A Digital Twin for Shortening Waiting Times in Emergency Departments during Respiratory Disease Peaks

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Abstract. Emergency departments (EDs) are vital components of healthcare systems, often operating under extreme pressure, especially during seasonal peaks of respiratory diseases like influenza, Respiratory Syncytial Virus (RSV), or COVID-19. These peaks lead to significant overcrowding, prolonged waiting times, and increased strain on clinical staff, which compromise patient outcomes and system efficiency. The challenge lies in dynamically allocating resources and predicting patient flow with enough accuracy to maintain operational stability. Digital twin (DT) technology, a virtual real-time representation of physical systems, offers a transformative solution. By mirroring the ED operations and continuously synchronising with real-world data, digital twins can simulate various scenarios and inform optimal decision-making strategies. This paper presents the application of digital twins for shortening waiting times in EDs during respiratory disease peaks. First, we characterized the patient journey within the ED using the Supplier-Input-Process-Output-Customer (SIPOC) diagram. Secondly, we performed an input data analysis and then modelled the ED through a DT designed in ARENA® software. After this, we validated the model by conducting a 1-sample t test on the waiting time for treatment in ED (3-5 triaged patients). Finally, we implemented a what-if analysis considering two scenarios: i) increasing the number of beds and general doctors, ii) reducing delays caused by clinical labs in delivering test results. The proposed approach was verified in a European hospital group during one of the first COVID-19 waves. The results showed that the treatment waiting time in 3-5 triaged patients (4.682 hours) can be significantly lessened if both scenarios are applied.

Keywords: Digital Twin (DT), Respiratory Syncytial Virus (RSV), Emergency Departments (EDs), Healthcare.

1 Introduction

Emergency Departments (EDs) worldwide face escalating pressures during seasonal peaks of respiratory illnesses such as influenza, Respiratory Syncytial Virus (RSV), and COVID-19. These surges often drive patient demand beyond ED capacity, resulting in severe overcrowding, prolonged waiting times, and strain on healthcare staff [1]. ED overcrowding has been recognized as a critical problem since the 1980s, reflecting an imbalance between incoming patient volume and the resources available for care [1]. Seasonal epidemics, such as winter influenza outbreaks, can suddenly increase ED attendance by large margins, a factor largely outside the ED's control. Recent convergences of multiple respiratory viruses (a so-called "tripledemic" of flu, RSV, and COVID-19) exemplify this challenge as the simultaneous surges in 2022–2023 taxed hospitals to the point of near-overwhelm in many regions [2]. The consequences of such peaks are well-documented, as ED crowding is associated with decreased quality of care, higher patient morbidity and mortality, and an overall compromised ability to deliver timely emergency interventions [1]. This highlights an urgent need for more adaptive and proactive approaches to managing patient flow and resources during public health crises.

However, dynamically allocating resources and forecasting patient flow in an ED amid unpredictable surges is complex [3,4]. Traditional staffing algorithms and static capacity plans often fail to adjust to rapid changes in demand, contributing to extended length of stay and throughput bottlenecks [3]. Past studies have shown that ED overcrowding is multifactorial and resists a simple solution [4]. Key contributing factors include population aging and seasonal illness waves to inpatient bed shortages and process inefficiencies [1]. Hospitals have implemented various mitigation strategies, such as expanding surge capacity or redirecting low-acuity patients, but these measures are typically reactive and limited in scope. A clear gap exists for intelligent decision-support tools to anticipate surges and optimize ED operations in real-time. In other words, healthcare systems require predictive, data-driven solutions that go beyond retrospective analysis to continuously model the evolving state of an ED and guide timely interventions.

Digital twin (DT) technology offers a novel and promising path to fill this gap [5-6]. A digital twin is a virtual, real-time representation of a physical system maintained through continuous data synchronisation between the physical entity and its digital counterpart [5,7]. In the context of an ED, a digital twin serves as a live, computational mirror of the department, ingesting real-world data (e.g., patient arrivals, triage statuses, bed occupancy) and running simulations of ED processes in parallel to actual operations. Unlike traditional simulations or dashboards, a true digital twin is adaptive as it updates itself with streaming data and can monitor the current state ("digital shadow") and project future states through predictive modelling. This capability allows stakeholders to experiment with "what-if" scenarios on the virtual ED to identify optimal responses before implementing changes on the floor [5]. Recent work in hospital systems likens this approach to an Industry 4.0 transformation, where digital twins leverage real-time data, IoT sensors, and AI analytics to enable faster data access and simulation-enhanced decision-making [5,7]. Indeed, the use of digital twins across industries has surged in recent years, and healthcare is now viewed as a frontier where DTs could revolutionise system management and service delivery [6]. By creating a virtual replica of a hospital or ED, administrators can review operational strategies, predict future challenges under various outbreak scenarios, and optimise resource allocation proactively [7]. The potential impact of such technology on patient outcomes and system efficiency during crises is significant, as it effectively provides a safe testing ground for interventions and a foresight tool for impending demand.

In this paper, we address the above research gap by deploying a digital twin to shorten ED waiting times during peaks of respiratory disease activity. We present a simulation-based DT model of an ED that is continuously informed by hospital data and integrated with predictive analytics. In our approach, we first mapped the ED patient journey and processes using a Supplier-Input-Process-Output-Customer (SIPOC) framework to understand key delay points. We then performed an input data analysis (examining arrival rates and service times) to assess variability and fit to statistical distributions, ensuring the simulation model is grounded in real-world patterns. The ED digital twin was implemented in Arena® discrete-event simulation software, calibrated with empirical data from a European hospital network. We validated the model by comparing simulated waiting time distributions against historical ED data (using a 1-sample t-test on treatment waiting times for mid-acuity triage levels 3–5) to confirm that the twin accurately mirrors the physical ED's performance. Finally, we conducted a series of what-if analyses through the digital twin to evaluate potential surge management strategies. In particular, we simulated two intervention scenarios: (i) increasing critical resources (adding ED beds and on-call physicians) and (ii) reducing internal process delays (expediting laboratory test turnaround times to shorten the length of stay). The digital twin experiments, applied to data from one of the first COVID-19 waves in 2020, revealed that these measures can achieve substantial reductions in patient treatment waiting times under peak conditions. Notably, for moderate-acuity patients (triage levels 3–5), the average waiting time of 4.68 hours was significantly lowered when extra staffing was combined with faster lab results. These findings illustrate how a digital twin can guide data-informed decisions to bolster ED resilience during respiratory disease surges. In the following sections, we review related work and position our contribution within the literature before detailing the methodology and results of our study.

2 Literature Review

2.1 Digital Twins in Healthcare and Emergency Departments

Digital twin technology has rapidly gained traction in healthcare, motivated by its success in engineering domains and the growing availability of real-time health data [6]. Broadly, a digital twin for health (DT4H) is envisioned as a virtual replica of a healthcare entity, whether an individual patient, an organ, or an entire clinical system, that continuously mirrors the state of its physical counterpart and enables advanced analysis and forecasting [5-6]. Early applications of healthcare digital twins have focused on personalised medicine (e.g., patient-specific cardiac models or virtual organs). Still, increasingly there is interest in operational and system-level twins that can improve how care is delivered [8]. By integrating streams of data (e.g., sensor readings, electronic health records) with AI and simulation, digital twins have demonstrated potential benefits such as streamlining care processes, optimising facility management, and enhancing patient safety [7]. For instance, recent reviews highlight that digital twins have been used to model entire hospitals, creating virtual testbeds to refine workflows, assess resource needs, and identify bottlenecks under different scenarios [7-8]. These capabilities translate directly into improved efficiency and quality of care since a well-implemented digital twin can predict patient volumes, evaluate intervention impacts in silico, and recommend adjustments to prevent disruptions in service delivery.

In the context of emergency departments, digital twin research is still emerging but shows great promise for patient flow management [5]. An ED is a complex, high-variety environment where conditions change by the minute, and this makes it an ideal but challenging candidate for DT modelling. Moyaux et al. in [5] proposed an agent-based architecture for an ED digital twin explicitly designed to improve the management of patient pathways. In their framework, software agents represent key ED entities (staff, equipment, patients) within the twin, and the twin's information system stays regularly synchronised with the hospital's real-time data. The ED digital twin can operate in multiple modes: a digital shadow for real-time monitoring of the current state, a synchronised twin that runs predictive simulations in parallel with live data to foresee short-term future states, and an exploratory twin for running scenario analyses (e.g., Monte Carlo experiments) to test various "what-if" situations. Notably, the synchronised digital twin mode acts as a decision-support system for the ED. It continuously projects ahead based on current conditions, allowing decision-makers to anticipate problems (like an impending bed shortage or staff overload) before they fully materialise [5]. This work demonstrated the feasibility of maintaining a live ED model that could virtually alert managers to future performance trajectories and evaluate interventions. Few real-world EDs have such digital counterparts yet, but these results underscore how a DT can bridge the gap between monitoring and forecasting in emergency care.

Another example of ED-oriented digital twin innovation is the study in [7], which explored a novel emergency service model using digital twins to expedite patient treatment. Here, the focus was on patients arriving without readily available medical histories (e.g., unconscious or unidentified). The proposed system created a digital twin for the patient's journey, leveraging biometric identification (face recognition) to retrieve the patient's digital health records quickly and prior conditions. By doing so, clinicians could immediately access critical information and initiate appropriate care without delay. This DT-enabled fast-tracking significantly reduced the length of stay in the ED, as doctors no longer wasted time obtaining medical history or duplicate tests [7]. It also improved triage accuracy since the digital twin helped match unknown patients to their records with over 80% success rate. This work also illustrates a different facet of digital twins in emergency care, as it is about modelling system operations and enhancing individual patient processing through data integration and IoT technologies. The digital twin effectively served as a coordination hub, bringing together identification, medical data, and communication with external parties (family, specialists, insurers) to streamline the care of emergency patients.

Beyond these, more incipient works apply digital twins for ED management. Some projects aim to formalise the requirements and design considerations for a full ED digital twin platform (e.g., specifying data integration needs, visualisation, and user interface for real-time decision support) [9]. Others have drawn parallels to related domains; for example, a simulation-based digital twin was used to assess emergency call centre operations in France, revealing how reorganising call dispatch could improve service response times [10]. These studies collectively reinforce the notion that digital twins can serve as adaptive, learning systems in healthcare operations. A DT can provide hospital leaders with unprecedented situational awareness and agility by continuously updating real data and employing high-fidelity simulations. Nevertheless, challenges remain. Researchers have noted interoperability and data governance as major hurdles for implementing digital twins at scale in healthcare [8]. Large volumes of heterogeneous data must be processed securely and in real-time for a DT to be effective, and integrating these with existing hospital IT systems is non-trivial [8]. Despite these challenges, the trajectory is clear since digital twin technology is steadily moving from concept to reality in healthcare. EDs benefit immensely from its capabilities to forecast demand surges, test interventions virtually, and support critical decision-making during peak crises.

2.2 AI, Simulation, and Hybrid Modelling for Patient Flow Management

The use of simulation and artificial intelligence in modelling patient flow and hospital operations has a rich history, which is now evolving into more hybrid, intelligent methodologies. Discrete-event simulation (DES) and related techniques have long been employed to study ED crowding and to evaluate interventions for reducing waiting times. For example, numerous DES models have been built to identify bottlenecks in ED processes and to estimate how changes, such as adding a new triage nurse or expanding bed capacity, would impact patient length of stay [3]. Agent-based simulation (ABS) has likewise been used to capture the interactions of individual patients and staff, offering fine-grained insight into dynamics like patient diversion or workflow rerouting [5]. Such simulation studies have repeatedly shown benefits since simulation is an effective tool for improving complex systems like EDs, particularly by tackling challenges of variable patient arrivals and resource allocation in a risk-free virtual environment [3]. In fact, most hospitals that have optimised operations have done so by experimenting with models to determine how many resources are needed at peak times and where the worst delays occur. Traditionally, these models assume a certain static set of inputs (like average arrival rate or service time distributions) and yield strategic recommendations (e.g., increasing the number of doctors to reduce waiting time). While valuable, static models struggle to capture the real-time fluctuations inherent to EDs.

This is where Artificial Intelligence (AI) and Machine Learning (ML) have increasingly been introduced to complement simulation. AI techniques, especially predictive modelling, can analyse historical and real-time data to forecast ED conditions in the future. For instance, predicting how many patients will arrive in the next hour or which admitted patients will likely deteriorate and require ICU care. Accurate prediction of ED arrivals is key to optimising staffing and resources, thereby cutting patient waiting times [3, 11]. Many researchers have focused on forecasting patient attendance using time-series models like ARIMA and exponential smoothing [11]. These statistical models are effective when patterns are regular but falter with irregular surges and complex nonlinear trends. To address this, recent studies have turned to machine learning algorithms (such as random forests, gradient boosting, and neural networks), which can incorporate a wider range of features, such as calendar effects, weather data, upstream infection rates, etc., to improve forecast accuracy. Notably, hybrid approaches have been proposed that combine traditional time-series methods with machine learning and even text mining of contextual information [11]. Such hybrid models have demonstrated superior predictive performance compared to any single modelling approach, particularly in forecasting ED arrivals. For example, Porto and Fogliatto in [11] report that an ensemble of machine learning models (e.g., XGBoost and neural network autoregression) after feature engineering achieved 5–14% mean absolute percentage error in predicting daily ED visits, outperforming prior ARIMA-based studies. The implication is that leveraging AI for prediction can provide the foresight needed to initiate preemptive actions (like calling in additional staff or opening surge areas) rather than reacting after queues have already formed.

The true power for operations management emerges when these predictive tools are integrated with simulation in a hybrid modelling framework. The work presented in [4] developed a hybrid system combining real-time forecasting with discrete-event simulation to support short-term decision-making in urgent care networks. Their approach used seasonal ARIMA models to continuously forecast patient arrivals across multiple EDs, triggering scenario simulations of the EDs under various diversion policies. By doing so, the system could proactively identify when an ED's projected queue would become unmanageable and then simulate diverting a portion of low-acuity patients to alternative clinics before the ED became overwhelmed. This hybrid forecasting–simulation strategy, essentially an early form of a digital twin, allowed the researchers to achieve proactive service recovery in the ED: instead of waiting for crowding to cause harm, the model would advise interventions (like patient re-direction or resource reallocation) ahead of time. Similarly, this work showed that sharing real-time data across an integrated simulation model can support dynamic ED control policies – for example, temporarily rerouting incoming ambulances when predicted wait times exceed a threshold [4]. The results indicated a clear benefit in reducing patient congestion and avoiding service breakdowns.

Another study [12] focused on hospitalisation departments during respiratory disease seasons and integrated artificial intelligence with DES to shorten bed waiting times. In that work, machine learning models predicted the probability of clinical deterioration for each admitted patient and the likely length of stay, information which was fed into a simulation of hospital bed management. This hybrid model optimised bed assignments and prioritised transfers, yielding an impressive reduction of nearly 8 hours in the average bed waiting time during peak respiratory illness periods. Although that study dealt with inpatient beds, the principle is highly relevant to ED operations by anticipating bottlenecks (in their case, predicting which patients would soon need a bed and clearing capacity), the combination of AI forecasting and simulation can dramatically improve flow. The ED is tightly coupled with downstream units like wards and Intensive Care Units (ICUs), so forecasting admissions and expediting throughput directly benefits ED waiting times. Ortíz-Barrios et al. [12] effectively prevented backlogs in the ED by ensuring beds were ready when needed, demonstrating how hybrid AI-simulation systems can mitigate the domino effect of crowding.

Beyond patient forecasting and bed management, AI is also used in resource scheduling and operational optimisation in conjunction with simulation. A recent study by Kim in [3] developed a simulation model of an ED and applied machine learning to dynamically select the best physician scheduling policy in response to current conditions. Six different staffing schedules (varying mixes of senior and junior doctors by shift) were embedded in the simulation, and a learning algorithm was trained on historical data to pick which policy would minimize patient length of stay for a given incoming patient load. This integrated ML–DES approach achieved about 90% accuracy in matching the optimal schedule to the situation, and the resulting average patient length of stay in the ED fell to ~323 minutes, compared to ~327 minutes under a static scheduling method [3]. While the improvement might seem modest, it underscores the potential of real-time adaptive scheduling powered by AI, as even small reductions in average LOS can translate to dozens of freed bed hours and markedly improved waiting times across hundreds of patients. More importantly, the study highlights that increasing resources is not always feasible (due to financial or personnel constraints); thus optimising the utilisation of existing staff is crucial. Machine learning provides a way to make optimal use decisions on the fly, something traditional heuristic schedules cannot accomplish. We see similar trends in operating rooms, inpatient units, and ambulance services, where AI and simulation coalesce to tackle complex scheduling and routing problems better than either could alone.

In summary, the literature on patient flow management is moving toward the convergence of AI and simulation, effectively laying the groundwork for hospital digital twins. Discrete-event and agent-based simulations supply a tested framework for modelling the ED and evaluating interventions. In contrast, AI supplies predictive and adaptive capabilities to inform those models with up-to-the-minute insights. Hybrid models have been shown to prevent overcrowding by acting ahead of time, streamlining hospital pathways by intelligent resource allocation, and enhancing the precision of operational decisions (like scheduling) under uncertainty [4]. These advances directly reduce patient waiting times and improve throughput, especially during demand surges. The ongoing challenge is integrating these components into a cohesive system that can run continuously in a real hospital setting – precisely the ambition of a true digital twin.

2.3 Decision-support Systems and Forecasting during Public Health Crises

Public health crises, such as pandemic waves or severe seasonal outbreaks, put extraordinary pressure on hospitals and demand robust decision-support systems for effective response. In these situations, having tools that forecast patient surges and support rapid operational adjustments is invaluable. During the COVID-19 pandemic, for example, many health systems learned the importance of real-time situational awareness and predictive analytics to manage capacity [1-2]. Large hospital networks like NYC Health + Hospitals (the largest municipal system in the US) activated emergency coordination centres that relied on analytic tools and live dashboards to track incoming cases, available beds, ventilators, and staffing levels across the city. This real-time data visibility, combined with predictive models, enabled administrators to anticipate where resources would be overwhelmed and to redistribute patients or staff accordingly. Indeed, situational awareness and forecasting are critical components of crisis response, allowing decision-makers to stay ahead of rapidly evolving demand [2]. For respiratory virus surges, this might include short-term forecasts of ED visits based on community infection trends or early warning triggers when a certain threshold of flu cases is reached. Even simple time-series models (e.g., weekly ARIMA forecasts of ED respiratory cases) have been shown to improve preparedness by giving a few days lead time to implement surge protocols [4,11].

At a more advanced level, digital twin and simulation approaches have been explored as decision-support systems during crises. The idea is that a hospital or regional healthcare system can maintain a continuously running simulation model, fed by current data, to test the impact of different emergency strategies. For instance, researchers in Denmark created a detailed nation-level simulation (termed a digital twin of the population's health status) to evaluate COVID-19 mitigation measures [13]. Their simulation results showed that without certain interventions (mass testing and targeted lockdowns), hospital admissions would have surged by 150% during the Alpha variant wave. While that study was on a public health scale, the underlying principle applies to ED operations. Virtual scenario testing can inform policy decisions that directly affect waiting times and outcomes. In an ED setting, this could mean simulating various triage protocols during a pandemic (e.g. streaming respiratory patients to separate zones) or testing the effect of expanding ED capacity using hall beds or field units. By comparing scenarios in the twin, hospital leaders can choose strategies that best mitigate overcrowding and treatment delays before implementing them on the ground [4-5].

One concrete example of an ED-focused decision support system is the hybrid forecasting simulation model presented in [4]. Although developed prior to COVID-19, it essentially functioned as a crisis management tool, enabling proactive diversion of patients when an impending overflow was predicted. In practice, such a system during a respiratory pandemic could automate decisions like directing ambulances between hospitals or activating urgent care centres to absorb low-acuity cases when a surge is anticipated. The value of this approach was endured during COVID-19 as many regions that fared better did so by balancing loads across hospitals and utilising alternate care sites, actions that rely on timely data and forecasts. A digital twin of a hospital network can facilitate these decisions by continuously computing scenarios of patient distribution and resource utilisation under current conditions. Researchers have noted that digital twins, by virtue of their real-time fidelity, can serve as nerve centres during crises, aggregating data, analysing risks, and recommending interventions in one unified platform [5]. In other words, a digital twin is a model and an intelligent agent in the decision loop, advising human operators on the best course of action to preserve care quality.

During the COVID-19 pandemic, numerous predictive tools were developed to forecast hospital admissions, ICU demand, and ED presentations. Machine learning models using live syndromic surveillance data could predict COVID-related ED visits several days in advance, helping emergency departments plan for surges in respiratory patients [1]. In parallel, decision-support dashboards integrated these forecasts with hospital capacity information to trigger predefined escalation plans (such as converting recovery rooms into ICU beds or calling reserve clinicians). Khan et al., in a scoping review of digital twins for COVID-19 [14], identified hospital capacity management as a key area where DTs were proposed to aid the pandemic response. By simulating patient flow and resource consumption, a hospital digital twin can forecast when critical resources (like isolation beds or ventilators) will run out and evaluate the impact of mitigation steps (cancelling elective surgeries, expanding telemedicine triage, etc.) [15]. The review noted that while many such applications were conceptual, they highlight a consensus that DT technology can greatly enhance crisis decision-making by providing a system-wide perspective and predictive insight beyond human intuition alone.

Crucially, public health emergencies often require decisions that balance competing needs and uncertain outcomes. A decision-support system grounded in simulation and AI can illuminate the likely consequences of each option. For example, during the 2022 flu/RSV/COVID tripledemic, paediatric EDs had to decide whether to cohort patients, divert them, or stretch staff ratios, each with trade-offs in patient wait and safety. With a digital twin, they could simulate these options: how would opening a fast-track for flu patients affect overall wait times? What if 10% of lower-priority cases were redirected to urgent care clinics? By examining such questions virtually, hospitals can choose strategies that minimize harm [16]. Real-world experience from NYC during the tripledemic showed the importance of improving comprehensive situational awareness and adjusting resource levels system-wide promptly [2]. Hospitals that employed central monitoring and agile reconfiguration (such as shifting staff to EDs under strain or pooling ICU beds across a system) managed better throughput than those that didn't. These are essentially manual precursors to what a digital twin could automate – continuously sensing the load and recommending reallocation of resources or rerouting of patients to prevent any one facility from collapsing under pressure [17].

In summary, the literature and recent crisis experiences underscore that forecasting and decision-support tools are indispensable during public health surges. Integrating forecasting models (ARIMA, ML, etc.) with ED operations allows hospitals to act before queues mount [4,11,18,19]. Simulation-based decision support enables scenario planning for worst-case conditions and optimal use of scarce resources [5,13,20,21]. Digital twins represent the cutting edge of these capabilities, bringing together real-time data, predictive analytics, and simulation in a cohesive platform. Although still in the early stages of deployment, they have been envisioned as key assets for enhancing resilience in healthcare [22, 23].

3 Proposed Methodology

The proposed methodology entails the implementation of four main phases, as fine-grained in Fig. 1. The details of each component are described below:

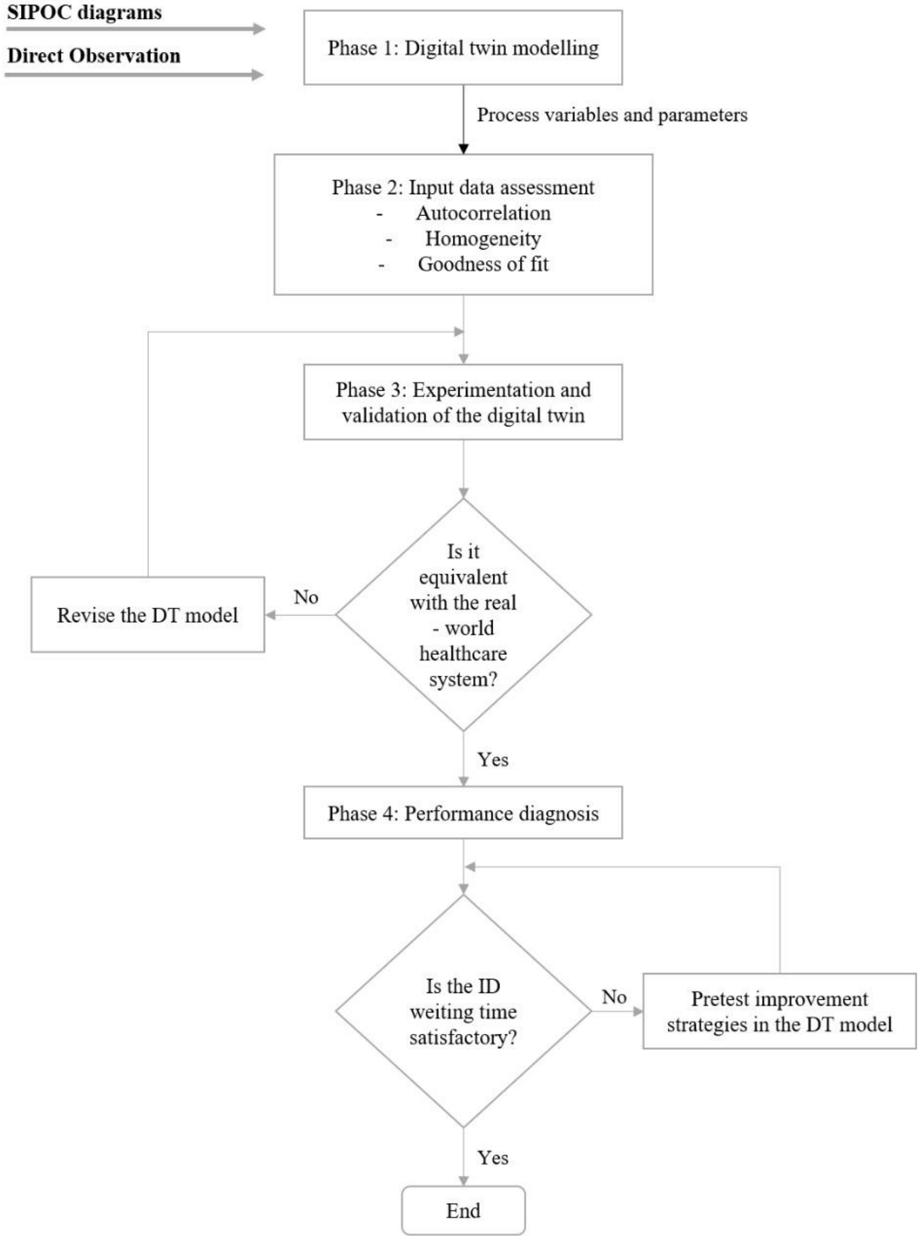

Fig. 1. The step-by-step procedure for reducing the ED waiting times using digital twins

Phase 1 - Digital twin modelling: Direct observation and Supplier-Input-Process-Output-Customer (SIPOC) diagram are utilized to identify the main stations of the patient journey within the ED, discriminate parameters/process variables, and hypothesize the potential causes of ED deficiencies during Respiratory Disease Seasons (RDSs).

Phase 2 - Input data assessment: In this phase, we evaluate the process variable data's autocorrelation, homogeneity, and goodness-of-fit. While the autocorrelation is analyzed using a run test ($\alpha = 0.01$), the homogeneity is elucidated through an Analysis of Variance (ANOVA) test ($\alpha = 0.01$). Finally, the goodness-of-fit is examined by employing a Kolmogorov-Smirnov (KS) test ($\alpha = 0.01$).

Phase 3 - Experimentation and validation of the digital twin model: The probability expressions derived from the KS tests are included in the digital twin model. This model is diagrammed in Arena ® software considering the findings of previous steps. A pre-sample of 10 iterations is then run to estimate the variability of the waiting times [24]. With this information, a final sample size is calculated, and the digital twin model is validated through a 1-sample t-test ($\alpha = 0.01$). If the digital twin model is comparable with the real-world ED, performance diagnosis and further can be performed; otherwise, the model must be checked and calibrated.

Phase 4 - Performance diagnosis: The waiting time performance metrics emanated from the validated digital twin are now examined for ED operational diagnosis. No intervention will be necessary if the waiting time is satisfactory ($\leq$ 20 minutes). Otherwise, improvement strategies should be created and pretested in the digital twin. The intervention will be categorized as effective if it significantly lowers the waiting time.

4 Results

Seasonal Respiratory Diseases (SRDs) put EDs under pressure and, it is, therefore, necessary to anticipatedly pretest interventions that significantly lower the associated waiting times and the consequent negative effects on patient's health and operational costs [25-26]. A large European hospital group experienced these shortcomings during one of the first COVID-19 waves in 2020. Being aware of this situation, the ED managers decided to build a robust dataset containing patient data, attendance times, triage times, treatment times, and other critical process variables to model the patient pathway in a digital twin. Official approval was given by the ethics committee of the hospital group (Consent number: 14-12-2021-004; Access request ID:39) to employ the data. Thereby, it was possible to lay the groundwork for devising remedies tackling the main operational problems during current and future SRDs. Specifically, we focused on diminishing the waiting time for ED treatment in 3-5 triaged respiratory-affected patients, considering its high association with overcrowding, intra-hospital infection, and the probability of poor health evolution.

The following sub-sections will describe how the proposed methodology was deployed in this case and how the outcomes improved the ED response during the SRD ("tri-pledemic" of flu, RSV, and COVID-19).

4.1 Digital Twin Modelling

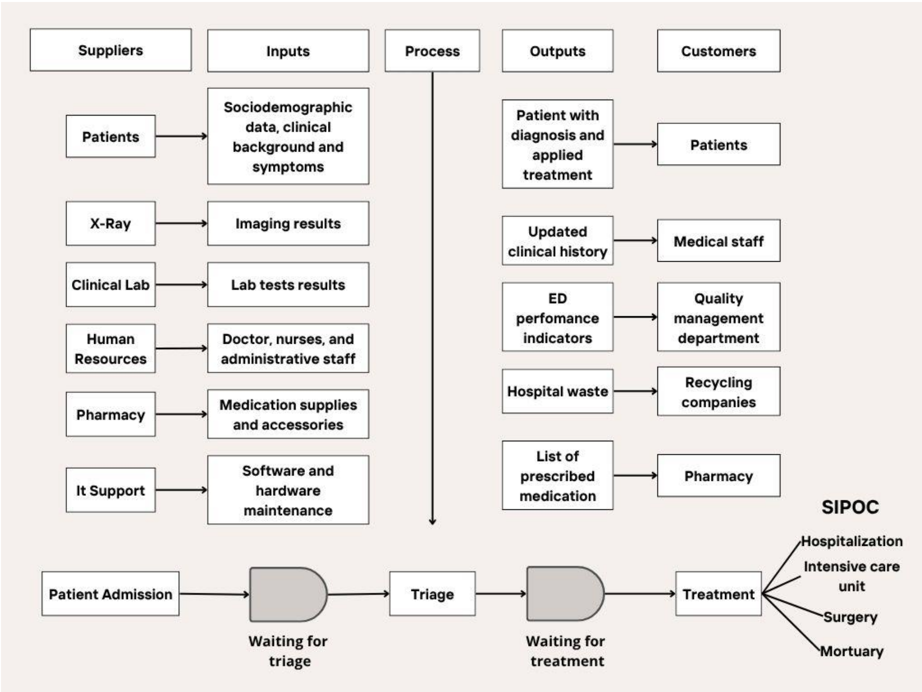

Fig. 2. SIPOC diagram for describing the ED journey and its interactions with suppliers and customers

Direct observation and a SIPOC diagram were used to identify the ED care stations, suppliers, inputs, outputs, and customers. It is good to highlight that patients and pharmacies behave as both suppliers and customers, which demonstrates the key role that they play in EDs during SRDs. Also, waiting times for triage and treatment were identified and corroborated by direct observation and waiting time indicators. Likewise, it became glaring how EDs depend on different satellite processes, indicating that intervening in ED response requires designing improvement strategies at different operational levels.

4.2 Input Data Assessment

The SIPOC diagram allowed us to identify three principal process variables: Time between arrivals of respiratory-affected patients, Triage categorization time, and Length of Stay in the emergency ward. The next step involves analyzing the data representing these variables. Initially, run tests are undertaken to verify potential autocorrelations ($\alpha = 0.01$). *P*-values higher than the significance level and absolute *T* values not exceeding 2 support the independence behaviour in all three variables. Afterwards, the Analysis of Variance (ANOVA) was carried out to discriminate subgroups of data within the main datasets ($\alpha = 0.01$). Upon examining the times between arrivals, it was concluded that the number of attendances is significantly different depending on the day of the week and time slot (A: 00:00 – 08:00; B: 08:00 – 16:00; C: 16:00 – 00:00) (Fobs = 4.9; *p*-value = 0). Similarly, diverse triage categorization times (*Group 1*: 1-2; *Group 2:* 3-5) were observed, evidencing assorted characteristics of ED respiratory-related admissions during the tripledemic surge (Fobs = 16; *p*-value = 0) [27]. Given above, a probability expression was defined for each heterogeneous subset (Table 1).

Table 1. Probability expressions incorporated into the digital twin

Process variable		**Probability expression**	***p*-value**
Time between arrivals of respiratory-affected	Monday – A	GAMM(120.18, 978) min	>0.10
	Monday – B	-1.2 + LOGN(26.4, 57) min	>0.10
	Monday – C	-1.2 + LOGN(18.6, 28.8) min	0.2
	Tuesday – A	WEIB(91.2, 1164.6) min	>0.10
	Tuesday – B	-1.2 + LOGN(31.8, 60.6) min	>0.10
	Tuesday – C	-1.2 + LOGN(18, 26.4) min	>0.10
	Wednesday – A	WEIB(89.4, 840.6) min	>0.10
	Wednesday – B	-1.2 + WEIB(32.4, 1101.6) min	0.08
	Wednesday – C	-1.2 + LOGN(19.2, 25.8) min	>0.10
	Thursday – A	WEIB(70.8, 1141.8) min	>0.10
	Thursday – B	-1.2 + LOGN(42.6, 92.4) min	>0.10
	Thursday – C	-1.2 + LOGN(18, 28.2) min	>0.10
	Friday – A	WEIB(69.6, 990) min	>0.10
	Friday – B	-1.2 + LOGN(34.8, 71.4) min	>0.10
	Friday – C	-1.2 + LOGN(19.2, 31.8) min	0.08
	Saturday – A	-1.2 + GAMM(74.4, 1203.6) min	>0.10
	Saturday – B	-1.2 + LOGN(40.8, 81) min	>0.10
	Saturday – C	-1.2 + LOGN(23.4, 36.6) min	>0.10
	Sunday – A	-1.2 + GAMM(129, 780) min	0.07
	Sunday – B	-1.2 + LOGN(36, 69.6) min	>0.10
	Sunday – C	-1.2 + GAMM(25.8, 1353.6) min	0.07
Triage categorization time	Group 1	UNIF(4, 12) min	0.2
	Group 2	TRIA(4, 4, 12) min	0.2
Length of Stay in the emergency ward		(60 + 2100*BETA(56.16, 60.6))/450 min	>0.10

4.3 Experimentation and Validation of the Digital Twin Model

The probability expressions derived from the input data assessment were then inserted into Arena® 16.10.00 software to create the digital twin mimicking the ED response during the tripledemic. The replication term considered in the DT was two weeks with 24 hours per day, given the characteristics of ED operations. Meanwhile, four months were deemed necessary to stabilize the DT.

A pre-sample of ten iterations was run to estimate the repetitions required for denoting the current real system variability. The validation procedure was concentrated on the ED waiting time for moderate-acuity patients (triage levels 3–5). In view of the significant variability observed in the DT, more than 300 runs were necessary to epitomize the real ED under the tripledemic context. Then, a 1-sample t-test was executed to compare the DT and real models. The statistical test provided enough support for the equivalence hypothesis (p-value = 0.8; μ = 4.68 hours), and the DT can be therefore utilized for performance analysis and remedy pretesting if needed.

4.4 Performance analysis

The average waiting time for moderate-acuity ED patients (4.68 hours) is a clear symptom of the congestion, cost overruns, and poor efficiency reported by the ED decision-makers during the tripledemic. Given this critical outcome derived from the DT model, the board of supervisors has been asked to underpin the expected design of improvement strategies tackling the problem [28]. Working closely with those involved in the day-to-day routine of the ED is important to ensure the generation of feasible remedies. As a result, two potential remedies were proposed: i) increasing the number of beds and general doctors, ii) reducing the length of stay by diminishing delays caused by clinical labs in delivering test results.

The improvement strategies were modeled and simulated into the DT (Fig. 3). The strategy (i) generates a waiting time for III-IV triaged patients oscillating between 1.34 and 1.98 hours (95% CI) with a mean of 1.66 hours. On the other hand, scenario (ii) would lead the ED to range from 2.49 hours to 5.18 hours (95% CI) with a mean of 3.83 hours. Therefore, scenario (i) would be the winning solution and is hence recommended for implementation in the wild.

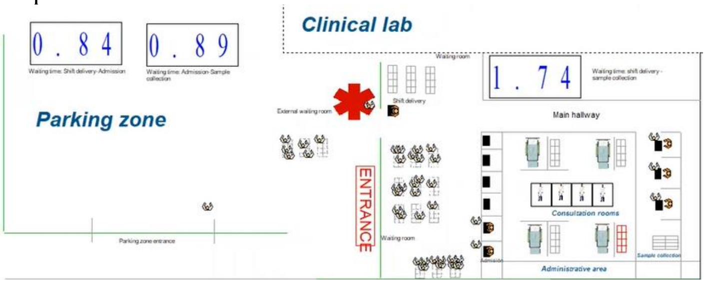

Fig. 3. Digital twin mimicking the ED ward: Clinical lab-ED interface

5. Conclusions and Future Directions

This study demonstrates the great potential of digital twin technology (DT) to improve the operational efficiency of hospital emergency departments (EDs), particularly during seasonal peaks of respiratory diseases such as influenza, RSV, and COVID-19. This research successfully identified and tested reductions in patient wait times by developing a simulation-based DT model using primary data and validating it with statistical tests. Implementing two key strategies—increasing critical resources and reducing laboratory delays—proved to be effective in reducing treatment wait times in patients at triage levels 3 to 5. These findings emphasize the value of DTs as proactive decision-support tools capable of simulating complex healthcare scenarios and guiding appropriate data-driven interventions. In conclusion, this approach improves patient clinical outcomes, reduces healthcare congestion, and increases EDs resilience during public health crises.

Future work suggests integrating digital twins with real-time hospital and social data systems to enable real-time decision-making. Implementing this approach in other hospital units is also advised to provide a more comprehensive view of hospital operations and improve interdepartmental coordination. Likewise, integrating advanced machine learning models into the DT models could improve their predictive capabilities, enabling more accurate forecasting of patient arrivals and resource needs. Ultimately, exploring the development of individualized TDs for patients could facilitate personalized care pathways and improve triage and treatment decisions in emergency settings.

Disclosure of Interests. The authors have no competing interests to declare that are relevant to the content of this article.

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