A 4.0-Based Dual-Stage Model for Human Resource Optimization in ICU. Theoretical Design and Experimental Investigation of the Boston B.I.D. Database

Teresa Murino, Lorenza Paulone, Emma Salatiello, and Silvestro Vespoli

Abstract The article is focused on a new operation model for the management of ICU human resources, designed through a multi-layer architecture grouped into two stages with continuous interaction between them. On one hand the first stage is based on four layers (defined by as many calculation tools, including a neural net) designed to prognosticate the risk associated with the individual patient admitted to the ICU. On the other hand, the output of the first stage is used as input for the second. Thanks to this interaction it is possible to associate the riskiness of the individual patient calculated with the first model, with the riskiness of the entire ICU. The primary objective of ICU hospitalization is to stabilize patients' vital functions. The provision of healthcare services in the ICU involves both planned tasks and sudden emergency interventions. To address this challenge, the authors propose an ANN-based model that optimizes the utilization of specialized medical personnel. The model considers various factors such as patient acuity, staff availability and workload distribution to make informed decisions on personnel allocation. The proposed model aims to improve the efficiency and effectiveness of healthcare delivery in the ICU by optimizing the use of specialized medical personnel, by ensuring that the right medical resource is available at the right time, and minimizing the waiting times during emergencies.

Keywords ANN neural network · Healthcare prediction · Logistic regression · Human resources allocation · Healthcare system improvement

T. Murino (✉) · L. Paulone · E. Salatiello · S. Vespoli
University of Naples Federico II, Naples, Italy
e-mail: murino@unina.it

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1 Introduction

The primary goal of ICU hospitalization is to stabilize patients' vital functions and potentially transfer them to specialized sub-intensive units for specific pathology treatment. This requires round-the-clock monitoring and the use of technological devices to support cardiovascular and respiratory functions. Due to the unique and complex nature of patient treatment, the number of ICU beds is typically low compared to regular wards, making it crucial to avoid capacity saturation.

To optimize ICU management, proactive and preventive measures are essential [1]. In addition to advanced devices and technologies [2], the analysis of health and management data can help avoid critical situations. Various data analysis strategies [3], such as Statistical Analysis [4] and Logistic Regression [5], are commonly used to study clinical variables [6]. Modern Machine Learning (ML) techniques and tools [7], such us the Feed Forward Network (FFN) [8], or the Renforcement Learning (RL) [9] are also gaining traction in healthcare [10], offering additional support for data analysis and management techniques [11] like Health Technology Assessment [12] and Lean methods [13] and Six Sigma approach [14]. In this context, the development of a predictive model [15] for patients' conditions can greatly assist ICU personnel. By utilizing ML techniques, this family of models can analyze patient data [16] and make predictions [17] to aid in decision-making and proactive interventions [18]. Such a predictive tool, these models can enhance the efficiency and effectiveness of ICU management, ultimately improving patient outcomes [19].

Overall, the paper highlights the importance of leveraging data analysis and ML techniques to support ICU personnel in managing patients' conditions and avoiding critical situations.

2 Problem Statement

The managerial problem addressed by the scientific research described in this article concerns the possibility of supporting the decision-making process through a Machine Learning tool, with which the interventions of the ICU medical staff (carried out outside the department) are scheduled. In particular the main research question of this paper consists in defining the scientific condition and the technological tools, needed to develop a model with the aim to connect the interventions scheduling of ICU medical resources (toward patients outside the unit) to the short-term prognostic survival probability of patients, hospitalized inside the ICU. The proposed model involves a concatenation of machine learning algorithms to prognostic about the patients' health state at the next time step of their ICU stay.

The main hypothesis of the study is that all choices made in the model follow a rational doctor logic.

3 Dual-Stage Model Architecture

The proposed model is based on a dual-stage architecture that provides the interaction of a multi-layer mathematic tools. The first stage is based on four layers designed to prognosticate through a machine learning approach the risk associated with the individual patient admitted to the ICU. The output of the first stage is used as input for the second. Thanks to this interaction it is possible to associate the riskiness of the individual patient calculated with the first model, with the riskiness of the entire ICU.

Basically, the whole model design can be summarized as follows:

i. First Stage (Patient focused)
   (a) Patient vital data acquisition;
   (b) Degradation modeling of the monitored patient;
   (c) Prognostic generation model
   (d) Survival probability normalization (as administered therapy function);

ii. Second Stage (Medical Human Resources oriented)
   (e) Intervention data request collection from other hospital units;
   (f) ICU Human Resources optimized management.

The methodological approach aims to provide hospital human resources with information about the expected health state of ICU patients at the next time step. The methodology begins by collecting clinical variables through multi-parameter monitors and laboratory tests. These variables are used to describe each patient's health state at a specific time step of their ICU hospitalization. The recorded data are then inputted into a Logistic Regression tool, which processes the data and provides the associated patient's survival probability.

The survival probability sequence is then fed into a Long Short-Term Memory Neural Network (LSTM). The LSTM, with its ability to store input history, predicts the survival probability at the next time step by considering the patient's entire health trajectory.

Finally, the obtained short-term prognostic is normalized by the patients' drug therapy. Two alternative Feed-Forward Neural Networks are trained to calculate the increase or decrease in survival probability resulting from the dispensation of a specific therapy compared to another.

Overall, the proposed approach aims to provide ICU personnel with predictive information about patients' survival probability in the short term. By using machine learning algorithms, it can assist in decision-making and intervention planning in the ICU (Fig. 1).

3.1 Data Acquisition of (in ICU-) Hospitalized Patients' Vital Signs

The proposed approach involves acquiring data through laboratory test results and multi-parameter monitors placed next to the hospitalized patients' beds. Multi-parameter monitors are medical devices designed to continuously monitor patients' vital signs, including body temperature, blood pressure, cardiac activity, and oxygen saturation. These monitors not only record the current values of these parameters but also track their evolution over time. They are equipped with indicator lights and acoustic alarms that alert medical staff to any anomalies or values exceeding minimum or maximum thresholds. The most important characteristic of this type of data is the very high quality of information. In fact, being of a numerical nature and, above all, being able to be recorded without any contribution from the operators present in the department, they constitute a database of very high information quality.

3.2 Degradation Modeling of the Monitored Patient

In the Logistic Regression tool, the relationship between the dependent and independent variables is nonlinear. The probability of the occurrence of a specific combination of inputs, which reflects the patient's health state at a specific time step, is expressed using Eq. (1).

$$\text{Prob(event)} = P(\vec{x}) = \frac{e^{(\alpha+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_n x_n)}}{1+e^{(\alpha+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_n x_n)}} \tag{1}$$

In (1), the vector $x = \times 1 + \times 2 + \cdots + x_n$ represents the independent input variables that describe the patient's health state at a specific time step. The coefficients $\alpha, \beta_1, \beta_2, \ldots, \beta_n$ are the logistic regression coefficients, which act as weights for each input parameter in determining the final output, i.e., the probability of the specific combination of inputs occurring.

3.3 Prognostic Generation Model

The proposed approach justifies the use of a Long Short-Term Memory Network (LSTM) due to the importance of considering clinical information from previous time steps to provide context for forecasting patients' pathological conditions. LSTM is a type of recurrent neural network that has a sophisticated structure designed to capture and retain information from past inputs.

In the proposed approach, the LSTM takes as input the temporal sequence of patients' survival probabilities in each ICU time step and predicts the survival probability for the next time step [20]. The LSTM's architecture allows it to remember and utilize information about the patients' health status from previous time steps, enabling a more accurate short-term forecast [21].

By incorporating both historical and current health data throughout the ICU stay [22], the LSTM can capture patterns and dependencies in the patients' health trajectory [23]. This contextual information enhances the accuracy of the short-term forecast, as it considers the evolution of the patients' health conditions over time.

The use of LSTM in the proposed approach aligns with the goal of optimizing the utilization of specialized medical personnel in the ICU. By providing accurate short-term forecasts, the approach can assist ICU personnel in making informed decisions about possible interventions promptly and carefully.

Overall, the LSTM's ability to retain and utilize information from previous time steps contributes to a more accurate short-term forecast of patients' survival probabilities, enhancing the effectiveness of the proposed approach in optimizing ICU management.

3.4 Survival Probability Normalization as a Function of Therapy

In the proposed approach, the forecasting model is applicable to the critical context of the intensive care unit (ICU). To enhance the comprehensive understanding of future health conditions and improve the precision of the prognosis, the impact of specific pharmacological treatments is suggested to be incorporated [24].

However, due to the lack of specific data in the pharmacological literature regarding the effects of drug combinations on patients' health conditions, machine learning tools cannot be trained on such specifics [25]. Therefore, the study takes a first step towards a more realistic short-term prognosis by considering the severity degree of therapies, as defined by the healthcare team [26]. Three classes of therapies are identified based on their severity degree: Soft, Medium and Heavy [27].

The study uses soft therapy as the initial reference and maintains the previous forecast in the proposed approach. To incorporate the impact of different therapies, two alternative Feed-Forward Neural Networks are established. These networks have a simpler architecture than LSTM and have a unidirectional information flow [28].

The first network takes the survival probability sequence of patients under soft therapy as input and predicts the sequence under medium therapy. Similarly, the second network predicts the survival probability sequence under hard therapy. These networks aim to identify the relationship between different therapies and forecast the increase or decrease in survival probability resulting from various therapeutic administrations [29].

The correction in the short-term prognosis involves considering therapeutic administration with a 6-hour frequency and a 3-hour half-life. The options include soft, medium, or hard therapies, and the neural networks help predict the impact of these therapies on the patients' survival probability [30].

By incorporating the impact of different therapies, the proposed approach provides a more comprehensive and realistic short-term prognosis. This information can assist ICU personnel in making decisions about therapeutic interventions and further optimize the management of patients in the ICU.

3.5 Hospital Human Resources Optimal Management

The final step of the proposed model aims to optimize the allocation of hospital human resources in the ICU. By providing accurate short-term forecasts about the patient's health state until the next time step, medical and nursing staff can make informed decisions about their presence in the ICU [31].

When the forecasts indicate a positive outlook for the patient's health, it may be possible for hospital staff to temporarily be absent from the ICU and provide support in other critical departments of the hospital. This could include areas such as the Emergency Room, the Intensive Care Unit, or the Operating Block, where their expertise and assistance are needed [32].

By reallocating resources based on the positive forecasts, the proposed model enables hospital staff to be present where their action and expertise are most needed at any given time. This optimization of human resources can help improve the overall efficiency and effectiveness of hospital operations, ensuring that critical departments receives the support needed, reaching the quality of care in the ICU.

Indeed, the decision to allocate staff to other departments should always prioritize the well-being and safety of the patients [33]. The forecasts provided by the model should be used as a valuable tool to support these decisions, but they should be complemented by clinical judgment and expertise.

It is important to consider the cost and expertise of the hospital staff working in the ICU, such as anesthetists and nurses. These professionals possess specific skills and have a wide range of job responsibilities. Optimizing these human resources employment, through new recruitments may be not the most cost-effective or efficient solution, both from an economic and organization standpoint [34].

By using the proposed models, it becomes possible to minimize the downtime of hospital staff and make the best use of their high levels of expertise. This allows for the efficient allocation of resources, ensuring that staff members are present where their skills are most needed, minimizing the risk [35] of fatal events for the purposes of care provided in the ICU.

The models presented in this paper provide a valuable tool to optimize the utilization of hospital staff [36], enabling them to provide their expertise and support in critical departments beyond the ICU. This approach can help maximize the efficiency of resource allocation and enhance patient care throughout the hospital.

The Intensive Care Unit of a hospital has the following specific properties.

1. It is a highly technological department;
2. It consists of a large number of standardized processes managed in parallel;
3. It can supply quality and highly repetitive services.

Considering the listed features, it can be likened, in terms of Reliability, to an industrial production system with components in parallel (partial redundancy) [37].

Furthermore considering:

- k as the total number of doctors and nurses available on the ward;
- p as the number of doctors and nurses you want to remove temporarily from the ICU to provide care elsewhere, within the hospital.
  For having a 'functioning' system state, it must be the case that:
  - n° patients in a crisis $\leq k$.

More precisely, the k parameter is defined as a condition of functioning reliability 'myopic' of the system. The term 'myopic' refers to the fact that the formula takes into account only the reliability of the ICU and not also the one of the other critical hospital's departments. For having a 360° view of the entire hospital, it is necessary to calculate the Reliability of all the most critical departments; in this way, decisions regarding the displacement of medical and nursing staff from the ICU can be made, considering the emergency situations in the entire hospital [38].

In order to decide whether allowing hospital staff to leave their ICU station or not for eventually taking action in critical situations in the Operating Block, Emergency Room, or other departments, the obtained ICU Reliability value must be greater than or equal to the set threshold value [39]. Considering the following parameters:

- P: ICU reliability value;
- $\bar{P}$: threshold value set by the Hospital's policy.
- It occurs that:
- If $P \geq \bar{P} \rightarrow$ Hospital Staff can leave the ICU;
- If $P < \bar{P} \rightarrow$ Hospital Staff may not leave, it must remain in the ICU. It is happening that one or more patients' health status is potentially worsening and doctors and nurses must be ready for possible actions.

4 Experimental Investigation Though B.I.D. Database

To assess the potential of the proposed approach, it was implemented on the MIMIC-III database. The MIMIC-III database is a comprehensive and freely accessible collection of anonymized clinical information from the Beth Israel Deaconess Medical Center ICU, covering the period from 2001 to 2012. It contains 26 tables with data on multi-parameter monitors, laboratory tests, procedures, drug administration, hospital transfers, and patient information.

The MIMIC-III database was chosen for its completeness of information and its widespread use in scientific articles related to machine learning applications in ICU settings. Given the wealth of clinical information and the specificity of drug treatments for different pathology classes, the approach focused specifically on pneumological patients.

Eight parameters were selected to describe the patients' health states, including five vital signs continuously monitored (respiratory rate, heart rate, oxygen saturation, systolic and mean blood pressure) and three variables from laboratory tests (hemoglobin, creatinine, and potassium). To account for variations in data collection intervals, a uniform one-hour time lapse was set to provide simultaneous inputs to the machine learning algorithms.

The degradation model was created using designated software and the results were supervised by an anesthetist. The statistical tool in the software automated calculations and generated graphs, facilitating easier and quicker data analysis and result interpretation. Through the maximum likelihood method, the regression coefficients' values are thus determined:

$$\begin{aligned}\text{Prob(surv.)} = \text{Prob}(\vec{x}) &= \alpha + \beta_1 x_1 + \beta_2 x_2 \\ &+ \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + \beta_7 x_7 + \beta_8 x_8 \end{aligned} \tag{2}$$

where x_1 is respiratory rate, x_2 is heart rate, x_3 is oxygen saturation, x_4 is systolic (or maximum) blood pressure, x_5 is mean blood pressure, x_6 is hemoglobin, x_7 is creatinine and x_8 is potassium. Replacing the designated software values in (2), the Eq. (3) is obtained:

$$\begin{aligned}\text{Prob(Surv.)} = 9.54 &- 0.0032\ \text{RR} - 0.0466\ \text{HR} + 0.0921\ s\text{pO}_2 \\ &- 0.0021\ \text{NBP Systolic} - 0.0239\ \text{NBP Mean} \\ &+ 0.087\ \text{Hemoglobin} + 0.591\ \text{Creatinine} - 1.743\ \text{Potassium}\end{aligned} \tag{3}$$

The analysis revealed that creatinine and potassium exhibit the highest regression coefficient values, indicating their significant impact on determining patients' survival probability. Subsequently, the construction of the Long Short-Term Memory Neural Network's architecture was carried out using MATLAB R2020b, a platform for data analysis, algorithm development, and model creation. The LSTM takes the patients' survival probability sequence, an output from the previous degradation model step, and produces each patient's forecasted survival probability for the next hour. To enhance network training, especially in recognizing patients with gradually decreasing survival probability, the decision was made to provide only an 8-hour observation window as input, rather than the entire time sequence. The initial database was divided into a training set (80%) and a testing set (20%) to optimize the LSTM's learning process. The starting database is divided as follows: a training set of 80% and a testing set of 20%.

The initial parameters are summarized in Table 1:

The training options are summarized in Table 2:

Table 1 LSTM initial parameters

Windows	Input size	#Hidden units	# Responses
8	8	300	1

Table 2 Training options dataset

Max epochs	Initial learn rate	Gradient threshold	Learn rate schedule	Learn rate drop period	Learn rate drop factor	Verbose
200	0.0005	1	Piecewise	125	0.2	0

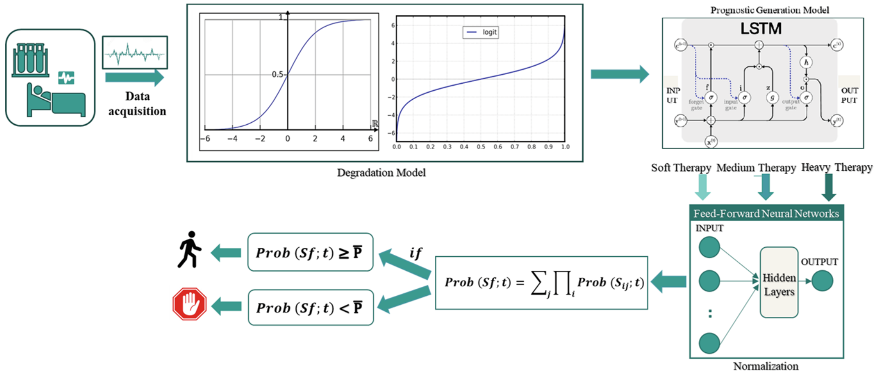

Fig. 1 Dual-stage model architecture

In order to the configuration of LSTM, Fig. 2 shows a qualitative flowchart of the LSTM's constitutive layers.

Testing the network functionality on MIMIC patients, it performed with a Root Mean Squared Error (RMSE) [25, 26] of 0.0334, or approximately 3.3%, as showed in Eq. 4:

$$\text{RMSE} = \sqrt{([[(Y_{(\text{pred})} - Y_t\text{est})^2)} = \sqrt{([[(0.6167 - 0.5833)^2)} = 0.0334 \quad (4)$$

A Regression Plot is depictable, illustrating the relationship between targets (the sequence of survival probabilities for patients undergoing Medium therapy) and the outputs generated by the network. In an ideal training scenario, these two sets of values would coincide perfectly, but such alignment rarely occurs in practical applications.

In Table 3, the FNN the main results s are shown (in terms of MSE and Regression during training, validation, and testing phases of the Network) [40].

The results obtained in the previous steps give information about the survival probability of individual patients. It can be calculated for each hour during which the individual ICU admission is divided. It has to be considered that a generic ICU

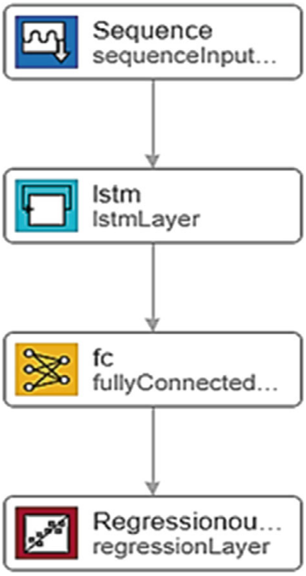

Fig. 2 LSTM architecture literature *source* (https://it.mathworks.com)

Table 3 Regression model results

	MSE	Regression
Training	$1.36012 * e^{-4}$	$9.44350 * e^{-1}$
Validation	$2.86795 * e^{-5}$	$9.77658 * e^{-1}$
Testing	$7.38161 * e^{-5}$	$9.64147 * e^{-1}$

consists of beds in a number dependent on the size of the hospital. The aim of the paper is to make forecasts, in terms of the reliability of the entire ICU [29].

The ICU presented in the investigated case consists of 6 beds. In the ward there are 3 hospital members available (divided between anesthetist doctors, reanimators, and nurses). There are no empty beds, i.e., not occupied by in-patients (worst-case scenario). The variables to be considered are the following ones:

- n = total number of beds = 6;
- k = total number of doctors and nurses available in the ward = 3;
- p = number of hospital staff members needed to be removed from the intensive care unit = 2.

It is necessary that the number of patients about to go into crisis is at most maximum equal to the number of doctors and nurses available on the ward.

This ensures that there is at least one member of the medical staff available for each needy person.

A 'myopic' functional reliability condition of the Intensive Care Unit is:

$$\text{n}^\circ \text{ patients in a crisis } \leq k \text{with } k = 3$$

Table 4 Probability of survival of the 6 hospitalized patients at next time step (1 h)

	Patient 1	Patient 2	Patient 3	Patient 4	Patient 5	Patient 6
Survival probability	0.880	0.880	0.880	0.880	0.880	0.880

The patients' survival probability values of the 6 patients admitted to the ICU are extracted from the results of the neural networks at 6 p.m. on 10/02, and shown Table 4, basing the calculation process on the MIMIC-III database of B.I.D. Medical Center of Boston:

The aim is to calculate the reliability of the entire Intensive Care Unit, in order to, determine whether and in what number remove doctors and nurses from the ICU.

Table 5 shows all the possible combinations of survival probability for the 6 considered patients at the next hour, with a number of seizures respectively equal to 0, 1, 2 and 3 [35].

The data shown in Table 5 are broken down as follows:

- in row 1 there are the survival probabilities of the 6 patients with no crisis;
- from row 2 to row 7 there are the survival probabilities of the 6 patients with the prediction of a single seizure event;
- from row 8 to row 22 there are the survival probabilities of the 6 patients with 2 crisis predictions;
- from row 23 to row 42 there are the survival probabilities of the 6 patients with 3 crisis predictions;
- finally, in the last column there are the multiplications of the survival probabilities for the 6 patients.

To quantify the reliability of the Intensive Care Unit, all values listed in the last column of Table 5 are produced all together.

5 Results Discussion and Conclusions

The prediction of the neural tool is calculated for each hour into which the individual ICU admission is divided. It must, however, be considered that a generic Intensive Care unit is made up of beds whose number depends on the size of the hospital. The future development of the presented research is to make predictions in terms of the reliability of the entire intensive care unit in order to optimize the resources used in The ICU wards. We can develop a specific optimizing tool, stanting from the knowledge of number of ICU beds and the number medical staff members available for the department (shared between anesthetists and intensive care doctors and nurses). Furthermore, in the worst case optics, it's possible applying the prediction tool under the hypothesis of empty beds absence (i.e. not occupied by hospitalized patients), in order to determine the available time for employing medical staff in other emergency activity during a short period (equal to the short period, set up for the

Table 5 Patients' survival probability with severe crises in numbers of 0, 1, 2, and 3

# Possible combination	Patient 1	Patient 2	Patient 3	Patient 4	Patient 5	Patient 6	Combined probability
1	0.880	0.971	0.964	0.941	0.975	0.877	0.663
2	0.120	0.971	0.964	0.941	0.975	0.877	0.090
3	0.880	0.029	0.964	0.941	0.975	0.877	0.020
4	0.880	0.971	0.036	0.941	0.975	0.877	0.025
5	0.880	0.971	0.964	0.059	0.975	0.877	0.042
6	0.880	0.971	0.964	0.941	0.025	0.877	0.017
7	0.880	0.971	0.964	0.941	0.975	0.123	0.093
8	0.120	0.029	0.964	0.941	0.975	0.877	0.003
9	0.120	0.971	0.036	0.941	0.975	0.877	0.003
10	0.120	0.971	0.964	0.059	0.975	0.877	0.006
11	0.120	0.971	0.964	0.941	0.025	0.877	0.002
12	0.120	0.971	0.964	0.941	0.975	0.123	0.013
13	0.880	0.029	0.036	0.941	0.975	0.877	0.001
14	0.880	0.029	0.964	0.059	0.975	0.877	0.001
15	0.880	0.029	0.964	0.941	0.025	0.877	0.001
16	0.880	0.029	0.964	0.941	0.975	0.123	0.003
17	0.880	0.971	0.036	0.059	0.975	0.877	0.002
18	0.880	0.971	0.036	0.941	0.025	0.877	0.001
19	0.880	0.971	0.036	0.941	0.975	0.123	0.003
20	0.880	0.971	0.964	0.059	0.025	0.877	0.001
21	0.880	0.971	0.964	0.059	0.975	0.123	0.006
22	0.880	0.971	0.964	0.941	0.025	0.123	0.002
23	0.120	0.029	0.036	0.941	0.975	0.877	0.000
24	0.120	0.029	0.964	0.059	0.975	0.877	0.000
25	0.120	0.029	0.964	0.941	0.025	0.877	0.000
26	0.120	0.029	0.964	0.941	0.975	0.123	0.000
27	0.120	0.971	0.036	0.059	0.975	0.877	0.000
28	0.120	0.971	0.036	0.941	0.025	0.877	0.000
29	0.120	0.971	0.036	0.941	0.975	0.123	0.000
30	0.120	0.971	0.964	0.059	0.025	0.877	0.000
31	0.120	0.971	0.964	0.059	0.975	0.123	0.001
32	0.120	0.971	0.964	0.941	0.025	0.123	0.000
33	0.880	0.029	0.036	0.059	0.975	0.877	0.000
34	0.880	0.029	0.036	0.941	0.025	0.877	0.000
35	0.880	0.029	0.036	0.941	0.975	0.123	0.000
36	0.880	0.029	0.964	0.059	0.025	0.877	0.000

(continued)

Table 5 (continued)

# Possible combination	Patient 1	Patient 2	Patient 3	Patient 4	Patient 5	Patient 6	Combined probability
37	0.880	0.029	0.964	0.059	0.975	0.123	0.000
38	0.880	0.029	0.964	0.941	0.025	0.123	0.000
39	0.880	0.971	0.036	0.059	0.025	0.877	0.000
40	0.880	0.971	0.036	0.059	0.975	0.123	0.000
41	0.880	0.971	0.036	0.941	0.025	0.123	0.000
42	0.880	0.971	0.964	0.059	0.025	0.123	0.000

neural net). To support and validate the conclusion, the study's results could undergo a preliminary data mining process, oriented to deep learning analysis, designed for healthcare system prediction (as the MIMIC-III used data base). The computational findings can contribute to provide new insights into expected LOS trends and guiding corrective actions in healthcare management, focused on hospital sustainability, KPI improvement and medical staff safety [41].

The final step involves the calculation of the reliability of the entire Intensive Care Unit, based on the concept of system state space.

If the obtained reliability value is less than or equal to a threshold set by the hospital's Medical Directorate, a certain number of doctors and nurses can safely leave the ICU, offering support in other departments of the hospital, such as: Emergency Room, Operating Block, or Reanimation Room.

There are two main innovations brought about by the proposed models.

Firstly, the consideration, never done before, of the therapy administered to patients as a normalizing factor in predicting patient survival. This contribution makes the predictions more accurate and truthful.

Secondly, the decision-making support provided by the hospital staff and resulting from the calculation of the reliability of the entire Intensive Care Unit. It makes it possible to significantly reduce downtime for doctors and nurses, as well as increasing the amount of beneficial interventions that they can perform, where warranted, on patients in need outside the ICU.

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