Addressing bed waiting times in intensive care units during respiratory demand peaks: A digital twin application.

Alexandros Konios[1[0000-0001-5281-1911]], Miguel Ortíz-Barrios[2[0000-0001-6890-7547]], and Zaury-Estela Fernández-Mendoza[3[0009-0006-1543-8576]]

[1] Department of Computer Science, Nottingham Trent University, Nottingham, 4081112, UK, alexandros.konios@ntu.ac.uk

[2] Department of Productivity and Innovation, Universidad de la Costa CUC, 080002, Barranquilla, Colombia, mortiz1@cuc.edu.co

[3] Department of Engineering, Institución Universitaria ITSA, Barranquilla, Colombia, zefernandez@unibarranquilla.edu.co

Abstract. During respiratory demand peaks, such as seasonal influenza outbreaks or COVID-19 surges, healthcare systems often face significant strain, especially in Intensive Care Units (ICUs). Bed shortages and long waiting times can lead to delayed care and worsened patient outcomes. To address this, healthcare systems increasingly turn to digital technologies, such as digital twins, to optimise patient flow and resource allocation. This paper illustrates the implementation of digital twins for managing bed waiting times in intensive care units during respiratory demand peaks. First, we described the patient's journey from the ED to the ICU using Supplier-Input-Process-Output-Customer (SIPOC) diagrams. After this, we analyzed input data analysis, verifying the process variable data's randomness, heterogeneity, and goodness-of-fit. We then modelled the ED through a digital twin designed in ARENA® software. Following this, we validated the model by applying a Kruskal Wallis test on the waiting time for ICU beds. Lastly, we pretested two improvement scenarios: increasing the number of ICU beds by i) 3 and ii) 5. The suggested method was applied in a European hospital group during one of the first COVID-19 waves. The outcomes revealed that the waiting time for ICU beds (1.88 hours) can be meaningfully reduced if strategy ii) is applied.

Keywords: Digital Twin (DT), Intensive Care Units (ICUs), Healthcare, Respiratory Syncytial Virus (RSV), Influenza, COVID-19

1 Introduction

Intensive care units (ICUs) often face surge periods of respiratory illness, such as the COVID-19 pandemic and seasonal influenza waves, which lead to demand spikes for critical care beds. During the COVID-19 crisis, many hospitals experienced unprecedented ICU demand, requiring the conversion of non-ICU spaces into critical care beds [1]. Similarly, peak influenza seasons have strained ICU capacity; one U.S. study found that 41% of ICUs had to alter staffing or refuse transfers at the height of a severe flu season [2]. These scenarios underscore a pressing problem that has to do with ICU bed waiting times increasing when demand exceeds supply, forcing critically ill patients to board in emergency departments or other wards while awaiting ICU admission.

Delayed admission to ICU is not just a trivial inconvenience, as it significantly affects patient outcomes and hospital operations. Research has consistently shown that delays in ICU transfer correlate with higher mortality and morbidity. A meta-analysis in [1] reported approximately a 60% increase in odds of death for patients with delayed ICU admission compared to timely admission. It also showed that each hour of ICU admission delay was associated with an approximately 1.5% increase in ICU mortality risk. These delays also prolong ventilation times and ICU length of stay, compounding resource strain [3,4]. In short, when critically ill patients cannot access ICU care promptly, their condition may deteriorate, leading to worse outcomes [1]. Operationally, backlogs of patients waiting for ICU beds create bottlenecks, occupying emergency department bays or general ward resources and hampering the flow of new patients. ICU bed shortages have even been identified as forcing elective surgery cancellation and refusal of inter-hospital transfers during surges [2]. The problem is worsened in health systems with limited baseline critical care capacity (e.g., the UK's average of 6.2 ICU beds per 100,000 people, one of the lowest in Europe [5]). Thus, reducing ICU waiting times during demand peaks is crucial to improve patient survival and maintain hospital throughput.

Approaches to address ICU bed crises range from expanding physical capacity to improving the existing resource management. During COVID-19, hospitals worldwide rapidly added surge ICU beds and redistributed resources to meet explosive demand [6]. However, simply adding beds has limits, as the study presented in [5] found that increasing ICU capacity did not fully avert high occupancy if discharge delays persisted. Effective solutions must also optimise how patients flow through the system. For example, reducing downstream delays (expediting transfers out of ICU when ready) cut ICU crowding by a more than a 20% bed increase [5]. This suggests that smarter utilisation of ICU resources can significantly alleviate waiting times. In this context, advanced decision-support technologies have become attractive. Digital twin technology, in particular, has emerged as a promising tool to model and manage complex healthcare operations in real-time. A digital twin is essentially a virtual replica of a physical system, continuously fed with data, enabling simulation of scenarios and forecasting system behaviour [7]. In healthcare, digital twins are increasingly seen as a way to optimise patient flow and resource allocation [7-8]. By linking real hospital data to a live simulation model, a hospital or ICU twin can test what-if interventions (like opening surge beds, adjusting staffing, or rerouting patients) without risk to patients and provide clinicians and managers with decision support for reducing bottlenecks.

Delayed ICU admissions during respiratory demand peaks represent a critical challenge with both clinical and operational implications. Traditional capacity planning methods often lack the agility and predictive power to handle sudden surges. Digital twin technology offers a novel, data-driven approach to anticipate and mitigate ICU bottlenecks. For instance, a hospital ICU digital twin could forecast incoming critical cases, highlight impending bed shortages, and evaluate interventions (e.g., diverting admissions or expediting discharges) in silico to minimise wait times. A digital twin can support timely decisions that ensure critically ill patients receive care without dangerous delays by providing a real-time, system-wide view of ICU operations and running scenarios. In this paper, we address the problem of ICU bed waiting times during respiratory surges through a digital twin application. The following sections define the state of the art and methodologies that inform our approach.

2 Literature Review

2.1 Digital Twins in Healthcare and ICU Operations

Digital twin (DT) technology, i.e., maintaining a digital, dynamically updated model of a physical system, has gained growing interest in healthcare. Originally established in engineering, DTs integrate real-time data with simulation models to mirror system states and predict future behaviour [7]. Researchers and practitioners in healthcare are exploring DTs to improve patient-specific care and operational management. The review in [8] notes that although most early healthcare DT applications focused on precision medicine and personal health, an emerging class of DTs targets healthcare systems and processes. These system-level DTs are designed to optimise patient flows, resource utilisation, and care delivery with minimal risk, essentially creating “living” simulations of hospital operations. For example, Elkefi and Asan [8] found that digital twin studies for health system management, though limited in number (17 studies by 2022), demonstrated functions like safety monitoring, operational control, and performance optimisation in hospitals. This signals a promising but significant trend toward using DTs to support decision-making in complex care environments.

In the ICU context, digital twins promise to transform critical care delivery. Halpern et al. [7] describe the ICU as a prime opportunity for cyber-physical-human systems driven by DT technology, where real-time data from patients and units feed into virtual models to inform care and logistics. A DT can simulate scenarios at multiple scales, from an individual patient or organ to an entire ICU or hospital. This enables stakeholders to experiment with interventions in silico before applying them in practice [7]. Early applications in critical care include virtual patient models for medical education and decision support. For instance, [7] also describes that a patient digital twin for ICU training was developed to let trainees practice managing virtual critical illness cases safely. Augmented with AI algorithms, Intelligent digital twins are also being explored for real-time clinical decision support such as early warning of deterioration and personalised treatment predictions [9]. In cardiovascular care, prototypes of DTs can predict how a patient will respond to therapies (e.g., simulating cardiac resynchronisation outcomes) by continuously updating the model with patient data [10]. These examples illustrate the broad potential of DTs in improving ICU patient outcomes.

Several studies have proposed or implemented DTs replicating the hospital or ICU environment to assist with resource management. Karakra et al. built an early hospital digital twin prototype by integrating pervasive IoT data with a discrete-event simulation of patient pathways [11]. Their approach, termed "HospiT'Win", created a near-real-time model of hospital units, demonstrating how a DT could continuously monitor patient flow and test improvements in bed allocation or scheduling [12]. In the critical care domain, Zhong et al. developed a multidisciplinary framework for a digital twin of ICU care processes [13]. This work outlined how to combine clinical data, simulation modelling, and clinician input to mirror ICU delivery and evaluate interventions (e.g., admission triage rules or staffing changes). Another work by Trevena et al. [14], modelled critically ill patient pathways using a digital twin approach to support ICU service planning. Their model, validated on intensive care workflows, allowed the exploration of how patients move through critical care, from emergency presentation to ICU admission, transfers, and discharge, under different policies. Such applications indicate that digital twins can be used to optimise ICU operations by providing a testbed for strategies to reduce waiting times, balance occupancy, and improve overall throughput.

Despite these advances, the literature reveals that digital twin adoption for ICU logistics is still in the early stages. Many reported "ICU digital twins" remain conceptual or in pilot phases [7,15]. For instance, several prototypes focus on ventilator management or sepsis treatment within a virtual patient model [16,17] rather than system-wide flow. There is a clear opportunity to extend digital twin methods to hospital-wide surge management. Khan et al. conducted a scoping review of digital twins during the COVID-19 pandemic and highlighted the technology's potential in pandemic response, but also noted the lack of fully implemented ICU-wide twins for managing resource spikes [18]. In summary, digital twin research in healthcare shows promises (with early successes in personalised care and operational modelling), yet applications that specifically tackle ICU bed capacity and patient flow during demand peaks are only beginning to emerge. Our work aims to contribute to this area by developing a digital twin focused on ICU bed waiting times in surge conditions.

2.2 Simulation and AI Approaches for ICU Capacity Management

To ground our digital twin approach, we review related methodological strategies used to study and mitigate ICU bottlenecks. Discrete-event simulation (DES) has long been employed in health operations research to model patient flow and resource utilisation. A recent systematic review by Vecillas-Martin et al. analysed 616 healthcare DES studies and confirmed its growing diffusion, especially following the COVID-19 pandemic [19]. DES models represent healthcare processes (admissions, transfers, discharges, etc.) as sequences of events, enabling analysts to run virtual scenarios without risking patient care. In hospitals, DES is commonly used to identify process improvements that reduce wait times and optimise capacity. For instance, simulation has been applied to emergency departments and surgical units to test interventions and has shown significant benefits like throughput increases and wait time reductions. Notably, many DES case studies report reductions in patient waiting times, the review in [19] found about

32% of published healthcare DES projects achieved waiting time improvements as an outcome. This underscores the simulation's value in determining and relieving bottlenecks.

In the ICU context, DES has demonstrated particular utility in capacity planning. Griffiths et al. used discrete-event simulation to determine optimal ICU bed numbers and nurse staffing, showing that better capacity planning could reduce ICU admission delays by approximately 28% [20]. Their study modelled ICU patient arrivals and lengths of stay to evaluate how often patients would be deferred if only a given number of beds were available. More recently, Williams et al. built a comprehensive ICU flow simulation to support a UK health board's decision-making for a merged ICU unit [5]. Using 2 years of patient data, their DES model was validated against real admission and occupancy patterns. The simulation explored what-if scenarios such as increasing bed count, altering admission rates, and reducing discharge delays. A key finding was that reducing the proportion of patients experiencing transfer delays out of the ICU yielded a greater drop in ICU occupancy and full capacity time than adding extra beds. This result highlights that operational improvements (e.g., speeding up step-down transfers or improving ward availability) can markedly relieve ICU congestion [5]. Overall, the literature supports DES as a powerful tool to test interventions for ICU capacity management, from adjusting staffing levels to dividing patients into groups and to quantify their impact on wait times and outcomes. It is, therefore, natural that DES often forms the backbone of healthcare digital twins, providing the simulation engine that runs the virtual ICU.

While DES models the system at a macroscopic process level, agent-based modelling (ABM) offers a complementary approach by simulating agents' individual behaviours and interactions (e.g., patients, staff, or even microscopic entities). In an ABM, each agent follows simple rules and complex system dynamics emerge from their collective behaviour. In [21], ABM has been used to capture phenomena like hospital infection transmission or the cascading effects of individual patient decisions on system load. For ICU operations, ABM can incorporate heterogeneous patient characteristics and stochastic events such as sudden clinical deterioration. For example, an agent-based model could simulate each patient's trajectory (with varying acuity, length of stay, etc.) and how they compete for limited ICU beds. Though ABM is less prevalent than DES in this domain, it has been applied to problems like patient-to-patient interactions and staff scheduling. It also provides flexibility in modelling adaptive behaviours (such as dynamic triage decisions). Some researchers have combined ABM with DES to leverage both strengths: a hybrid model might use DES for high-level patient flow and ABM for detailed interactions. During the COVID-19 pandemic, hybrid simulation proved useful. For instance, Adamczyk et al. integrated ABM and DES in a regional COVID-19 management model to simulate hospital responses across multiple ICUs [22]. Such hybrid approaches allowed representation of individual hospitals (with agents for each ICU or patient) within a DES of the broader network, helping policymakers evaluate strategies like patient transfers between ICUs. This indicates the value of multi-method simulations for complex, multi-scale challenges like pandemic surges.

Another crucial methodological thread is incorporating artificial intelligence (AI) and real-time analytics into ICU capacity management. AI techniques can enhance simulation models by providing data-driven predictions (for example, forecasting how many ICU admissions are likely in the next 24 hours) and adaptive decision rules. A study by Ortiz-Barrios et al. combined machine learning with DES to support ICU bed management during COVID-19. They first trained a Random Forest classifier to predict ICU admission probability for incoming emergency patients based on clinical features [23]. The output of this AI model (a prognosis of how many patients would need ICU care) was then fed into a DES model of the hospital's ICU to evaluate different capacity expansion plans. The hospital could use this AI-informed simulation to test interventions like adding surge beds or adjusting admission thresholds. The results were significant by proactively reallocating resources based on the model, the median ICU bed waiting time dropped by 32–48 minutes in their case study. This demonstrates how AI integration can make simulations prescriptive in real time, essentially forming a digital twin that not only mirrors the current state but also recommends actions.

Real-time data feeds (e.g., from electronic health records, monitoring systems, or IoT devices) are a pillar of digital twin systems. Traditional simulations are often run offline with static datasets, but a digital twin for ICU operations should update continuously with live data like admissions, discharges, vital signs, etc. Karakra et al. demonstrated this concept by linking IoT sensors tracking hospital patients to a DES model, creating a continuously updating "living simulation" of hospital workflow [11]. This approach enabled near real-time bed occupancy and patient locations monitoring and could alert managers to developing bottlenecks. The literature indicates that such real-time or streaming data integration is still challenging (due to interoperability and data quality issues), but it is being actively explored. Chase et al. (2023) discuss ICU digital twins with closed-loop control, where the twin can autonomously suggest or trigger actions like calling in reserve staff or triaging patients to intermediate units [24]. While fully autonomous control is futuristic, even current studies show that timely analytics and simulation can help ICU teams optimise resource use under pressure. During pandemic peaks, for instance, some hospitals developed dashboard systems (akin to simplified twins) to track capacity and trigger load-balancing between ICUs [25]. These efforts align with the vision of a digital twin that not only forecasts problems but also aids in coordinating response across the hospital or region.

2.3 Resource Optimisation During Demand Peaks

The COVID-19 pandemic prompted several studies on crisis capacity management. Beyond the aforementioned Ortiz-Barrios study [23], other researchers used simulations to evaluate emergency policies like cancelling elective surgeries, inter-hospital transfers, or temporary ICU expansions. One study at Addenbrooke's Hospital in the UK found that proactive cancellation and temporary ICU expansion significantly reduced ICU occupancy and staff workload compared to doing nothing [26]. Another study by Alban et al. reported using a process simulation to manage ICU surge capacity in Amsterdam, helping to anticipate when COVID admissions would overwhelm ICU beds and guiding the activation of additional beds and staff [27]. Their approach illustrated how modelling could support adaptive responses in real-time. Likewise, scenario analyses were conducted in various countries to project ICU bed demand under different outbreak trajectories, often influencing policy decisions on lockdowns or patient transfers. These studies underscore that data-driven planning was vital to mitigating ICU overload in COVID-19's peak phases.

Seasonal influenza surges, while smaller in scale, have also been examined. Lane et al. (2022) performed a multicentre prospective study on ICU operational stress during a severe flu season [2]. They found that nearly half of participating ICUs had to implement extraordinary measures (like stretching staffing ratios or declining external admissions) during peak influenza activity. Notably, 17% of sites reported potential avoidable patient harm due to resource shortfalls. This evidence highlights why proactive strategies are needed by the time an ICU is scrambling during a surge; patient care may already suffer. It also stresses the multi-faceted nature of resource optimisation as it's not just about beds but also about staffing, triage protocols, and inter-departmental coordination.

The literature suggests several key tactics to improve ICU capacity management during peaks: (1) dynamic staffing and flexible care models (e.g., "critical care without walls" where ICU expertise is deployed to monitor patients in step-down units when ICU beds are full [1]), (2) streamlined admissions and discharges (for instance, using rapid response teams to identify patients who can be transferred out sooner); (3) cross-training and repurposing of staff/rooms (as was done in COVID-19 by turning recovery rooms into ICU pods [1]), and (4) load-balancing across networks (transferring patients between hospitals to avoid any single ICU exceeding capacity). Simulation and digital twin studies have begun to evaluate such interventions. For example, Harper, in [28], showed that modelling multiple hospital departments together (rather than an ICU in isolation) improved overall efficiency by 15%, as it captured how relieving one bottleneck (like step-down bed availability) affects the whole system.

Researchers have applied simulation, modelling, and AI to understand and improve ICU patient flow, demonstrating that delayed ICU admissions significantly harm patients and that proactive management can reduce these delays. Discrete-event simulations have quantified how changes in capacity or process might alleviate waiting times, while newer digital twin frameworks aim to make these simulations continuously responsive to real-world data. However, a gap remains in fully realising digital twin solutions for surge scenarios. To the best of our knowledge, the literature lacks documented cases of a true real-time ICU digital twin deployed during events like a flu pandemic or COVID wave. Most studies either retrospectively simulate scenarios or run prospective models offline. Thus, there is a compelling need for research that implements and evaluates a digital twin in practice for ICU capacity optimisation. This work addresses that need by proposing a digital twin application tailored to ICU bed waiting times during respiratory demand peaks. Building on the methods and findings reviewed above, our approach integrates discrete-event simulation, real-time data feeds, and AI-based predictive components to create a dynamic model of ICU operations. In the next sections, we detail the design of this digital twin and assess its potential to support ICU decision-makers in ensuring timely critical care access when it is most challenged.

3 Proposed Methodology

Digital twins must be reliable and representative of the real healthcare system to provide appropriate support for decision-makers. In this regard, it is necessary to follow a step-by-step procedure described below (Fig. 1) [29]:

Phase 1 – Description of ED-ICU pathway: The pathway to upstream healthcare services includes several stations that depend on the patient's health evolution and multiple treatment options. This must be clearly portrayed through Supplier-Input-Process-Output-Customer (SIPOC) maps complemented by Gemba walks. Thereby, it is possible to pinpoint the main process variables/parameters, principal stations, and potential inefficiencies during Respiratory Disease Seasons (RDSs).

Phase 2 - Input variable analysis: In addition to verifying the data quality, it is essential to derive the stochastic expressions denoting the behaviour of each process variable in the system. Three statistical tests are required to achieve this aim: interdependence, homogeneity, and goodness-of-fit. The run test ($\alpha = 0.01$) evaluates whether the variable is random. Afterwards, the Analysis of Variance (ANOVA) ($\alpha = 0.01$) is utilized to verify if the variable can be decomposed into several layers. A stochastic expression must be defined per layer if heterogeneity is detected. Otherwise, only one probability distribution is enough to represent the variable's behaviour. Kolmogorov-Smirnov (KS) tests ($\alpha = 0.01$) are recommended to reach these distributions.

Phase 3 - Digital twin creation and validation: The stochastic distributions are later inserted into the digital twin designed in the Arena ® software. As recommended, a pre-sample of 10 runs is deployed to assess the variance of the bed waiting times. The required number of iterations is finally computed considering this variance. The validation process evaluates whether the DT produces a similar waiting time for ICU beds compared to the one derived from the real system. A Mann-Whitney test ($\alpha = 0.01$) supports this process. If the DT is statistically equivalent to the real-world ICU in terms of this key indicator, decision-makers and ICU managers can proceed with the response diagnosis; otherwise, the model must be refined until its reliability can be certified.

Phase 4 – Operability analysis: The ICU bed waiting time derived from the DT is now analyzed against the standard required in this service. In case of inefficiency, DT can provide helpful information for studying ICU interactions with other services while identifying stations that are wasting time. Besides, it will be necessary to formulate some improvement scenarios with the hospital administrators and clinical staff. Such remedies can be pretested in the DT to determine if they will be effective in case of implementation. Comparative statistical tests (α = 0.01) will be employed to reach this conclusion.

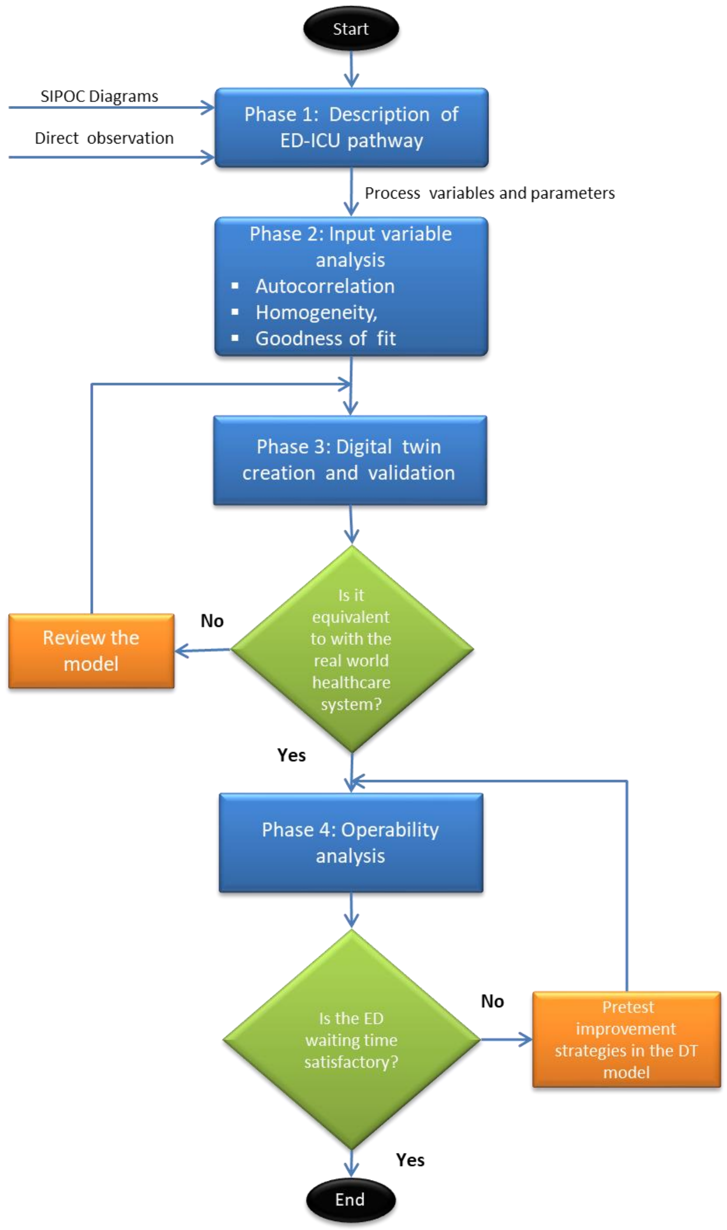

Fig. 1. The methodological framework for addressing bed waiting times in ICUs based on digital twins

4 Results

SRDs provoke a huge burden on ICUs, which, in some cases, do not respond timely in bed provision. The problem is even more sharpened considering the convergence of several respiratory pathogens whose spread rates tend to peak every season. This is the context of an extensive European medical group during the initial COVID-19 surges.

The General Management Office of the hospital group collected relevant process data to underpin the deployment of a digital twin. The primary aim was to evaluate its current performance during the pandemic and devise feasible remedies if necessary. The project received informed approval from the ethical body (Consent number: 14-12-2021-004; Access request ID:39) to use and analyze the gathered data for improvement purposes. The decision-makers also considered employing the model to define how to increase its readiness when addressing future respiratory-related outbreaks. Likewise, the intervention was directed towards the ICU bed waiting time as it had been identified as highly correlated with elevated cost overruns and greater patient mortality probability.

The next subsections will illustrate how the proposed methodology was deployed in this case study and what outputs were derived from each phase.

4.1 Description of ED-ICU pathway

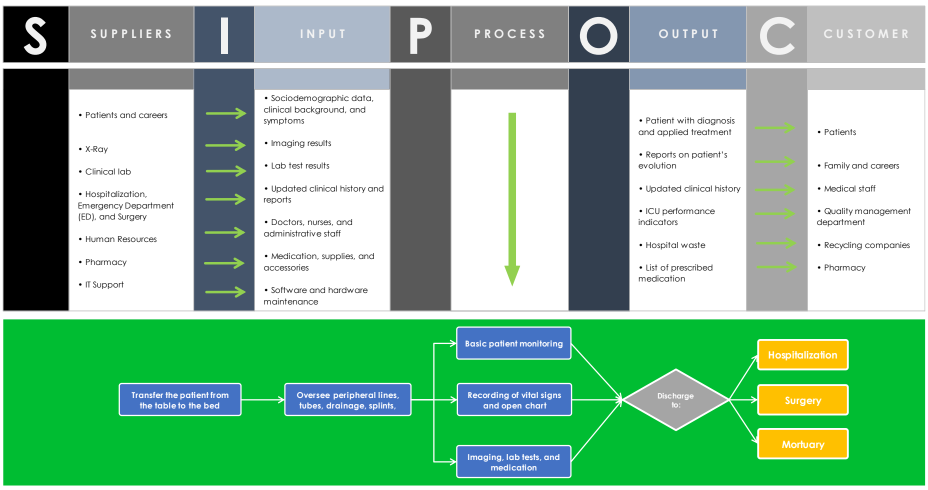

Fig. 2. SIPOC diagram for characterizing the patient journey from ED to ICU

Gemba walks, and a SIPOC diagram (Fig. 2) were used to discriminate the suppliers, inputs, process steps, outputs, and clients. It is good to note that patients act as both providers and customers, highlighting these actors' critical role. Also, it is evident how clinical history travels along the healthcare system while recording the patient's evolution. This means that this document is a key source of information from which the digital twin can be fed and updated. No less important is the role of pharmacy in the correct and timely provision of medication, which is highly associated with prolonged length of stay and elevated bed waiting times. Likewise, the SIPOC map reflects how interactive the ICU is with other healthcare stations, demonstrating the need to effectively administer the interdependences beyond an individual view over the ICU.

4.2 Input variable analysis

After characterizing the healthcare system, four process variables were pinpointed to be analyzed: Time between attendances in the ED, Triage classification time, ED Length of Stay, and ICU stay period. First, we confirmed the interdependence assumption of the variables through run tests ($\alpha = 0.01$; p-value > 0.15). Then, we performed an Analysis of Variance (ANOVA) to validate the presence of subsets within each variable. The results evidenced that all the variables ($\alpha = 0.01$; p-value > 0.073), except the Triage classification time, are heterogeneous, and a probability expression must be defined for each data stratum (Table 1). The likelihood distributions were determined through χ^2 tests ($\alpha = 0.01$).

Table 1. Likelihood distributions of process variables inserted in the digital twin

Process variable	Likelihood distributions	*p*-value
Time between attendances in the ED	EXPONENTIAL, LOGNORMAL, WEIBULL	>0.06
Triage classification time	UNIFORM	>0.15
ED Length of Stay	UNIFORM	>0.15
ICU stay period	GAMMA, EXPONENTIAL	>0.092

4.3 Digital twin creation and validation

The input data analysis and process characterization results were employed to design a digital twin imitating the real functioning of the ICU. The Arena® 16.10.00 software was utilized for this aim, given its advantage of modeling by blocks, its user-friendly interface, and its versatility to represent the inefficiencies of operational workflows. The replication length defined for the digital twin was 15 days with 24 hours/day. This is because healthcare operations, including intensive care, are constantly open to the public.

An initial sample of 10 runs was executed to calculate the number of iterations required for portraying the real variability of bed waiting times derived from the intensive care operations. The outcomes evidenced that more than 2,100 replications are necessary to clear understand the ICU operability under the SRD pressure. Following this, a

1-sample sign test (α = 0.01) was implemented to verify whether the digital twin is comparable with the real ED-ICU operation regarding bed waiting times. The test underpinned the similarity (p-value = 0.7; η = 1 hour), and the virtual model can be hence adopted for operability assessment and design of effective interventions if needful.

4.4 Operability analysis

The digital twin revealed that the median waiting time for an ICU bed was 1.88 hours. This is an undeniable sign that the patient flow from the ED and other downstream services has surpassed ICU installed capacity. Of note, operational healthcare mismatches in the presence of rapidly-evolving respiratory viruses threaten patients' health and thus claim unified improvements. Embedding effective solutions is urgently needed to tackle this problem. The digital twin comes to the ground again to empower decision-makers on what to do in a highly iteratively interacted healthcare system [30]. Two proposals were envisioned and examined to tackle the bed waiting time problem: augmenting the number of ICU beds by i) 3, ii) 5.

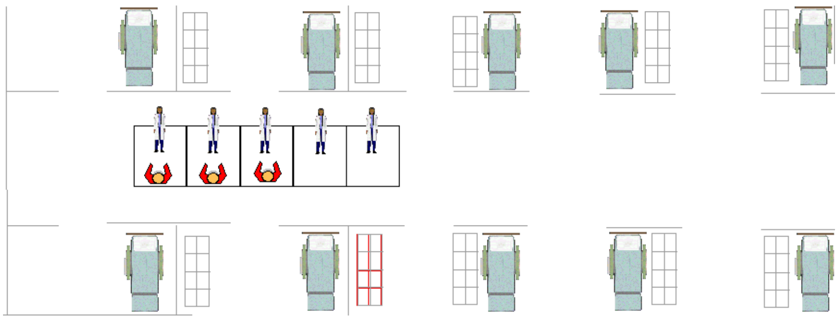

Fig. 3. ICU interface in the digital twin model

After retrieving the information from the digital twin runs, we observed that the waiting time indicator would reduce between 6.48 min and 9.60 min (95% CI) if intervention (i) is implemented. In turn, the remedy (ii) would shorten this time between 10.8 min and 16.01 min (95% CI). Although the winning solution is (ii), there is still room for improvement. Hence, integrating this remedy with other solution perspectives is fundamental, which can contribute to a more favorable outcome.

Conclusions

Shaping the future response of ICUs when undergoing SRDs is pivotal to ensure more auspicious outputs in respiratory-affected patients. The core fabric of this project will be the correct administration of unit-to-unit interactions along the ED-ICU pathway.

One-size-fits-all solutions are inefficient and do not correspond to the intrinsic characteristics of each system. The underlying digital twin model is a promising alternative to address the operational problems that ICUs may face during respiratory-disease outbreaks, including out-of-control waiting times. The respiratory disease burden is expected to ramp up every season in the coming decades, and healthcare decision-makers will need advanced approaches like the digital twins to strengthen the supporting operational pillars.

The road forward dictates that these virtual replicas will be even more fundamental if combined with endeavors from the Artificial Intelligence field. Extracting high-quality data will ensure the reliability and usability of these integrations. In this regard, ICU managers are challenged to monitor the data culture within their departments continuously. Ultimately, it is advised to cross the ICU boundaries and establish collaborative agreements with other ICUs where some patients can be transferred to other units that can guarantee timelier care [31-33].

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