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Artificial intelligence and discrete-event simulation for capacity management of intensive care units during the Covid-19 pandemic: A case study

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ABSTRACT

The Covid-19 pandemic has pushed the Intensive Care Units (ICUs) into significant operational disruptions. The rapid evolution of this disease, the bed capacity constraints, the wide variety of patient profiles, and the imbalances within health supply chains still represent a challenge for policymakers. This paper aims to use Artificial Intelligence (AI) and Discrete-Event Simulation (DES) to support ICU bed capacity management during Covid-19. The proposed approach was validated in a Spanish hospital chain where we initially identified the predictors of ICU admission in Covid-19 patients. Second, we applied Random Forest (RF) to predict ICU admission likelihood using patient data collected in the Emergency Department (ED). Finally, we included the RF outcomes in a DES model to assist decision-makers in evaluating new ICU bed configurations responding to the patient transfer expected from downstream services. The results evidenced that the median bed waiting time declined between 32.42 and 48.03 min after intervention.

1. Introduction

In the last two years, hospitals worldwide had to quickly adapt their way to providing healthcare services to a suddenly increased number of patients who often required critical care in the ICU (Birkmeyer et al., 2020). The novelty of the Covid-19 virus pushed organizations to explore new methods that could assist them to survive in an unprecedented time (Frid-Adar et al., 2021).

Therefore, many studies have been conducted suggesting a variety of management tools and methods that can help in handling a situation characterized by emergency and urgency such as the Covid-19 pandemic (Upadhyay et al., 2022). Health organizations collected more data than ever before and adopted a range of techniques to support decision-making processes under uncertainties (Wang et al., 2022) such as data analytics or Artificial Intelligence (AI). Indeed, AI is starting to play a fundamental role in providing support to managers in health systems (Huang, Yang, et al., 2021; Piccialli et al., 2021; Thakur et al., 2012) and the use of data analytics and AI methods can help organisations to better deal in such circumstances (Behl et al., 2022). It is estimated that 90 % of US healthcare organisations are ready to implement AI strategies (Sage Growth Report, 2021), and also according to Forbes (2022), the use of AI represents an important innovation for hospitals. Therefore, world-leading healthcare organisations are adopting AI strategies (Marwaha et al., 2022) such as Harvard Medical School or the National Health Service in the UK where an innovation lab has been created with several projects concerning the application of AI to healthcare (NHS, 2022).

The use of AI techniques has been boosted during the Covid-19 pandemic when they were adopted to deal with a variety of aspects from the prediction of a Covid-19 diagnosis, especially during the first phase of the pandemic when testing was not readily available (Alballa & Al-Turaiki, 2021), to the development of treatments (Lalmuanawma et al., 2020), to the social behaviour of the population (Sheng et al.,

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2021).

However, despite the increasing use of AI for supporting the decision-making process in the healthcare context, there is still a gap in developing data analytics and AI methods to better manage health supply chains (Donthu & Gustafsson, 2020). Those supply chains have been affected at an incredible speed during the pandemic (Raj et al., 2022; Yusriza et al., 2022) and they can present several bottlenecks points and it is fundamental to take them into account when operating in rapidly changing environments (Muhammad et al., 2022). This is even truer for what concerns the inventory planning stage of health supply chains which has shown to have a major impact on the healthcare service (Rahman et al., 2022). The scarcity of various medical devices and personal protective equipment at the frontline staff showed how critical and complex are health supply chains (Chakravorty et al., 2018) and how their disruption translates into the loss of lives (Iyengar et al., 2020).

Indeed, several health organisations require new procedures to estimate the number of patients admitted to the hospital, to improve their inventory planning, and it became essential for them to predict how the number of patients will evolve into more severe diseases over time (i.e. Verity et al., 2020). At the same time, hospitals still had to provide healthcare services for all the patients not affected by Covid-19, i.e., managing the capacity of the hospitals, and a challenging balance between the two necessities needed to be pursued (Yang et al., 2021).

This paper presents a hybrid method that combines AI techniques, particularly a Random Forest method, with the Discrete Event Simulation (DES) methods. We aim to predict the demand for intensive beds by modelling the flow of the patients affected by Covid-19 within ICU departments and improving several intervention targets such as waiting time for a bed. First, we consider which predictors should be adopted to estimate the likelihood of ICU admission, adopting a statistical approach to test their significance. This is essential for ensuring that the framework can get results as close as possible to reality (Vickers et al., 2011). Once the choice of the predictors has been confirmed and a dataset of data for patients has been coherently constructed thanks to an appropriate preprocessing phase, a Random Forest model, recognised as one of the most accurate AI techniques for predictions, allows estimating the probability of the patients to be admitted to the ICU. Those probability values are the input of the DES model that simulates the inflow of patients in the ICU and their potential of becoming critical (importance of doing that). Finally, statistical validation tests are conducted to verify the validity of the DES model proposed.

The combination of those methods has the intention of reaching the following aims:

- The accurate selection of the indicators and the test of their statistical significance allows to robustly base the framework and to overcome difficulties from missing data or analyzing indicators that are not relevant (Štěpánková et al., 2003).
- The use of the RF method permits accurately predicting the likelihood of developing severe disease and it has been selected for its beneficial aspects outperforming other AI techniques. The RF can deal with large databases and detect complex non-linear relationships in addition to the interaction between the features (Simsekler et al., 2020).
- The use of the DES model allows discerning between several potential interventions that can be carried out to improve the several targeting interventions considered. Its benefits are related to the possibility of modeling diverse scenarios, also under very uncertain conditions as during a pandemic of a new virus (Jun et al., 1999). Also, the combination of the DES with statistical testing for validation of the model permits us to verify the validity of the DES model implemented.

We applied the framework to a case study in a Spanish hospital chain characterized by a huge number of ICU admissions and the need of improving their responsiveness to the pandemic. This implementation has been marked by a constant enrollment of different actors from the hospital sector which provides a full comprehension of the ICU context under the pandemic as well as the definition of realistic improvement scenarios considering the ICU transfer predictions derived from the RF model.

To the best of our knowledge, this study depicts a novel data-analytics-and-AI approach underpinning the ICU's effective capacity management, which has not been previously reported in the literature. The study illustrated the critical role that AI and DES may play in the design of in-time interventions diminishing the bed waiting times for incoming Covid-19 patients. The ICU expansion and the creation of satellite ICUs were pre-tested and analyzed for providing timely care to patients in critical condition and with urgent need of invasive mechanical ventilation, continuous hemodialysis, Extracorporeal Membrane Oxygenation, and other treatments required to counteract the more complex virus effects.

The paper certainly responds to the following research questions:

- Can data-driven inventory planning methods cope with unexpected increases in demand for overcrowded health environments?
- Can AI and DES techniques be merged to simulate the demand for intensive beds in health systems?
- Can DES methods be employed to design improvement strategies upgrading the response of ICUs in terms of the bed waiting times experienced by Covid-19 patients?

Therefore, the objectives of the paper can be stated as follows:

- developing an AI and data-analytics-based framework to predict the likelihood of the patients requiring treatments in ICU departments even in a pandemic situation;
- simulating the supply chain demand of health systems and its capacity management, i.e. the inflow of patients in the ICU department, their waiting time for a bed, and better management of the available resources;
- designing and evaluating the effectiveness of various improvement strategies in reducing the ICU bed waiting time experienced by Covid-19 patients using DES.

The rest of the paper is structured as follows. In Section 2, we review the literature on the application of AI and DES methods for Covid-19 patients. In Section 3, we present the proposed methodology while in Section 4 we describe the case study results with a discussion on them introduced in Section 5. Finally, Section 6 concludes the paper.

2. Literature review

Our paper explores the use of AI techniques and in particular, RF merged with DES techniques to manage inventory planning for health supply chains and more in detail, to predict the outcomes of patients affected by Covid-19 once they are admitted to the hospital. In the following, we review the theories on which our paper is based focusing on the concepts of inventory planning and what are the techniques most adopted to handle it. Then, we concentrate on how DES and AI have been employed in this field. Finally, we focus on the more specific problem of predicting the outcome in patients affected by Covid-19, again highlighting the use of AI and DES in this context.

2.1. Inventory planning management in health supply chains

Inventory planning management in health supply chains has been recognised as one of the most demanding issues for health systems for a variety of reasons such as little information shared among organizations and unique characteristics in terms of resources needed (Privett & Gonsalvez, 2014). Several studies have been regularly conducted throughout the years (for a review see e.g. Jack & Powers, 2009) for both concerning the demand management aspect i.e. predicting where, when, and how demand for healthcare services will happen (Klassen & Rohleder, 2001), and the capacity management aspects (as the one explored through the ICU bed capacity management decisions during the pandemic), i.e. making sure that health organisations can deal with the level of demand (Heineke, 1995). Despite the interest of the research community, a limited number of studies was developed before the pandemic concerning the management of the demand in very critical situations with only some examples concerning the SARS outbreak (Govindan et al., 2020) while in the past two years, the number of publications on this theme exponentially grew (Ortíz-Barrios et al., 2021). In addition to guaranteeing the satisfaction of the demand, health supply chains should pursue sustainable objectives (Lotfi et al., 2022) and in this sense, digital supply chains (Sharma et al., 2022) that employ AI methods (Agrawal et al., 2021) or even Blockchain technologies can enhance sustainable performance (Jraisat et al., 2022) also in combination with human resource practices (Mukhuty et al., 2022).

2.2. Methodologies for inventory planning management in health supply chains

A plethora of methodologies have been proposed to study inventory planning in health supply chains. To predict the demand for healthcare services, forecasting methods have been adopted in different cases. For example, Kadri et al. (2014) employed time series analysis and autoregressive integrated moving average to predict the demand in the emergency department in a retrospective study of a French hospital. Similarly, Luo et al. (2017) adopted a combination of an exponential and a smoothing forecasting model to predict the number of outpatient daily basis visits for a hospital in China. Other stochastic methods, such as regression analysis, have been extensively studied, for instance in Kumar and Mo (2010), to stimulate the demand for bed occupancy in a hospital in Singapore. To stimulate the flow of patients in organisations, queueing theory has been employed in several studies (e.g. Gorunescu et al., 2002). Although very much used, forecasting methods and queuing theory approaches present some difficulties such as coping with variations of the demand that do not follow the selected distributions of the models or they can be inadequate to take into account the complexity of the analysed process (Zhu et al., 2012).

To allocate resources (nurses and doctors but also beds and medicine) within the organisation to effectively manage the demand, optimisation models from operations research (e.g. Sitepu et al., 2018) and resolution techniques such as the direct neighbourhood search approach have been used. A relevant section of studies also employs scheduling methods to allocate patients to beds and minimise their waiting time (e.g. Kortbeek et al., 2015; Abdalkareem et al., 2021). However, these methods present major drawbacks because of the deterministic characteristics associated with this type of problem (Restrepo et al., 2020) that do not fully represent the reality in the hospitals.

In addition to that, other simulation techniques can be adopted such as Markov simulation processes. However, it has been shown that in situations where there are supply shortages, the DES simulation outperforms the Markov simulation process (Standfield et al., 2014).

2.3. AI and DES for inventory planning management in health supply chains

DES has been employed in a plethora of sectors (e.g. (Zhang, 2018; Ortíz-Barrios & Alfaro-Saíz, 2020a)) and consists in simulating a process in a series of steps that happen throughout time. It has been applied and used in a plethora of applications to obtain a robust result for the system that is being represented thanks to a series of experiments (Robinson, 2002). Its extreme flexibility is particularly useful when an analytic method to handle a problem is missing and/or when the system is too complex to be handled (Sumari et al., 2013). The evolution of DES methods is generally connected with the evolution of computing (Robinson, 2005) and one of their main uses is to model healthcare services (Zhang, 2018).

They have been adopted several times for simulating the demand for services in healthcare organisations (Günal & Pidd, 2010). For example, Melman et al. (2021) adopted discrete event simulation methods to understand which strategy among a predefined set of potential strategies would perform better in terms of finding a trade-off between the necessity of taking care of Covid-19 patients and the need to cancel the surgery and other interventions normally delivered by the hospital. On a similar note, Le Lay et al. (2020) simulated the bed occupancy impact due to the influx of Covid-19 patients.

DES methods have been extensively employed in the health supply chain because it allows overtaking the drawbacks of more traditional methods such as the ones introduced in the previous subsection and they also allowed the participation of the stakeholders in the process (Brennan et al., 2006).

Artificial Intelligence is representing a game changer in how healthcare is delivered (Yu et al., 2018). Applications of AI techniques are flourishing and the pandemic has further boosted this trend (Secinaro et al., 2021). AI methods are nowadays employed by healthcare organisations in several ways and among them, we can mention the tracking of patients' health and the support to administrative work (Bohr & Memarzadeh, 2020). Machine learning methods, the dominant approach in AI, represent a massive opportunity for healthcare organisations to make sense of the big data collected in the various organisations and to support evidence-based decision-making optimising the performance of the organisation (Chen & Decary, 2020). Among the machine learning methods, RF has been used in several contexts for classification and regression and other tasks thanks to the construction of decision trees on different samples. It has been adopted in a variety of contexts (for a review see e.g. Belgiu & Drăguţ, 2016). In the healthcare contexts, it has been applied to predict the occurrence of disease (Khalilia et al., 2011) and it is appreciated for the speed to handle such problems (Fawagreh & Gaber, 2020) and the possibility of dealing with incomplete databases (Khalilia et al., 2011) which are expected in a pandemic scenario. In the management of the supply chain context, RF has also been employed in several fields including forecasting products' backorder (Islam & Amin, 2020).

One of the fast-growing trends (Ordu et al., 2021) is represented by the possibility of combining hybrid models that integrate several techniques such as AI and DES embedded in a proper framework. For instance, DES methods have also been integrated with other methodologies. For example, Tavakoli et al. (2022) integrated them with data envelopment analysis and a machine learning technique to identify critical points that can create a bottleneck in the flow of patients. Also, Kim et al. (2021) adopted a combination of machine learning algorithms together with a discrete event simulation method to better design the flow of patients to the hospital starting from the triage model. New challenges connected to the application of such methods such as lack of resources to dedicate to the implementation of the new systems can arise and supporting methods to understand the innovation route needs to be introduced (Chatterjee et al., 2021; Srivastava et al., 2022).

2.4. Predicting intensive beds occupancy from patients affected by Covid-19

Among the issues related to the definition of patients' demand, we find the prediction of the patient's outcome once they are admitted to the hospital. Indeed, identifying such patterns could help decision-makers to deal with the suddenly increased number of patients (Heldt et al., 2021). In some cases, the authors collected historical data on patients to analyse the most common characteristics that guide them to a critical illness or a lengthy stay in hospital. For example, Petrilli et al. (2020) identified the most common factors in a group of >5000 patients. In addition to that, studies were also focusing on the main characteristics of the population affected and on their geographical location (Di Castelnuovo et al., 2020).

Within this aim, several machine learning techniques have been adopted and compared to predict which clinical factors, parameters, and characteristics of the patients can suggest a severe course for the patients (Alakus and Turkoglu, 2020). For example, Pourhomayoun and Shakibi (2021) developed several different types of machine learning methods including Support Vector Machine, Artificial Neural Networks, Random Forest, Decision Tree, Logistic Regression, and K-Nearest Neighbour to determine the health risk and predict the mortality risk of patients with COVID-19 with a quite consistent database of patients' data collected worldwide. In this regard, the decision of which indicator to adopt is quite diversified. For instance, Sun et al. (2020) use the support machine vector method to analyse >200 potential indicators on >300 cases to identify 36 significant factors, while Mauer et al. (2021) defined clustering techniques and regression analysis to predict the course of the illness adopting not only clinical characteristics but also measured parameters such as the level of oxygen monitored. In some cases, also the genome type of the patients and the phenotypic comorbidity of the patients were measured (Wang, Wang, et al., 2020), whereas (Patel et al., 2021) provided a combination of socio-demographic data, clinical data, and blood panel profile data. On a different note, Banerjee et al. (2020) estimated the severity of the outcome only from the full blood count of the patients without analysing the patients' previous medical history. Also, Gök and Olgun (2021) initiated their analysis from the blood samples of the patients, pointing out the essential role of a preprocessing phase of the data to make more consistent predictions. Among the machine learning methods, random forest algorithms were employed several times. For example, Casiraghi et al. (2020) employed the random forest for its ease of use and the possibility of easily integrating the method into a computerised system that could help doctors in assessing the seriousness of the disease. The possibility of integrating multiple classifiers in the boosted version of the algorithm can even make the methods more robust (Iwendi et al., 2020).

Considering the reported literature, it is evident the need for i) creating data analytics and AI methods underpinning decision-making processes in health supply chains influenced by rapidly changing contexts, ii) developing procedures predicting the expected demand for healthcare services presenting bottlenecks, and iii) constructing approaches articulating the demand for these services with resource and capacity management models focused on critical materials. More specifically, the evidence base also highlights the lack of a methodological approach that simultaneously assists healthcare decision-makers in: i) predicting the likelihood of ICU admission in Covid-19 patients based on emergency care data, ii) anticipatedly evaluating the response of ICUs against the expected Covid-19 admissions in terms of the bed waiting time, and iii) pretesting improvement scenarios that target ICU bed waiting time reduction. It additionally became clear that both the use of machine learning algorithms and the adoption of discrete event simulation studies can help support decisions in the healthcare context during challenging times. Therefore, our manuscript bridges the above-mentioned gaps by presenting a real case study fully exploiting the advantages of these methods in lessening the ICU bed waiting time experienced by Covid-19 patients. The contribution of this study is threefold: i) an AI and data-analytics-based model to predict the likelihood of ICU admission for Covid-19 patients attended in EDs, ii) a simulation model evaluating the ICU bed waiting time taking into account the predicted inflow of Covid-19 patients, and iii) a framework for the anticipated design of capacity management strategies minimizing the ICU bed waiting time in future demand scenarios.

3. Conceptual framework

Conceptually, what is being recommended is that AI and DES may operate as the pillars underpinning a decision-making framework that allows ICUs to respond quickly and effectively against the expected volume of Covid-19 admissions from the downstream services. Fig. 1 depicts the conceptual model suggested for this aim but with a special focus on bed inventory planning management.

This framework starts with efficient database management where medical records, process variables, and demand data can be stored under high-quality standards, thereby supporting the *informative* nature of the hospital data administration systems. Extracting these data will propel the development of AI solutions capable of predicting the expected volume of ICU admissions within the next few hours after ED arrival. This forecast must be later absorbed by the DES model which can be used by the decision-makers to evaluate the balance between the current ICU bed capacity and the expected flow of patients. Simultaneously, the DES model must feed parameters and process data from the ED health records helping to shape a more realistic representation of the operational ICU context during the pandemic outbreak. In case of off-balance, the simulated may be employed by the administrators to design improvement interventions with anticipated and proven success. Otherwise, it will only confirm that the current intensive bed capacity is sufficient to address the expected demand.

A key aspect in this framework is the role of the health supply chains in underpinning new intensive bed configurations. As these are networks of system entities, all actors (including transportation companies, suppliers, and retailers) must be coordinated and integrated to function as an operative scheme responding at lower lead times and costs. Reducing the Bullwhip effect will depend on the implementation plans derived from the DES model accompanied by an effective deployment strategy led by the hospital. Nonetheless, the bed inventory planning management cannot be only restricted to this critical resource but also directed towards coordinating the associated medical equipment supply chains and medical staff required to offer intensive care to Covid-19 patients. The proposed scheme must also cope with the changing dynamics of the virus to build a suitable bed configuration responding to

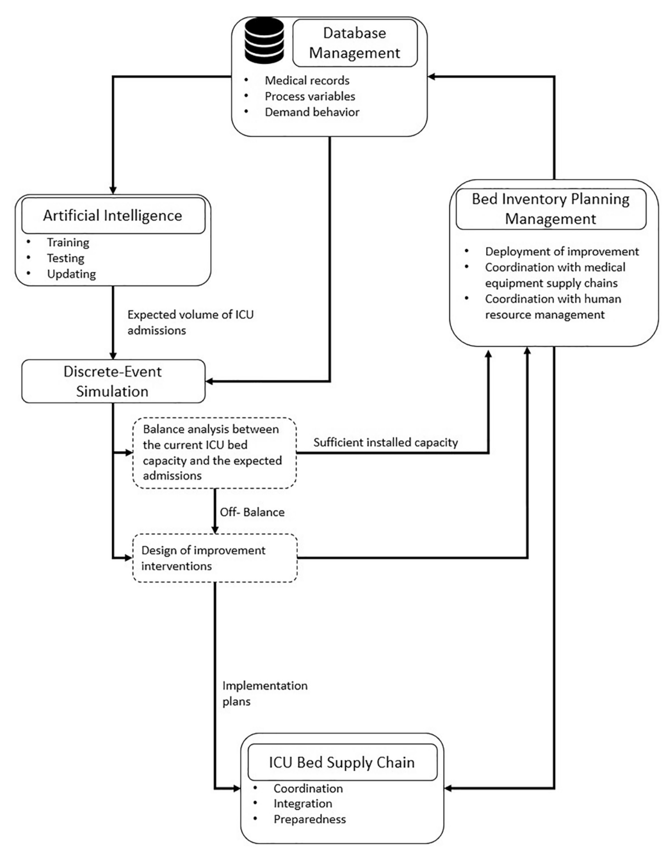

Fig. 1. The conceptual framework for supporting the bed inventory planning management during the Covid-19 outbreak.

the different demand scenarios. Incorporating the most recent operational variables and medical data into the AI and DES models will be pivotal to achieving this flexibility. The next section will outline how this conceptual framework can be implemented in a practical way practically at both tactical and operative levels of the ED-ICU interaction. In addition, the advantages of the AI-DES approach will be coupled with the pandemic decision-making scenario to clarify how this methodological proposal can deal with the bed waiting time problem faced by the ICUs.

4. Proposed methodology

The methodology described here integrates the RF and DES techniques to provide policymakers, ICU managers, and healthcare authorities with a solid decision-making groundwork helping to improve ICU bed capacity management. It is also good to highlight that embedding RF results in a DES model is novel in the healthcare context. The result is a realistic model simulating the Covid-19 patient journey within the hospital with a particular focus on intensive care. Such a model parses out the ICU Length of Stay (ICU-LOS) behaviour in those patients with a high probability of ICU transferring. It is worth noting that these estimations are derived when the patient is first admitted to the emergency department thereby facilitating the anticipated design of operational interventions tackling the disruptions caused by the unexpected behaviour of the Covid-19 pandemic. The general procedure is described below (Fig. 2):

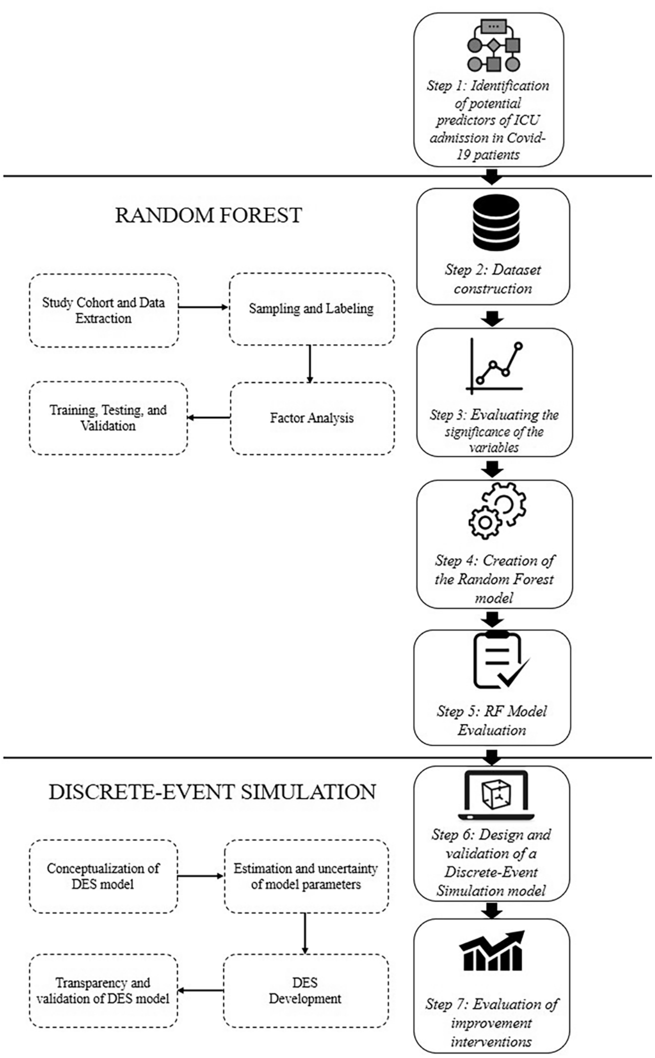

Fig. 2. The proposed RF-DES integrated approach for upgrading the intensive bed inventory management in presence of the Covid-19 outbreak.

Step 1. Identification of potential ICU admission predictors in Covid-19 patients: A list of features probably influencing the probability of ICU admission is established considering the pertinent scientific literature and doctors' experience during the struggle against Covid-19. The significant variables will be further used to predict the probability of ICU admission after a few hours of ED arrival.

Step 2. Dataset construction: The dataset is built by extracting high-quality and appropriate patient data associated with the previously identified features. These data are usually reported and stored in information systems according to predefined data management protocols. Nevertheless, the healthcare database continues to evidence incomplete and missing records (Bihri et al., 2022; Nijman et al., 2022). In this case, the missing information for each feature will be addressed by employing median imputation across the treatments of the response variable in the cohort (Kabir et al., 2020). At this stage, it is therefore necessary to clean and link the resulting data, thereby increasing the final model's accuracy and then producing better predictions. This entails a substantial amount of data pre-processing that will enable our data-driven model to learn interactions among the diverse types of features (single time point, discrete, and continuous).

Step 3. Evaluating the significance of the variables: The potential predictors are further investigated by applying the ANOVA test. In this case, indicators such as the p-value and their coefficients are used to support the feature ranking and selection. Factors with $p\text{-value} < 0.05$ are considered as "predictors" while factors with $p\text{-value} \geq 0.05$ are discarded. On the other hand, the Mean Decrease in Gini Coefficient (MDGC) is also calculated for each variable. The higher the MDGC, the higher the relevance of the feature in predicting the response variable.

Step 4. Creation of the Random Forest model: In this step, the data are initially verified for balance between the classes. Random under-sampling techniques will be applied where necessary to deal with potential imbalance problems if detected (Lin et al., 2021). After creating the final feature vector, RF will be used to derive the models predicting the probability of a patient in the emergency department ending up in the ICU. During modelling, the feature vector is split into independent training and testing sets. Also, *k*-fold cross-validation will be used for model verification (Gupta et al., 2021).

Step 5. Model Evaluation: The predictive capacity of the model is evaluated using performance indicators including accuracy, sensitivity, specificity, positive, and negative predictive values. In this regard, the Receiver Operating Characteristic curve (ROC curve) assesses the model considering two parameters: true positive rate (sensitivity) and false positive rate (specificity). The Area Under Curve (AUC) is also a measure of discrimination and will indicate how well the model differentiates between patients who will need ICU support and those who will not. Larger values of all these metrics denote a better RF prediction model (over 90 % values denote excellent discrimination).

Step 6. Design and validation of a Discrete-event simulation model: The predictive likelihood of ICU admission obtained with RF is later inserted into a DES model to specify whether the patient will be transferred to the ICU. Following this, the model is validated through statistical tests to determine if it is statistically comparable with the real-world system.

Step 7. Evaluation of improvement interventions: The simulated system is now utilized to pretest potential interventions upgrading the intensive bed inventory management in response to the expected volume of Covid-19 patients forecasted by the RF model. The interventions are proposed by the hospital decision-makers, health authorities, and ICU managers considering the pandemic context and the associated health supply chains. Each intervention is later modelled, run, and assessed by statistical comparison techniques to determine if it is effective in terms of the bed waiting time. The strategy with the major bed waiting time reduction is then recommended for implementation in the wild and becomes a roadmap for downstream members who will be in charge of activating their logistics operational scheme in view of rapid deployment.

The next subsections will detail the RF and DES techniques to provide a clear understanding of their step-by-step application while evidencing their usability in supporting the bed inventory management activities within the ICUs.

4.1. Random Forest

The use of artificial intelligence (AI) tools is gaining attention in healthcare. Typically, the application of AI is focused on the analysis of the link between prevention, treatment, and patient outcomes. Although its use is in its early stages, AI approaches have been reported to be useful for improving the operational performance of different modern healthcare systems (Ellahham et al., 2020; Gopinath, 2021; Sun, 2021). One of the subsets of AI is Machine Learning (ML) which comprises the use of computational learning for making successful predictions based on past experiences. Its use in healthcare can be evidenced in predictions of COVID-19 mortality (Feng et al., 2021), detection and prediction of diseases (Jadhav et al., 2017), and it also promises to improve and accelerate medical processes (Oala et al., 2021).

One of the main ML techniques is Random Forest (RF) which allows the construction of decision trees through the bagging technique (Breiman, 2001; Gumaei et al., 2022). In other words, RF creates multiple decision trees that are merged to obtain a more accurate prediction of outcome variables. The different decision trees establish models that are comparable to a real tree (Iwendi et al., 2020). The data are divided into smaller subsets originating from the branches of the tree. Subsequently, decision nodes containing two or more branches are originated. Each branch represents the features and leaf nodes containing the value of the result (Iwendi et al., 2020). The different decision trees generated from the above subsets or set of classifiers are represented as $h_1(x), h_2(x), \cdots, h_k(x)$, and the training data are represented as vectors $< X, Y >$ (Breiman, 2001; Gumaei et al., 2022; Iwendi et al., 2020).

The margin function ($mg(X, Y)$) for each decision tree is expressed in Eq. (1):

$$mg(X,Y) = av_k I(h_k(X) = Y) - \max_{j \neq Y} av_k I(h_k(X) = j) \tag{1}$$

The generalization error is given by Eq. (2):

$$PE^* = P_{X,Y}(mg(X,Y) < 0) \tag{2}$$

It is known that the number of decision trees increases for all tree sequences considering that RF $h_k(X) = h(X, \Theta_k)$. Therefore, followed by the strong law of large numbers and the tree structure, the prediction accuracy for each tree is given by Eq. (3) whose result explains why RF does not overfit as more trees are added (Breiman, 2001):

$$P_{(X,Y)}(P_\theta(h(X-\theta) = Y) - max_{j \neq Y} P_\theta(h(X-\theta) = j)\langle 0) \tag{3}$$

RF has been proven to outperform other methods regarding prediction accuracy while providing an autonomous representation of interactions in large datasets (Patel et al., 2021; Simsekler et al., 2021). Besides, RF helps to rank the independent variables by considering their contribution to the outcome variable (Simsekler et al., 2021). On the other hand, RF allows detecting complex nonlinear relationships, handling big data, and identifying high-dimensional interactions between features (Chowdhury et al., 2021; Simsekler et al., 2020; Sujatha & Krishna, 2022). RF also evidences high resistance to overtraining as each tree is an independent random experiment even in presence of a considerable number of trees. No need to rescale, transform or change data is another RF benefit representing a potential time reduction in preprocessing activities. This is critical in pandemic times when rapid and effective solutions are required to alleviate the burden faced by the ICU units. Not less important is its capability to deal with both continuous and discrete features as those expected to be gathered in ED settings from the sociodemographic and clinical profile of Covid-19 patients.

The proposed RF model is developed based on the step-by-step approach described by Cheng, Joshi, et al. (2020), Vijiyakumar et al. (2019), and Breiman (2001) (Fig. 3):

- Choose significant R predictors from a predefined set of m features (usually $R \ll m$) after implementing the instructions within Step 3.
- Select the node employing the best-split point considering R.
- Divide the selected node into daughter nodes utilizing the best split.
- Iterate the first step until l nodes have been derived.
- Create a forest via iterating the previous steps for a times to finally produce n trees.
- Generate the prediction for the target variable (in this case, the ICU admission likelihood for Covid-19 patients arriving at the ED). All these steps can be further operated through a software environment for statistical computing and graphics (e.g. R)

4.2. Discrete-Event Simulation (DES)

Now, we describe the step-by-step procedure of Discrete-Event Simulation (DES) according to the ISPOR-SMDM Task-Forces series which outlines a solid framework for healthcare modelling (Caro et al., 2010; Gillespie et al., 2016):

(i). Conceptualization of DES model: The simulation model is proposed as a tool that allows for achieving an equivalence to the real system (Ahmad et al., 2020; McGlothlin et al., 2018). In this case, DES is implemented to simulate the operations concerning the pathway between the ED and ICU. To do this, it is necessary to fully describe the stages of the Covid-19 patient pathway within the hospital paying particular attention to the intensive care services. Also, modelers are requested to identify the interactions with other healthcare services as well as the critical process variables to make the model comparable to the real-world system. In this respect, it is first advised to draw a flow diagram capable of representing the entire Covid-19 patient journey within the hospital with a special focus on emergency and intensive care. Such a graph is fed by the documented healthcare procedures, the associated protocols, and direct observation outputs. Ultimately, critical/secondary process variables and parameters are identified.

(ii).Calculation of uncertainty in simulation parameters: Uncertainties exist according to the volatile context of a pandemic scenario mainly evidenced in significant variations of bed demand, LOS, and other measures derived from daily hospital operations (Lu et al., 2021). In this regard, Gillespie et al. (2016) and Garcia-Vicuña et al. (2021) state that it is important to incorporate the heterogeneity, and parameter uncertainty into the DES model to ensure equivalence to the real-world ICUs. Therefore, part of the model uncertainty derived from this application will be intrinsically linked to the insights provided by the RF model (likelihood of ICU admission). Following this, input data analysis (randomness, homogeneity, and goodness-of-fit) will be performed on the process variables identified in the previous phase.

- o *Randomness:* Run tests ($\alpha = 0.01$) will be carried out to verify whether the variable is independent. If the resulting p-value is higher than the significance level α, the variable is then concluded to be randomly distributed. Otherwise, it is identified to be dependent on other factors. The resulting p-value is based on K which is the comparison reference score helping to elucidate the observed number of auto-correlations.
- o *Homogeneity:* ANOVA tests ($\alpha = 0.01$) will be executed to detect potential subgroups of data within the variable dataset. If the ensuing p-value is greater than the error level α, the variable is homogeneous and only one probability distribution is necessary to describe its behaviour. Otherwise, the variable is deemed heterogeneous and a probability expression is therefore required to represent each subgroup of data. The observed F score is a complementary metric confirming the decision achieved through the p-value. In

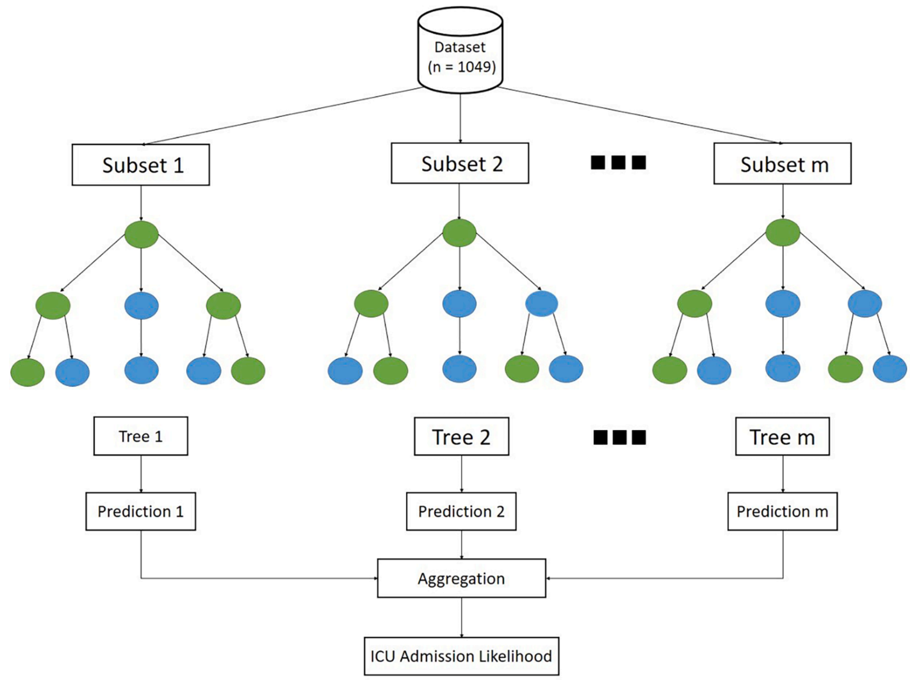

Fig. 3. The RF procedure within the ICU bed inventory management project.

particular, if this indicator is higher than the theoretical *F* score, the homogeneity assumption is rejected; on the contrary, it is accepted.

o *Goodness-of-fit:* Goodness-of-fit tests will be deployed to estimate the probability distributions of each variable including those evidencing subgroups of data. Kolmogorov-Smirnov tests ($\alpha = 0.01$) will be used for this aim. The key metric is again the *p*-value which favors a particular distribution family if it is higher than the error level. In case of different probability expressions capable of describing the variable, the modelers should select the one with the major *p*-value.

(iii). DES Development: In a healthcare context, the use of DES is appropriate for discovering a wide range of operational problems such as bottlenecks and inefficient use of resources (Casier et al., 2015; Vázquez-Serrano et al., 2021). Besides, it allows contrasting different scenarios without a real implementation (What-If analysis), therefore making it possible to explore their consequences in the real-world system (Amantea et al., 2020; Barrios et al., 2015; Castanheira-Pinto et al., 2021; Garcia-Vicuña et al., 2021). In this step, the design, development, and simulation of the DES model are carried out through a simulator (e.g. Arena Rockwell Software) which animates the Covid-19 patient journey within the hospital, thereby facilitating engagement with the different stakeholders and underpinning the model validation. The modelling process is possible thanks to the insertion of blocks denoting the different steps of the Covid-19 patient journey identified in phase *(i)*. Likewise, the RF insights (Step 4) and probability distributions (Phase ii) are included in this model, thereby providing a robust and connected decision-support system.

(iv). Transparency, validation, and pretesting: Validation and transparency are important to demonstrate the degree to which the proposed model represents the real ICU (Melman et al., 2021). This is achieved through a statistical comparison between the proposed model and reality using performance metrics as evidenced in different works (Doneda et al., 2021; Garcia-Vicuña et al., 2021; Melman et al., 2021). On the other hand, transparency must be achieved by clearly presenting the model structure, assumptions, and details according to the model validation, (Corro Ramos et al., 2020; Gillespie et al., 2016). The successful validation of the model also opens the door to the execution of simulations with different parameters (improvement interventions) searching for those scenarios with satisfactory performance in the context framed by the predicted likelihood of ICU admission. This is also defined with the aid of comparative statistical analysis, such as the 1-sample sign test, which is performed on the metrics derived from a sample of runs. The number of iterations is based on the variations detected in a pre-sample of 10 runs as exemplified in Ortiz-Barrios and Alfaro-Saiz (2020b). In this case, three performance indicators will be employed to validate the model: Waiting time in ED for I-II triaged patients, Waiting time in ED for III-V triaged patients, and ICU bed waiting time. If the consequent *p*-value is major than α, the model is then concluded to be comparable with the real-world system; otherwise, the model must be reviewed and updated until achieving this condition. Once reached, the model can be used for performance diagnosis and simulation of improvement interventions. For the latter, Mann-Whitney tests (with $H_1 : \eta_{ps} - \eta_{nis} < 0$) will be applied to determine if the proposed strategy (ps) would reduce the ICU bed waiting time compared to a non-intervention scenario (nis). In this case, if the *p*-value is found to be higher than α, the intervention is deemed to be non-effective in lessening the delays experienced by Covid-19 patients needing ICU beds. However, if this metric is lower than the error level, the intervention can be recommended for application in the wild.

5. Results

Inadequate management of ICU installed capacity may result in an increased risk of Covid-19 mortality and higher healthcare costs. Being aware of this, a Spanish hospital chain decided to advance the understanding of this virus by collecting suitable data supporting the design of AI models, epidemiological studies, and phase-type algorithms to lay the groundwork for healthcare decision-making in upstream services (surgery, hospitalization, and intensive care). Moreover, this group has reported >4400 Covid-19-related admissions in the emergency departments (EDs) and continues to combat this pandemic based on the existing protocols. However, the intricacy inherent to the ICU and the disaster context motivates the implementation of more robust methodological approaches augmenting the resilience, flexibility, and responsiveness of these units thereby reducing the waiting times for a bed and extended LOS experienced by the infected patients. The project described here was approved by the showcased group of hospitals (Agreement number: 14–12-2021–004; Access request ID:39) which also provided full informed consent about the activities to be performed in this intervention. The following sub-sections will depict the results obtained after executing the proposed framework while building an evidence base underpinning the creation of strategies that anticipatedly prepare the ICUs against the expected demand peaks.

5.1. Potential predictors of ICU admission in Covid-19 patients

The likelihood of ICU admission in Covid-19 patients is the result of combining different predictors from the sociodemographic (Age, sex) and clinical domains (Diastolic blood pressure, Systolic blood pressure, Heart rate, Blood oxygen saturation, Temperature). Table 1 enlists a set of factors that may potentially contribute to this probability in a significant manner considering previous findings from the reported literature and the opinion of different specialists involved in the healthcare sector. These features were measured by the Spanish hospital chain in each confirmed Covid-19 patient during the current outbreak. It is good to note that only features to be collected in the emergency departments were considered given the aim of predicting the probability of ICU transfer anticipatedly.

5.2. Dataset construction

5.2.1. Study cohort and data extraction

The initial dataset, constructed under the "COVID DATA SAVE LIVES" project, contains the anonymized healthcare records of 4479 patients between the ages of 1 and 106 years. The use of these data counts on the formal approval by the Ethical Research Committee of the Spanish hospital chain. Specifically, the individual patient data was gleaned from the electronic hospital health records and included information on diagnosis, ICU admissions, lab results, treatments, vital signs, and type of discharge. These patients were admitted to the emergency departments of the hospital group between 5 February 2020 and 13 February 2021. The Covid-19 diagnosis was reached considering the prior assessment by a specialist and/or clinical findings of a Reverse Transcription Polymerase Chain Reaction (RT-PCR) test. The data was extracted from *Doctoris*, the Health Information System employed by the showcased hospitals.

Table 1
List of potential predictors of ICU admission due to Covid-19.

Potential predictor	Predictor description	Previous studies using the predictor
Sex	Sex of the Covid-19 suspected/infected patient.	Mesas et al. (2020), Figliozzi et al. (2020), Hu et al. (2020)
Age	Age of the Covid-19 suspected/infected patient.	Mesas et al. (2020), Figliozzi et al. (2020), Gallo Marin et al. (2021); Dergaa et al. (2022)
Diastolic blood pressure	Record of minimum blood pressure taken at the Emergency Department.	Guo et al. (2020); Ikemura et al. (2021), Wang et al. (2021)
Systolic blood pressure	Record of maximum blood pressure taken at the Emergency Department.	Guo et al. (2020); Caillon et al. (2021), Ikemura et al. (2021), Wang et al. (2021)
Heart rate	Heart rate record taken at the Emergency department.	Guo et al. (2020); Mudatsir et al. (2021), Mehrabadi et al. (2021),
Oxygen saturation level	Record of oxygen saturation taken at the Emergency department.	Akhavan et al. (2020), Assaf et al. (2020), Mejía et al. (2020)
Temperature	Temperature record taken at the Emergency department.	Tharakan et al. (2020), Drewry et al. (2020), Leung (2020)
D-Dimer level	First D-dimer record calculated by the lab at the Emergency Department	Soni et al. (2020), Cheng, Hu, et al. (2020), Zhang et al. (2020)

5.2.2. Sampling and labeling

The final sample selected for the prediction model was reduced to 1049 patients since the presence of incongruent data in some of the features. In this case, missing information for each potential predictor was imputed by using the median value across the levels of the response variable in the cohort (Batista & Monard, 2003; Cheng, Joshi, et al., 2020) In some features (Systolic blood pressure, Diastolic blood pressure, Heart rate, Body temperature and Blood oxygen saturation), two measures were gathered at different instances to evidence the evolution of the patient along the time (time-series data). The primary outcome of this intervention was the likelihood of ICU transfer. In this case, the labeling was the following: indicate with "1″ if the Covid-19 patient was transferred to the ICU; otherwise "0".

5.3. Factor analysis: Significance tests

Table 2 and Fig. 4a–4m depict the characteristics of patients included in the study cohort and provide specific profiles of both Covid-19 patients in the ICU and those who did not necessitate this service. An advantage of this research is that the database contains patients from all age groups and it is therefore illustrative of the Covid-19 affectation

Table 2
Characteristics of patients transferred and not transferred to the ICUs in the showcased hospitals.

Patient characteristics	Transferred to ICU N (%) or Mean (SD)	Not transferred to ICU N (%) or Mean (SD)	P-value
Total patients	398 (37.9 %)	651(62.1 %)	
Age (AGE)			
Mean	64.95 (15.25)	66.29 (16.93)	
Median	67	67	
Interquartile range	60 to 75	54 to 80	
0 to 10	8 (2.0 %)	1(0.2 %)	
11 to 20	0 (0.0 %)	2 (0.3 %)	
21 to 30	6 (1.5 %)	15 (2.3 %)	
31 to 40	7 (1.8 %)	25 (3.8 %)	
41 to 50	29 (7.3 %)	77 (11.8 %)	0.000
51 to 60	60 (15.1 %)	114 (17.5 %)	
61 to 70	130 (32.6 %)	135 (20.7 %)	
71 to 80	123 (30.9 %)	131 (20.1 %)	
81 to 90	33 (8.3 %)	117 (18.0 %)	
91 to 100	2 (0.5 %)	33 (5.1 %)	
100 onwards	0 (0.0 %)	1 (0.2 %)	
Sex (SEX)			
Male	292 (73.36 %)	378 (58.06 %)	0.000
Female	106 (26.64 %)	273 (41.93 %)	
Temperature (°C)			
First measure in EDs (TEMP_1)	36.83 (0.72)	36.60 (0.67)	0.000
Second measure in EDs (TEMP_2)	36.84 (0.75)	36.62 (0.71)	0.000
Diastolic blood pressure (mm Hg)			
First measure in EDs (DBP_1)	76.19 (9.50)	76.14 (10.96)	0.000
Second measure in EDs (DBP_2)	76.45 (10.77)	76.17 (11.64)	0.000
Systolic blood pressure (mm Hg)			
First measure in EDs (SBP_1)	130.97 (14.81)	133.44 (17.07)	0.000
Second measure in EDs (SBP_2)	131.08 (16.45)	133.27 (17.60)	0.000
Heart rate (Number of heartbeats)			
First measure in EDs (HR_1)	91.48 (14.34)	87.87 (13.69)	0.000
Second measure in EDs (HR_2)	91.95 (14.80)	88.40 (14.52)	0.000
Oxygen saturation level (%)			
First measure in EDs (OSL_1)	90.22 (7.58)	93.75 (4.73)	0.000
Second measure in EDs (OSL_2)	89.66 (8.73)	93.62 (5.04)	0.000
D-dimer level (μg/ml) (D.DIMER)	1944.72 (3512.83)	1017.38 (2658.99)	0.000

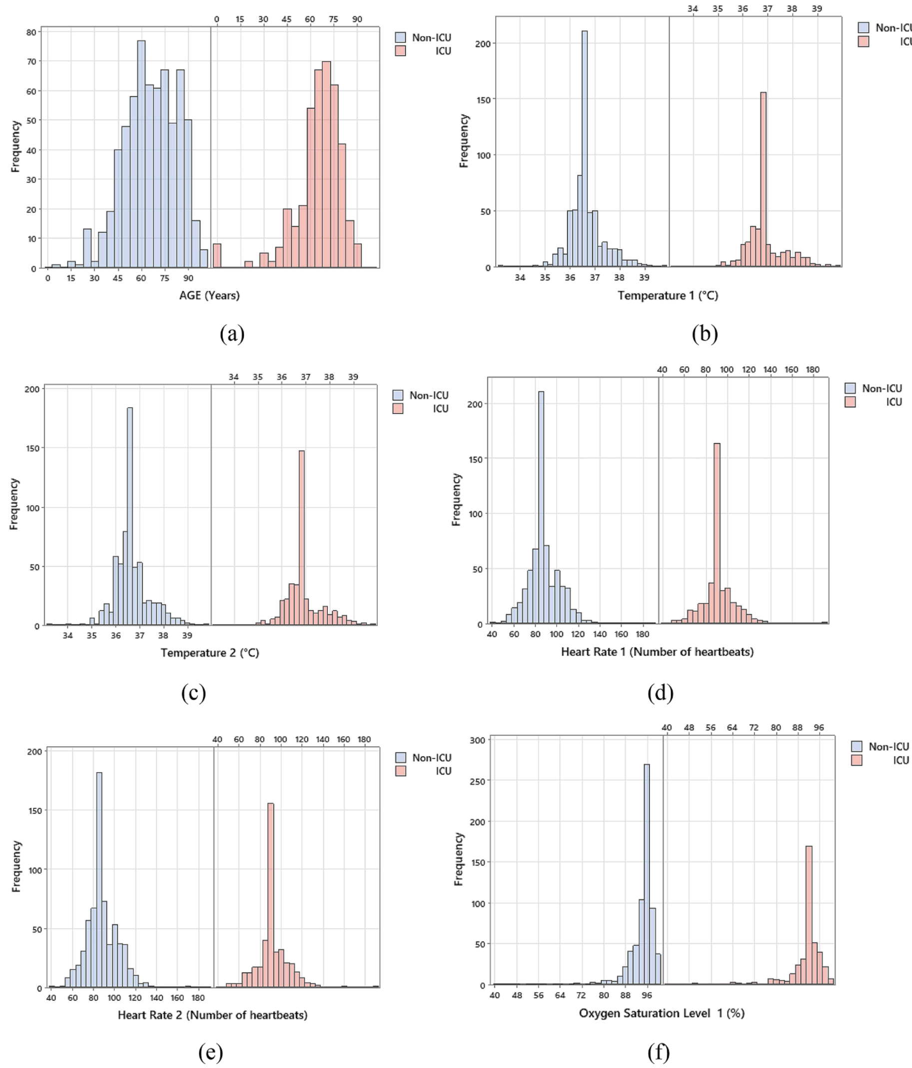

Fig. 4. Histograms representing the significant features a) AGE, b) TEMP_1, c) TEMP_2, d) HR_1, e) HR_2, f) OSL_1, g) OSL_2, h) D.DIMER, i) DBP_1, j) DBP_2, k) SBP_1, l) SBP_2, and m) SEX in ICU-admission and Non-ICU-admission Covid-19 patients.

along the different human life phases. For instance, of the 398 patients transferred to the ICUs between 5 February 2020 and 13 February 2021, 153 (63.5 %) were aged between 61 and 80. It is interesting to note that most of these patients between the ages of 81 to 102 years (151; 81.18 %) were not transferred to ICU while the majority of transferred Covid-19 patients were male (292; 73.36 %).

Regarding the clinical features, it is evident that both first and second body temperature measures were significantly higher in ICU patients (TEMP_1: 36.83; TEMP_2: 36.84; p-value = 0) compared to those who did not pass to these units (TEMP_1: 36.60; TEMP_2: 36.62; p-value = 0). Also, the diastolic blood pressures were concluded to be meaningfully larger in the ICU Covid-19 patients (DBP_1: 76.19; DBP_2: 76.45; p-value = 0) contrasted with those in emergency and hospitalization units (DBP_1: 76.14; DBP_2: 76.17; p-value = 0). Likewise, the heart rates (Mean difference for HR_1: 3.71 heartbeats; HR_2: 3.55 heartbeats) were statistically greater in the ICU patients (p-value = 0). It is also interesting to underscore that lower oxygen saturation levels were reported in transferred patients (Mean difference for OSL_1: −3.53 %; OSL_2: −3.96 % p-value = 0) who also experience high D-dimer values in comparison with those having mild health condition (Mean difference for D.DIMER: 927.34 μg/ml; p-value = 0).

Following this, Analysis-of-Variance (ANOVA) tests were performed to validate whether the above-mentioned factors were contributing to the probability of ICU transfer for a Covid-19 patient considering an alpha level of 0.05. In this case, all the factors were found to be significant to this likelihood (p-value = 0) and can be therefore adopted by the RF model to predict this transitory state. Furthermore, 2-order and 3-order interactions were explored to upgrade the model performance in terms of accuracy, positive/negative predictive value, Area Under Curve (AUC), sensitivity, and specificity (see Table 3 and Fig. 5). Herein, "CR" and "SR" indicate cubic and square roots respectively whilst "LN" represents the natural logarithm. As a result, the 2-order interactions ("SR_OSL", "SR_HR", "SR_DBP", "TEMP_1xTEMP_2", "SR_SBP", "HRxOSL", "DBPxHR", "D.DIMERxOSL" and "D.DIMERxAGE") and 3-order interactions ("CR_OSL", "CR_TEMP_2", "CR_SBP") were determined to be contributors to ICU stay based on the Mean Decrease in Gini Coefficient (MDGC). It is relevant to point out that the most important predictors are those related to the D-dimer level (MDGC = 106.110) and their interactions with age (MDGC = 32.721) and oxygen saturation level (MDGC = 84.610).

5.4. The Random Forest model: Training, testing, and validation

The cohort was randomly divided into training and test subsets according to a 70/30 proportion. The ICU transfer ratio was 8.89 % which generated an imbalance between the positive class (patients who were

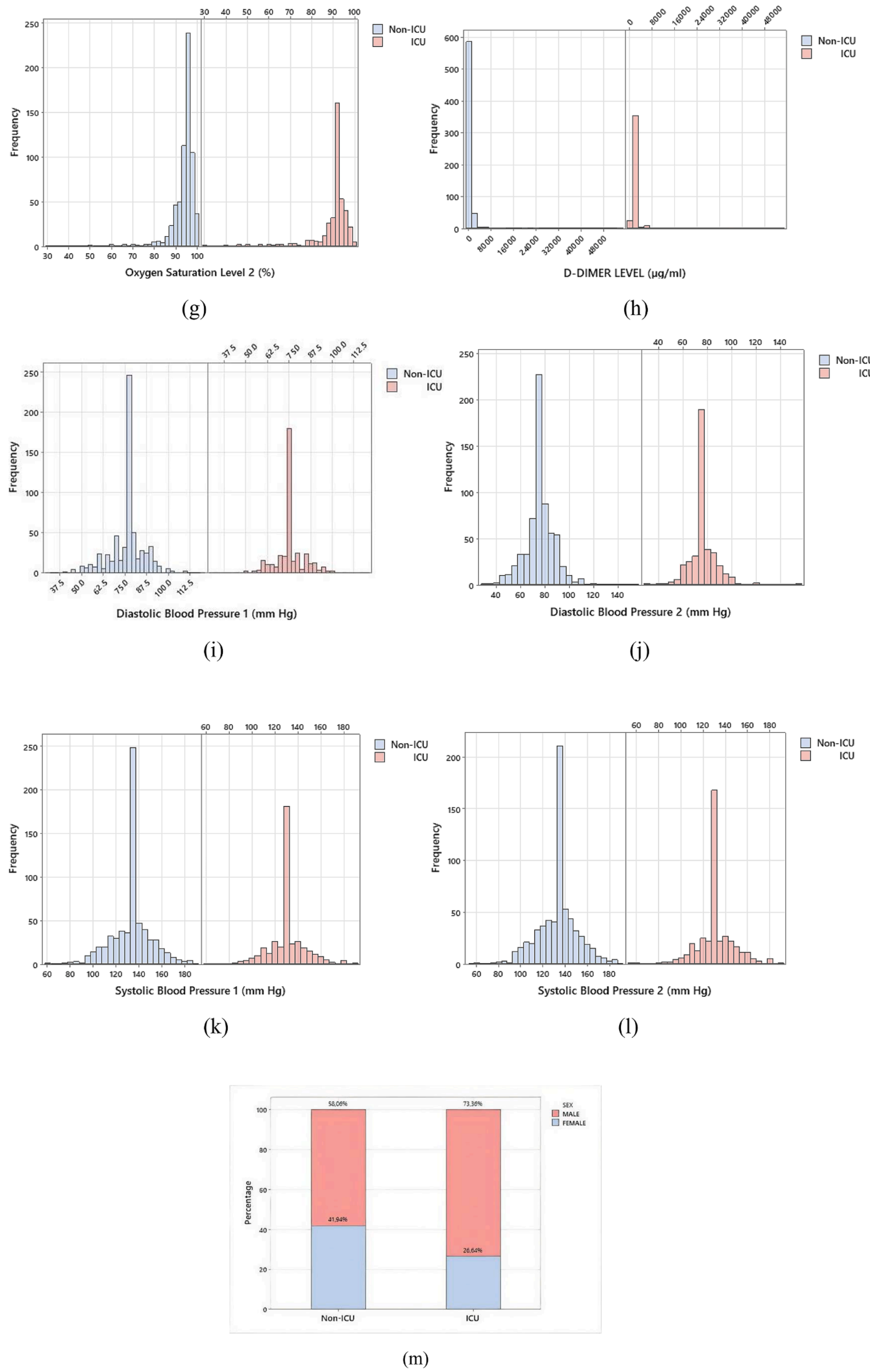

Fig. 4. (*continued*).

not transferred to the ICUs) and the negative label (patients who were moved to the ICU). We then undertook random undersampling on the training dataset to balance both classes and avoid bias in the prediction model (Hsu et al., 2015; More & Rana, 2017; Sawangarreerak & Thanathamathee, 2020) (Fig. 6). We employed the Rstudio software version 4.1.2 to apply RF and reach the prediction model. Following this, we carried out a 10-fold cross-validation to adjust the hyperparameters and employed these libraries: epiR (v.2.0.44), Caret (v.6.0–90) (Mercatelli et al., 2021), randomForest (v.4.7–1) (Fontaine et al. 2018), and ROCR (v.1.0–11).

Moreover, seven performance metrics were used not only to specify their average score but also to define a 95 % confidence interval (95 % CI) for better variability representation and model robustness evaluation: Sensitivity, Specificity, Accuracy, Positive predictive value, Negative predictive value, Area Under Curve (AUC), and McNemar's test p-value. These indicators were estimated in the Rstudio environment (Xie et al., 2022) by implementing custom scripts and the aforementioned libraries. Table 4 reports the final values of the metrics. In this case, McNemar's test p-value (0.153) was concluded to be higher than the error level (0.05) which supports the homogeneity assumption between the percentage of misclassified cases for the two class levels. On the other hand, most of the metrics are over 90 % which evidences good

Table 3
Mean decrease in Gini coefficient for factors and their interactions.

Factor/Interaction	Mean decrease in Gini coefficient
AGE	5.029
SEX	0.707
SBP_1	9.527
DBP_1	5.984
TEMP_1	4.230
HR_1	3.520
OSL_1	12.270
SBP_2	4.925
DBP_2	4.136
TEMP_2	3.144
HR_2	2.712
OSL_2	6.931
SR_OSL	9.229
SR_HR	4.735
SR_DBP	5.074
CR_OSL	10.299
CR_TEMP_2	2.046
TEMP_1xTEMP_2	3.609
SR_SBP	8.035
HRxOSL	3.917
CR_SBP	7.287
DBPxHR	3.744
LN_SBP	6.509
D.DIMER	106.110
D.DIMERxOSL	84.610
D.DIMERxAGE	32.721

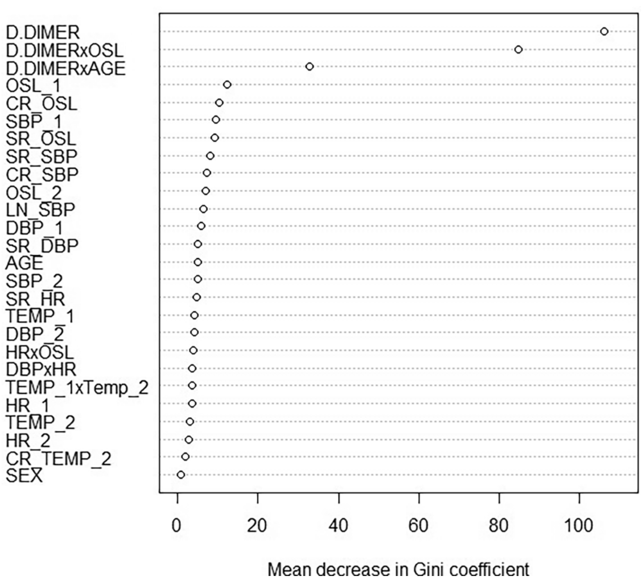

Fig. 5. Mean decrease in Gini coefficients for factors and interactions.

discrimination by the RF model when identifying patients with a need of intensive care ICU and those who do not necessitate this service. This is also confirmed by the Receiving Operator Characteristic (ROC) curve plot (Fig. 7) whose AUC (95.48 %, 95 %CI (89.73 %–100 %)) exhibits excellent discrimination between the Covid-19 patients with/without the need for ICU admission. Likewise, the specificity (93.50 %, 95 %CI (87.58 %–97.15 %)) denotes that out of 100 patients with no ICU admission need, the model will forecast between 87 and 97 correctly. In the meantime, the sensitivity (90.18 %, 95 %CI (84.54 %–94.28 %) points out that out of 100 Covid-19 patients needing transfer to ICU, the RF model will predict between 84 and 94 accurately. On the other hand, the positive predictive value (94.84 %, 95 %CI (90.08 %–97–74 %) evidences that between 90 and 97 of every 100 Covid-19 patients with ICU admission prediction, will be ultimately moved to this unit. Meanwhile, the negative predictive value (87.79 %, 95 %CI (80.92 %–92.85 %) reveals that between 80 and 92 out of 100 Covid-19 patients with non-ICU transfer forecast, will not be certainly discharged to this stage.

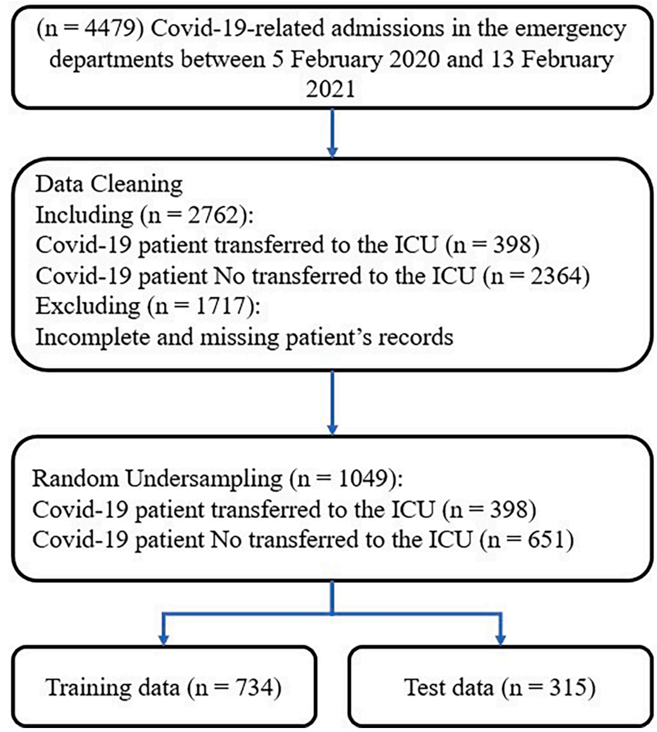

Fig. 6. The procedure for the derivation of training and test cohorts.

5.5. *The DES model: Design and validation*

The predictions derived from the RF algorithm were then incorporated into a DES model whose aim is three-fold: i) Measure the waiting time for an ICU bed, ii) Determine if the number of available ICU beds is enough to meet the demand, and iii) Define how the ICUs can be reconfigured to minimize the waiting times considering the number of patients that are expected to be admitted in these units. The next subsections will describe how these objectives were addressed and what recommendations emanated from this implementation pursuing the effective capacity management of Intensive Care Units during the Covid-19 pandemic.

5.5.1. *Conceptualization of DES model*

To model the ED-ICU interaction correctly, it was necessary to count on the opinion of medical staff and the administrative personnel involved in the Quality Management and Logistics departments complemented by the information derived from the related procedures, protocols, and fieldwork allowing us to identify the main process components of the Covid-19 patient journey, the different patient states, the interactions among services, and the associated data. The result is a flow diagram detailing the Covid-19 healthcare from the EDs to the ICU (Fig. 8).

5.5.2. *Calculation of uncertainty in simulation parameters*

In this system, four process variables were considered within the modelling phase: Time between arrivals of Covid-19 patients, Triage consultation time, Diagnosis/Treatment time in the ED, and ICU-LOS. Run tests were first undertaken to verify the randomness of these variables (alpha level = 0.01). The resulting outcomes in terms of the *K* score and *p*-value are presented in Table 5. It is noted that "Time between arrivals of Covid-19 patients" was stratified into "day of the week" and "time slots" (P1: 00:00–08:00; P2: 08:00–16:00; P3: 16:00–00:00)

Table 4
Performance metrics of the ICU likelihood predictive model based on RF (95 % confidence intervals).

Sensitivity (%)	Specificity (%)	Accuracy (%)	Positive predictive value (%)	Negative predictive value (%)	AUC – ROC (%)	McNemar's test p-value
90.18 (84.54–94.28)	93.50 (87.58–97.15)	91.61 (87.7–94.55)	94.84 (90.08–97.74)	87.79 (80.92–92.85)	95.48 (89.73–100)	0.153

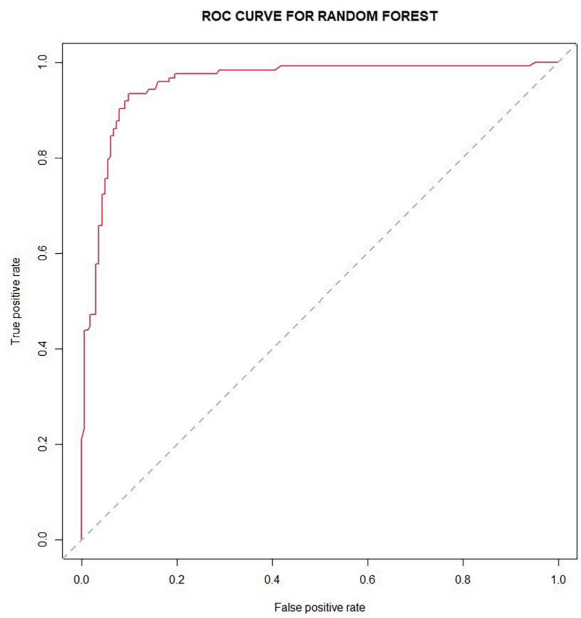

Fig. 7. ROC curve for the test set in the RF prediction model.

considering the p-values (0) derived from the initial run tests. This is consistent with Gul and Guneri (2012) and De Santis et al. (2021) where this pattern was also observed in the ED patient arrival process. For this case, the *p*-values and *K* scores provided sufficient evidence for accepting the intra-variable independence of the process variables. Afterward, homogeneity tests were performed using the ANOVA method (alpha level = 0.05) (Table 6). The results supported the existence of different demand behaviours depending upon the day of the week and time slot (Fobs = 8.65; *p*-value = 0) as well as the identification of two types of ICU patients (intermediate, critical) considering the significant differences between the groups (Fobs = 5.92; *p*-value = 0.015). In these cases, a mathematical expression needs to be defined for each pipeline. In the remaining variables, the homogeneity assumption was accepted (*p*-value > 0.05) and one probability expression is therefore enough to describe their trends and patterns. Kolmogorov-Smirnov tests ($\alpha = 0.01$) were then carried out to define the probability distribution that better fits each variable. The resulting mathematical expression with the *p*-values underpinning the goodness of fit was also inserted in Table 6.

5.5.3. DES development and validation

After completing the input-data analysis depicted in the previous sub-section, we proceeded with creating a virtual model of the healthcare system using Arena® 16.10.00 software. The Covid-19 patient journey described in Fig. 8 and the mathematical expressions obtained through the Goodness-of-fit tests were included in this representation. As all the healthcare units involved in this pathway operate constantly, the length of replication was defined to be 15 days with 24 h per simulated day. Also, a warm-up time length of 100 days was established considering an approximate blocking probability of 0 which denotes a stable state of the computational model. Following this, the simulated system was initially iterated 10 times to estimate the final number of replications that will be taken into account in the validation stage. The waiting times in EDs for I-II/III-V triage levels as well as the waiting time in ICU were measured in each iteration. In this case, 2,183 replications were deemed necessary to fully mimic the current variation of the real Covid-19 healthcare system. Lately, the equivalence hypothesis was assessed by a 1-sample sign test ($\alpha = 0.05$) given the asymmetric distribution of the data in each indicator (p-value < 0.005; AD > 4.924): Waiting time in ED for I-II triaged patients (Ho: $\eta = 240$ min || Ha: $\eta \neq 240$ min; p-value = 0.578), Waiting time in ED for III-V triaged patients (Ho: $\eta = 270$ min || Ha: $\eta \neq 270$ min; p-value = 0.257), and ICU bed waiting time (Ho: $\eta = 60$ min || Ha: $\eta \neq 60$ min; p-value = 0.7). The results evidenced that the simulated system is statistically comparable with the real Covid-19 patient journey and can therefore be used for performance diagnosis and further pre-testing of operational improvement interventions as detailed in the next subsection.

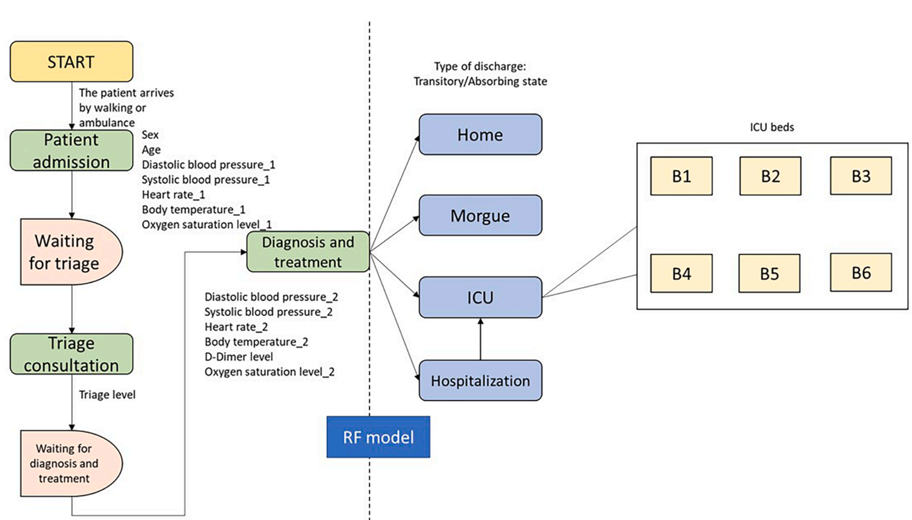

Fig. 8. Flow diagram: Covid-19 patient journey within the showcased hospitals.

Table 5
Results of randomness tests.

Process variable		*K*	*p*-value
Triage consultation time		>0.09	>0.15
Diagnosis/Treatment time in the ED		6.926	0.537
ICU-LOS		9.302	0.386
Intermediate		17.280	0.326
Critical			
Time between arrivals of Covid-19 patients considering day and time slot			
Day of the week	Time slot	K	p-value
	P1	0.057	0.127
Monday	P2	0.026	0.788
	P3	0.012	0.895
	P1	0.072	0.139
Tuesday	P2	0.022	0.826
	P3	0.012	0.618
	P1	0.105	0.472
Wednesday	P2	0.027	0.012
	P3	0.013	0.338
	P1	0.058	0.692
Thursday	P2	0.034	0.245
	P3	0.012	0.409
	P1	0.064	0.111
Friday	P2	0.026	0.854
	P3	0.013	0.290
	P1	0.042	0.701
Saturday	P2	0.036	0.283
	P3	0.016	0.043
	P1	0.047	0.020
Sunday	P2	0.029	0.558
	P3	0.015	0.079

5.6. *Evaluating improvement interventions*

The Covid-19 virus has been noted for its rapid evolution in some patients who, in a few hours, need to be transferred from the ED to the ICU to decrease the risk of mortality and potential sequelae in their health (Whitworth, 2020). It is therefore fundamental to anticipate the likelihood of patients being admitted to the ICUs so that hospital administrators and policymakers can ensure a high probability of having a bed when required. An over-90 %-accuracy RF model based on socio-demographic and recent patient clinical data was illustrated in the past subsections to deal with this decision-making context. However, the question now is: How can this model be rolled out at a grassroots level to timely warn ICU managers about possible bed shortages in the future? The first step is to gather the input data required by the RF model; in this respect, an initial collection is undertaken during patient admission/triage and the second set of data is then obtained while diagnosis and treatment in the ED (see Fig. 3). Once the collection process is complete, the RF can anticipatedly provide an overview of the number of patients that may be transferred to the ICU within the next seven days. The ICU administrator can then pre-test and parse out different alternative solutions through DES so that the most effective (minimum median waiting time for ICU beds) can be timely identified and implemented in the real scenario before the patients' arrival. A test set (n = 286 patients) was used as an example of this application. In this case, 45.81 % (n = 131) of the patients admitted to the ED were predicted with a high ICU transferring probability. In this regard, Fig. 4 reveals that not timely intervening in the ICU would represent a median waiting time (95 % CI) between 106.55 and 119.55 min for incoming Covid-19 patients. The predictions derived from the model were later included in the simulation model to evaluate the effectiveness of two potential interventions proposed by the decision-makers: (i) enable an internal space, usually employed for administrative purposes, as a new ICU with a maximum installed capacity of 15 beds, and (ii) transfer patients to a satellite ICU when the internal ICU is fully occupied. The proposed strategies have been evaluated in terms of waiting time for an ICU bed and compared to a non-intervention scenario (Fig. 9).

We also performed a Mann-Whitney test to verify if the suggested

Table 6
Homogeneity and goodness-of-fit tests.

Process variable		Homogeneity test		Goodness-of-fit test	
		F-score	p-value	Mathematical expression	p-value
Time between arrivals of Covid-19 patients	Monday – P1	8.65	0.000	LOGN(0.0632, 0.156) d	>0.15
	Monday – P2			−0.001 + LOGN (0.0187, 0.0399) d	>0.15
	Monday – P3			−0.001 + LOGN (0.0133, 0.0203) d	0.247
	Tuesday – P1			LOGN(0.087, 0.215) d	>0.15
	Tuesday – P2			−0.001 + LOGN (0.0221, 0.0422) d	>0.15
	Tuesday – P3			−0.001 + LOGN (0.0126, 0.0184) d	>0.15
	Wednesday – P1			LOGN(0.136, 0.727) d	>0.15
	Wednesday – P2			−0.001 + LOGN (0.0252, 0.0455) d	>0.15
	Wednesday – P3			−0.001 + LOGN (0.0134, 0.018) d	>0.15
	Thursday – P1			EXPO(0.0582) d	>0.15
	Thursday – P2			−0.001 + LOGN (0.0297, 0.0642) d	>0.15
	Thursday – P3			−0.001 + LOGN (0.0129, 0.0199) d	>0.15
	Friday – P1			WEIB(0.0486, 0.688) d	>0.15
	Friday – P2			−0.001 + LOGN (0.0242, 0.0497) d	>0.15
	Friday – P3			−0.001 + LOGN (0.0137, 0.0221) d	0.074
	Saturday – P1			−0.001 + WEIB (0.041, 0.891) d	>0.15
	Saturday – P2			−0.001 + LOGN (0.0284, 0.0565) d	>0.15
	Saturday – P3			−0.001 + LOGN (0.0165, 0.0257) d	>0.15
	Sunday – P1			−0.001 + LOGN (0.0528, 0.175) d	>0.15
	Sunday – P2			−0.001 + LOGN (0.0253, 0.0484) d	>0.15
	Sunday – P3			−0.001 + LOGN (0.0161, 0.0235) d	>0.15
Triage consultation time		0.74	0.566	UNIF (10,15) min	>0.15
Diagnosis/Treatment time in the ED	Triage 1–2	3088.7	0.000	UNIF (20,30) min	>0.15
	Triage 3–5			UNIF (20,40) min	>0.15
ICU-LOS	Intermediate	5.92	0.015	GAM (15.3, 0.609) h	0.093
	Critical			EXPO (17.3) h	0.146

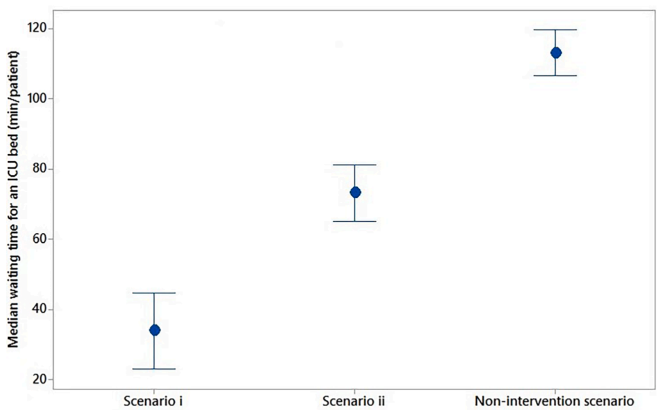

Fig. 9. Median waiting times for an ICU bed in Scenarios i and ii compared to a non-intervention context.

scenarios would cause a significant lessening in the waiting times. The results revealed that, in case of implementation, Scenario (i) would represent a reduction between 32.42 and 48.03 min (95 % CI; p-value = 0; W = 127,439; Improvement percentage = −64.41 %) in the median waiting time while Scenario (ii) would cause a decline ranging from 21.69 and 29.52 min (95 % CI; p-value = 0; W = 1,491,546.5; Improvement percentage = −77.35 %) for the same performance metric in contrast with a non-intervention context.

6. Discussion

6.1. Findings from the RF model

The collection of clinical and demographic patient data is the starting point for achieving better control of the Covid-19 disease through prediction. Data such as temperature (Tharakan et al., 2020), age (Albitar et al., 2020), sex (Sharma et al., 2020), heart rate (Wang, Gheblawi, et al., 2020), systolic and diastolic blood pressure (Jarrett et al., 2020), oxygen saturation (Jarrett et al., 2020), and D-dimer (Rostami & Mansouritorghabeh, 2020) have helped decision-makers to predict the health evolution of Covid-19 patients in terms of survival and life quality. Our RF model has considered all these factors in both single and hybrid ways to predict the likelihood of ICU admission so that the preparedness of these units can be significantly augmented during new Covid-19 peaks. Specifically, the results uncovered that SBP_1 (MDGC = 9.527) and DBP_1 (MDGC = 5.984) are significant predictors of ICU admission in Covid-19 patients. Similarly, second measures of these factors ($MDGC_{SBP\_2}$ = 4.925; $MDGC_{DBP\_2}$ = 4.136) within the emergency departments were found to provide a good prognosis of health worsening due to Covid-19. Both systolic and diastolic blood pressures have been considered high predictors of mortality risk (Ikemura et al., 2021). Increased mortality has been associated with very low diastolic blood pressure (Moledina et al., 2020), while systolic blood pressure and hypertension have been associated with high mortality and respiratory distress (Caillon et al., 2021). In addition, a combination between DBP and heart rate ($MDGC_{DBPxHR}$ = 4.136) was concluded to be contributing to an increase in this probability and can be therefore deemed as an intervention point by both medical and administrative staff of the hospitals in the battle against the pandemic. A Covid-19 patient with these conditions has a high risk of cardiac arrest which may be avoided when transferred to the ICU. In these units, intravenous medications can be provided to these patients to increase cardiac output and improve blood circulation in all the tissues.

On the other hand, the significance tests detected that OSL_1 (MDGC = 12.270), OSL_2 (MDGC = 6.931), SR_OSL (MDGC = 9.229), CR_OSL (MDGC = 10.229) meaningfully influence the ICU transfer likelihood of a Covid-19 patient. This is consistent with the findings of a study in Peru which identified below-90 % oxygen saturation as a predictor of hospital mortality (Mejía et al., 2020), and that a sudden decrease in saturation level may cause a serious clinical deterioration in the patient's health (Jarrett et al., 2020). Also, a significant interaction was detected between this factor and HR ($MDGC_{HRxOSL}$ = 3.917) which may be explained by the need for intubation and invasive mechanical ventilation to diminish the risk of respiratory paralysis. In addition, a combination with high D-dimer levels was proved to be one of the conditions that most augments the ICU transfer probability ($MDGC_{D.DIMERxOSL}$ = 84.610). A Covid-19 patient with this pattern may experience stroke and it is hence essential to give blood-thinning medicines and implement thrombolysis/thrombectomy to lessen the risk of cardiorespiratory arrest while continuously monitoring the patient's health due to the potential risk of blood loss related to these treatments.

Another interesting finding is associated with the predictive ability of body temperature in the likelihood of ICU admission: Temp_1 (MDGC = 4.230), Temp_2 (MDGC = 3.144), CR_Temp_2 (MDGC = 2.046), and Temp_1xTemp_2 (MDGC = 3.609). High temperatures have been also shown to be a predictor of Covid-19 mortality (Choron et al., 2021; Tharakan et al., 2020). In fact, some results of interventions conducted in New York hospitals concluded that hyperthermia is a predictor of mortality among critically ill Covid-19 patients who were admitted to ICUs (Choron et al., 2021). In fact, over-39.5 °C fevers were common in patients dying in the ICU (Choron et al., 2021; Tharakan et al., 2020). Likewise, increased age was confirmed as a high-risk factor for ICU admission among Covid-19 patients (MDGC = 5.029). This is consistent with Albitar et al. (2020), Aly et al. (2020), and Zhou et al. (2020) where this feature was also associated with death. It is good to note that most of the patients (not all) between the ages of 81–102 years (151; 81.18 %) were not transferred to ICU. In other words, 35 patients (19.82 %) categorized in this age group were certainly admitted to these units. The rationale behind these results is that the survival probability of some over-80 patients tends to be very low due to the limited family support that they count on and the fragility of their immune systems. In this sense, some hospital managers have calculated the Years of Life Potential Lost (YLPL) which, in these cases, are significantly minor compared to under-80 Covid-19 patients. Therefore, the latter are prioritized for ICU admission. The decision of transferring the 35 over-80 Covid-19 patients pointed out in this study is underpinned by the presence of family carers committed to providing the attention required for avoiding 72-hour readmission to the ED and death at home, which may be expected outcomes given the rapid evolution and initial consequences of the Covid-19 virus in these patients. It is also good to highlight that a merge of elevated D-dimer levels and aging conditions was defined as highly contributing to ICU admission in these patients (MDGC = 32.721). The elderly tend to be more fragile and therefore prone to develop more severe pulmonary and cardiac complications that added to non-normal D-dimer concentration may cause cardiac arrest. UCIs are then called to apply thrombolytic therapy or thrombectomy when considered to counteract the effects of the disease and then increase life expectancy.

Our study additionally proved the significance of heart rates in a poor evolution of Covid-19 and an increased probability of ICU admission accordingly: HR_1 (MDGC = 3.520), HR_2 (MDGC = 2.712), and SR_HR (MDGC = 4.735). In this regard, Wang, Wang, et al. (2020) concluded that Covid-19 patients have relatively increased heart rates in sinus rhythm and a high risk of arrhythmias. Tachycardia has been the most reported complication followed by Atrial Fibrillation (AF) with elevated rates between 123 and 160 bpm. Furthermore, it was observed how Covid-19 infection could induce electrophysiological abnormalities in patients with no history of heart disease (Wang, Wang, et al., 2020). Concerning this, Long et al. (2021) found that Covid-19 may hurt the cardiovascular system and cause Electrocardiographic (ECG) abnormalities given the presence of cytokine storm, plaque rupture, coronary artery spasm, microthrombi, as well as direct endothelial or myocardial injury.

Sex has been also identified as a risk factor for Covid-19-related ICU admission (MDGC = 0.707) which is consistent with Albitar et al. (2020) and Sharma et al. (2020). In this case, most transferred Covid-19 patients were male (292; 73.36 %; p-value = 0) which supports the fact that men are more susceptible to Covid-19 infection than women by evidence of higher viral load titers and accumulation of alveolar macrophages and neutrophils in the lungs. In particular, Sharma et al. (2020) concluded that sex hormones including estrogens, progesterone, and androgens contribute to the differential regulation of immune responses (Sharma et al., 2020). Another explanation for this statistical significance is the number of angiotensin-converting enzyme (ACE2) receptors which are the main route of Covid-19 infection and therefore a driver for disease susceptibility and worse outcomes. ACE2 receptors have been found with density differences in the reproductive organs (Sharma et al., 2020) and also at high levels in the lungs, myocardium, kidneys, and gastrointestinal system (Wang, Guo, et al., 2020).

Another predictor to be considered in Covid-19 patients is the elevated D-dimer which is highly associated with thrombotic status and denotes hypercoagulability due to serious inflammatory reaction (Griffin et al., 2020; Rostami & Mansouritorghabeh, 2020). Indeed, our study stipulates that this characteristic is a top predictor of ICU admission among Covid-19 patients (MDGC = 106.110) which is reasonable considering that thrombolytic therapies are usually administered in these departments. Furthermore, D-dimer levels have been employed as predictors of mechanical ventilation, a procedure that needs constant monitoring by the medical staff as the one provided at UCIs given the risks associated with this treatment (Naymagon et al., 2020; Rostami & Mansouritorghabeh, 2020). Definitively, controlling D-dimer levels is a key point in predicting the discharge to ICUs and it is therefore very useful for increasing the accuracy and other performance measures of machine learning models.

Generating accuracy and timely predictions of the ICU transfer likelihood is easier when having a set of significant factors combined with the use of a powerful ensemble ML technique like RF. The outputs are accordingly satisfactory and competitive for the practical clinical scenario. In fact, a predictive model with an accuracy of 0.9161 (95 % CI 0.877–0.9455) is a robust tool with the ability to provide reliable decision-making support for both administrative staff and frontline doctors. This is also supported by an AUC of 0.9548 (95 % CI 0.8973–1) which denotes outstanding discrimination as pointed out by Hosmer et al. (2013). Besides, it is important to stress the balance between the specificity (0.9350 95 % CI: 0.8758–0.9715) and sensitivity (0.9018 95 % CI: 0.845 4–0.9428) values added to their high predictive capacity. Likewise, the positive predictive value (0.9484 95 % CI: 0.908–0.9774) and negative predictive values (0.8779 95 % CI: 0.8092–0.9285) evidence that the model mostly predicts well which patient is (is not) transferred to ICU to all those who were (were not) transferred correspondingly.

Several attempts have been made to predict ICU admission among Covid-19 patients since the onset of the pandemic (Aznar-Gimeno et al., 2021; Famiglini et al., 2022; Fernandes et al., 2021; Heldt et al., 2021; Hou et al., 2021; Huang, Liu, et al., 2021; Li et al., 2020; Nazir & Ampadu, 2022; Patel et al., 2021; Pezoulas et al., 2022; Schwab et al., 2020; Shanbehzadeh et al., 2022); however, our model outperforms these studies in several indicators (Table 7). It was also found to present a better sensitivity contrasted with the one achieved by Schwab et al. (2020) (0.600). In such a study, a recommendation for using symptoms data was made to upgrade the performance of the predictive model, which was fully addressed in this investigation. Notably, the AUC obtained in this application was superior to the ones presented in Aznar-Gimeno et al. (2021) (0.821), Heldt et al. (2021) (0.840), Shanbehzadeh et al. (2022) (0.822), and Nazir and Ampadu (2022) (0.884). It is interesting to note that these results are based on a multi-center project, increasing the potential for replicability and generalization. Accordingly, these outcomes lay the groundwork for the deployment of AI in the healthcare business and more specifically in ICUs where huge amounts of medical records have been gathered to support the response to the pandemic.

Table 7
Comparison of our proposed method with previous works in terms of AUC, sensitivity, and specificity.

Study	AUC	Sensitivity	Specificity
Famiglini et al. (2022)	0.850	0.660	0.900
Fernandes et al. (2021)	0.920	0.920	0.820
Hou et al. (2021)	0.781	0.764	0.895
Huang, Liu, et al. (2021)	0.940	0.880	0.930
Li et al. (2020)	0.780	0.760	0.709
Patel et al. (2021)	0.800	0.730	0.700
Pezoulas et al. (2022)	0.910	0.830	0.830
This paper	**0.955**	**0.902**	**0.935**

Despite the satisfactory results, this work holds several limitations. First, the RF model may be restricted to the Spanish healthcare system given the considerable differences that may exist among the countries regarding their healthcare structure. Second, confounding factors depending on each patient profile were not explored and remain an open challenge to tackle in future studies. Furthermore, the effectiveness of treatments provided in ED wards and hospitalization units was not deemed. Also, it is good to mention that the database used in this study only contained lab test results, prescribed treatments, sociodemographic features, and vital signs measurements collected in the emergency department. In this regard, a limitation is the lack of data related to the past medical history of Covid-19 patients which may increase the performance of the RF model. Finally, the RF algorithm did not study other blood indicators highlighted as good biomarkers of ICU admission due to a lack of high-quality data.

6.2. Findings from the DES model

All the works reporting the use of predictive models focused on measuring the ICU admission likelihood of Covid-19 patients represent a significant body of evidence that can be further employed by hospital administrators as a basis for the design of aggressive improvement interventions in the healthcare system. This activity has been underpinned using DES models providing a widen overview of the healthcare system and more specifically, focusing on the interaction between the ED and ICU. Thereby, decision-makers can further evaluate the use of resources, waiting times, congestions, and other process inefficiencies during pandemic situations. In this respect, Currie et al. (2020) highlighted the critical role that DES may play to evaluate the capacity of hospital beds in critical care and diminish the impact of operational ICU shortcomings on patients' health conditions. On the other hand, the DES models are based on real high-quality process and demand data collected from the hospital chain database which increases its equivalence with the real ICU. In particular, the availability of demand data was identified as a limitation in Wood et al. (2020) where the authors had to employ projections from the UK government for modeling the number of admissions and expected times between arrivals. Likewise, the lack of cleansed data in the DES model provoked some validation inconsistencies in Le Lay et al. (2020) when comparing their virtual representation with the real-world healthcare system.

Although important DES-based efforts have been reported in different studies (Caro et al., 2021; Irvine et al., 2021; Melman et al., 2021; Rees et al., 2020; Wood et al., 2020) referring to the response of ICUs against the Covid-19, various challenges restricting their applicability in the real world remain. For example, Melman et al. (2021) presented an interesting DES implementation helping hospitals to appraise the resource allocation strategies during Covid-19; nevertheless, ICU LOS was modelled as a fixed variable which is not consistent with real-world behavior. Also, Caro et al. (2021) used the DES modelling framework for ICU service improvement during the pandemic times, but without considering the heterogeneity of hospital patient-based journeys. In contrast to these interventions, multiple Covid-19 patient pathways and stochastic variables were integrated into our proposed model to generate a better approximation of the real-world healthcare system. An interesting difference regarding the modelling procedure is the probability distributions used for representing the process variables. For instance, Garcia-Vicuna et al. (2020) used the Weibull distribution for denoting the ICU-LOS behaviour which is contrary to the ones utilized in this study (Gamma and Expo). In this regard, it would be beneficial to explore how the model validity may be affected if all these stochastic distributions are compared for a particular showcased ICU. This methodological approach is more effective compared to the use of predictive models which employ deterministic ICU-LOS for each patient and do not consider interrelations among services (Melman et al., 2021; Rees et al., 2020). The result of this process is a simulation model that is statistically equivalent to the real system as the p-value in each validation indicator (Waiting time in ED for I-II triaged patients and Waiting time in ICU) was found to be higher than 0.25. Our application is more precise than the one proposed by Irvine et al. (2021) when predicting non-critical care, a critical variable helping decision-makers to avoid unnecessary bed assignments.

Several works like the one exposed in Possik et al. (2022) and Sala and Quarto (2022) limited the use of DES techniques only for process diagnosis and operational measurement of healthcare systems during the Covid-19 outbreak. Nonetheless, an important further step in this intervention is the exploration of various strategies dealing with the ICU admissions pointed out by the RF model and the potential shortage of beds. Balancing scarce ICU beds with this demand is then critical for the rapid deployment of medical interventions trying to counteract the effects and sequels of Covid-19 as well as minimizing the risk of death. In this case, two proposals were proposed and pretested in reply to the off-balance observed between the ICU installed capacity and the predicted Covid-19 admissions: i) enable a new ICU with a maximum installed capacity of 15 beds, and (ii) transfer patients to a satellite ICU when the internal ICU is fully occupied. In summary, both scenarios were concluded to outperform a non-intervention context (p-value = 0) and are then effective for implementation in the real world. The use of outdoor spaces for intensive care was also explored as an alternative by Melman et al. (2021) who contemplated the opening of theaters when the ICU utilization was higher than 95 %. However, in this case, strategy (i) evidenced a superior performance in terms of ICU bed waiting time (p-value) vs strategy (ii); in other words, under strategy (i), a Covid-19 patient would wait between 23.09 and 44.76 min contrasted with a time interval of 64.99 and 81.29 min expected with the application of strategy (ii). This of course favors the adoption of strategy (i) since Covid-19 patients transferred to ICUs need to be intervened quickly to diminish the risk of mortality and sequels downgrading the quality of life. This is consistent with the results uncovered by Wood et al. (2020) where increasing from 45 to 100 intensive beds may diminish the mortality rate by 75 % if complemented with minimizing LOS by 25 % and flattening the admission curve to 26 admissions per day.

In summary, the application of DES for evaluating new ICU bed configurations responding to the patient transfer expected from downstream services is an advantage of this study in contrast with similar works. Garcia-Vicuna et al. (2020), Wood et al. (2020), Le Lay et al. (2020), and Melman et al. (2021) did not consider the bed waiting time experienced by Covid-19 patients needing the intensive care service and were only limited to determine the number of required beds without incorporating conjoint health supply chain strategies like the one analysing the use of satellite ICUs as deeply examined in this research. This should be taken into account considering the importance of upstream and downstream members in overcoming the operational disruptions in healthcare (Kochan et al., 2018; Meijboom et al., 2011). Nonetheless, the simulation model presented in this paper holds two limitations. On the one hand, we only deemed ICU beds as the most prioritized constrained resource in the hospital chain; our application can be, however, extended to other resources including ventilators, medical staff, intravenous catheters, and high-flow cannulas. On the other hand, interactions with clinical labs, surgery units, and imaging services were not explicitly included in the DES model; nonetheless, their effects are incorporated in the stochastic representation of the ICU LOS variable.

7. Managerial and policy implications

The unexpected occurrence of pandemics, epidemics, and seasonal respiratory diseases have increased the burden faced by the ICUs, thereby evidencing an aggravation of several well-known disruptions in healthcare operations including over-crowdedness, lengthy stays, and prolonged waiting times (Almeida & Vales, 2020; Davis et al., 2020; Ortíz-Barrios et al., 2021). It is then necessary to design and deploy robust methodological approaches to upgrading the response of ICUs so that the risk of mortality and long-term health sequels can be further minimized. The necessitated interventions go beyond a particular healthcare service and require to be extended to a health supply chain perspective since interactions among downstream and upstream actors will ultimately impact patients. This is even sharpening in presence of a rapidly evolving virus forcing the logistics operations to function more quickly, flexibly, coordinated, and integrated.

AI-related applications have emerged as an alternative to tackle the above-mentioned inefficiencies by taking advantage of the large amounts of medical records stored in hospital databases. In this regard, data managers are expected to ensure the data's high quality and completeness. For instance, in our case study, some features (diuresis and glucose) could not be examined and further utilized due to registration errors. Likewise, it has been perceived that sensitive patient data are not gathered constantly over time thereby impeding the proper monitoring of patient's health and the creation of more accurate operational healthcare models. It is then advised to perform in-depth audits on the data management systems to early detect these drawbacks and develop action plans to increase the effectiveness of these platforms as support of decision-making processes. Furthermore, AI models need valuable and sufficient data for an efficacious training process. Otherwise, these data-driven solutions will lack applicability and scalability in the real healthcare scenario. Also, the modelers are recommended to work closely with the medical and administrative staff from EDs and ICUs to produce a model representing the day-to-day routine of the Covid-19 patient pathway within the hospitals.

The use of AI definitively automates and accelerates decision-making processes by providing healthcare managers with accurate predictions on the evolution of patients in short intervals. Such forecasting allows anticipatedly administering the capacity of upstream services thus facilitating the creation of operational scenarios responding to the demand adequately. In this case, the AI model predicts how probable a Covid-19 patient is to be admitted to ICU during the next few hours. With this information, the ICU administrator can establish the expected transfers within a time frame and evaluate if the installed capacity is enough for providing in-time intensive care. The implementation of these data-driven applications should be user-friendly to diminish delays and interpretation failures. It is additionally important to consider features that can be gleaned quickly to decrease resistance to change during the introduction process of the AI models. This is the case of our RF model which considers sociodemographic (Sex and Age) and clinical indicators (Heart rate, diastolic and systolic blood pressures, body temperature, oxygen saturation, and D-dimer concentration) that are commonly measured in the ED settings and can be imported in real-time from the databases. Moreover, these features are not restricted to a subjective evaluation which avoids the inclusion of bias in the model. Gathering significant predictors of poor Covid-19 evolution in downstream services is then critical to prepare ICUs and the associated health supply chains to address the demand as fastest as possible. This is, considering that patients who are transferred to ICUs have serious health conditions and process delays can be therefore deemed as a catalyst to irreversible outcomes or death. The data-analytics experts should constantly monitor and update the RF model performance (if necessary) to guarantee pertinence with the medical and logistics framework by measuring its accuracy, sensitivity, specificity, AUC, and positive/negative predictive values.

Once hospital administrators receive the prediction results in terms of ICU admission likelihood for each patient, the next step is to define which strategies need to be rolled out to diminish waiting times for ICU beds (see Section 5.2) while in the latter, it is necessary to ensure the correct allocation of constrained resources (i.e. beds, ventilators, specialists). Therefore, the RF outcomes should be inserted in a DES model which provides decision-makers, ICU administrators, and healthcare authorities with a strong basis for the constant evaluation of this critical service under different pandemics. Moreover, it supports bed inventory management which was found one of the weakest pillars when coping with the demand peaks during the Covid-19 pandemic. Thereby, the decision-makers can evaluate different improvement scenarios before receiving the Covid-19 patients and know if they will be effective in terms of the bed waiting time. Hospital logistics managers can then elaborate health supply chain plans underpinning the deployment of the selected scenario at the right time and a reasonable investment. It is then evident that bed supply chains and the internal maintenance department must be coordinated with the head of the logistics staff to bring the scenario to reality. Moreover, the hospitals should set purchasing agreements with the intensive bed suppliers and the associated equipment/materials with tight lead times to balance the admission rate with the capacity. In parallel, hospital managers are suggested to establish contingency procedures for the rapid adequation of administrative or outdoor spaces propelled by the RF outcomes. Therefore, it will be possible to anticipate possible ICU breakdowns as experienced in the first waves (Caro et al., 2021). Likewise, effective investment allocation can be better granted in time-sensitive and resource-constrained environments like the ones experienced during the current outbreak.

The above-mentioned interventions should be propelled by the health authorities who can take advantage of this AI-DES solution for ensuring a massive application within the healthcare business strategy. In this way, the ICUs would be able to increase their preparedness against this outbreak and similar scenarios like seasonal respiratory diseases. In addition, a dashboard with projected ICU capacity indicators derived from the AI-DES model may be implemented by the government during high-stress periods to make the decision-making process more flexible and adaptive to the changing environment expected in a pandemic. Finally, the health authorities must work on strengthening the partnership agreements between hospitals and geriatric homes so that required support can be provided for over-80 patients without committed family carers. Thereby, a combination of ICU admission and homecare intervention may be useful for increasing their life expectancy while guaranteeing their right to healthcare.

8. Conclusions

The rapid evolution of the Covid-19 pandemic has challenged the healthcare system worldwide by producing a large number of many admissions that, in some cases, overpasses the installed capacity of different services. While the healthcare authorities have been engaged in registering and informing the daily behaviour of the virus, robust modelling techniques are required to adapt these systems to the pandemic dynamics. In the meantime, this outbreak has triggered an increased need for ICU care given the severe health complications produced by the virus which may threaten the patient's life if effective treatment is not timely provided. However, some operational problems including prolonged bed waiting times, shortage of medical equipment, and extended length of stay have been reported, thereby evidencing the internal off-balance within the health supply chains, the low preparedness of ICUs, and the lack of real-time decision-making systems supporting process improvement interventions. The major concern is that these disruptions may threaten human lives and generate irreversible outcomes in Covid-19 who ultimately perceive the Bullwhip effect.

Being aware of these difficulties, our paper has provided hospital administrators with a robust decision-making approach underpinning effective ICU bed capacity management during the Covid-19 pandemic. A merger between AI and DES was concluded to be necessary for evaluating interventions to reduce the bed waiting times experienced by patients with an immediate need for care. In this regard, the predictions derived from an RF model were considered to estimate the expected number of patients with a high probability of being transferred from the ED to critical care in a short time interval. Thereby, it is feasible to design an anticipated response granting enough ICU beds supported by a flexible supply chain committed to delivering the needed medication, medical equipment, and accessories when required.

The application illustrated in this paper has evidenced that designing new configurations of healthcare services must consider stochastic process variables and interactions among units to generate a good representation of the multiple pathways and outcomes that Covid-19 patients undertake. In this respect, it is essential to count on high-quality and detailed data supporting the correct implementation of DES and RF techniques. Likewise, modelers are called to work closely with health professionals and administrative staff to ensure that the resulting AI-DES models are realistic and applicable in the practical scenario. In particular, the inclusion of AI techniques in the healthcare business allows for increasing the decision-making speed thereby empowering policy-makers with the adequate basis for designing rapid bed capacity adaptations. As a result, it will be possible to roll out pre-tested actions balancing the number of beds with the expected demand while propelling the efficient use of scarce medical resources and the consequent financial sustainability of hospitals as pillars ramping up their preparedness against new waves and variants. This research then moves beyond the existing modus operandi characterized by the application of time-consuming inventory planning models (i.e., bed capacity management models) restricting the flexibility of ICUs against the context derived from the pandemic.

The results emanating from this study uncovered the robustness of the RF model in predicting the likelihood of ICU admission based on sociodemographic and clinical patient data (Accuracy: 0.9161 (95 % CI 0.877–0.9455) || AUC: 0.9548 (95 % CI 0.8973–1)) despite the difficulties in considering confounding factors in clinical practice. Moreover, it is important to highlight the balance between the specificity (0.9350 95 % CI: 0.8758–0.9715) and sensitivity (0.9018 95 % CI: 0.8454–0.9428). Likewise, the positive predictive value (0.9484 95 % CI: 0.908–0.9774) and negative predictive value (0.8779 95 % CI: 0.8092–0.9285) denote that the model mostly predicts well which patient is (is not) transferred to ICU to all those who were (were not) transferred respectively. On a different tack, DES was proven to be a very useful technique assisting decision-makers to simulate and pretest interventions on ICU capacity before implementation. More specifically, the scenarios considering separately an expansion of the current installed capacity and the creation of a satellite ICU were proved to obtain significant reductions in the median bed waiting times (scenario i: 32.42–48.03 min || scenario ii: 21.69 and 29.52 min) thereby accelerating the ICU interventions required to tackle the unfavorable progress of the virus. Being aware of these results, it is concluded that adopting on-time efficient improvement strategies is critical to enhance operational excellence during pandemic contexts; in this case, implementing a better intensive bed configuration may diminish the risk of mortality and the appearance of sequels in Covid-19 patients.

An interesting direction to investigate as future work entails the inclusion of interactions among ICU, clinical labs, and imaging services to explore more integrated interventions. It is also expected to employ the AI-DES approach to support health supply chain operations including logistics planning (Mehmood et al., 2017), coordination and integration (Ivanov et al., 2019), supplier selection (Choi et al., 2018), and demand forecasting for respiratory seasonal diseases (Roßmann et al., 2018). Likewise, it is advised to employ a holistic multi-criteria-decision-making approach to evaluate the preparedness of ICUs against pandemics considering bed waiting time as one of the performance criteria. On the other hand, evaluating other machine learning algorithms and factors is recommended to upgrade the ICU admission predictions and perform comparative analysis. Another promising pathway is the inclusion of features related to the past medical history of Covid-19 including the presence of cardiovascular disease, diabetes, chronic respiratory disease, and cancer, which may upgrade the performance of the proposed AI model. Lately, we plan to pretest new improvement scenarios not only considering the availability of beds but also mechanical ventilators, high-flow cannulas, intravenous medication, and health professionals that are necessary for effective ICU provision.

CRediT authorship contribution statement

Miguel Ortiz-Barrios: Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation. **Sebastián Arias-Fonseca:** Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation. **Alessio Ishizaka:** Writing – original draft, Investigation, Conceptualization. **Maria Barbati:** Writing – original draft, Investigation, Conceptualization. **Betty Avendaño-Collante:** Investigation, Formal analysis, Conceptualization. **Eduardo Navarro-Jiménez:** Software, Investigation, Data curation, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

References

Abdalkareem, Z. A., Amir, A., Al-Betar, M. A., Ekhan, P., & Hammouri, A. I. (2021). Healthcare scheduling in optimization context: A review. *Health and Technology, 11*(3), 445–469.

Agrawal, R., Wankhede, V. A., Kumar, A., Upadhyay, A., & Garza-Reyes, J. A. (2021). Nexus of circular economy and sustainable business performance in the era of digitalization. *International Journal of Productivity and Performance Management, 71*(3), 748–774.

Ahmad, J., Iqbal, J., Ahmad, I., Khan, Z. A., Tiwana, M. I., & Khan, K. (2020). A simulation based study for managing hospital resources by reducing patient waiting time. *IEEE Access, 8*, 193523–193531. https://doi.org/10.1109/ACCESS.2020.3032760

Akhavan, A. R., Habboushe, J. P., Gulati, R., Iheagwara, O., Watterson, J., Thomas, S., … Lee, D. C. (2020). Risk stratification of covid-19 patients using ambulatory oxygen saturation in the emergency department. *Western Journal of Emergency Medicine, 21*(6). https://doi.org/10.5811/WESTJEM.2020.8.48701

Alakus, T. B., & Turkoglu, I. (2020). Comparison of deep learning approaches to predict COVID-19 infection. *Chaos, Solitons and Fractals, 140*. https://doi.org/10.1016/j.chaos.2020.110120

Alballa, N., & Al-Turaiki, I. (2021). Machine learning approaches in COVID-19 diagnosis, mortality, and severity risk prediction: A review. *Informatics in Medicine Unlocked, 24*, Article 100564. https://doi.org/10.1016/j.imu.2021.100564

Albitar, O., Ballouze, R., Ooi, J. P., & Sheikh Ghadzi, S. M. (2020). Risk factors for mortality among COVID-19 patients. *Diabetes Research and Clinical Practice, 166*, Article 108293. https://doi.org/10.1016/j.diabres.2020.108293

Almeida, A., & Vales, J. (2020). The impact of primary health care reform on hospital emergency department overcrowding: Evidence from the portuguese reform. *International Journal of Health Planning and Management, 35*(1), 368–377. https://doi.org/10.1002/hpm.2939

Aly, M. H., Rahman, S. S., Ahmed, W. A., Alghamedi, M. H., Al Shehri, A. A., Alkalkami, A. M., & Hassan, M. H. (2020). Indicators of critical illness and predictors of mortality in COVID-19 patients. *Infection and Drug Resistance, 13*, 1995–2000. https://doi.org/10.2147/IDR.S261159

Amantea, I. A., Di Leva, A., & Sulis, E. (2020). A simulation-driven approach to decision support in process reorganization: A case study in healthcare. *Lecture Notes in Information Systems and Organisation, 33*, 223–235. https://doi.org/10.1007/978-3-030-23665-6_16

Assaf, D., Gutman, Y., Neuman, Y., Segal, G., Amit, S., Gefen-Halevi, S., … Tirosh, A. (2020). Utilization of machine-learning models to accurately predict the risk for critical COVID-19. *Internal and Emergency Medicine, 15*(8), 1435–1443. https://doi.org/10.1007/s11739-020-02475-0

Aznar-Gimeno, R., Esteban, L. M., Labata-Lezaun, G., Del-Hoyo-alonso, R., Abadia-Gallego, D., Paño-Pardo, J. R., Esquillor-Rodrigo, M. J., Lanas, Á., & Serrano, M. T. (2021). A clinical decision web to predict ICU admission or death for patients hospitalised with COVID-19 using machine learning algorithms. *International Journal of Environmental Research and Public Health, 18*(16). https://doi.org/10.3390/ijerph18168677

Banerjee, A., Ray, S., Vorselaars, B., Kitson, J., Mamalakis, M., Weeks, S., … Mackenzie, L. S. (2020). Use of machine learning and artificial intelligence to predict SARS-CoV-2 infection from full blood counts in a population. *International Immunopharmacology, 86*, Article 106705. https://doi.org/10.1016/j.intimp.2020.106705

Barrios, M. A. O., Caballero, J. E., & Sánchez, F. S. (2015). *A methodology for the creation of integrated service networks in outpatient internal medicine*. doi: 10.1007/978-3-319-26508-7_24.

Batista, G. E. A. P. A., & Monard, M. C. (2003). An analysis of four missing data treatment methods for supervised learning. *Applied Artificial Intelligence, 17*(5–6), 519–533. https://doi.org/10.1080/713827181

Behl, A., Gaur, J., Pereira, V., Yadav, R., & Laker, B. (2022). Role of big data analytics capabilities to improve sustainable competitive advantage of MSME service firms during COVID-19–A multi-theoretical approach. *Journal of Business Research, 148*, 378–389.

Belgiu, M., & Drăguţ, L. (2016). Random forest in remote sensing: A review of applications and future directions. *ISPRS Journal of Photogrammetry and Remote Sensing, 114*, 24–31.

Bihri, H., Hsaini, S., Nejjari, R., Azzouzi, S., & Charaf M.E.H. (2022). Missing data analysis in the healthcare field: COVID-19 case study. In *Networking, intelligent systems and security. Smart innovation, systems and technologies* (Vol. 237). Ssingapore: Springer. doi: 10.1007/978-981-16-3637-0_61.

Birkmeyer, J. D., Barnato, A., Birkmeyer, N., Bessler, R., & Skinner, J. (2020). The impact of the COVID-19 pandemic on hospital admissions in the United States: Study examines trends in US hospital admissions during the COVID-19 pandemic. *Health Affairs, 39*(11), 2010–2017. https://doi.org/10.1377/hlthaff.2020.00980

Bohr, A., & Memarzadeh, K. (2020). The rise of artificial intelligence in healthcare applications. In *Artificial intelligence in healthcare* (pp. 25–60). Academic Press.

Breiman, L. (2001). Random forests. *Machine Learning, 45*, 5–32. https://doi.org/10.1023/A:1010933404324

Brennan, A., Chick, S. E., & Davies, R. (2006). A taxonomy of model structures for economic evaluation of health technologies. *Health economics, 15*(12), 1295–1310.

Caillon, A., Zhao, K., Klein, K. O., Greenwood, C. M. T., Lu, Z., Paradis, P., & Schiffrin, E. L. (2021). High systolic blood pressure at hospital admission is an important risk factor in models predicting outcome of COVID-19 patients. *American Journal of Hypertension, 34*(3), 282–290. https://doi.org/10.1093/ajh/hpaa225

Caro, J. J., Möller, J., & Getsios, D. (2010). Discrete event simulation: The preferred technique for Health Economic Evaluations? *Value in Health, 13*(8), 1056–1060. https://doi.org/10.1111/j.1524-4733.2010.00775.x

Caro, J. J., Möller, J., Santhirapala, V., Gill, H., Johnston, J., El-Boghdadly, K., Santhirapala, R., Kelly, P., & McGuire, A. (2021). Predicting hospital resource use during COVID-19 surges: A simple but flexible discretely integrated condition event simulation of individual patient-hospital trajectories. *Value in Health, 24*(11), 1570–1577. https://doi.org/10.1016/j.jval.2021.05.023

Casier, G., Casier, K., Van Ooteghem, J., & Verbrugge, S. (2015). Application of a discrete event simulator for healthcare processes. In *BMSD 2015 - Proceedings of the 5th international symposium on business modeling and software design*. https://doi.org/10.5220/0005887702410246

Casiraghi, E., Malchiodi, D., Trucco, G., Frasca, M., Cappelletti, L., Fontana, T., … Valentini, G. (2020). Explainable machine learning for early assessment of COVID-19 risk prediction in emergency departments. *IEEE Access, 8*, 196299–196325. https://doi.org/10.1109/ACCESS.2020.3034032

Castanheira-Pinto, A., Gonçalves, B. S., Lima, R. M., & Dinis-Carvalho, J. (2021). Modeling, assessment and design of an emergency department of a public hospital through discrete-event simulation. *Applied Sciences (Switzerland), 11*(2), 1–25. https://doi.org/10.3390/app11020805

Chakravorty, T., Jha, K., & Barthwal, S. (2018). Digital technologies as enablers of care-quality and performance: A conceptual review of hospital supply chain network. *IUP Journal of Supply Chain Management, 15*(3), 7–25.

Chatterjee, S., Chaudhuri, R., & Vrontis, D. (2021). Does data-driven culture impact innovation and performance of a firm? An empirical examination. *Annals of Operations Research*, 1–26.

Chen, M., & Decary, M. (2020). Artificial intelligence in healthcare: An essential guide for health leaders. In *Healthcare management forum* (Vol. 33, No. 1, pp. 10–18). Los Angeles, CA: SAGE Publications.

Cheng, F. Y., Joshi, H., Tandon, P., Freeman, R., Reich, D. L., Mazumdar, M., Kohli-seth, R., Levin, M., Timsina, P., & Kia, A. (2020). Using machine learning to predict ICU transfer in hospitalized COVID-19 patients. *Journal of Clinical Medicine*, *9*(6). doi: 10.3390/jcm9061668.

Cheng, A., Hu, L., Wang, Y., Huang, L., Zhao, L., Zhang, C., … Liu, Q. (2020). Diagnostic performance of initial blood urea nitrogen combined with D-dimer levels for predicting in-hospital mortality in COVID-19 patients. *International Journal of Antimicrobial Agents, 56*(3). https://doi.org/10.1016/j.ijantimicag.2020.106110

Choi, Y., Lee, H., & Irani, Z. (2018). Big data-driven fuzzy cognitive map for prioritising IT service procurement in the public sector. *Annals of Operations Research, 270*(1–2), 75–104. https://doi.org/10.1007/s10479-016-2281-6

Choron, R. L., Butts, C. A., Bargoud, C., Krumrei, N. J., Teichman, A. L., Schroeder, M. E., Bover Manderski, M. T., Cai, J., Song, C., Rodricks, M. B., Lissauer, M., & Gupta, R.

(2021). Fever in the ICU: A Predictor of Mortality in Mechanically Ventilated COVID-19 Patients. *Journal of Intensive Care Medicine, 36*(4), 484–493. https://doi.org/10.1177/0885066620979622

Chowdhury, M., Cervantes, E. G., Chan, W. Y., & Seitz, D. P. (2021). Use of machine learning and artificial intelligence methods in geriatric mental health research involving electronic health record or administrative claims data: A systematic review. *Frontiers Psychiatry, 12*(September). https://doi.org/10.3389/fpsyt.2021.738466

Corro Ramos, I., Hoogendoorn, M., & Rutten-van Mölken, M. P. M. H. (2020). How to address uncertainty in health economic discrete-event simulation models: An illustration for chronic obstructive pulmonary disease. *Medical Decision Making, 40*(5), 619–632. https://doi.org/10.1177/0272989X20932145

Currie, C. S. M., Fowler, J. W., Kotiadis, K., Monks, T., Onggo, B. S., Robertson, D. A., & Tako, A. A. (2020). How simulation modelling can help reduce the impact of COVID-19. *Journal of Simulation, 14*(2), 83–97. https://doi.org/10.1080/17477778.2020.1751570

Davis, Z., Zobel, C. W., Khansa, L., & Glick, R. E. (2020). Emergency department resilience to disaster-level overcrowding: A component resilience framework for analysis and predictive modeling. *Journal of Operations Management, 66*(1–2), 54–66. https://doi.org/10.1002/joom.1017

De Santis, A., Giovannelli, T., Lucidi, S., Messedaglia, M., & Roma, M. (2021). Determining the optimal piecewise constant approximation for the nonhomogeneous Poisson process rate of emergency department patient arrivals. *Flexible Services and Manufacturing Journal, 1–34*. https://doi.org/10.1007/s10696-021-09408-9

Dergaa, I., Abubaker, M., Souissi, A., Mohammed, A. R., Varma, A., Musa, S., Al Naama, A., Mkaouer, B., & Saad, H. B. (2022). Age and clinical signs as predictors of COVID-19 symptoms and cycle threshold value. *Libyan Journal of Medicine*, *17*(1). doi: 10.1080/19932820.2021.2010337.

Di Castelnuovo, A., Bonaccio, M., Costanzo, S., Gialluisi, A., Antinori, A., Berselli, N., … COVID, T. (2020). Common cardiovascular risk factors and in-hospital mortality in 3,894 patients with COVID-19: Survival analysis and machine learning-based findings from the multicentre Italian CORIST study. *Nutrition, Metabolism and Cardiovascular Diseases*, *30*(11), 1899–1913. doi:10.1016/j.numecd.2020.07.031.

Doneda, M., Yalçındağ, S., Marques, I., & Lanzarone, E. (2021). A discrete-event simulation model for analysing and improving operations in a blood donation centre. *Vox Sanguinis, 116*(10), 1060–1075. https://doi.org/10.1111/vox.13111

Donthu, N., & Gustafsson, A. (2020). Effects of COVID-19 on business and research. *Journal of Business Research, 117*, 284–289. https://doi.org/10.1016/j.jbusres.2020.06.008

Drewry, A. M., Hotchkiss, R., & Kulstad, E. (2020). Response to "body temperature correlates with mortality in COVID-19 patients". *Critical Care, 24*(1). https://doi.org/10.1186/s13054-020-03186-w

Ellahham, S., Ellahham, N., & Simsekler, M. C. E. (2020). Application of artificial intelligence in the health care safety context: Opportunities and challenges. *American Journal of Medical Quality, 35*(4), 341–348. https://doi.org/10.1177/1062860619878515

Famiglini, L., Campagner, A., Carobene, A., & Cabitza, F. (2022). A robust and parsimonious machine learning method to predict ICU admission of COVID-19 patients. *Medical and Biological Engineering and Computing.* , Article 0123456789. https://doi.org/10.1007/s11517-022-02543-x

Fawagreh, K., & Gaber, M. M. (2020). Resource-efficient fast prediction in healthcare data analytics: A pruned Random Forest regression approach. *Computing, 102*(5), 1187–1198.

Feng, C., Kephart, G., & Juarez-Colunga, E. (2021). Predicting COVID-19 mortality risk in Toronto, Canada: A comparison of tree-based and regression-based machine learning methods. *BMC Medical Research Methodology, 21*(1), 1–14. https://doi.org/10.1186/s12874-021-01441-4

Fernandes, F. T., de Oliveira, T. A., Teixeira, C. E., Batista, A. F. de M., Dalla Costa, G., & Chiavegatto Filho, A. D. P. (2021). A multipurpose machine learning approach to predict COVID-19 negative prognosis in São Paulo, Brazil. *Scientific Reports*, *11*(1), 1–7. doi: 10.1038/s41598-021-82885-y.

Figliozzi, S., Masci, P. G., Ahmadi, N., Tondi, L., Koutli, E., Aimo, A., … Georgiopoulos, G. (2020). Predictors of adverse prognosis in COVID-19: A systematic review and meta-analysis. *European Journal of Clinical Investigation, 50*(10). https://doi.org/10.1111/eci.13362

Forbes (2022). *AI for health and hope: How machine learning is being used in hospitals*. Available at: https://www.forbes.com/sites/forbestechcouncil/2022/02/16/ai-for-health-and-hope-how-machine-learning-is-being-used-in-hospitals/ (Accessed: 10-10-2022).

Frid-Adar, M., Amer, R., Gozes, O., Nassar, J., & Greenspan, H. (2021). COVID-19 in CXR: From detection and severity scoring to patient disease monitoring. *IEEE Journal of Biomedical and Health Informatics, 25*(6), 1892–1903. https://doi.org/10.1109/JBHI.2021.3069169

Gallo Marin, B., Aghagoli, G., Lavine, K., Yang, L., Siff, E. J., Chiang, S. S., … Michelow, I. C. (2021). Predictors of COVID-19 severity: A literature review. *Reviews in Medical Virology, 31*(1), 1–10. https://doi.org/10.1002/rmv.2146

Garcia-Vicuña, D., Esparza, L., & Mallor, F. (2021). Hospital preparedness during epidemics using simulation: The case of COVID-19. *Central European Journal of Operations Research*. https://doi.org/10.1007/s10100-021-00779-w

Garcia-Vicuna, D., Mallor, F., & Esparza, L. (2020). Planning ward and intensive care unit beds for COVID-19 patients using a discrete event simulation model. In *Paper presented at the proceedings - winter simulation conference, 2020-December* (pp. 759–770). doi: 10.1109/WSC48552.2020.9383939.

Gillespie, J., McClean, S., Garg, L., Barton, M., Scotney, B., & Fullerton, K. (2016). A multi-phase DES modelling framework for patient-centred care. *Journal of the Operational Research Society, 67*(10), 1239–1249. https://doi.org/10.1057/jors.2015.114

Gök, E. C., & Olgun, M. O. (2021). SMOTE-NC and gradient boosting imputation based random forest classifier for predicting severity level of covid-19 patients with blood samples. *Neural Computing and Applications, 33*(22), 15693–15707. https://doi.org/10.1007/s00521-021-06189-y

Gopinath, N. (2021). Artificial intelligence: Potential tool to subside SARS-CoV-2 pandemic. *Process Biochemistry, 110*(August), 94–99. https://doi.org/10.1016/j.procbio.2021.08.001

Gorunescu, F., McClean, S. I., & Millard, P. H. (2002). A queueing model for bed-occupancy management and planning of hospitals. *Journal of the Operational Research Society, 53*(1), 19–24.

Govindan, K., Mina, H., & Alavi, B. (2020). A decision support system for demand management in healthcare supply chains considering the epidemic outbreaks: A case study of coronavirus disease 2019 (COVID-19). *Transportation Research Part E: Logistics and Transportation Review, 138*, Article 101967.

Griffin, D. O., Griffin, D. O., Jensen, A., Khan, M., Chin, J., Chin, K., … Patel, D. (2020). Pulmonary embolism and increased levels of D-dimer in patients with coronavirus disease. *Emerging Infectious Diseases, 26*(8), 1941–1943. https://doi.org/10.3201/eid2608.201477

Gul, M., & Guneri, A. F. (2012). A computer simulation model to reduce patient length of stay and to improve resource utilization rate in an emergency department service system. *International Journal of Industrial Engineering, 19*(5), 221–231. 10.23055/ijietap.2012.19.5.793.

Gumaei, A., Ismail, W. N., Rafiul Hassan, M., Hassan, M. M., Mohamed, E., Alelaiwi, A., & Fortino, G. (2022). A decision-level fusion method for COVID-19 patient health prediction. *Big Data Research, 27*, Article 100287. https://doi.org/10.1016/j.bdr.2021.100287

Günal, M. M., & Pidd, M. (2010). Discrete event simulation for performance modelling in health care: A review of the literature. *Journal of Simulation, 4*, 42–51. https://doi.org/10.1057/jos.2009.25

Guo, T., Fan, Y., Chen, M., Xiaoyan, W.u., Zhang, L., He, T., Wang, H., Wan, J., Wang, X., & Zhibing, L.u. (2020). Cardiovascular implications of fatal outcomes of patients with coronavirus disease 2019 (COVID-19). *JAMA Cardiology, 5*(7), 811–888. https://doi.org/10.1001/jamacardio.2020.1017

Gupta, V. K., Gupta, A., Kumar, D., & Sardana, A. (2021). Prediction of COVID-19 confirmed, death, and cured cases in india using random forest model. *Big Data Mining and Analytics, 4*(2), 116–123. https://doi.org/10.26599/BDMA.2020.9020016

Heineke, J. (1995). Strategic operations management decisions and professional performance in US HMOs. *Journal of Operations Management, 13*(4), 255–272.

Heldt, F. S., Vizcaychipi, M. P., Peacock, S., Cinelli, M., McLachlan, L., Andreotti, F., … Khan, R. T. (2021). Early risk assessment for COVID-19 patients from emergency department data using machine learning. *Scientific Reports*, *11*(1), 1–13. doi: 10.1038/s41598-021-83784-y.

Hosmer, D. W. Jr., Lemeshow, S., Sturdivant, R.X. (2013). *Applied logistic regression* (Vol. 398). New York, NY: John Wiley & Sons.

Hou, W., Zhao, Z., Chen, A., Li, H., & Duong, T. Q. (2021). Machining learning predicts the need for escalated care and mortality in covid-19 patients from clinical variables. *International Journal of Medical Sciences*, *18*(8), 1739–1745. doi: 10.7150/ijms.51235.

Hsu, J., Hung, P., Lin, H., & Hsieh, C. (2015). Applying under-sampling techniques and cost-sensitive learning methods on risk assessment of breast cancer. *Journal of Medical Systems*, *39*(4) doi: 10.1007/s10916-015-0210-x.

Hu, J., Zhou, J., Dong, F., Tan, J., Wang, S., Li, Z., … Huang, T. (2020). Combination of serum lactate dehydrogenase and sex is predictive of severe disease in patients with COVID-19. *Medicine, 99*(42), e22774.

Huang, H. F., Liu, Y., Li, J. X., Dong, H., Gao, S., Huang, Z. Y., Fu, S. Z., Yang, L. Y., Lu, H. Z., Xia, L. Y., Cao, S., Gao, Y., & Yu, X. X. (2021). Validated tool for early prediction of intensive care unit admission in COVID-19 patients. *World Journal of Clinical Cases, 9*(28), 8388–8403. 10.12998/wjcc.v9.i28.8388.

Huang, S., Yang, J., Fong, S., & Zhao, Q. (2021). Artificial intelligence in the diagnosis of COVID-19: Challenges and perspectives. *International Journal of Biological Sciences, 17*(6), 1581. https://doi.org/10.7150/ijbs.58855

Ikemura, K., Bellin, E., Yagi, Y., Billett, H., Saada, M., Simone, K., … Gil, M. R. (2021). Using automated machine learning to predict the mortality of patients with COVID-19: Prediction model development study. *Journal of Medical Internet Research, 23*(2). https://doi.org/10.2196/23458

Irvine, N., Anderson, G., Sinha, C., McCabe, H., & Van der Meer, R. (2021). Collaborative critical care prediction and resource planning during the COVID-19 pandemic using computer simulation modelling: Future urgent planning lessons. *Future Healthcare Journal, 8*(2), e317–e321. https://doi.org/10.7861/fhj.2020-0194

Islam, S., & Amin, S. H. (2020). Prediction of probable backorder scenarios in the supply chain using Distributed Random Forest and Gradient Boosting Machine learning techniques. *Journal of Big Data, 7*(1), 1–22.

Ivanov, D., Dolgui, A., & Sokolov, B. (2019). The impact of digital technology and industry 4.0 on the ripple effect and supply chain risk analytics. *International Journal of Production Research, 57*(3), 829–846. https://doi.org/10.1080/00207543.2018.1488086

Iwendi, C., Bashir, A. K., Peshkar, A., Sujatha, R., Chatterjee, J. M., Pasupuleti, S., Mishra, R., Pillai, S., & Jo, O. (2020). COVID-19 patient health prediction using boosted random forest algorithm. *Frontiers in Public Health, 8*(July), 1–9. https://doi.org/10.3389/fpubh.2020.00357

Iyengar, K. P., Vaishya, R., Bahl, S., & Vaish, A. (2020). Impact of the coronavirus pandemic on the supply chain in healthcare. *British Journal of Healthcare Management, 26*(6), 1–4.

Jack, E. P., & Powers, T. L. (2009). A review and synthesis of demand management, capacity management and performance in health-care services. *International Journal of Management Reviews, 11*, 149–174. https://doi.org/10.1111/j.1468-2370.2008.00235.x

Jadhav, S., Kasar, R., Lade, N., Patil, M., & Kolte, S. (2017). Disease prediction by machine learning from healthcare communities. *International Journal of Scientific Research in Science and Technology*, 29–35. 10.32628/ijsrst19633.

Jarrett, M., Schultz, S., Lyall, J., Wang, J., Stier, L., de Geronimo, M., & Nelson, K. (2020). Clinical mortality in a large COVID-19 cohort: Observational study. *Journal of Medical Internet Research, 22*(9). https://doi.org/10.2196/23565

Jraisat, L., Jreissat, M., Upadhyay, A., & Kumar, A. (2022). Blockchain technology: The role of integrated reverse supply chain networks in sustainability. In *Supply chain forum: An international journal* (pp. 1–14). Taylor & Francis.

Jun, J. B., Jacobson, S. H., & Swisher, J. R. (1999). Application of discrete-event simulation in health care clinics: A survey. *Journal of the Operational Research Society, 50*(2), 109–123. https://doi.org/10.1057/palgrave.jors.2600669

Kabir, G., Tesfamariam, S., Hemsing, J., & Sadiq, R. (2020). Handling incomplete and missing data in water network database using imputation methods. *Sustainable and Resilient Infrastructure, 5*(6), 365–377. https://doi.org/10.1080/23789689.2019.1600960

Kadri, F., Harrou, F., Chaabane, S., & Tahon, C. (2014). Time series modelling and forecasting of emergency department overcrowding. *Journal of Medical Systems, 38*(9), 1–20.

Khalilia, M., Chakraborty, S., & Popescu, M. (2011). Predicting disease risks from highly imbalanced data using random forest. *BMC Medical Informatics and Decision Making, 11*(1), 1–13.

Kim, J., Lim, H., Ahn, J. H., Lee, K. H., Lee, K. S., & Koo, K. C. (2021). Optimal triage for COVID-19 patients under limited health care resources with a parsimonious machine learning prediction model and threshold optimization using discrete-event simulation: Development study. *JMIR Medical Informatics, 9*(11), e32726.

Klassen, K. J., & Rohleder, T. R. (2001). Combining operations and marketing to manage capacity and demand in services. *Service Industries Journal, 21*(2), 1–30.

Kochan, C., Nowicki, D. R., Sauser, B., & Randall, W. S. (2018). Impact of cloud-based information sharing on hospital supply chain performance: A system dynamics framework. *International Journal of Production Economics, 195*, 168–185. https://doi.org/10.1016/j.ijpe.2017.10.008

Kortbeek, N., Braaksma, A., Smeenk, F. H., Bakker, P. J., & Boucherie, R. J. (2015). Integral resource capacity planning for inpatient care services based on bed census predictions by hour. *Journal of the Operational Research Society, 66*(7), 1061–1076.

Kumar, A., & Mo, J. (2010). Models for bed occupancy management of a hospital in Singapore. In *Proceedings of the 2010 international conference on industrial engineering and operations management* (pp. 1–6). IIEOM & cosponsored by INFORMS.

Lalmuanawma, S., Hussain, J., & Chhakchhuak, L. (2020). Applications of machine learning and artificial intelligence for Covid-19 (SARS-CoV-2) pandemic: A review. *Chaos, Solitons & Fractals, 139*, Article 110059. https://doi.org/10.1016/j.chaos.2020.110059

Le Lay, J., Augusto, V., Xie, X., Alfonso-Lizarazo, E., Bongue, B., Celarier, T., … Masmoudi, M. (2020). Impact of covid-19 epidemics on bed requirements in a healthcare center using data-driven discrete-event simulation. In *2020 Winter simulation conference (WSC)* (pp. 771–781). IEEE. doi: 10.1109/WSC48552.2020.9384093.

Leung, C. (2020). Risk factors for predicting mortality in elderly patients with COVID-19: A review of clinical data in china. *Mechanisms of Ageing and Development, 188*. https://doi.org/10.1016/j.mad.2020.111255

Li, X., Ge, P., Zhu, J., Li, H., Graham, J., Singer, A., Richman, P. S., & Duong, T. Q. (2020). Deep learning prediction of likelihood of ICU admission and mortality in COVID-19 patients using clinical variables. *PeerJ, 8*(December 2019), 1–19. https://doi.org/10.7717/peerj.10337

Lin, G., Feng, X., Guo, W., Cui, X., Liu, S., Jin, W., … Ding, Y. (2021). Electricity theft detection based on stacked autoencoder and the undersampling and resampling based random forest algorithm. *IEEE Access, 9*, 124044–124058. https://doi.org/10.1109/ACCESS.2021.3110510

Long, B., Brady, W. J., Bridwell, R. E., Ramzy, M., Montrief, T., Singh, M., & Gottlieb, M. (2021). Electrocardiographic manifestations of COVID-19. *American Journal of Emergency Medicine, 41*, 96–103. https://doi.org/10.1016/j.ajem.2020.12.060

Lotfi, R., Kargar, B., Rajabzadeh, M., Hesabi, F., & Özceylan, E. (2022). Hybrid fuzzy and data-driven robust optimization for resilience and sustainable health care supply chain with vendor-managed inventory approach. *International Journal of Fuzzy Systems, 24*(2), 1216–1231.

Lu, Y., Guan, Y., Zhong, X., Fishe, J. N., & Hogan, T. (2021). Hospital beds planning and admission control policies for COVID-19 pandemic: A hybrid computer simulation approach. In *IEEE international conference on automation science and engineering, 2021-Augus* (pp. 956–961). doi: 10.1109/CASE49439.2021.9551589.

Luo, L., Luo, L., Zhang, X., & He, X. (2017). Hospital daily outpatient visits forecasting using a combinatorial model based on ARIMA and SES models. *BMC Health Services Research, 17*(1), 1–13.

Marwaha, J. S., Beaulieu-Jones, B. R., Kennedy, C. J., Nathanson, L. A., Robinson, K., Tandon, M., & Brat, G. A. (2022). Design, implementation, and clinical impact of a machine learning-assisted intervention bundle to improve opioid prescribing. *NEJM Catalyst Innovations in Care Delivery, 3*(4), CAT-21.

Mauer, E., Lee, J., Choi, J., Zhang, H., Hoffman, K. L., Easthausen, I. J., … Banerjee, S. (2021). A predictive model of clinical deterioration among hospitalized COVID-19 patients by harnessing hospital course trajectories. *Journal of Biomedical Informatics, 118*, Article 103794. https://doi.org/10.1016/j.jbi.2021.103794

McGlothlin, J. P., Vedire, S., Srinivasan, H., Madugula, A., Rajagopalan, S., & Khan, L. (2018). Predicting hospital capacity and efficiency. In *HEALTHINF 2018 - 11th international conference on health informatics, proceedings; part of 11th international joint conference on biomedical engineering systems and technologies, BIOSTEC 2018, 5* (Biostec) (pp. 562–570). doi: 10.5220/0006658905620570.

Mehmood, R., Meriton, R., Graham, G., Hennelly, P., & Kumar, M. (2017). Exploring the influence of big data on city transport operations: A markovian approach. *International Journal of Operations and Production Management, 37*(1), 75–104. https://doi.org/10.1108/IJOPM-03-2015-0179

Mehrabadi, M. A., Aqajari, S. A. H., Azimi, I., Downs, C. A., Dutt, N., & Rahmani, A. M. (2021). Detection of COVID-19 using heart rate and blood pressure: Lessons learned from patients with ARDS. In *Paper presented at the proceedings of the annual international conference of the IEEE engineering in medicine and biology society, EMBS* (pp. 2140–2143). doi: 10.1109/EMBC46164.2021.9629794.

Meijboom, B., Schmidt-Bakx, S., & Westert, G. (2011). Supply chain management practices for improving patient-oriented care. *Supply Chain Management, 16*(3), 166–175. https://doi.org/10.1108/13598541111127155

Mejía, F., Medina, C., Cornejo, E., Morello, E., Vásquez, S., Alave, J., … Málaga, G. (2020). Oxygen saturation as a predictor of mortality in hospitalized adult patients with COVID-19 in a public hospital in Lima, Peru. *PLoS ONE, 15*(12 December) doi: 10.1371/journal.pone.0244171.

Melman, G. J., Parlikad, A. K., & Cameron, E. A. B. (2021). Balancing scarce hospital resources during the COVID-19 pandemic using discrete-event simulation. *Health Care Management Science, 19*, 356–374. https://doi.org/10.1007/s10729-021-09548-2

Mercatelli, D., Formaggio, F., Caprini, M., Holding, A., & Giorgi, F. M. (2021). Detection of subtype-specific breast cancer surface protein biomarkers via a novel transcriptomics approach. *Bioscience Reports, 41*(12). https://doi.org/10.1042/BSR20212218

Mesas, A. E., Cavero-Redondo, I., Álvarez-Bueno, C., Cabrera, M. A. S., de Andrade, S. M., Sequí-Dominguez, I., & Martínez-Vizcaíno, V. (2020). Predictors of in-hospital COVID-19 mortality: A comprehensive systematic review and meta-analysis exploring differences by age, sex and health conditions. *PLoS ONE, 15*(11 November). doi: 10.1371/journal.pone.0241742.

Moledina, S. M., Maini, A. A., Gargan, A., Harland, W., Jenney, H., Phillips, G., Thomas, K., Chauhan, D., & Fertleman, M. (2020). Clinical characteristics and predictors of mortality in patients with COVID-19 infection outside intensive care. *International Journal of General Medicine, 13*, 1157–1165. https://doi.org/10.2147/IJGM.S271432

More, A. S., & Rana, D. P. (2017). Review of random forest classification techniques to resolve data imbalance. In *2017 1st International conference on intelligent systems and information management (ICISIM)* (pp. 72–78).

Mudatsir, M., Fajar, J. K., Wulandari, L., Soegiarto, G., Ilmawan, M., Purnamasari, Y., … Harapan, H. (2021). Predictors of COVID-19 severity: A systematic review and meta-analysis [version 2; peer review: 2 approved]. *F1000Research, 9*, 1–26. doi: 10.12688/F1000RESEARCH.26186.2.

Muhammad, N., Upadhyay, A., Kumar, A., & Gilani, H. (2022). Achieving operational excellence through the lens of lean and Six Sigma during the COVID-19 pandemic. *The International Journal of Logistics Management.*

Mukhuty, S., Upadhyay, A., & Rothwell, H. (2022). Strategic sustainable development of Industry 4.0 through the lens of social responsibility: The role of human resource practices. *Business Strategy and the Environment.*

Naymagon, L., Zubizarreta, N., Feld, J., van Gerwen, M., Alsen, M., Thibaud, S., Kessler, A., Venugopal, S., Makki, I., Qin, Q., Dharmapuri, S., Jun, T., Bhalla, S., Berwick, S., Christian, K., Mascarenhas, J., Dembitzer, F., Moshier, E., & Tremblay, D. (2020). Admission D-dimer levels, D-dimer trends, and outcomes in COVID-19. *Thrombosis Research, 196*(June), 99–105. doi: 10.1016/j.thromres.2020.08.032.

Nazir, A., & Ampadu, H. K. (2022). Interpretable deep learning for the prediction of ICU admission likelihood and mortality of COVID-19 patients. *PeerJ Computer Science, 8*(January 2020), e889.

NHS (2022). *AI Skunkworks projects*. Available at: https://transform.england.nhs.uk/ai-lab/ai-lab-programmes/skunkworks/ai-skunkworks-projects/ (Accessed: 12-10-2022).

Nijman, S., Leeuwenberg, A., Beekers, I., Verkouter, I., Jacobs, J., Bots, M., Asselbergs, F., Moons, K., & Debray, T. (2022). Missing data is poorly handled and reported in prediction model studies using machine learning: A literature review. *Journal of Clinical Epidemiology, 142*, 218–229. https://doi.org/10.1016/j.jclinepi.2021.11.023

Oala, L., Murchison, A. G., Balachandran, P., Choudhary, S., Fehr, J., Leite, A. W., … Wiegand, T. (2021). Machine learning for health: Algorithm auditing & quality control. *Journal of Medical Systems, 45*(12). https://doi.org/10.1007/s10916-021-01783-y

Ordu, M., Demir, E., Tofallis, C., & Gunal, M. M. (2021). A novel healthcare resource allocation decision support tool: A forecasting-simulation-optimization approach. *Journal of the Operational Research Society, 72*(3), 485–500. https://doi.org/10.1080/01605682.2019.1700186

Ortíz-Barrios, M. A., & Alfaro-Saíz, J. (2020). Methodological approaches to support process improvement in emergency departments: A systematic review. *International Journal of Environmental Research and Public Health, 17*(8). https://doi.org/10.3390/ijerph17082664

Ortiz-Barrios, M., & Alfaro-Saiz, J. (2020). An integrated approach for designing in-time and economically sustainable emergency care networks: A case study in the public sector. *PLoS ONE, 15*(6 June). doi: 10.1371/journal.pone.0234984.

Ortíz-Barrios, M. A., Coba-Blanco, D. M., Alfaro-Saíz, J. J., & Stand-González, D. (2021). Process improvement approaches for increasing the response of emergency departments against the COVID-19 pandemic: A systematic review. *International Journal of Environmental Research and Public Health, 18*(16), 8814. https://doi.org/10.3390/ijerph18168814

Patel, D., Kher, V., Desai, B., Lei, X., Cen, S., Nanda, N., Gholamrezanezhad, A., Duddalwar, V., Varghese, B., & Oberai, A. A. (2021). Machine learning based predictors for COVID-19 disease severity. *Scientific Reports, 11*(1), 1–7. https://doi.org/10.1038/s41598-021-83967-7

Petrilli, C. M., Jones, S. A., Yang, J., Rajagopalan, H., O'Donnell, L., Chernyak, Y., … Horwitz, L. I. (2020). Factors associated with hospital admission and critical illness among 5279 people with coronavirus disease 2019 in New York City: Prospective cohort study. *BMJ, 369*. https://doi.org/10.1136/bmj.m1966

Pezoulas, V. C., Kourou, K. D., Mylona, E., Papaloukas, C., Liontos, A., Biros, D., Milionis, O. I., Kyriakopoulos, C., Kostikas, K., Milionis, H., & Fotiadis, D. I. (2022). ICU admission and mortality classifiers for COVID-19 patients based on subgroups of dynamically associated profiles across multiple timepoints. *Computers in Biology and Medicine, 141*(November 2021), Article 105176. https://doi.org/10.1016/j.compbiomed.2021.105176

Piccialli, F., di Cola, V. S., Giampaolo, F., & Cuomo, S. (2021). The role of artificial intelligence in fighting the COVID-19 pandemic. *Information Systems Frontiers, 23*(6), 1467–1497. https://doi.org/10.1007/s10796-021-10131-x

Possik, J., Asgary, A., Solis, A. O., Zacharewicz, G., Shafiee, M. A., Najafabadi, M. M., … Wu, J. (2022). An agent-based modeling and virtual reality application using distributed simulation: Case of a COVID-19 intensive care unit. *IEEE Transactions on Engineering Management, 1–13*. https://doi.org/10.1109/TEM.2022.3195813

Pourhomayoun, M., & Shakibi, M. (2021). Predicting mortality risk in patients with COVID-19 using machine learning to help medical decision-making. *Smart Health, 20*, Article 100178. https://doi.org/10.1016/j.smhl.2020.100178

Privett, N., & Gonsalvez, D. (2014). The top ten global health supply chain issues: Perspectives from the field. *Operations Research for Health Care, 3*(4), 226–230.

Rahman, N. A. A., Ahmi, A., Jraisat, L., & Upadhyay, A. (2022). Examining the trend of humanitarian supply chain studies: Pre, during and post COVID-19 pandemic. *Journal of Humanitarian Logistics and Supply Chain Management* (ahead-of-print).

Raj, A., Mukherjee, A. A., de Sousa Jabbour, A. B. L., & Srivastava, S. K. (2022). Supply chain management during and post-COVID-19 pandemic: Mitigation strategies and practical lessons learned. *Journal of Business Research, 142*, 1125–1139.

Rees, E. M., Nightingale, E. S., Jafari, Y., Waterlow, N. R., Clifford, S., Carl, C. A., Group, C. W., Jombart, T., Procter, S. R., & Knight, G. M. (2020). COVID-19 length of hospital stay: A systematic review and data synthesis. *BMC Medicine, 18*(1). https://doi.org/10.1186/s12916-020-01726-3

Restrepo, M. I., Rousseau, L. M., & Vallée, J. (2020). Home healthcare integrated staffing and scheduling. *Omega, 95*, Article 102057.

Robinson, S. (2002). General concepts of quality for discrete-event simulation. *European Journal of Operational Research, 138*(1), 103–117.

Robinson, S. (2005). Discrete-event simulation: From the pioneers to the present, what next? *Journal of the Operational Research Society, 56*(6), 619–629.

Roßmann, B., Canzaniello, A., von der Gracht, H., & Hartmann, E. (2018). The future and social impact of big data analytics in supply chain management: Results from a Delphi study. *Technological Forecasting and Social Change, 130*, 135–149. https://doi.org/10.1016/j.techfore.2017.10.005

Rostami, M., & Mansouritorghabeh, H. (2020). D-dimer level in COVID-19 infection: A systematic review. *Expert Review of Hematology, 13*(11), 1265–1275. https://doi.org/10.1080/17474086.2020.1831383

Sage Growth Report (2021). *The state of healthcare automation*. Available at: http://go.sage-growth.com/healthcare-automation-success-030921-ms (Accessed: 10-10-2022).

Sala, F., Quarto, M., & D'urso, G. (2022). Simulation study of the impact of COVID-19 policies on the efficiency of a smart clinic MRI service. *Healthcare (Switzerland), 10*(4) doi: 10.3390/healthcare10040619.

Sawangarreerak, S., & Thanathamathee, P. (2020). Random forest with sampling techniques for handling imbalanced prediction of university student depression. *Information, 11*(11), 1–13. https://doi.org/10.3390/info11110519

Schwab, P., Schütte, A. D. M., Dietz, B., & Bauer, S. (2020). Clinical predictive models for COVID-19: Systematic study. *Journal of Medical Internet Research, 22*(10). https://doi.org/10.2196/21439

Secinaro, S., Calandra, D., Secinaro, A., Muthurangu, V., & Biancone, P. (2021). The role of artificial intelligence in healthcare: A structured literature review. *BMC Medical Informatics and Decision Making, 21*(1), 1–23.

Shanbehzadeh, M., Nopour, R., & Kazemi-Arpanahi, H. (2022). Using decision tree algorithms for estimating ICU admission of COVID-19 patients. *Informatics in Medicine Unlocked, 30*(February), Article 100919. https://doi.org/10.1016/j.imu.2022.100919

Sharma, M., Kumar, A., Luthra, S., Joshi, S., & Upadhyay, A. (2022). The impact of environmental dynamism on low-carbon practices and digital supply chain networks to enhance sustainable performance: An empirical analysis. *Business Strategy and the Environment.*

Sharma, G., Volgman, A. S., & Michos, E. D. (2020). Sex differences in mortality from COVID-19 pandemic: Are men vulnerable and women protected? *JACC: Case Reports, 2*(9), 1407–1410. https://doi.org/10.1016/j.jaccas.2020.04.027

Sheng, J., Amankwah-Amoah, J., Khan, Z., & Wang, X. (2021). COVID-19 pandemic in the new era of big data analytics: Methodological innovations and future research directions. *British Journal of Management, 32*(4), 1164–1183. https://doi.org/10.1111/1467-8551.12441

Simsekler, M. C. E., Alhashmi, N. H., Azar, E., King, N., Luqman, R. A. M. A., & Al Mulla, A. (2021). Exploring drivers of patient satisfaction using a random forest algorithm. *BMC Medical Informatics and Decision Making, 21*(1), 1–9. https://doi.org/10.1186/s12911-021-01519-5

Simsekler, M. C. E., Qazi, A., Alalami, M. A., Ellahham, S., & Ozonoff, A. (2020). Evaluation of patient safety culture using a random forest algorithm. *Reliability Engineering and System Safety, 204*(April), Article 107186. https://doi.org/10.1016/j.ress.2020.107186

Sitepu, S., Mawengkang, H., & Husein, I. (2018). Optimization model for capacity management and bed scheduling for hospital. In *IOP conference series: Materials science and engineering* (Vol. 300, No. 1, p. 012016). IOP Publishing.

Soni, M., Gopalakrishnan, R., Vaishya, R., & Prabu, P. (2020). D-dimer level is a useful predictor for mortality in patients with COVID-19: Analysis of 483 cases. *Diabetes and Metabolic Syndrome: Clinical Research and Reviews, 14*(6), 2245–2249. https://doi.org/10.1016/j.dsx.2020.11.007

Srivastava, D. K., Kumar, V., Ekren, B. Y., Upadhyay, A., Tyagi, M., & Kumari, A. (2022). Adopting Industry 4.0 by leveraging organisational factors. *Technological Forecasting and Social Change, 176*, Article 121439.

Standfield, L., Comans, T., & Scuffham, P. (2014). Markov modeling and discrete event simulation in health care: A systematic comparison. *International Journal of Technology Assessment in Health Care, 30*(2), 165–172.

Štěpánková, O., Aubrecht, P., Kouba, Z., & Mikšovský, P. (2003). Preprocessing for data mining and decision support. In *Data mining and decision support* (pp. 107–117). Boston, MA: Springer. https://doi.org/10.1007/978-1-4615-0286-9_9.

Sujatha, R., Venkata Siva Krishna, B., Chatterjee, J. M., Naidu, P. R., Jhanjhi, N. Z., Charita, C., Mariya, E. N., & Baz, M. (2022). Prediction of suitable candidates for covid-19 vaccination. *Intelligent Automation and Soft Computing, 32*(1), 525–541. doi: 10.32604/iasc.2022.021216.

Sumari, S., Ibrahim, R., Zakaria, N. H., & Ab Hamid, A. H. (2013). Comparing three simulation model using taxonomy: System dynamic simulation, discrete event simulation and agent based simulation. *International Journal of Management Excellence, 1*(3), 54–59.

Sun, T. Q. (2021). Adopting artificial intelligence in public healthcare: The effect of social power and learning algorithms. *International Journal of Environmental Research and Public Health, 18*(23). https://doi.org/10.3390/ijerph182312682

Sun, L., Song, F., Shi, N., Liu, F., Li, S., Li, P., … Shi, Y. (2020). Combination of four clinical indicators predicts the severe/critical symptom of patients infected COVID-19. *Journal of Clinical Virology, 128*, Article 104431. https://doi.org/10.1016/j.jcv.2020.104431

Tavakoli, M., Tavakkoli-Moghaddam, R., Mesbahi, R., Ghanavati-Nejad, M., & Tajally, A. (2022). Simulation of the COVID-19 patient flow and investigation of the future patient arrival using a time-series prediction model: A real-case study. *Medical & Biological Engineering & Computing, 1–22*. https://doi.org/10.1007/s11517-022-02525-z

Thakur, R., Hsu, S. H. Y., & Fontenot, G. (2012). Innovation in healthcare: Issues and future trends. *Journal of Business Research, 65*(4), 562–569. https://doi.org/10.1016/j.jbusres.2011.02.022

Tharakan, S., Nomoto, K., Miyashita, S., & Ishikawa, K. (2020). Body temperature correlates with mortality in COVID-19 patients. *Critical Care, 24*(1). https://doi.org/10.1186/s13054-020-03045-8

Upadhyay, A., Hernandez, M. J. P., & Balodi, K. C. (2022). Covid-19 Disaster relief projects management: An exploratory study of critical success factors. *Operations Management Research*, 1–12.

Vázquez-Serrano, J. I., Peimbert-García, R. E., & Cárdenas-Barrón, L. E. (2021). Discrete-event simulation modeling in healthcare: A comprehensive review. *International Journal of Environmental Research and Public Health, 18*(22). https://doi.org/10.3390/ijerph182212262

Verity, R., Okell, L. C., Dorigatti, I., Winskill, P., Whittaker, C., Imai, N., … Ferguson, N. M. (2020). Estimates of the severity of coronavirus disease 2019: A model-based analysis. *The Lancet Infectious Diseases, 20*(6), 669–677. https://doi.org/10.1016/S1473-3099(20)30243-7

Vickers, A. J., Cronin, A. M., & Begg, C. B. (2011). One statistical test is sufficient for assessing new predictive markers. *BMC Medical Research Methodology, 11*(1), 1–7. https://doi.org/10.1186/1471-2288-11-13

Vijiyakumar, K., Lavanya, B., Nirmala, I., & Sofia Caroline, S. (2019). Random forest algorithm for the prediction of diabetes. In *Paper presented at the 2019 IEEE international conference on system, computation, automation and networking*. https://doi.org/10.1109/ICSCAN.2019.8878802

Wang, R. Y., Guo, T. Q., Li, L. G., Jiao, J. Y., & Wang, L. Y. (2020). Predictions of COVID-19 infection severity based on co-associations between the SNPs of co-morbid diseases and COVID-19 through machine learning of genetic data. In *2020 IEEE 8th International conference on computer science and network technology (ICCSNT)* (pp. 92–96). IEEE. doi: 10.1109/ICCSNT50940.2020.9304990.

Wang, Z., Upadhyay, A., & Kumar, A. (2022). A real options approach to growth opportunities and resilience aftermath of the COVID-19 pandemic. *Journal of Modelling in Management* (ahead-of-print).

Wang, K., Gheblawi, M., & Oudit, G. Y. (2020). Angiotensin converting enzyme 2: A double-edged sword. *Circulation, 142*(5), 426–428. https://doi.org/10.1161/CIRCULATIONAHA.120.047049

Wang, T., Tang, R., Ruan, H., Chen, R., Zhang, Z., Sang, L., & China Medical Treatment Expert Group for COVID-19. (2021). Predictors of fatal outcomes among hospitalized COVID-19 patients with pre-existing hypertension in china. *Clinical Respiratory Journal, 15*(8), 915–924. https://doi.org/10.1111/crj.13382

Wang, Y., Wang, Z., Tse, G., Zhang, L., Wan, E. Y., Guo, Y., Lip, G. Y. H., Li, G., Lu, Z., & Liu, T. (2020). Cardiac arrhythmias in patients with COVID-19. *Journal of Arrhythmia, 36*(5), 827–836. https://doi.org/10.1002/joa3.12405

Whitworth, J. (2020). COVID-19: A fast evolving pandemic. *Transactions of the Royal Society of Tropical Medicine and Hygiene, 114*(4), 227–228. https://doi.org/10.1093/trstmh/traa025

Wood, R. M., McWilliams, C. J., Thomas, M. J., Bourdeaux, C. P., & Vasilakis, C. (2020). COVID-19 scenario modelling for the mitigation of capacity-dependent deaths in intensive care. *Health Care Management Science, 23*(3), 315–324. https://doi.org/10.1007/s10729-020-09511-7

Xie, Q., Chen, Y., Hu, Y., Zeng, F., Wang, P., Xu, L., … Zeng, F. (2022). Development and validation of a machine learning-derived radiomics model for diagnosis of osteoporosis and osteopenia using quantitative computed tomography. *BMC Medical Imaging, 22*(1). https://doi.org/10.1186/s12880-022-00868-5

Yang, P., Yang, G., Qi, J., Sheng, B., Yang, Y., Zhang, S., … Mao, X. (2021). The effect of multiple interventions to balance healthcare demand for controlling COVID-19 outbreaks: A modelling study. *Scientific Reports, 11*(1), 1–13. https://doi.org/10.1038/s41598-021-82170-y

Yu, K.-H., Beam, A. L., & Kohane, I. S. (2018). Artificial intelligence in healthcare. *Nature Biomedical Engineering, 2*(10), 719–731. https://doi.org/10.1038/s41551-018-0305-z

Yusriza, F. A., Abdul Rahman, N. A., Jraisat, L., & Upadhyay, A. (2022). Airline catering supply chain performance during pandemic disruption: A bayesian network modelling approach. *International Journal of Quality and Reliability Management*. https://doi.org/10.1108/IJQRM-01-2022-0027

Zhang, X. (2018). Application of discrete event simulation in health care: A systematic review. *BMC Health Services Research, 18*(1), 1–11. https://doi.org/10.1186/s12913-018-3456-4

Zhang, L., Yan, X., Fan, Q., Liu, H., Liu, X., Liu, Z., & Zhang, Z. (2020). D-dimer levels on admission to predict in-hospital mortality in patients with covid-19. *Journal of Thrombosis and Haemostasis, 18*(6), 1324–1329. https://doi.org/10.1111/jth.14859

Zhou, F., Yu, T., Du, R., Fan, G., Liu, Y., Liu, Z., Xiang, J., Wang, Y., Song, B., Gu, X., Guan, L., Wei, Y., Li, H., Wu, X., Xu, J., Tu, S., Zhang, Y., Chen, H., & Cao, B. (2020). Clinical course and risk factors for mortality of adult inpatients with COVID-19 in Wuhan, China: A retrospective cohort study. *The Lancet, 395*(10229), 1054–1062. https://doi.org/10.1016/S0140-6736(20)30566-3

Zhu, Z., Hen, B. H., & Teow, K. L. (2012). Estimating ICU bed capacity using discrete event simulation. *International Journal of Health Care Quality Assurance, 25*(2), 134–144. https://doi.org/10.1108/09526861211198290

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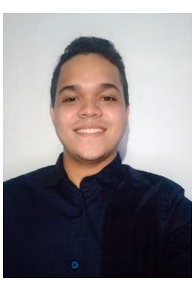

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