangiorgi 2010) and designing (or redesigning) healthcare processes from the patients' point of view have been proposed as a key concept to obtain improvements (Lee 2019).

2.3.*Chance of integrating the two approaches*

The literature has presented simulation studies as robust tools for understanding, modelling and deciding upon statistically relevant interventions. However, the weakness of this approach lies in the implementation phase, where stakeholders' reactions and organisational constraints limit applications of the results (e.g., Mohiuddin et al. 2017; Long and Meadows 2018). On the other hand, the design thinking community relies on approaches such as human-centred design, participatory design and prototyping to understand stakeholders' needs and work with them to decide what valuable intervention can be produced and implemented. While this approach is effective, it lacks a strong data-driven decision-making process.

Even though simulation studies and human-centred design present complementary strengths, we are not aware of any case studies that try to structurally integrate these two approaches. Our study developed a methodology that integrates these two approaches and validated the synthesis through a successfully implemented case study.

3. Methodology: simulation integrated into a design thinking process

In our work, we developed and tested a methodology that integrates Design Thinking (DT) with a Discrete Event Simulation (DES) approach. To this end, we designed a processual integration of the two approaches. We aligned the two approaches so they would have matching phases, and specified the tools that might be used in each phase. We tested this integrated methodology in a major Italian ED, seeking to reduce patients' waiting times and improve employees' satisfaction in a quick implementation of the proposed solution. To compare the two methodologies and identify their affiliated phases, we followed the DT framework by Beckman and Barry (2007).

Design thinking is first an approach and a mindset (Dosi et al. 2018); to turn it into a more comprehensible toolkit, scholars and institutions have tried to frame it as a method or a sequence of phases. There are several DT representations in this vein, with models from influential schools (e.g., Stanford, RotmanSchool, DardenSchool) and models from big firms, consultancy companies and institutions (e.g., Continuum, IDEO, IBM, SAP, Design council). Lietdka (2015) and Micheli et al. (2019) briefly compared some of these models. The number of phases used in the models serve to highlight the different cognitive efforts required. However, they do not change the true essence of the approach that all the models share. Here, we build on a four-phase representation (from Beckman and Barry 2007) to simplify the presentation of a parallel use among DT and DES. This version defines the DT process as a sequence of four phases: (i)

comprehension, (ii) abstraction, (iii) ideation, and (iv) solution. This process was chosen because it is easily comparable with the classical DES model (Robinson et al. 2014), where the first phase of comprehension aims at structuring the problem; the second phase abstracts the model to implement it into a conceptual model in a computer; the third one experiments with different scenarios to identify the best-performing solution, and the fourth stage leaves the implementation to the client (DES usually assumes that the optimal solution is acceptable to the organisation).

Table 1 presents the activities and techniques applied at each phase of the proposed process. In the comprehension phase, the design team collects information regarding the organisation, its professionals and processes. In the abstraction phase, the team develops an abstract synthesis of the context: from a design thinking approach, the team develops maps of the problems and stakeholders' needs; from a simulation-driven approach, the team develops a DES model that replicates the ED's current setting and implements it in a computer. After the current system setting is modelled, the model is then validated and the problems are identified. In the ideation and solution phases, DT leverages ideation and prototyping techniques, while the DES-driven approach proposes and evaluates what-if improvement scenarios. The last phase is dedicated to solution testing and implementation efforts. The following sections detail the applications and results for each phase.

Table 1. Activities performed in the ED for each phase: DES integrated into a DT process

Phases	Activities performed with an integrated approach ('DT' for Design thinking driven approach; 'DES' for simulation-driven approach)

(i) comprehension	Interviews (DT) Observations (DT) Identification of workaround (DT) Benchmark and trends (DT) Consistent database containing nine months of quantitative data Extra analysis on laboratory database and x-rays database (DES) Field observations and interviews of EDs' staff for data concerning queue rules/priorities currently adopted by the organisation (DES) Information about personnel work shifts and resource availability (DES) Report on KPIs received from physicians and nurses (DES) In loco data and time measurement survey collection for visit lengths (DES)
(ii) abstraction	Problem-evidence-opportunity exhibits (DT) Needs map (with met and unmet needs of different stakeholders) (DT) Personas (DT) User Journey (DT) ED flowchart and ED Team shifts (DES) Model definition and Model Validation Fig. 3-8 (DES) Model discussion with stakeholders (DES) Insights from data-driven analyses (DES)
(iii) ideation	'How might we' session (DT) Brainstorming, body-storming and other creative methods (DT) Prototyping session (DT) Scenario proposition identification (DES) Scenario proposition analysis (DES)
(iv) testing and implementation	Presentation, Discussion and Validation of scenario results (DES) Choice of the scenario (DES+DT) Test of the organisational capability to enact the solution (DT)

4. Case study - *Comprehension phase*

In this study, we investigate an ED located in northern Italy that covers a region with more than one million inhabitants and admits more than 80,000 patients per year. Given the general dissatisfaction of ED employees (doctors, nurses, and aid nurses) and conflicts

among professionals, the hospital's top management and the head physician asked the authors for support. The project lasted 18 months. The ED design aimed to improve the actual processes: to find possible ways to improve the ED system, in general, and ED professionals' working habits, in particular, so that professionals could be supported in their everyday routines. The top management asked us to design a solution that could be implemented within 18 months from the beginning of the project, as there was a management turnover after this period. It is important to note that the ED under study was renowned as a conservative and hard-to-manage organisation. In the last 15 years, different actors had proposed various interventions—and most of them had failed during implementation. We created an ad-hoc group with professionals of the ED department (five doctors, eleven nurses, four aid-nurses, head nurse, head of physicians and a doctor from the management direction) who were involved in the design process and the decision-making. The group met once every ten days, while the hospital's top management was involved once every three months. From now on, we refer to the multi-professional group as the 'design team'.

The comprehension phase seeks to understand the context. From the DT process, the team collected contextual information through more than 90 hours of observations and 33 semi-structured interviews. These ethnographic (non-participatory) observations aimed at understanding routines and habits in the different areas, as well as workarounds that professionals use to solve recurrent problems. The team collected 80 hours of observations in different areas of the ED (i.e., waiting room for walking patients, waiting room for patients on stretchers, patients acceptance point, triage, areas where medical équipes visit the patients, observation unit), 6 hours of observation in the radiology department, 4 hours in the intensity observation unit, and 2 hours in the emergency medicine ward. The team interviewed professionals from the ED (six doctors, two nurses,

two process nurses, four aid-nurses) and 12 other professionals from ED services, which included radiology professionals (both doctors and technicians), doctors from other specialities (e.g., neurology and cardiology) and hospital bed managers. Interviews were held as semi-structured interviews, in which the interviewees had to explain their everyday work, the problems they face, and the dreams they have. The interviews included support tools such as guided tours, card sorting and conversation starters[1].

From a simulation-driven approach, the comprehension phase entailed defining the patients' flow through ED staff interviews, as well as collecting quantitative data that clarified how the process is structured. Initially, the patients arrive at the ED and meet the triage. The triage process identifies patients' needs and assigns them to an urgency category. The ED under study follows the Italian triage system (i.e., Parenti et al. 2010) and considers four urgency levels, from the least to the most urgent: (i) white, (ii) green, (iii) yellow, and (iv) red. In practice, patients classified with the red code are immediately directed to the high-urgency general treatment room. The patients with other urgency codes are directed to the waiting room and wait to be treated. Treatment starts with a visit from the doctor of the équipe: red or yellow patients are treated by a high-urgency équipe, while white and green codes are likely to be handled by the low-urgency équipe (but they can be treated by a high-urgency équipe if one is unoccupied). After the first visit, the doctor can require further examinations, such as laboratory analysis, x-ray exams or consultation from other doctors (e.g., dermatologist, cardiologist, neurologist, or others). If laboratory analysis is requested, it should be done before other eventual exams, since laboratory exams can inform other exams' interpretation. When all additional examinations are done, the patient is eligible to attend the last visit. She thus goes back

[1] http://www.designkit.org/methods/ to deepen those interviews' tools.

to the waiting room until she can see her doctor. Following this last visit, the patient is dismissed (i.e., she leaves the ED) (see Figure 1 for a workflow representation).

Figure 1. ED flowchart

In addition to the interviews, the team collected input data to set-up the simulation model: service times distribution, patient arrival rates, patient urgency distributions, resources availability, schedules, and queue rules, among others. To retrieve this information, we applied two different techniques: (i) data collection and analysis, and (ii) quantitative time and motion observation. The former allows one to obtain the required inputs by analysing historical data; the latter is usually adopted when historical data is scarce or does not permit one to obtain the main inputs needed. In our case, we had access to a database containing nine months of quantitative data, but some information could not be directly obtained. To establish an accurate service time evaluation, we performed an extra data collection to assess:

- general visit and last visit length, with in loco observation, time measurement and

meetings with the design team;

- patients' permanence in the temporary observation area, assessed via extensive data collected by the professionals who served in the area, who had been recording every patient's entrance to and exit from the area for three weeks;
- Laboratory activity (a different historical dataset provided by the hospital);
- Radiological activity (a different historical dataset provided by the hospital).

Information about personnel work shifts and resource availability was provided by the ED staff, while the information about the organisation's currently adopted queue rules/priorities was retrieved during the observation step and by interviewed experts. The ED has six working teams (i.e., équipes) available per day as depicted in Figure 2 (four teams during daytime on the shift from 8:00 to 20:00 and two teams during night-time on the shift from 20:00 to 8:00) to serve incoming patients in the current setting. Each équipe is composed of a doctor and a nurse who are associated with the low- or high-intensity area; aid-nurses are associated with a specific area of the ED (e.g., low-acuity area) and are asked for help when needed. These teams are mainly dedicated to the general first and last visits, as additional examinations have dedicated personnel.

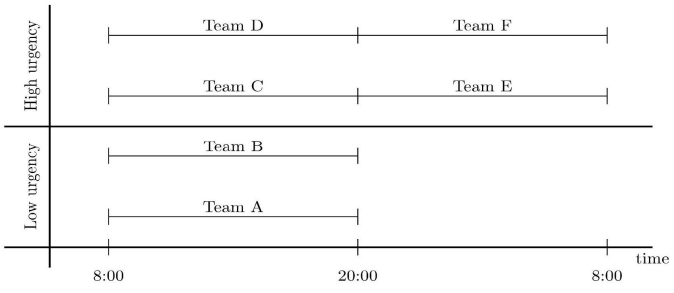

Figure 2. Teams shifts

Furthermore, we directly extracted consistent quantitative information from the database regarding the distributions of patients' arrival rates, urgency and exam requirements, as well as the service times of additional exams (such as laboratory and x-

ray). Information about some service times (such as for the general visits) that could not be obtained from the database was obtained by *in loco* observation and by interviewing the ED's staff. Figures 3 and 4 illustrate the profiles of the urgency code and the patients' arrival distributions per hour of the day, respectively. From these figures, it is possible to observe that the majority of patients entering the ED were from the green category and that most of them arrived at the ED between 8:00 and 12:00.

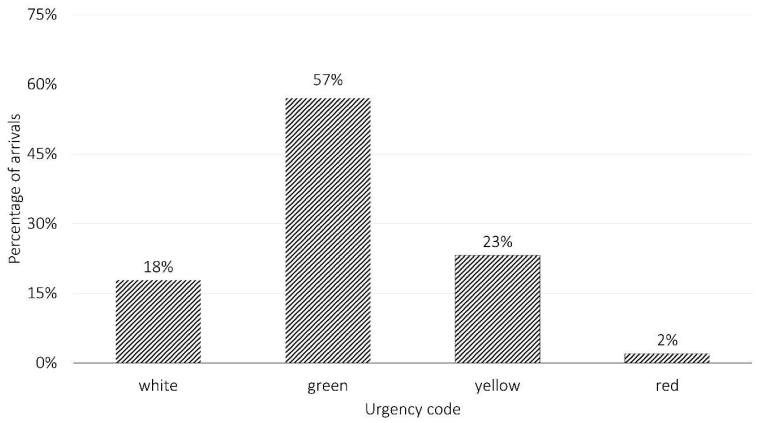

Figure 3. Urgency code distribution

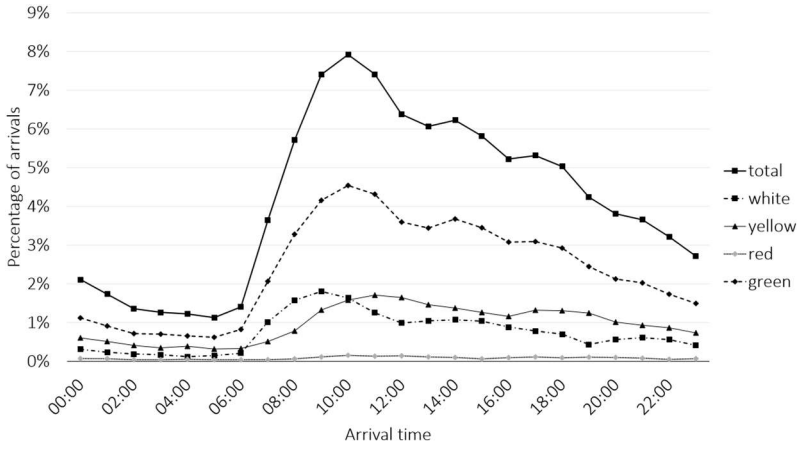

Figure 4. Arrival distribution per urgency code and time of day

Regarding the additional exams required by ED patients in the past, we observed that approximately 85% of them required less than four extra examinations, as detailed in

Figure 5. Among all patients admitted to the ED, 57% were visited at the radiology area and 54% required laboratory exams. Altogether, these two types of exams represented about 70% of all exams performed.

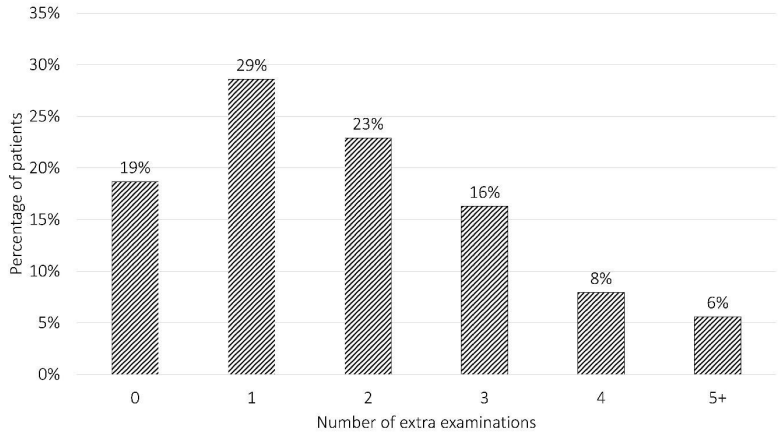

Figure 5. Extra examinations required apart from the first visit

The laboratory exams are performed in a building close to the ED. An external service retailer handles the test tubes' transportation from the ED to the laboratory every half-hour (the waiting time for transportation and the transportation time itself directly impact the total laboratory examination time).

5. Case study - Abstraction phase

Information collected in the comprehension phase led to the abstraction of different elements. Coherently with a DT approach, the team identified four ED problems (considered as horizontal elements that touch different professions and areas of the ED), as well as developed two healthcare professionals' needs maps.

Each ED problem is presented in a Problem exhibit (expressed with the PEO problem-evidence-opportunity tool[2]). Here, as an example, we report the 'Global view' PEO, reported in Figure 6.

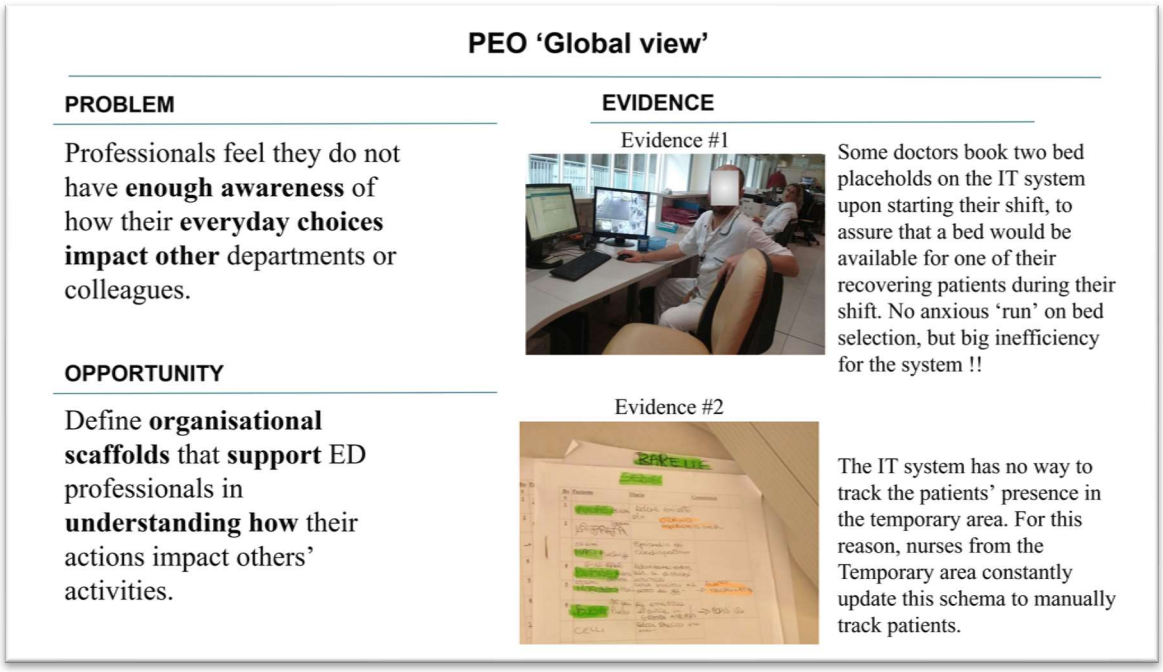

Figure 6. PEO tool – Global view

The 'Global view' problem relates to the fact that professionals feel they do not have enough awareness of how their everyday choices impact other departments or colleagues. Among the evidence, the exhibit reports behaviours that are inefficient or adverse to the ED functioning. For example, a common issue stems from ED patients who cannot go home and need to be admitted in the hospital wards, but the hospital lacks sufficient beds. Doctors explained how that issue carried much emotional distress—to the point that some of them booked two bed placeholds (one for men and one for women) on the information system upon starting their shift. This gave them assurance that a bed would be available for one of their recovering patients during their shift. This behaviour helps doctors avoid the anxious 'run' on bed selection, but represents an inefficiency for

[2] See Problem-Evidence-Opportunity tool from Design thinking tools that help frame the problem.

the system: after all, the IT system considers the reserved bed as taken even if it is empty (and other doctors' patients could use it).

Another evidence related to the 'Global view' problem comes from the temporary observation area. That area hosts patients who are waiting for tests execution and results, but cannot stay in the general waiting room because of their critical conditions. A nurse explained that patients are often brought into this area without information or advice, and since the IT system has no way to track the patients' presence in the temporary area, the location is hard to control. Based on the 'Global view' problem definition and related evidence, the exhibit in Figure 6 identifies a design opportunity: to define organisational scaffolds that support ED professionals in understanding how their actions impact others' activities.

The abstraction phase synthesises stakeholders' need identification as well, so that the design team will be able to design around stakeholders' needs in the following phases. For example, nurses in the triage and waiting area feel the need to work without being continuously interrupted by waiting patients, their relatives or other colleagues. Meanwhile, doctors in the visiting area need to diminish the number of 'inherited' patients from the previous équipe, so that their shift can start smoothly and the system can diminish the duplication of activities (while facilitating shorter handovers).

The abstraction phase of the simulation-driven approach defines and validates the simulation model. The developed model is structured around the patient flow process described above and represented in Figure 1. Since the aim of the project is to address overcrowding in the general ED, the model only traces patients that affect the general ED and needs to highlight the ED personnel space of the agency (e.g., triage and équipes

decisions regarding queue priorities or extra exams), as well as the interaction among ED and other services.

In the model, the patient arrivals are modelled using the inter-arrival data extracted from the hospital database. In the following part, we present the essential elements of the process that we decided to represent in the model, together with the percentages computed from the data. The patients' arrival rate follows a daily cycle, as presented in Figure 4. We analysed the arrival of patients per hour of the day and per day of the week, and we considered only 'patients per hour' as significant seasonality. The patient goes through a triage that identifies both the patient's first visit type (general ED for 79% of patients, orthopaedic ED for 16%, dermatological ED for 5%) and the patient's category (following the data in Figure 4). The three EDs have only triage in common, and patients in orthopaedic or dermatological EDs then disappear from the model. Patients are then moved to the waiting room, and the first available équipe that fits the urgency serves the patient. Low-urgency équipes serve white (18%) and green (57%) patients, and high-urgency équipes serve yellow (23%) and red (2%) patients, but when idle, high-urgency équipes also serve green and white patients. The queue follows the first-in-first-out rule by category, i.e., red category patients have maximum priority, yellow category patients have priority over green and white ones, and so on. During the first visit, doctors can require exams (the number of exams required follows data in Figure 5), such as laboratory examination (with 54% of probability), x-rays examinations (55%), therapies interventions such as intravenous therapies (11%), special visits such as otolaryngology (7%), orthopaedics (3%), cardiology (3%), neurology (2%) and other exams (17%). Laboratory exams are executed first. Once all exams are performed, patients wait for the last visit, meaning that they line up in the queue with all the other patients (including the ones waiting for the first visit), and the patient's urgency drives the priority. Once visited,

patients can leave the system. Regarding exams' delivery, the actual laboratory capacity (i.e., number of exams that can be processed in parallel) is so high that it can be considered practically unlimited.

We defined the simulation objectives by selecting a set of KPIs from the ED literature and then choosing the most significant KPIs with the design team. Out of this first round of discussion, we selected *length of stay* (LoS), *waiting time* (WT) for the first visit, and *percentage of outliers* as a percentage of patients who wait more than a given threshold time. Threshold values depend on the patients' urgency code and the ED's internal, regional and national regulations, which were obtained from the guidelines document by the Italian Ministry of Health (Ministero della Salute 2001). In a second discussion, the team agreed on the KPIs' relevance, but suggested that outliers were the least relevant KPI: based on the ED periodical report, the ED's outliers are largely below the suggested thresholds.

From data-driven analyses, we gathered some significant insights to facilitate discussions about further solutions. First, work shifts do not fit the patients' arrival pattern, meaning that the number of équipes is always the same during the day and does not follow the curve of patients' arrivals. Second, the average waiting times (Figure 7) show that when there is a change in the équipes (end of shift - start of shift), the waiting time increases in the following hour. Third, the actually fixed priority rules for the visit may cause long waiting times for the less urgent patients (see Figure 8).

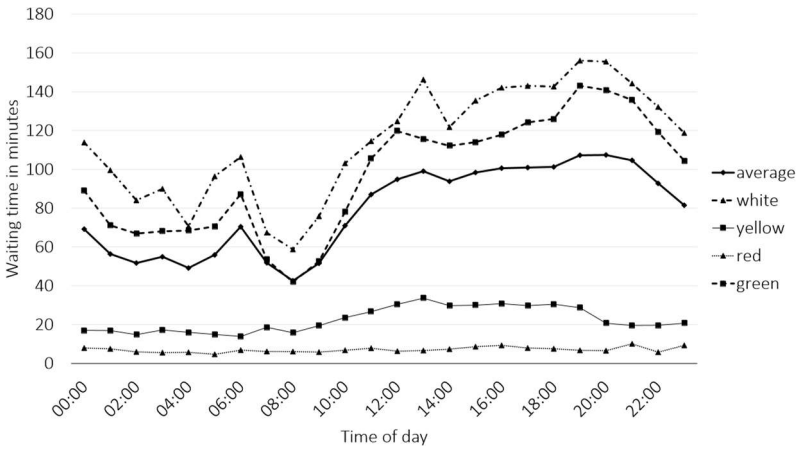

Figure 7. Average waiting times per urgency code and time of the day

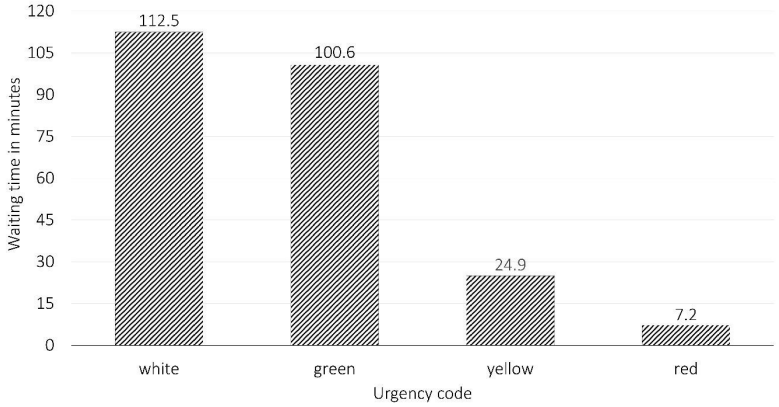

Figure 8. Average waiting times per urgency code

Moreover, the model confirmed ED professionals' suggestion that laboratory tests represented a process bottleneck. We thus investigated the total laboratory examination through another database, and we observed that this time is mainly composed of (i) waiting time, (ii) effective examination time and (iii) miscellaneous times. Figure 9 shows how these different times vary during the day and impact total time. From this figure, it can be noted that the laboratory total time tends to be higher at the peak of patients' arrivals. We observed two peaks, at 7:00 and 19:00, demonstrating that the shift change also impacts the laboratory waiting times.

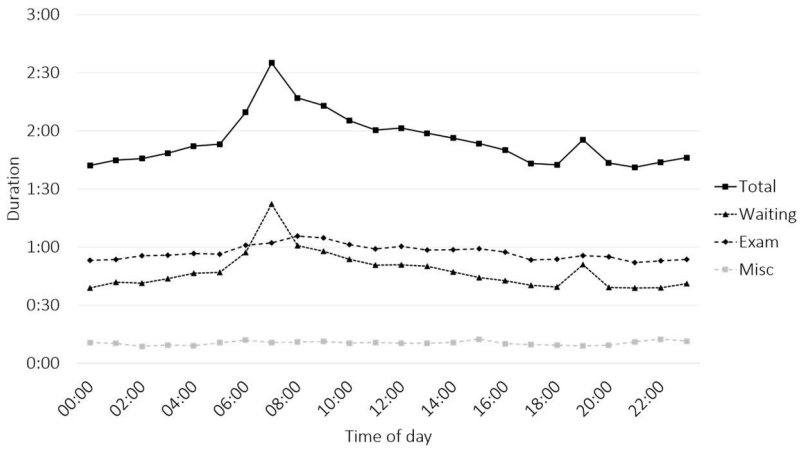

Figure 9. Laboratory service time composition

Once all crucial data were considered and integrated into the developed DES model, we moved to the model validation phase. In this crucial phase, we need to establish the model's accuracy in simulating the real system (e.g., Sargent 2011). We completed this step through multiple actions: The first validation is a face validation, meaning that ED stakeholders comment on the comparison between historical KPI data with simulated KPI data (validation mode aligned with Aringhieri 2010). Historical KPIs represent the average values for nine months of operations, and simulation KPIs were obtained by running the simulation model ten times, where each run simulates one month of ED work. The obtained average results are presented in Table 2: WT_{1st} *waiting time for the first visit* shows the average waiting time for the first visit, *LoS* shows the average length of stay (in minutes), and *Outliers (%)* presents the percentage of patients, by priority, that exceeded the threshold time for waiting for the first visit. WT_{1st} is the most important KPI, and while our results differ from the historical ones, this may be attributable to the presence of some outliers. In fact, if we exclude the 2.5% of the patients with the highest waiting times from the analysis, we obtain a historical WT_{1st} of 74.4 min. Regarding KPIs, we discussed the WT_{1st} value with the whole healthcare team. The design team explained that in reality, WT_{1st} ends when the doctor opens the patient's electronic folder, and thus

the system officially registers that the patient is in charge of a doctor, and the first visit starts. However, we realised that doctors often open the patients' folders only at the end of the visit to insert medical data. This means that in the past records, the WT_{1st} is longer than it is in reality. Based on the previous considerations, ED managers and staff involved in the study approved the model.

Table 2. Model validation results

Scenario	WT_{1st}	LoS	Outliers (%)	
			green	white
Historical	83.27	206.43	9.62	14.67
Simulation	70.52	208.60	3.88	25.47

The second action to validate the model was confidence intervals validation, a quantitative method for validating simulation models. We followed the procedure in Petty (2012). We selected the WT_{1st} and the *LoS* as the response variables and assumed that the population distribution is normally distributed; we executed our model ten times and calculated the mean and standard deviation (WT_{1st}: mean 70.53 - stDev 6.02 minutes; *LoS*: mean 208.60 - stDev. 9.06 minutes). By defining a confidence level of 95% and using the *t*-distribution with nine degrees of freedom, we obtained a confidence interval of [66.22; 74.83] for the WT_{1st} and [202.12; 215.08] for the *LoS*. The historical average value for the WT_{1st} (77.85) is slightly outside the confidence interval, but it is very close to the upper limit of the interval; the historical value for the *LoS* (202.57) is inside the confidence

interval. Based on these results and the other validation methods we performed, we consider the model to be valid and proceed to the next phase.

6. Case study - Ideation phase

The ideation phase with DT was first developed through a two-hour workshop, where ED participants ideated and developed ideas that could answer the needs identified in the abstraction phase. The authors facilitated the session and led a series of exercises. The first exercises presented the ED team with a list of 24 cards of 'How might we'[3] questions. Each card presented a front side with a persona (e.g., 'young nurse', 'patient's relative') and a quote representing her need, and a backside with the 'how might we' question (see Figure 10 for an example). Each participant was asked to express a preference for the three most urgent questions to address, by voting for them. Participants were then split into three different multi-professional sub-groups, and each sub-group was assigned to one of the most voted cards. They started a brainstorming session (under the brainstorming rules[4]) to define possible rough ideas that address the 'how might we question'. The sub-group had to then gut-check the most promising ideas and represent them with drawings, Legos, or role-play sketches. The other sub-groups had to deliver feedback.

[3] https://www.designkit.org/methods/how-might-we

[4] https://www.designkit.org/methods/brainstorm-rules

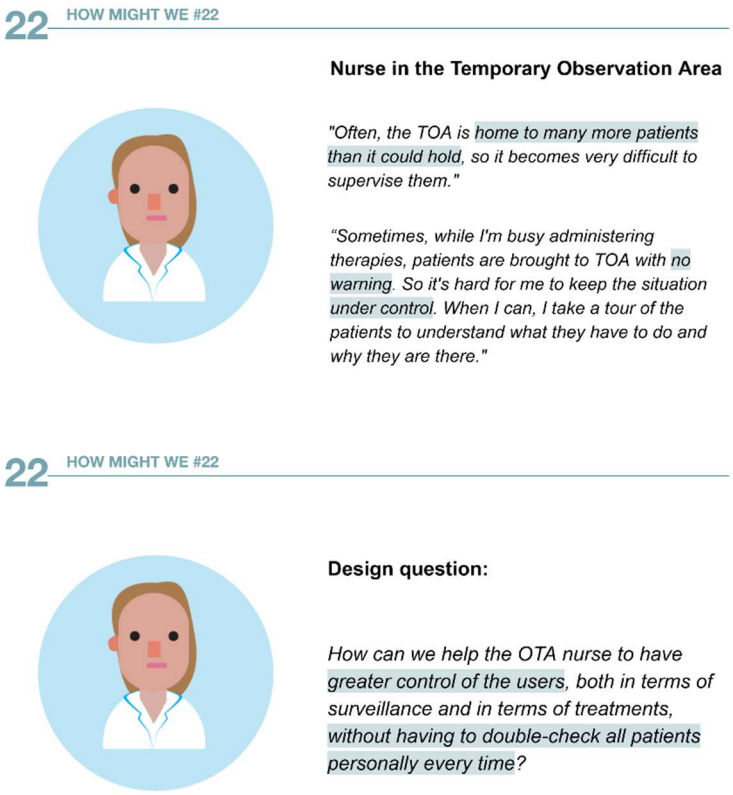

Figure 10. How might we card

In the next iterations, we held similar workshops with larger groups to address specific topics. For example, one of the workshops focused on the dynamics among radiology services and the ED; radiologist doctors and technicians were involved in the ED group for a joint ideation session. These meetings produced several ideas: for example, the team addressed the problem of white urgency patients who do not need emergency treatment, but need to feel safe with a doctor visit. The team thought of a senior doctor who pre-triages patients and, in cases where she identifies white priority patients, re-addresses them towards their family doctor, or perhaps a specific general-doctor office that could be next to the ED.

Regarding the simulation, the ideation phase produced a set of scenarios to improve the ED performance. In particular, we developed seven main what-if scenarios,

triggered by the problems that we identified in the comprehension and abstraction phases, complemented by common solutions from the literature. Table 3 lists the problems (and selected solutions) that we addressed in the simulation phase. Some of these problems were identified in the abstraction phase with a purely data-driven approach, such as the fact that (1) 'the work shifts do not fit the arrival pattern of the patients' or that (3) 'the fixed priority rules for the visit may cause long waiting times for the less urgent patients'. Other problems were informed by insights gained from observations and interviews in the field, and later confirmed with data analysis in the abstraction phase. Among those insights are the fact that (2) 'many patients wait a long time for the last visit before being dismissed' or that (7) 'the blood sample transportation required for the laboratory exams is very inefficient and usually requires a significant amount of time'. Other problems were significant enough for users that the team decided to address them in a workshop during the ideation phase. For example, the team addressed the problem (5) 'many of the patients admitted in the ED actually do not need emergency treatment'. During the workshop, the team ideated three solutions to avoid treating the white urgency patients, such as (i) pre-triaging patients and re-addressing those white patients to a different service; (ii) developing a strict collaboration among ED and local family doctors to make family doctors more present; (iii) an ED information car, going around the city to inform citizens about the cons of using ED when not necessary. After the gut check, the team decided to develop idea (i). Before deciding to test that solution 'for real' in the organisational arena, we developed a what-if scenario to assess whether problem (5), if solved, would significantly change the ED's performance.

Problem (6) was explicitly required by the ED personnel and developed just to avoid organisational resistance. Indeed, interviewees reported several times that the work teams are overworked (6) and asked for extra resources (i.e., one extra équipe). Top

management and directors reported that data did not show an overworked situation, and that they were against adding extra resources without improving the actual condition. However, a group of professionals asked to verify the feeling of 'overworking' and the effect of an extra équipe within the simulation. For this reason, we developed an ad-hoc simulation scenario.

To tackle the identified problems, we leveraged solutions from the literature as well as some best practices known to the team. For each problem, the design team identified the best practice (see Table 3 for the list) and referred to it while developing the respondent scenario.

Table 3 - Problems and solutions in the ED

ED problem (problem identification triggers)	*ED proposed solution*	*Scenario*
(1) the work shifts may not be fitted to patients' arrival pattern *(data analysis)*	(1) adjust the team shifts to the demand (Sinreich, Jabali, and Dellaert 2012)	A - considers a change in the personnel work shift
(2) many patients wait a long time for the last visit before being dismissed *(data analysis+observation)*	(2) increase the priority for the last visit over the first one (Vanbrabant, Braekers, and Ramaekers 2020)	B - gives priority to the last visits over the first ones
(3) the fixed priority rules for the visit may cause long waiting times for the less urgent patients *(data analysis+interviews+ observations)*	(3) dynamically change the patients' queue priority, based on their WT (Ferrand et al. 2018)	C - proposes a new dynamic priority rule for the queue to the first visit
(4) for most of the patients, laboratory exams are required, but only at the end of the first visit *(data analysis+interviews)*	(4) identify and require laboratory exams at the triage process *From ideation of design thinking + benchmarking in similar hospitals + literature review (Visintin, Caprara, and Puggelli 2019)*	*D - partially* anticipate the request of laboratory exams (requested during the triage process)

(5) many white urgency patients do not need any emergency service *(interviews+workshop)*	(5) reduce the number of non-eligible patients that arrive at the ED	E - seeks to reduce the number of non-eligible patients in the ED
(6) the work teams feel to be overworked *(interviews)*	(6) test the possibility of using additional work teams	F - evaluates the addition of one équipe for the last visit
(7) the blood sample transportation required for the laboratory exams is very inefficient and usually requires a significant amount of time *(interviews + data analysis on the supplemented laboratory dataset)*	(7) improve the transportation system for the blood samples	G - simulates the reduction in the laboratory lead time
The last scenarios, labelled Combinatory 'Cb', are formed by combining multiple types of scenarios from A to G.		

The following practical actions were associated with the aforementioned goals: (i) offset the starting and ending times for the team shifts; (ii) implement an alert system to support the dynamic priority rule; (iii) improve triage process by immediately dismissing non-eligible white urgency code patients and by requiring laboratory exams to a specific group of patients during this process; (iv) admit and train personnel for an additional work team; and (v) implement a more efficient transportation system.

We then modelled these practices into parametric solutions for our model. Based on the discussion above, we defined the following parameters to characterise our proposed scenarios:

(1) t: team shifts start (and finish) t hours later than in the current setting;

(2) p: if $p = 1$, then the last visit has priority over the first one; otherwise, if $p = 0$, the priority follows the current setting;

(3) τ_g and τ_w: patients with green or white codes are moved to the head of the queue for the first visit if their waiting time exceeds τ_g and τ_w minutes, respectively;

(4) e: e% of white code patients are not admitted to the ED, assuming that they could be directed to more appropriate facilities;

(5) l: l% of the laboratory exams could be required during the triage process;

(6) a: a additional work teams are considered;

(7) r: the lead time for laboratory exams is reduced by r minutes by avoiding long transportation times.

Table 4. Parameters

Parameter	Chosen values
t	1, 2
p	1
τ_g	60, 90, 120, 210
τ_w	120, 180, 210
e	5, 10, 15, 20
l	10, 15, 20, 50, 60, 75, 100
a	1
r	10, 15, 20, 25, 30

Table 4 shows the chosen parameter values. By combining them, we establish our scenarios. Hence, let us define $S = (t, p, \tau_g, \tau_w, e, l, a, r)$ as a generic scenario formed by a combination of these parameters. For example, a scenario $S = (-,-,120,-,5,-,-,10)$ means that: the queue priority for green-coded patients changes if their waiting time exceeds 120 minutes; 5% of white urgency code patients are dismissed during the triage process, and the lead time for laboratory exams is 10 minutes shorter. The "−" sign states that the current configuration is not changed. Based on this observation, Table 5 presents the proposed what-if scenarios.

The DES model was implemented using the software AnyLogic 8.1.0. The experiments were executed on a PC equipped with an Intel Core i7-7500U 2.70GHz processor and 12GB of RAM. Each proposed scenario was simulated ten times, where

each run simulated 30 days of working activity in the ED. We compared the average results of these runs with those obtained by the 30-day simulations of the current ED setting run 10 times, as shown in Table 2. We evaluated the scenarios by measuring their LoS, WT_{1st}, and number of outliers. In addition, for the simulated results, we also show the average results for the WT for the last visit, referred to as WT_{last}.

Table 5. Proposed scenarios

Id	Parameters								Id	Parameters							
	t	p	τ_g	τ_w	e	l	a	r		t	p	τ_g	τ_w	e	l	a	r
A.1	1	-	-	-	-	-	-	-	F.1	-	-	-	-	-	-	1	-
A.2	2	-	-	-	-	-	-	-	G.1	-	-	-	-	-	-	-	10
B.1	-	1	-	-	-	-	-	-	G.2	-	-	-	-	-	-	-	15
C.1	-	-	90	180	-	-	-	-	G.3	-	-	-	-	-	-	-	20
C.2	-	-	210	210	-	-	-	-	G.4	-	-	-	-	-	-	-	25
C.3	-	-	60	120	-	-	-	-	G.5	-	-	-	-	-	-	-	30
C.4	-	-	90	-	-	-	-	-	Cb.1	-	-	120	-	10	50	-	-
C.5	-	-	60	180	-	-	-	-	Cb.2	-	-	120	-	10	20	-	-
C.6	-	-	60	210	-	-	-	-	Cb.3	-	-	120	-	10	50	-	30
C.7	-	-	120	-	-	-	-	-	Cb.4	-	-	120	-	-	50	-	-
D.1	-	-	-	-	-	50	-	-	Cb.5	-	-	90	-	10	50	-	-
D.2	-	-	-	-	-	60	-	-	Cb.6	-	-	-	-	-	10	-	15
D.3	-	-	-	-	-	75	-	-	Cb.7	-	-	-	-	-	20	-	15
D.4	-	-	-	-	-	100	-	-	Cb.8	-	-	-	-	-	10	-	20
D.5	-	-	-	-	-	10	-	-	Cb.9	-	-	-	-	-	15	-	20
D.6	-	-	-	-	-	15	-	-	Cb.10	-	-	-	-	-	20	-	20
D.7	-	-	-	-	-	20	-	-	Cb.11	-	-	-	-	-	10	-	30
E.1	-	-	-	-	5	-	-	-	Cb.12	-	-	-	-	-	15	-	30
E.2	-	-	-	-	10	-	-	-	Cb.13	-	-	120	-	15	-	-	-
E.3	-	-	-	-	15	-	-	-	Cb.14	-	-	-	-	-	50	-	30
E.4	-	-	-	-	20	-	-	-	Cb.15	-	-	120	-	15	50	-	30

Table 6 summarises our obtained results. The values in boldface indicate a significant KPI change by the referenced simulated scenario when compared to the current simulated setting. The results obtained for scenario *A* indicate that offsetting the team shifts would contribute to reducing the patients' average LoS, mainly by reducing the waiting time for the last visit. The same was true for scenario *B* (where the last visits have priority over the first ones). However, the other considered KPIs worsened,

especially the waiting time for the first visit and the percentage of outliers. The scenarios of type C have a direct impact on the outliers indicator. This is expected because the queue priorities for patients with a long WT change when this value approximates the threshold values. The scenarios of type D consider that a percentage of laboratory exams are required during the triage process. As this service is performed without requiring the patients to be present, it helped to reduce waiting time and positively impact the LoS indicator (as presented in Table 6). Concerning the results for the scenarios of type E, the related actions directly impact the number of patients arriving at the ED and thus improve the values for most of the considered KPIs. Similarly, scenario F considered an additional work team and also saw improvements for all considered KPI. Scenarios G, as expected, achieved a consistent reduction in the LoS thanks to finalizing the laboratory results faster than in the current setting. In general, scenarios D and G act directly on the system bottleneck (i.e., the laboratory exams) and are thus very effective. Indeed, both cases reduced the average LoS. Likewise, all of the combined scenarios were able to improve the average LoS, mainly due to synthesising the best characteristics from scenarios of types C, D, E, and G. In particular, scenarios $Cb.3$ and $Cb.15$ presented a reduction in the LoS of about 16% and 19%, respectively.

Table 6. Results obtained for the scenarios

Scenario	In	WT_{1st}	WT_{last}	LoS	Outliers (%) green	Outliers (%) white
Curr. setting simulation	238.23	70.52	54.94	208.60	3.89	25.48
A.1	236.93	68.67	**45.34**	**198.42**	3.48	23.79
A.2	237.35	71.61	**38.58**	**195.37**	3.30	26.71
B.1	235.64	**99.91**	**5.93**	**196.31**	**12.04**	**37.95**
C.1	237.41	66.98	53.73	204.02	3.26	23.29
C.2	237.41	69.38	51.15	204.07	4.31	**8.75**
C.3	236.56	69.10	55.11	206.74	3.73	23.91
C.4	237.43	72.54	43.40	**199.67**	**0.00**	29.32
C.5	237.74	69.19	55.63	207.54	**1.61**	23.88
C.6	237.30	69.28	55.33	207.00	**1.23**	23.70

C.7	237.34	69.64	53.76	**205.97**	**0.24**	23.98
D.1	236.45	69.34	52.61	**194.42**	4.14	23.60
D.2	237.65	69.06	52.78	**191.92**	3.80	24.31
D.3	236.71	68.35	51.28	**186.85**	3.81	23.89
D.4	237.55	70.93	53.84	**185.97**	3.91	25.70
D.5	236.93	71.01	56.32	207.67	4.58	26.42
D.6	237.35	69.79	54.12	**202.90**	4.37	25.63
D.7	237.91	68.05	51.76	**198.47**	3.34	23.25
E.1	235.74	67.67	53.93	**203.98**	3.52	24.27
E.2	237.58	**62.91**	**47.23**	**195.00**	2.81	**20.45**
E.3	231.47	**59.93**	**45.19**	**190.78**	2.77	**20.75**
E.4	228.00	**53.88**	**40.25**	**182.05**	**1.97**	**16.73**
F.1	236.36	**39.91**	**24.36**	**154.97**	**0.37**	**7.17**
G.1	237.19	69.31	54.43	**202.25**	3.77	23.76
G.2	236.73	68.39	53.74	**199.30**	3.56	24.37
G.3	236.44	68.26	53.34	**197.83**	3.63	23.22
G.4	236.65	69.08	53.09	**196.80**	3.24	24.47
G.5	237.65	69.37	54.03	**195.42**	4.12	24.62
Cb.1	234.79	**65.38**	51.49	**191.07**	**0.04**	22.27
Cb.2	232.98	**63.22**	**47.81**	**192.54**	**0.13**	22.10
Cb.3	233.35	**61.38**	**45.72**	**174.29**	**0.08**	20.10
Cb.4	237.96	72.13	53.14	**197.02**	**0.14**	26.26
Cb.5	237.28	75.92	**45.11**	**194.79**	**0.02**	**32.06**
Cb.6	235.70	67.66	53.50	**196.74**	3.82	23.02
Cb.7	237.08	68.93	53.61	**195.86**	3.64	24.97
Cb.8	236.35	69.50	52.04	**195.50**	4.49	24.28
Cb.9	237.68	69.94	52.41	**195.33**	4.02	24.99
Cb.10	236.62	69.20	52.68	**194.46**	4.23	23.79
Cb.11	236.45	69.78	51.58	**192.45**	3.95	24.23
Cb.12	238.40	69.15	53.92	**192.68**	3.73	24.38
Cb.13	230.39	**56.55**	**44.46**	**187.19**	**0.08**	**18.18**
Cb.14	236.83	67.97	53.17	**185.73**	3.65	24.24
Cb.15	230.62	**57.56**	**41.69**	**168.37**	**0.12**	**18.84**

7. Case study - Solution phase

We presented the scenario results in a periodical meeting with the design team group and the top management. The opening was a detailed presentation of the scenarios and their effects on KPIs. During that meeting, the group proposed several elements of discussion regarding how each scenario (besides KPIs) could be accepted and implemented by the ED and hospital personnel. In particular, the team was asked to consider the feasibility (do we already have internal competences? Is technology available?) and viability (costs

and time for the implementation) of the solution.

The top management started by mentioning that hiring a new work team (like in scenario F) was not a viable option, and that 'we should improve working on ourselves rather than putting extra resources on the table'. From that point on, scenario F represented an external reference point for other scenarios. Scenario *A* was rejected by the group despite the positive results of the simulation, as no doctor or nurse wanted to go through a 'change of routines that would have destroyed their family lives'. In fact, arriving at work only one or two hours later meant skipping lunch or dinner with their families. Scenario B and C proposed interventions on the queue rules. Scenario B imposed a fixed rule whereby all doctors could re-evaluate patients, which represented a promising alternative to speeding up the dismissal process. However, the team evaluated the difficulties of imposing a formal rule to give priority to the re-evaluation visit over the first visit. Ultimately, the team decided to reject this scenario. Scenario *C* represented an alternative for managing the waiting room. After agreeing on a reference time for moving patients forward in the waiting list, the design team identified scenario C as an effective and straightforward rule that is easy to follow.

Scenarios *D* and *E* were accepted as promising options for reducing overcrowding, although the whole design team recognised the huge work necessary to implement such scenarios. In fact, implementing scenario D (triage nurses anticipating exam requirements) would require an in-depth training process and a supplemental investigation to identify the exams that could be required by the triage based on patients' symptoms. Doctors also warned the group about a legal debate regarding the degree to which nurses can substitute doctors in exam prescriptions. Similarly, scenario E (reducing non-eligible patients) meant building on concepts developed by the design team during

the ideation phase. Finally, scenario G quickened the sub-process of laboratory exams (from the moment the doctor requests a laboratory exam to the moment the laboratory receives the test tube) and was well accepted by everybody.

As a final decision, the design team identified scenario G as the preferable target for the first implementation effort and decided to postpone the implementation of scenarios C, D, and E to a later date. They wanted to understand whether other implementation options would require less training and impact on the organisation.

After receiving approval from top management, the team designed and planned practical actions for implementing scenario G with a design-thinking approach. Three organisational prototypes were hypothesised and simulated to hasten the sub-process of laboratory exams: (i) more frequent deliveries of test tubes to the central laboratory by the actual transport supplier; (ii) internal aid nurses dedicated to the transport of test tubes; (iii) a pneumatic post system. These hypotheses correspond to the tested scenarios G1 to G5. The detailed results obtained by simulating these scenarios are shown in Table 7. Column "Scenario" indicates the tested scenario, whereas columns "In", "WT_{1st}" and "LoS" respectively show the simulation outputs concerning the number of patients, waiting time for the first visit, and the length of stay. In this table, we present the calculated means, standard deviations and confidence intervals over ten runs for each tested scenario. The confidence intervals were calculated following the same procedure adopted to validate the model.

Table 7. Detailed results obtained for the G scenarios

Scenario	IN		WT_{1st}			LoS		
	mean	stDev.	mean	stDev.	Conf. Interval	mean	stDev.	Conf. Interval
G1	7116	107	69.31	9.70	[62,37; 76,25]	202.25	16.93	[190,14; 214,36]
G2	7102	76	68.39	7.22	[63,22; 73,55]	199.30	14.07	[189,23; 209,36]

G3	7093	72	68.26	8.73	[62,02; 74,51]	197.83	16.65	[185,92; 209,74]
G4	7100	59	69.08	7.77	[63,53; 74,64]	196.80	15.41	[185,78; 207,83]
G5	7130	69	69.37	6.08	[65,02; 73,72]	195.42	11.01	[187,54; 203,29]

The innovation office made a first assessment of the investments required by the three prototypes, and surprisingly, the pneumatic post had the highest ratio of cost savings/investments. The top management decided to extend the pneumatic post to the whole building where the ED is located, and they approved the rules to access the pneumatic post (hours of the day and urgency of exams). The top management allocated the budget for investing in a pneumatic post system across the hospital, connecting the ED building and the exam lab building. Thus, the pneumatic post requirement was designed by the hospital's innovation and technical office. A public announcement to build the pneumatic post system in the hospital was launched only a few months later. With precise data coming from the simulation, the top management and all the stakeholders had a clear picture of the increase in service quality for patients and staff, as well as the associated savings. This clarity helped to exert the right amount of pressure on the whole organisation so that the project could move fast. As of today, the expanded pneumatic post is operational at the hospital.

The project thus answered the top management's kick-off requirement that a solution be implemented and working in less than 18 months from the project kick-off.

8. Discussion: integrating simulation technique with design thinking

In our research, we exploited the main strengths of simulation and design thinking by integrating in the presented case study the use of rigorous and extensive simulation modelling, as well as the deep use and contextual understanding of the design thinking process. The case study emphasises the difference in organisational decisions that are

driven by a pure simulation approach versus a mixed approach featuring simulation and design-thinking. When reliable and verified data encounters concrete and tested organisational needs, information density increases and decision-makers have the confidence needed to move the projects forward

Indeed, the whole project assumes a richer perspective by integrating the two methods. In the comprehension and abstraction phase, we could understand the context both with an empathic-driven and numerical-driven approach. In fact, in those two phases, design-thinking drove information collection from users and professionals, mainly building on ethnographic tools to highlight the problems and needs of professionals and groups, both in areas of the ED and the ED as a whole. By contrast, the simulation-driven approach collected information about the systemic organisational processes, coupling a quantitative effort with qualitative information identified by the design-thinking process.

In the abstraction phase, both approaches help the design team identify the problems to tackle. By employing a user-journey, the design team has an emotional and needs-driven approach to visualizing patients' experience, while the process modelling supports the efficiency view and the control of process-driven KPIs. However, the two approaches ultimately identify different types of problems. On one side, the DES model alone helps to identify process bottlenecks, possible inefficiencies and system imbalances. The time required by laboratory exams, or the fact that work shifts do not fit patients' arrival pattern, are two such examples. On the other side, design thinking helps identify human needs and opens up new possibilities for deeply understanding the organisation. Doctors' behaviour of ordering extra beds for admission – even when no patient was there – shows that an emotional element affects organisational resource management; even worse, it affects the 'quality' of data that is stored in the ED databases.

In the comprehension and abstraction phases, integrating the two approaches also leads to their reciprocal enrichment. In this intertwinement, we used simulation to confirm or disconfirm perceptions and problems gleaned during the design thinking ethnographic approach. For example, design thinking led to the identification of a stressful relationship between the ED and the radiology department ('because they are always late') while the simulation model indicated that this was not the case (as the radiology did not represent a process bottleneck). This iteratively re-informed the design thinking process, leading the design team to more deeply probe the relationship among ED doctors and radiologists. As a result, the design team identified that the stressful element in this relationship involved the different use of priority codes between the two departments, which was rectified through a specific organisational intervention. Conversely, perception drove the simulation model: for example, the équipes reported that doctors and triage nurses sometimes decided not to follow organisational practices for queue management. Thus, the design team decided to specifically focus on queue priorities in the simulation modelling activity.

In the ideation and testing phases, we combined the rigorous measurement of simulation scenarios with the flexible and creative experimentation offered by design thinking. The operational research literature has affirmed the benefits of using simulation tools to model different solutions through what-if scenarios, as well as the need to involve different stakeholders in their definition, analysis, and evaluation (Tako and Kotiadis 2015). We interacted with stakeholders to definition the scenarios and discussed what could be easily implemented (or not) from the organisation. The use with DT pushed the organisation to maintain a divergent vision for solutions that exceeded the possible processes mapped in the simulation. For example, the design team ideated and tested prototypical solutions addressing the issue of white urgency code patients; among those

solutions, some services required new organisational roles that spanned outside the hospital. This would not have happened if we had used the simulation as a platform for solutions' ideation. In fact, when you ideate around the model, the model tends to represent the constraints of your ideation, and thus it limits the scope of the ideation process.

Coherently with the previous ideation effort, scenario E simulated a lower number of white code patients, who could be treated outside the ED. This scenario is not comparable per se with other scenarios (as fewer patients means different initial conditions), but it lets the design team understand whether its KPIs' improvements are worth the potential issues caused by implementing the design thinking solutions. The team needed to know how many white code patients the solutions should address in order to significantly impact on organisational KPIs. The same happened regarding the number of anticipated exams at triage (scenario D). How many exams need to be anticipated to have a significant impact on the process? In this hybrid scenario of DT and Simulation, the latter is useful for not only comparing different scenarios, but also testing how a possible organisational solution affects the KPIs and thereby spurring further discourse.

When selecting solutions, the team evaluated not only the solutions' KPIs, but also solutions' feasibility and viability. Indeed, the best scenario is not the one with the best KPIs, but the best combination of KPIs and implementation characteristics (feasibility and viability). This may seem obvious, but it is often not, as DES designers usually step out of the decisional process after scenarios are presented because they leave the implementation phase to the client (Tako and Kotiadis 2015). Among feasibility, we listed organisational competences and change resistance: Can we do that? How long would it take to learn that? Is the technology available? Will we have to face strong resistance from doctors, nurses or other groups? Among viability, we listed the costs and

time efforts. In this way, we identified the most implementable scenario.

9. Conclusions and future research direction

Given a problem, we identified a portfolio of possible solutions based on ideas in the literature, best practices known to the design team, and other eventual solutions from the ideation sessions. Among that portfolio of solutions, we had to select those that could be tested in a simulation scenario (scenarios identification). To that end, we asked the design team to discuss the identified solutions for each problem and decide which ones to simulate. For example, fixed priority usually assigns priority based on the patients' acuity level, which can turn into excessive waiting time for less severe patients (problem 3 described in Table 3). The literature suggests dynamic priority: patients' priority should change dynamically (Tan et al. 2012) using other variables, such as accumulated wait time or accumulated flow time. In response, the design team decided to test different thresholds of accumulated waiting time for green and white patients (class of scenarios C). However, the team could have chosen other scenarios from different variants of dynamic priorities, such as considering the amount of accumulated wait time and flow time (Ferrand et al. 2018), the stage of the healthcare treatment (Cildoz et al. 2019); the team could have chosen other common practices such as fast track (e.g., Ferrand et al. 2018). Other ways to select the solution could have been the number of citations per article (to leverage the literature) or the number of EDs in the local area that have applied that solution (to leverage practice). We suggest that both the literature and practice be considered: when we suggested the possible solution of anticipated treatment from the literature (Visitin et al. 2019), the healthcare practitioners were reluctant, but their stance changed after learning that the other three hospitals in the local area had applied that same solution. Moreover, the scenario selection phase followed the team's evaluations regarding desirability (KPIs), feasibility (organisational competences/technology

available) and viability (costs/time). However, those considerations were based on qualitative feedback from the design team and the hospital management. Thus, future research could pursue a simulation-optimization model that minimises the sum of the KPIs (WT_{1st}, LoS, Outliers) and other KPIs based on feasibility and viability considerations. The optimised scenario may work as a guideline for the ED's top managers.

In sum, our case study opens the way for hybrid methodologies that combine design thinking with discrete event simulation approaches, which can provide the right information density to accelerate decision-making processes in healthcare organisations.

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