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Application of healthcare data mining techniques to planning for nursing length of stay in surgical departments

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ABSTRACT

Effective allocation of nurse resources in surgical departments is essential for improving patient care and controlling operating costs in a health society. Length of stay (LOS) is the metric that connects clinical workload to staffing decisions, yet ward-level forecasting and its translation into daily nursing schedules remain limited. This study presents a hybrid, data-driven decision-support system that combines machine-learning LOS prediction with Reinforcement Learning (RL) for the surgical ward. A dataset of 137,145 records is used to evaluate Random Forest, Gradient Boosting, Decision Tree, and a Multi-layer Perceptron. Random Forest achieved the most accurate and stable performance ($R^2 = 0.84$; RMSE = 1.63), and its predicted LOS states drive an RL agent that adjusts staffing and triggers early-discharge reviews. The novelty lies in focusing on the understudied surgical ward, converting predicted LOS into a daily scheduling policy, and integrating forecasting with RL-based scheduling. The hybrid model reduced average LOS from 6.12 to 4.82 days, lowered weekly nurse overtime by approximately 47%, and improved staff utilization.

1. Introduction

Hospitals around the world face capacity and financial challenges year-round. The number of beds remains constant, while at the same time, there is an increase in the number of patients requiring emergency care and surgery each year, as well as careful budgetary considerations in most facilities. In such circumstances, the number of nurses employed and how they are scheduled becomes vital in terms of waiting time, efficiency of care delivery, and costs. Nursing planning is simply finding out the right number of nurses with the requisite skills needed to take care of patients. When done efficiently, the result is prompt care and a speedy recovery. The Length of Stay (LOS) is the measure that relates the clinical work to the decision-making for nursing staff. It refers to the period in which the patient is admitted and can be used to measure the utilization of resources, costs incurred, and the degree of severity of the illness. Abd-Elrazek et al. [1] proposed that accurately predicting LOS at admission was necessary for planning management, including bed availability, discharge scheduling, and assigning nursing staff to the most demanding shifts. This has led to the development of methods aimed at LOS reduction and prediction. With the introduction of hospital information systems, large-scale data are easily obtained from encounters, leading to the application of data mining and machine learning (ML) techniques in LOS prediction. Abujaber et al. [2] used Random Forest (RF), Gradient Boosting (GB), Support Vector Machine (SVM), ensemble trees, and neural network techniques, which have yielded an over 80% accuracy rate for LOS prediction within emergency rooms,

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ICUs, stroke units, and pediatric units. These contributions illustrate that ML can elucidate the nonlinear connections among demographic, clinical, and procedural variables that determine LOS. Three restrictions, however, limit their operational efficacy. Initially, the LOS prediction in the surgical ward is relatively under-researched compared to emergency and critical care settings. Secondly, numerous studies regard the LOS as a binary or categorical outcome and conclude at prediction, failing to translate the prognosis into specific staffing or scheduling decisions. Third, reinforcement learning (RL), while progressively employed for sequential resource-allocation challenges, has hardly been integrated with LOS projections to enhance nurse scheduling.

The decision-making process for surgery involves not just predicting but also incorporating it into an LOS algorithm. The process takes two stages, where at the first stage, ML algorithms predict the LOS from a sample of 137,145 records, while a reinforcement learner uses the predicted LOS to guide scheduling decisions in response to generated demands. Furthermore, besides predicting, the model creates a daily schedule based on the predicted LOS and performs association mining to find the most influential factors related to prolonged LOS. In general, the contributions of this paper can be described as follows:

- Proposing a two-stage decision-support framework in which ML models are first evaluated for nursing LOS prediction, and RL is then employed to optimize nursing scheduling policies under simulated demand scenarios.
- Evaluating four ML models (i.e., RF, GB, Decision Tree (DT), and Multi-layer Perceptron (MLP)) on a real-world dataset of 137,145 patient records, with the RF identified as the most accurate and stable predictor.
- Applying rule mining to uncover the high-impact factors influencing LOS intervals, such as age, surgical status, and department, thus supporting evidence-based healthcare planning.
- Assigning a daily nursing schedule on the basis of predicted LOS, providing a direct and reproducible link between forecasting and operational staffing decisions in the surgical ward.

The remaining article is organized as follows. In Section 2, a summary of the related works research conducted in the research field is given. The dataset and data mining approaches are overviewed in Section 3. Section 4 proposes the outcomes analysis and a discussion. Section 5 covers the discussion & limitations. Section 6 provides conclusions and some suggestions for future studies.

2. Literature review

This section provides an overview of nursing planning's LOS and DM within innovations, health, and systems. Investigations on the causes of LOS have frequently been published in the literature. The average LOS of men is higher than that of women. Therefore, an increase in age would lead to a reduction in average LOS. The central hospital in the northwest of Iran serves the population under study. This hospital not only serves the city but also neighboring cities. To demonstrate how artificial intelligence (AI) techniques could be used as a useful LOS stratification tool in the surgical department, Alahmar et al. [3] developed and implemented an application. According to [4], AIs could be used as a prediction tool to find individuals more likely to require lengthy critical care unit stays after heart surgery. They asserted that the reverse-propagation algorithm had not previously addressed this area. In a recovery center, Ayyoubzadeh et al. [5] investigated the inverse hazard regression (HR) model's ability to anticipate hospital stays for individuals with their first stroke. To forecast the typical nursing LOS for early discharge with stroke, they suggested utilizing the HR approach. The characteristics that distinguished between people with a mental health condition with short LOS (one week) and prolonged LOS (two to three weeks) were examined [6]. Age, degree of disability, and independent functioning were independent determinants of LOS.

The construction component of DM is condensing substantial amounts of data into more manageable forms. The patterns and information contained in the data are revealed through this procedure [7]. Compared to other healthcare policy sectors, DM for estimating nursing LOS remains under-researched. However, some studies examined factors influencing nursing LOS [8]. Hosseini-Shokouh et al. [9] presented a pattern recognition method based on a classical process mining framework. To help construct clinical pathways, this algorithm identified clinical routes. Kameg & Lee [10] investigated the care demands of nursing planning to identify the specific permutations of care requirements for these patients. Khajehali & Alizadeh [11] demonstrated that mining association rules could identify patterns of patient satisfaction for a large patient healthcare service in the emergency department in China. Khormi & Nataraj [12] employed a neural network to predict LOS for nursing and treatment staff in the chronic obstructive pulmonary disease (COPD) department. Length-of-stay prediction has been investigated across multiple clinical contexts, including emergency departments, intensive care units, and patients with traumatic brain injury [13,14]. Gurazada et al. [15] applied a SVM–based approach to predict hospital LOS in advance [16].

An ML model was developed to forecast long-term clinical outcomes, including hospital LOS and patient mortality. The study employed a reduced-feature modeling strategy, demonstrating satisfactory predictive performance [17]. The methods used in this study belong to a wider family of data-driven techniques whose value is well established across engineering and scientific domains, which supports their transfer to nursing LOS prediction and scheduling. Abbasi [18] reviewed statistical methods for fault diagnosis in power systems and showed how classification and feature analysis enable reliable decisions, a structure that mirrors the LOS classification task here. In their work on transformer fault analysis, Baroumand et al. [19] used an integration of logistic regression, wavelet transform, and neural networks to determine the effectiveness of a hybrid structure, which forms the basis of our proposed hybrid system. Zadehbagheri and Abbasi [20] applied a modified whale optimization algorithm to minimize energy cost in distribution networks, a resource-balancing goal analogous to the reinforcement-learning scheduling layer proposed here. Parkash and Abbasi [21] have proposed a cross-entropy-based method to interpret frequency response results, which is in line with the same emphasis on transparent, feature-level reasoning that motivates the association analysis in this work. These works demonstrate the generalizability of data mining, neural and optimization methods across domains, and provide a methodological foundation for the integrated prediction-and-optimization approach developed for the surgical ward.

Table 1 briefly overviews some significant recent developments in the healthcare LOS with DM technique topic to better outline the novelties of this research. As the primary goal of this article, a model will be proposed for planning a better response to LOS in the face of crises. Also, we consider the nursing daily duty schedule routine to get better, more reliable services, especially in the emergency department. Perliti Scorzoni et al. [22] advocated using a hybrid methodology, Classifier Fusion-LoS, which comprised two steps. In the preliminary phase, multiple classifiers were utilized, encompassing traditional models such as Logistic Regression, ExtraTrees, RF, KNN, and Support Vector Classifier. The findings indicated that the RF achieved the highest validation accuracy of 0.94.

To our knowledge, no study has applied ANN in the surgery ward. The other main difference between our study and the existing ones is that we scheduled nurses' daily programs based on predicted LOS using an ANN. This results in more effective use of facilities.

2.1. Research gaps and justification of the proposed approach

The previously reviewed studies mentioned above confirm that ML predicts hospital LOS with consistent accuracy, with several reporting R^2 above 0.80 or comparable classification performance. Despite this,

Table 1
Review of various variables and methods based on the LOS and DM methods topic.

Authors	Objectives			Variables			Nursing Planning		Methods				Solution approaches		
	Cost	Satisfaction	Service	Demographic	Disease	Comorbidities Clinical character	Yes	No	Descriptive	Case study	Predictive	Normalization	Fuzzy	DM	ML
Lee et al.[23]		*		*		*		*	*		*				*
Almeida et al. [24]	*		*		*	*	*		*	*				*	*
Boff Medeiros et al. [25]		*		*	*		*		*		*		*		
Abakasanga et al. [26]		*	*			*		*	*		*			*	
		*			*			*	*						*
Von Greisch et al. [27]	*			*		*	*			*	*		*		
Turgeman et al. [28]	*			*				*		*	*			*	
This research	*	*	*	*	*	*	*		*	*	*			*	

recurring limitations restrict their operational value, and the proposed framework addresses each one. Most prior work targets emergency, intensive-care, stroke, or pediatric settings, leaving the resource-intensive surgical ward comparatively under-represented; this study therefore develops LOS prediction and scheduling specifically for the surgical department. Many studies also frame LOS as a binary or categorical outcome, such as prolonged versus short stay, thereby discarding the granularity required for shift-level staffing. The present work models LOS as a continuous variable in hours. While previous literature uses only one approach, there are four methods (i.e., RF, GB, DT, and MLP), which are evaluated using the same set of performance measures, and the best method is selected. The second limitation is that, as far as we are aware, prediction is typically considered the goal, without any follow-up on staffing. In contrast, we use the predicted LOS to generate a nurse work schedule, which is then used by an RL algorithm that adjusts staff based on simulated demand. To strengthen reliability beyond the single train-test split common in this literature, performance is assessed through resampling, 95% confidence intervals, and ten-fold cross-validation. Finally, because influential LOS factors are often left implicit, association rule mining reveals the variables most strongly associated with extended stays, supporting interpretable, evidence-based nursing planning.

3. Material and methods

This section discusses the dataset used in this study and provides an overview of data mining approaches. Nursing length of stay (NLOS) is defined as the cumulative nursing care time associated with a patient episode, approximated as a function of patient LOS and ward-level nurse-to-patient staffing ratios.

3.1. Data mining approaches

Applications such as predicting nursing planning and management widely use data mining in the health and medical sectors. Due to the dimension of the database and other aspects, extracting connections, guidelines, and other crucial information from or related to the data is challenging. To achieve our objectives, we applied some of the most popular predictive DM techniques. Multi-variate approaches use ANNs to identify linear and nonlinear relationships among data variables. ANNs are the most widely used technique across several fields of medicine due to their excellent predictive performance [29]. Moreover, it helps support informed decision-making. Several node inputs, weighted interconnections, and other related processing elements are all included in an ANN. In the past few years, the SVM classification category has attracted increasing attention. It is a brand-new technique for differentiating between linear and non-linear data and a reliable algorithm for predicting accuracy.

Also, [30] applied nine data mining classifiers, including AdaBoost, SVM, Gradient Boosted Trees, RF, DT, Deep Learning, Logistic Regression, Generalized Linear Models, and Naïve Bayes, for LOS prediction. Among the predictive methods, ANN, as an effective algorithm in predicting LOS, is less studied in the literature. ANN algorithms can perform non-linear statistical modeling and provide an alternative to logistic regression. Also, they require less formal statistical training, the ability to implicitly detect complex non-linear relationships between dependent and independent variables, the ability to detect all possible interactions between predictor variables, and the availability of multiple training algorithms. Although it is the most commonly used method for developing predictive models of dichotomous outcomes in medicine, it has been applied in only a few studies to predict LOS. The current study aims to provide a framework for predicting LOS using ML techniques to support better decision-making and resource management. Before collecting data, it is essential to determine the real goal of the problem, what exactly we are looking for, and what we should obtain. We aim to predict the nurse's LOS based on information from the hospital department. Information here refers to the features needed to feed our ML algorithm to predict LOS. To build our ML model, we need to determine the dependent variable we aim to predict: the nurse's LOS. Then, identify the independent variables to predict the dependent variable. The dependent variable or output expresses the nurse's LOS in days. After building the predictive planning system, we considered LOS in hours so supervisors and nurses could appropriately plan resource use and services during their shifts. Independent variables also include both numerical and categorical variables. The study population included all patients admitted to the hospital, regardless of disease type or department. Because the pediatric department was not investigated in this study, we included patients aged 14–105 years.

3.2. Data collection

After analyzing the literature review articles, we selected the independent variables reported in them. In addition, the availability of these variables within the study population and the extracted dataset was taken into consideration. Therefore, selected variables were present in our dataset. We extracted the dataset from the Comprehensive Hospital Information Management System (CHIMS), which utilizes an SQL database. The hospital in question uses this comprehensive system. The dataset includes eight independent predictor variables and one response or dependent variable. The values for the output variable, LOS, were calculated by subtracting the patient's hospital entry date from the discharge date. Table 2 lists the independent features (variables) and their unique values.

3.3. Machine learning methods

Four ML algorithms were considered to create the predictive model (Fig. 1). After data pre-processing, the data set was fed into the ML algorithms, including RF, GB, MLP, and DT, to train the models. After training, their predictive power was assessed using error measures and R-squared. We utilized these ML models to compare their performance and select the model with the lowest error measures and highest R-squared. Table 3 provides information about these ML algorithms.

Although conventional inferential models such as Cox proportional hazards and generalized linear regression provide interpretability and causal understanding, their predictive efficacy may diminish in heterogeneous datasets characterized by nonlinear effects and categorical interactions. The CHIMS dataset encompasses a variety of patient and procedural characteristics that interact intricately, necessitating the application of ensemble ML methods for enhanced pattern recognition. The implementation of ML/DL models does not diminish the importance of interpretable baselines; future research will involve comparison analyses with sophisticated survival and regression models to evaluate prediction efficacy and improve clinical interpretability.

Table 2
Predictor independent variables.

Variable name	Unique values
Age	Between 14 and 105 years old
Gender	Man, Woman
Marital status	Married, Single, Deceased Spouse, Divorced
Section name	Men internal, General operating room, Women surgery department, Men surgery department, ICU, Emergency department
Doctor's specialty	Internal, Cardiovascular, Neurology, Infectious, General surgery, orthopedics, Emergency medicine, Urology, Eye, General, Ear, Digestive & Liver, Obstetrician gynecologist
Surgery	Yes, no
Blood transfusion	Yes, no
Insurance type	Rural, Social insurance, Tamin, Government employees, Golden insurance, Free, Random, Organizational insurance, Bank, Insurance other, Hospital

3.4. Hybrid ANN-RL model

This study combines an ANN with the RL model to enhance the applicability of LOS forecasts for dynamic decision-making in nursing resource allocation. The ANN component calculates each patient's anticipated LOS based on input variables such as age, surgical status, physician specialty, and insurance type. Using contextual feedback and continuous reinforcement, the RL agent employs LOS estimates to determine optimal actions, such as augmenting nursing staff, initiating early discharge reviews, or prioritizing high-risk patients. In Fig. 2, we indicate the overview of the interaction for the ANN-RL model.

Workflow of the LOS prediction and analysis framework. Solid arrows indicate standard, mandatory steps in the pipeline, including data cleaning, feature engineering, model training, and evaluation. The dotted arrow indicates a conditional/optional step, applied only when additional refinement or rule-based interpretation is required (e.g., association rule mining after model performance evaluation). A discrete state-action vector was established, with each state denoting the patient's anticipated LOS classification (short, medium, or long) and each action indicating potential resource strategies (e.g., allocating extra nursing hours and initiating intervention protocols). The incentive function included clinical outcomes (e.g., decreased extended LOS) and operational indicators (e.g., staff efficiency, reduced overtime). The hybrid ANN-Rl approach demonstrated the ability to dynamically adjust resource allocations based on anticipated patient profiles, thereby reducing average LOS and improving staff utilization compared with conventional rule-based scheduling. This method corresponds with the current transition towards intelligent hospital management systems that can derive optimal policies from practical data:

x_i= feature vector for patient (age, surgery, etc.) where x_i is the input feature vector for patient i, comprising the eight predictor variables listed in Table 2;

$$\hat{y}_i = f(x_i;\theta)$$

where $\hat{y}_i$ is the ANN-predicted LOS for patient i, $f(\cdot)$ is the trained neural-network mapping, and θ is the vector of network weights and biases;

$$L(\theta) = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2$$

where $L(\theta)$ is the mean squared training loss, $\hat{y}_i$ is the predicted LOS, y_i is the actual LOS, and n is the number of training samples.

Discretize ANN output into states:

$$s_t = \begin{Bmatrix} S_1, \hat{y}_t \le 3 \\ S_2, 3 \le \hat{y}_t \le 7 \\ S_3, \hat{y}_t > 7 \end{Bmatrix} \begin{matrix} (Short - stay) \\ (Medium - stay) \\ (Long - stay) \end{matrix} \quad (1)$$

where s_t is the discrete state assigned at step t, $\hat{y}_t$ is the predicted LOS in days, and S_1, S_2, and S_3 denote the short-, medium-, and long-stay classes.

Action space is defined as $A = \{a_1, a_2, a_3\}$, where A is the action set, a_1 increases nursing staff, a_2 initiates an early-discharge review, and a_3 applies first-come, first-served priority. Then, we have a final RL Q-learning update based on the above formal method as:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + a[r_t + \gamma \max Q(s_{t+1}, a') - Q(s_t, a_t) \quad (2)$$

where $Q(s_t, a_t)$ is the action-value of taking action a_t in state s_t, α is the learning rate $(0 < \alpha \le 1)$, γ is the discount factor $(0 \le \gamma \le 1)$, r_{t+1} is the reward returned by the environment after action a_t, s_t is the current state derived from the ANN-predicted LOS, s_{t+1} is the resulting next state, a_t is the action taken, and a' is a candidate action in the next state.

4. Results and analysis

The present study includes 137,145 patients treated in various hospital departments. The average age of these patients was 45 years, and

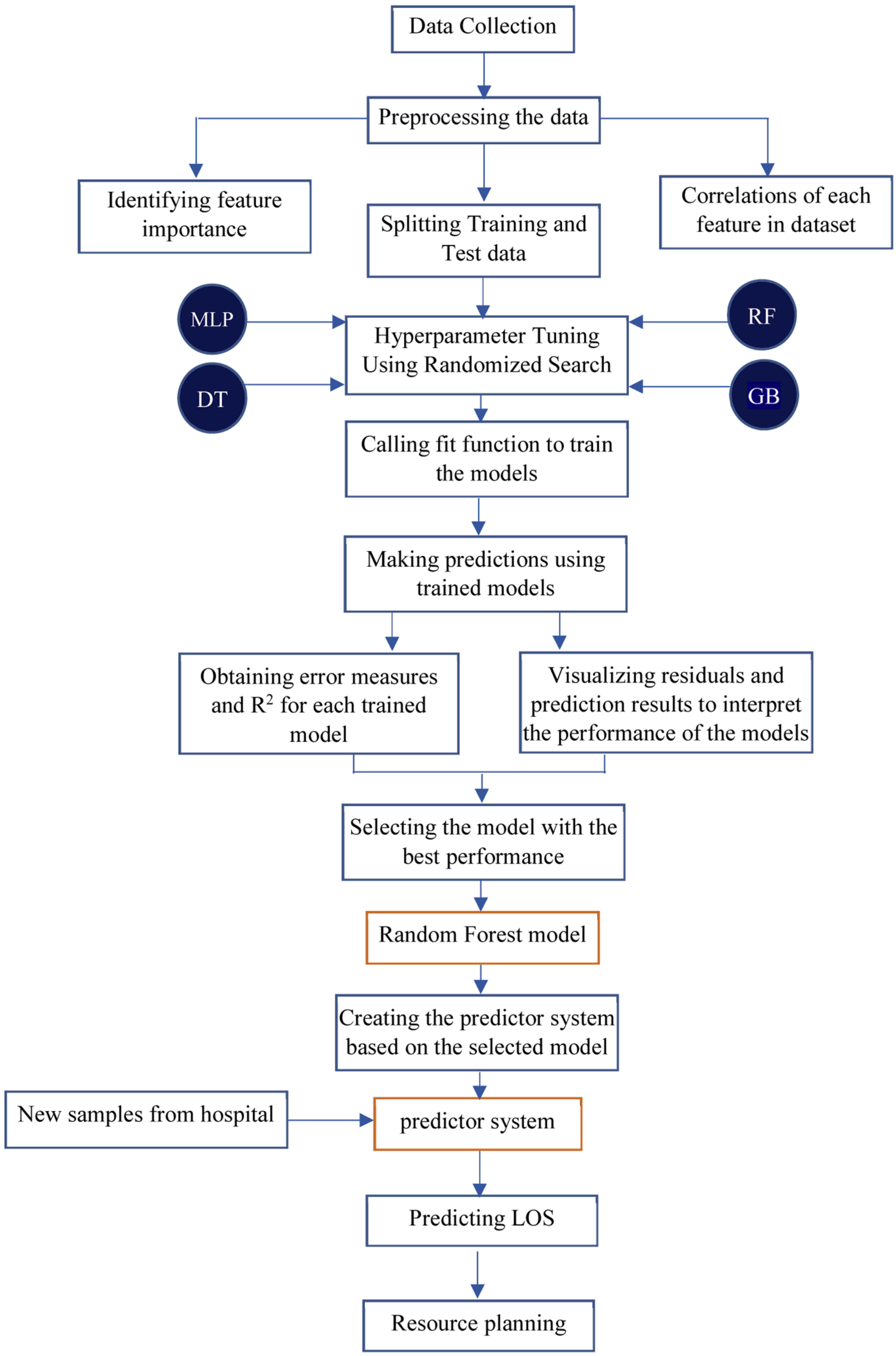

Fig. 1. Overview of LOS flowchart considering four various DM algorithms.

the average LOS was 54h. After cleaning the rows with missing values during pre-processing, we converted the categorical variables to binary values. This is needed to feed categorical data to some estimators in scikit-learn. We used a correlation heatmap to demonstrate the strength of relationships between variables (Fig. 3).

The correlation value ranges from −1 to +1, where +1 indicates a perfect positive correlation. An Extra Trees Regressor (ETR) from scikit-learn was used to assess the importance of the input features. Fig. 3 visualizes the eight most important features for predicting the target variable. Table 4 provides a general overview of our dataset. Based on this, we have seven categorical and two numerical variables. In the data preprocessing stage, due to the large dataset size, samples with missing values were discarded, leaving 137,145 remaining samples (rows).

Table 4 illustrates that a married patient aged 77 from the internal section has an LOS of around 130 in contrast to a woman patient aged 41 with single marital status who has an LOS of 13.54 in the emergency department. Table 5 represents a descriptive statistics summary of the given numerical columns in the dataset.

The CHIMS dataset comprises heterogeneous variables, numerical (e.g., age and LOS) and categorical (e.g., department, admission type) that

Table 3
Objectives of several machine learning algorithms used in this research.

Algorithm	Objectives
Random Forest	The goal of random forests is to increase the predicted precision of tree-based learning algorithms
Gradient Boosting	A class of robust machine-learning methods that have achieved notable success in a variety of real applications. They are quite adaptable to the application's specific requirements, such as being trained concerning various loss functions
Multi-layer Perceptron	It supplements the feed-forward neural network. The input layer, output layer, and hidden layer are the three different kinds of layers that make it up
Decision Tree	A Decision Tree is a predictive algorithm that divides the feature space recursively into subspaces as the foundation for prediction

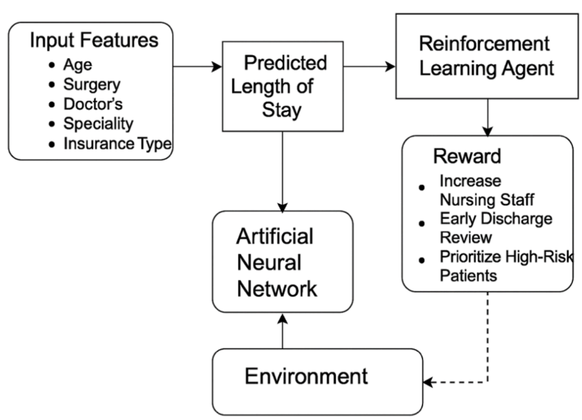

Fig. 2. Diagram showing the interaction between the ANN and the RL agent.

exhibit intricate nonlinear relationships. These attributes constrain the applicability of classical regression or proportional-hazards models, which presuppose linear or log-linear correlations and proportionate effects over time. Consequently, we utilized ML models (i.e., RF, GB, DT, MLP) that are adept at capturing nonlinearities and variable interactions while adhering to parametric assumptions. The study aimed for predicted accuracy and operational decision assistance, rather than causal inference.

Based on the results in Table 5, when the lowest percentage of patients were admitted to healthcare, LOS was at its minimum. Also, when 75% of patients were referred to the healthcare facility, LOS increased. Also, we considered several features of the ETR model (Fig. 4). The main benefits of ETR include its robustness against overfitting, reduced variance, and increased diversity in the ensemble. Introducing additional randomness during training can lead to better generalization and improved accuracy compared to traditional DTs, especially when dealing with noisy or high-dimensional datasets.

After preprocessing and preparing the data, we considered building three ML models. To this end, we split our data into the training dataset (70%) and the test dataset (30%). Before building our first ML model with the RF regressor, we performed hyperparameter tuning to find optimal parameter values. A randomized search CV was employed for parameter tuning. We specified *n_iter* (number of iterations) = 5 and *cv* (cross-validation) = 5, meaning the model will be fitted 25 times. The optimal hyperparameters for fitting the model can also be accessed after the model is fit. The same procedure was considered to build the second model using the GM algorithm. Table 6 shows the optimal hyperparameter combinations for the RF and GB models.

When the models were ready, predictions were made, and the error measures and R-squared values were obtained for each model. Table 7 represents these measures. Plotting the residual histogram, shown in Fig. 5, indicates that the variance is normally distributed, suggesting that the model's underlying assumptions are met. This means that the models we created performed statistically robustly. Fig. 5 also shows that the plots are linear for both models, indicating good predictive performance.

After creating ensemble models, we build the DT model. There was close competition between DT and GB, so the performance of both models was almost the same, but the GB model outperformed by a negligibly small amount. Then we considered several measure errors, including:

a) Root mean squared error (RMSE):

$$RSME = \sqrt{\frac{\sum_i (y - \hat{y}_i)^2}{N - P}}, \tag{3}$$

where y_i is the actual LOS for the i th observation, $\hat{y}_i$ is the predicted LOS for the i th observation, N is the number of observations, and P is the number of estimated parameters, including the constant term. Finding the root mean square error involves calculating the residual for each observation and squaring it. Then sum all the squared residuals and divide that sum by the error degrees of freedom (i.e., $(N - P)$) to find the average squared residual, more technically known as the mean squared error (MSE). Finally, take the square root to find the RMSE.

b) Mean absolute error (MAE):

$$MAE = \frac{\sum_i |y_i - x_i|}{N} \tag{4}$$

where y_i is the actual LOS for the i th observation, $\hat{y}_i$ is the predicted LOS for the i th observation, and N is the number of observations. MAE uses the same scale as the data being measured. Table 7 reports the predictive error measures (MAE, MSE, RMSE) and the R^2 for the RF, GB, and DT models, allowing a direct comparison of their accuracy. It shows that the RF performs best, with the lowest errors (MAE 0.736, RMSE 1.634) and the highest R^2 (0.844), ahead of GB and DT.

The model failed to achieve acceptable performance compared to the three other models in the study, ultimately achieving an R-squared of 63%. Table 8 shows the performance of the models based on RMSE and R-squared. The RL module was developed to evaluate dynamic scheduling rules with synthetic LOS values generated from the RF-predicted LOS distribution. Despite the evaluation of a fundamental feedforward artificial neural network within the modeling benchmark, its performance ($R^2 = 0.63$) was inadequate for robust policy control. Thus, the RL environment was parameterized via RF-based LOS estimates to maintain predictive authenticity. The resultant ANN–RL hybrid constitutes an experimental simulation framework rather than a sequential real-time process.

Table 9 highlights the predictive efficacy and statistical dependability of the assessed ML techniques for LOS forecasting. For each algorithm, the coefficient of determination (R^2) and root mean squared error (RMSE) are presented, along with their respective 95% confidence intervals, calculated via resampling. The RF model shows the most robust and consistent performance, achieving the highest R^2 (0.843) and the lowest RMSE (1.63 h) with tight confidence intervals, indicating strong generalization. Conversely, the DT and MLP exhibit diminished predictive accuracy and broader error margins, suggesting lower reliability. For consistency with the predictive analysis, operational LOS values are reported in hours.

Fig. 6 indicates the empirical distributions of RMSE, MAE, and R^2 from continuous resampling, along with their 95% confidence intervals. The restricted spread and unimodal distributions indicate strong predictive stability and low variation, while the narrow R^2 interval corroborates robust generalization performance. These findings affirm the statistical robustness of the RF model beyond a singular train-test division.

Fig. 7 illustrates the variation of R^2 scores across the 10 cross-validation folds, with the dashed line indicating the mean

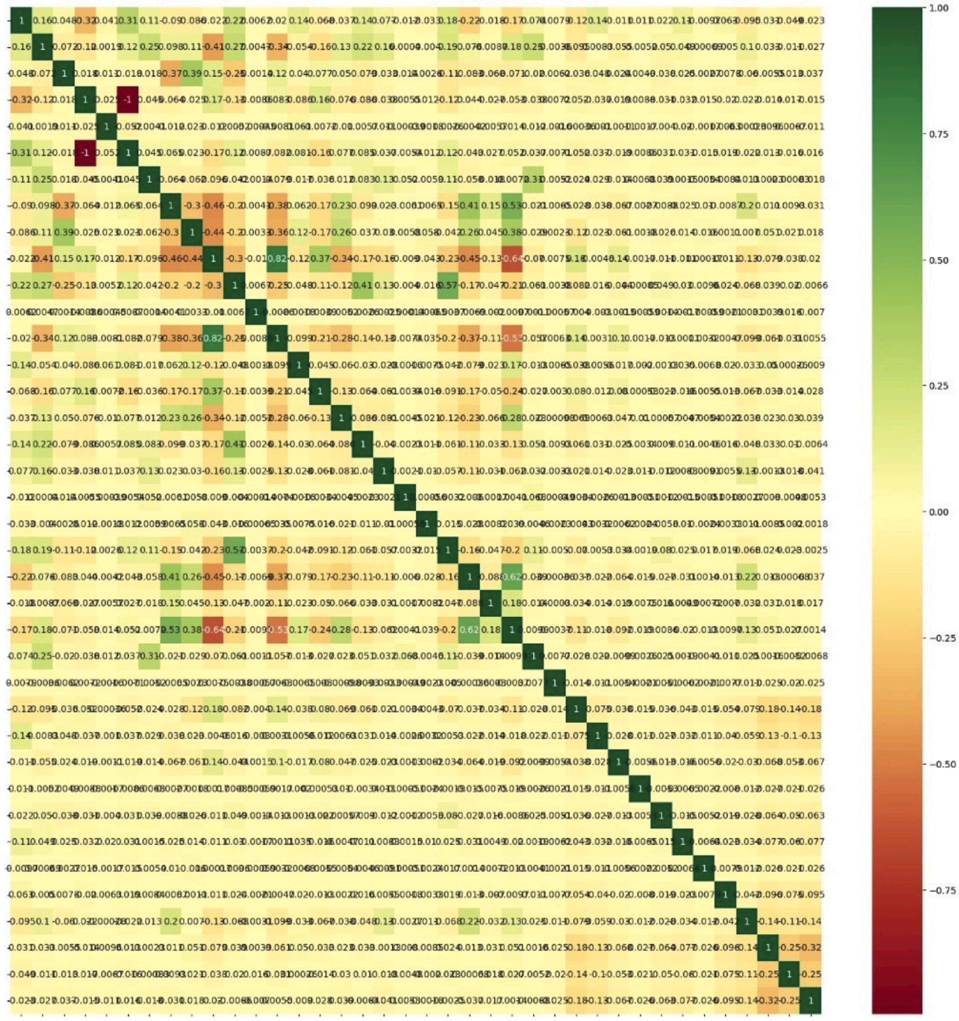

Fig. 3. Correlation heatmap for predicting the target variable.

Table 4
Overall view of the dataset results of the surgery department.

Gender	Age	Marital status	Section name	Doctor's specialty	Surgery	Blood transfusion	Insurance type	LOS (hours)
man	77	married	men_internal	internal	No	No	rural	**126.79**
man	35	married	men_internal	internal	No	No	social_insurance	15.53
man	54	married	men_internal	Cardiovascular	No	No	tamin	55.55
man	72	married	men_internal	Neurology	No	No	rural	91.89
…	…	…	…	…	…	…	…	…
woman	31	married	dept_women_surgery	orthopedics	yes	No	rural	35.99
woman	41	Single	emergency_dept	General	No	No	tamin	**13.54**
…	…	…	…	…	…	…	…	…

Table 5
Descriptive statistics summary of the results.

	Age	LOS (hours)
Count	137,145	137,145
Mean	45	54.13
std	20	104.2
Min	14	0.04728
25%	29	1.75
50%	43	25.39
75%	61	69.29
max	105	3178.76

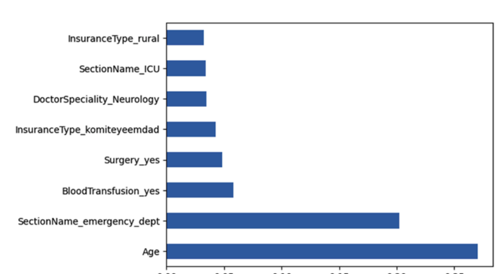

Fig. 4. Eight most useful features specified by the ETR model.

Table 6
Best hyperparameters for RF and GB models.

Parameter	Value	
	RF	GB
n_estimators	900	600
min_samples_split	5	10
min_samples_leaf	1	2
max_features	Sqrt	Sqrt
max_depth	25	15

performance. The limited fluctuation around the mean and absence of extreme drops demonstrate consistent model behavior across different data partitions. This confirms that the predictive performance is stable and not driven by a favorable data split.

Also, we considered different intervals of nursing LOS during the week. The number of patients from the beginning of the week to the end of the weekday was determined based on intervals of <1, between 1 and 4, between 4 and 8, and >8. According to the results given in Table 10, we can see that maximum LOS was shown in the interval of >8 for Monday and Friday as 104 and 112, respectively.

Moreover, the number of nurses by gender in internal, surgery, ICU, and emergency departments showed that women nurses had the longest LOS on the first weekday. In contrast, men had the shortest LOS on Friday (Table 11). The detailed results are illustrated in Table A.1 in the

Table 8
Performance results based on RMSE and R-squared.

Model	RMSE	R-squared	Rank based on the predictive power
RF	1.63427757123996	0.8436993652058247	1
GB	1.8047285955328893	0.8315742116694844	2
DT	1.8074678842198824	0.8310625369521035	3
MLP	2.68	0.63224	4

Table 9
Results of comprehensive inferential statistical analysis model for average LOS (hours).

Model	R^2 Score	95% CI for R^2	RMSE (h)	95% CI for RMSE
RF	0.843	[0.839, 0.847]	1.63	[1.61, 1.65]
GB	0.812	[0.808, 0.816]	1.84	[1.82, 1.86]
DT	0.795	[0.790, 0.800]	2.12	[2.09, 2.15]
MLP	0.63	[0.624, 0.636]	3.45	[3.41, 3.49]

Table 7
Various error measures for RF, DT and GB models.

Measures	Value		
	RF	GB	DT
MAE	0.7361381934999875	0.7450897993711975	0.7469302535337294
MSE	2.6708631798579825	3.257045303534115	3.266940152486298
RMSE	1.63427757123996	1.8047285955328893	1.8074678842198824
R-squared	0.8436993652058247	0.8315742116694844	0.8310625369521035

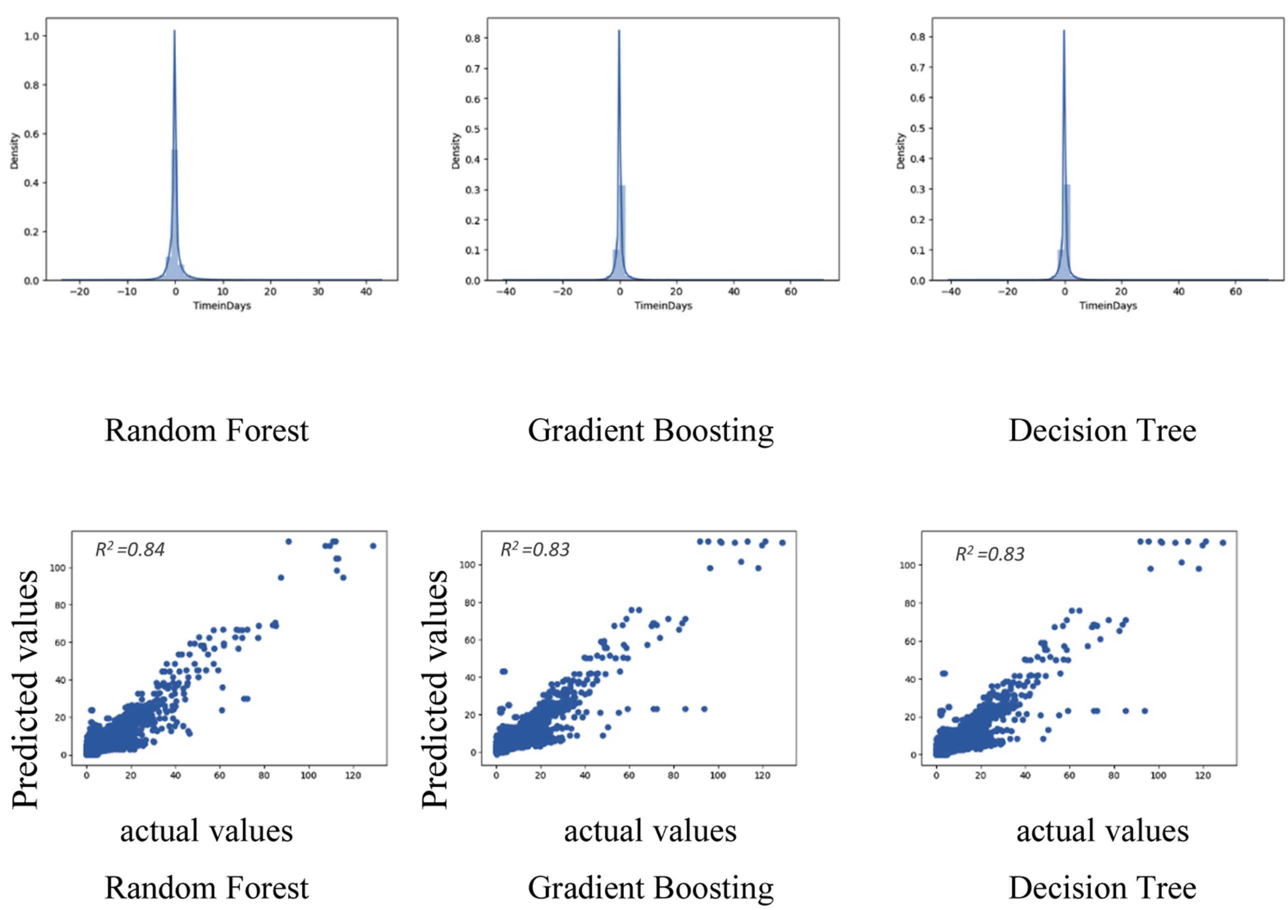

Fig. 5. Prediction plot distribution where actual targets.

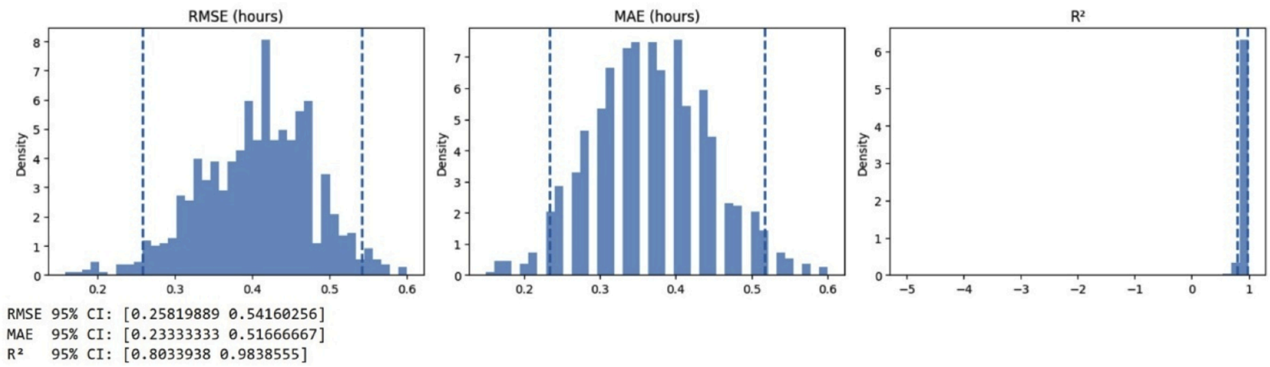

Fig. 6. Overview reporting R^2 and RMSE with confidence intervals.

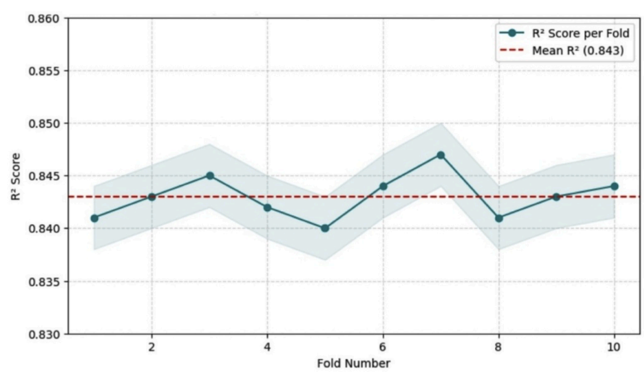

Fig. 7. Stability and robustness lines via 10-fold cross-validation.

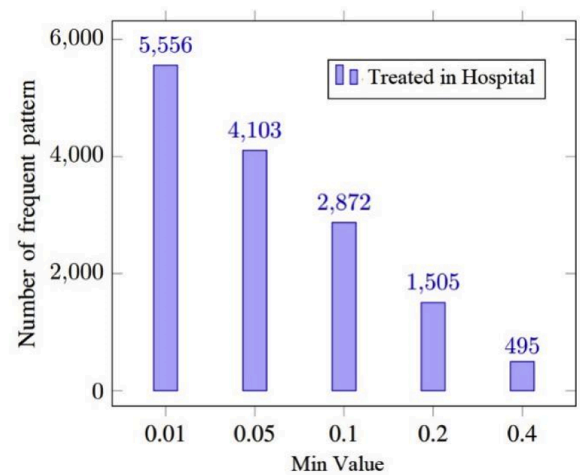

Fig. 8. Number of treated in hospital relative to a min value.

Table 10
Results of various intervals on different days for nurses' LOS.

Weekdays	Number of patients	LOS≤1	1<LOS<4	4≤LOS<8	LOS≥8
Monday	205	37	55	9	104
Tuesday	172	30	46	11	85
Wednesday	190	33	65	8	84
Thursday	164	30	54	6	74
Friday	98	13	37	13	35
Saturday	159	21	48	10	80
Sunday	197	26	46	13	112

Appendix.

Figs. 8 and 9 indicate the frequency of patterns and association rules according to the minimum value. The recurring patterns signify the typical hospital treatments. These details are essential for determining the type of admission and may be used to modify the hospital in the future to accommodate these patients.

Fig. 9 shows the association laws that can be applied to the prediction. Clustering the characteristics and the class (LOS) necessitates using the pattern and association rule amount.

Table 12 compares three methods for managing nursing LOS and optimizing personnel in the surgical department. The suggested ANN + RL hybrid model achieves the shortest mean LOS (4.82 days) and the lowest standard deviation (1.87), indicating shorter, more uniform hospital stays than the baseline and ANN-only methodologies. It dramatically decreases nurse overtime to 22.7h per week and enhances staff utilization to 84.3%, indicating improved workforce efficiency. Moreover, it achieves the lowest readmission rate (6.1%), indicating enhanced care quality and efficient patient management, facilitated by the model's adaptive decision-making capabilities. Operational enhancements are measured by the average and variability of critical indicators, LOS, and nurse overtime, alongside mean differences and their respective 95% confidence intervals. The persistently low *p*-values ($p < 0.0001$) demonstrate that the observed decreases in paired testing are unlikely to result from random fluctuations. Performance metrics were evaluated across N independent simulation replications, each initialized with a different random seed governing arrivals and LOS realizations. The results provide formal statistical validation of the suggested method's efficacy and directly address questions about its reliability and

Table 11
Results of various intervals on different days for various departments.

Weekdays	Number of patients	Dept_women_surgery	Emergency_dept	Men_internal	ICU	Dept_men_surgery
Monday	205	44	108	10	16	27
Tuesday	172	25	87	17	15	28
Wednesday	190	17	110	20	22	21
Thursday	164	24	91	22	8	19
Friday	98	10	67	9	7	5
Saturday	159	22	82	15	11	29
Sunday	197	37	86	24	19	31

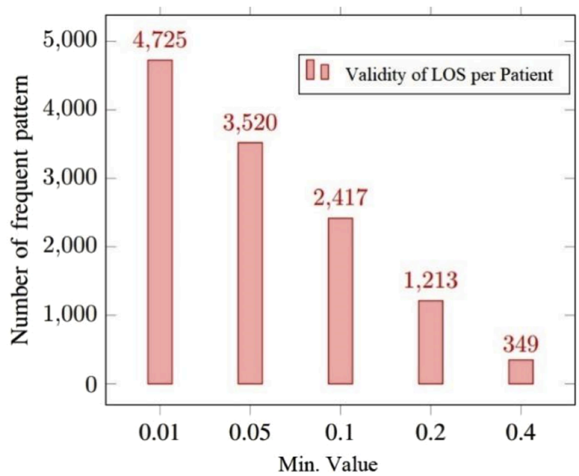

Fig. 9. Number of treated in hospital relative to a min value.

relevance.

The survey data indicates that the hospital conducts meetings at a frequency of 4 out of 10, for a total of 40%. This analysis suggests that LOS frequency is relatively low, indicating potential for improvement in overall effectiveness. Furthermore, the data mining results indicate that the hospital has a rating of 3.7 out of 10 for suboptimal nursing staff, constituting 40%. Fig. 10 demonstrates boxplots of patient LOS across three scheduling methods: baseline (no prediction), ANN-only forecasting, and the proposed ANN–RL framework. The gradual decline in medians and interquartile ranges indicates a steady decrease in LOS variability and central tendency from baseline to ANN and then to ANN–RL, with the p-value < 0.001 indicating differences among the techniques. The lower spread and fewer high-end outliers observed with the ANN–RL methodology underscore enhanced stability and more consistent patient discharge.

Table 13 represents the distribution of nursing workload by weekday in the women's and men's surgery departments, quantified by the number of nurses encountering extended length-of-stay hours. The women's surgical unit records its highest volume on Monday (44) and its lowest on Friday (10), while the men's unit records its highest volume on Sunday (31) and its lowest on Friday (5). Although both departments demonstrate significant weekday fluctuations, the aggregate trends do not indicate a persistent directional disparity across the week. The aforementioned descriptive variations prompted a second inferential comparison employing a two-sample *t*-test.

Fig. 11 represents the distribution of enhanced length-of-stay counts by weekday in the men's and women's surgery departments. The women's unit shows a significant decrease from Monday to Wednesday, followed by a gradual increase culminating on Sunday. Conversely, the men's unit exhibits a more even pattern, characterized by a pronounced dip on Friday followed by a rise throughout the weekend. Despite both departments demonstrating significant intra-week variability, the patterns diverge in both size and timing, indicating that workload pressures and peak-demand periods do not precisely synchronize between the units. The descriptive contrasts substantiate the ensuing statistical comparison in the study to evaluate whether the observed variances result in a substantial disparity in average LOS-related effort among departments.

Fig. 12 indicates the weekly distribution of extended nurse length-of-stay counts for the men's and women's surgical departments. The women's unit has shown increased variability throughout the week, with a broader interquartile range and a significantly elevated upper whisker, indicating intermittent spikes in effort. Conversely, the men's unit shows a more compact range, albeit with a distinct low outlier on Friday. This variability prompts subsequent inferential testing to determine whether the observed distributional differences in mean nursing workload by LOS across departments are significant.

The hybrid ANN–RL framework was used as a simulation-based decision-support model to evaluate potential resource allocation strategies under RF-predicted LOS scenarios. The observed reductions in LOS and improvements in staff utilization reflect optimization behavior within the simulated environment rather than outcomes from real-time clinical deployment. however, the highest predicted accuracy was achieved with the RF model ($R^2 = 0.84$; RMSE ≈ 1.63 h). The Multilayer Perceptron (MLP/ANN) framework achieved reduced fidelity ($R^2 = 0.63$) and was not used as the primary determinant in RL decisions. The RL module utilized RF-informed LOS distributions as the simulated setting for assessing scheduling and workload-balancing techniques. Consequently, the hybrid component should be viewed as a conceptual amalgamation rather than a direct succession of ANN predictions into RL behaviors. The robust operational outcomes observed in the ANN–RL simulation (diminished LOS and overtime) demonstrate the policy-optimization capabilities of RL-based on realistic LOS forecasts, rather than the independent predictive efficacy of the ANN alone.

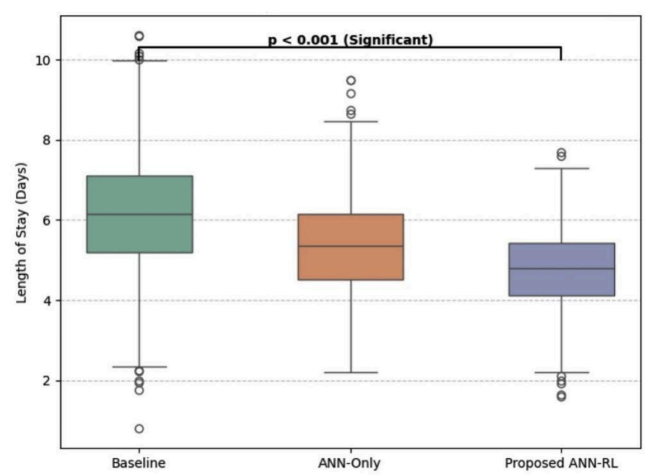

Fig. 10. Boxplot analysis of patient LOS across scheduling strategies.

Table 13
Weekly extended nursing LOS counts recorded in surgical departments.

Days	Dept_women_surgery	Dept_man_surgery
Monday	44	27
Tuesday	25	28
Wednesday	17	21
Thursday	24	19
Friday	10	5
Saturday	22	29
Sunday	37	31

Table 12
Results of various intervals on different days for various departments.

Model	Mean LOS (days)	Std. dev. LOS	95% CI for LOS	p-value	Nurse overtime (hrs./week)	Staff utilization (%)	Readmission rate (%)
Baseline (No Prediction)	6.12	2.74	[6.10, 6.14]	–	42.5	69.1	8.3
ANN Only (LOS Forecast)	5.38	2.13	[5.36, 5.40]	< 0.001	31.4	75.6	7.4
ANN + RL (Proposed)	**4.82**	**1.87**	**[4.81, 4.83]**	**< 0.001**	**22.7**	**84.3**	**6.1**

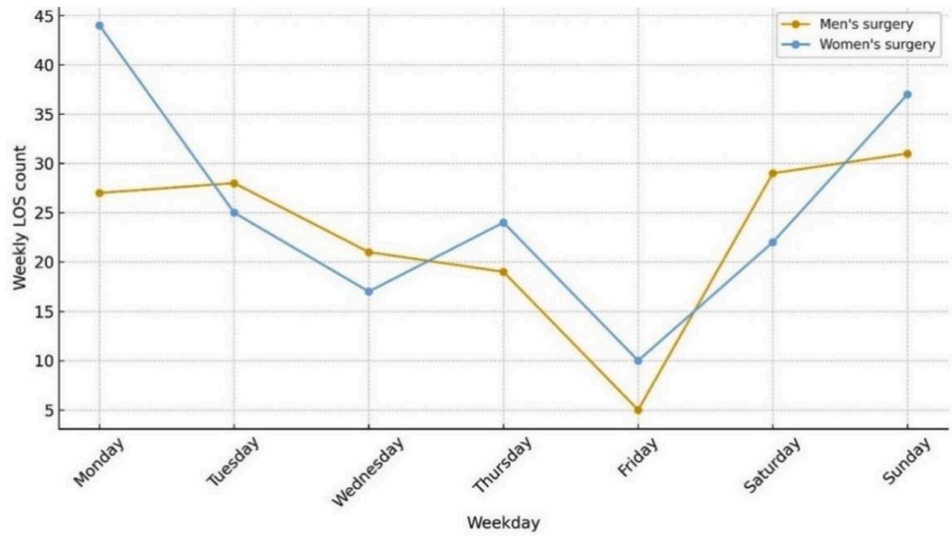

Fig. 11. Weekly distribution of extended nursing LOS across surgical departments.

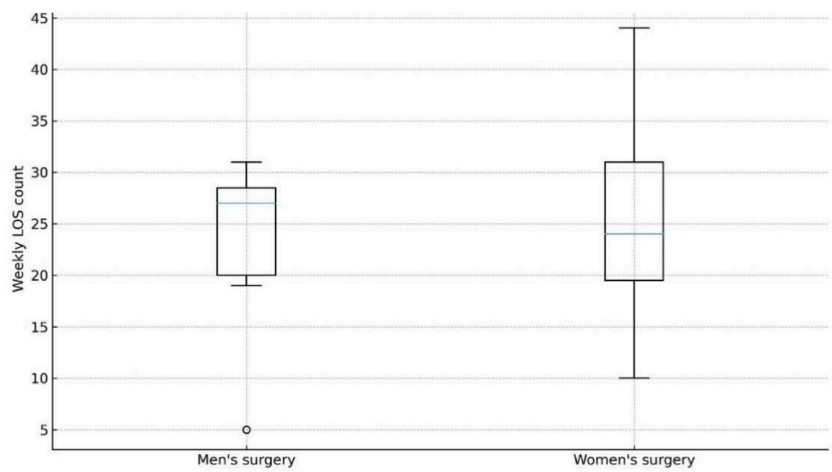

Fig. 12. Comparative distribution of weekly extended nursing LOS counts between surgical units.

Table 14
Statistical comparison of operational performance metrics across scheduling strategies.

Metric	Baseline Strategy (Mean ± SD)	ANN—Only Strategy (Mean ± SD)	Proposed ANN-RL (Mean ± SD)	p-value (Baseline vs. ANN-RL)
Patient LOS (days)	6.12 ± 1.45	5.38 ± 1.22	4.82 ± 0.98	< 0.0001
Nurse Overtime (h/wk)	42.5 ± 5.8	31.4 ± 4.2	22.7 ± 3.1	< 0.0001
Resource Utilization (%)	69.1 ± 7.4	75.6 ± 6.1	84.3 ± 4.2	< 0.001

Table 14 incorporates three major operational metrics patient LOS, nurse overtime, and resource utilization across the baseline strategy, ANN-only forecasting, and the proposed ANN–RL architecture, with results shown as mean ± standard deviation. Compared with the baseline, the ANN–RL methodology demonstrates a significant decrease in patient LOS (6.12 → 4.82 days) and nurse overtime (42.5 → 22.7h per week), coupled with a considerable increase in resource utilization (69.1% → 84.3%). The reported p-values demonstrate that the disparities between the baseline technique and the ANN–RL approach are $p < 0.001$. The ANN-only technique demonstrates moderate performance across all criteria and is presented to highlight the additional advantages of ML-based optimization.

A hospital may rate each delay, workload level, efficacy of discharge planning, and staff level adequacy on a scale from 1 to 10. It is possible to compute cumulative scores for every shift or day. Interventions can be put in place to deal with delays and heavy workloads if they continuously lead to higher scores and enhance LOS. Periodic monitoring on a regular basis aid in the identification of persistent issues and the proactive implementation of solutions. (Fig. 13)

Based on this study's findings, there is a connection among nurse staffing levels, readmission rates, and hospital stay duration. Diminished nurse staffing increases the likelihood of undesirable patient outcomes, while increased nurse staffing decreases the risk of delays or admissions to care, thereby averting these adverse consequences. The chance of early readmission following discharge increases with decreasing nurse staffing when patients receive insufficient care. Ensuring appropriate nurse staffing is crucial for positive patient outcomes when care is provided without failure. Utilize data mining techniques to find risk variables linked to longer nursing stays and nurse-to-patient ratios. Additionally, examine patient information, medical histories, and treatment regimens to identify factors that may contribute to longer hospital stays. This data can direct preemptive actions to reduce hazards

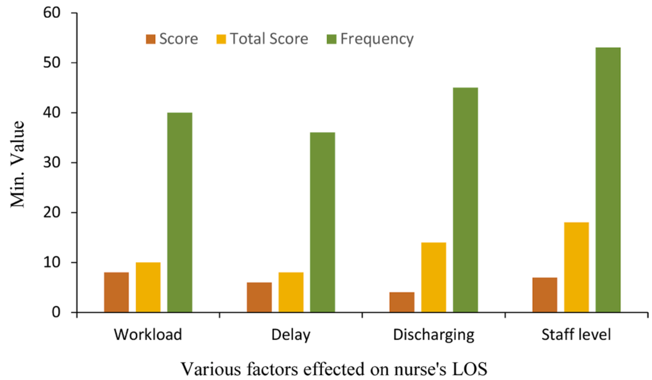

Fig. 13. A survey of the primary variables influencing nursing LOS.

and improve treatment schedules, as shown in Fig. 14.

It is crucial to remember that these elements' effects on LOS may be related. An accident resulting from drug use, for example, may have an impact on standards compliance and reporting procedures down the road. Healthcare facilities should aim for strict adherence to regulations, thorough reporting procedures, and preemptive actions to reduce the effect of mishaps and drug-related incidents on lost time. Frequent monitoring, incident report analysis, and ongoing quality improvement initiatives can reduce the detrimental effects on LOS and may even increase its impact.

The information indicates a lack of standardization in the hospital's medication practices and insufficient training. Nineteen patients need to learn how to store and use medications, with many needing proper training. Additionally, patients who underwent training needed to remember the necessary information. These findings underscore the need to improve the hospital's emergency response capabilities, particularly by strengthening training. The number of hospital beds, rehabilitation centers, and discharge options is an example of a non-disease-related factor that might impact LOS in healthcare settings, as well as those linked to the illness. Optimizing supply losses while accounting for constraints such as staffing shortages, inadequate medical facilities, and rising healthcare costs is imperative. It is critical to understand that various variables influence LOS, including weight, illness state, patient care procedures, hospital management, organizational characteristics, and other factors.

5. Discussion & limitations

This study focused on the factors that affect how long a nurse stays in the hospital's surgical department. Based on lab results or other measurable factors, research on hospital stays estimates how long patients will remain. Nursing workers in surgical lung or respiratory disease departments tended to stay longer. According to this study, the variety of counseling sessions, hospital wards, medical and nursing specialties and degrees, and the purpose of the encounter all impact how long a patient stays. A statistical and data mining technique based on electronic medical records revealed strong correlations between LOS and variables such asbed level, severity, illness frequency, operation, transfer time, discharge delay time, and insurance type. Nearly all the models in this study achieved respectable accuracy of >80%. As such, these models may estimate how long a patient will remain in the hospital. Compared with SVM and other approaches, the ANN method proved to be the most accurate and reliable predictive model in a study focused on LOS prediction for general surgery patients. However, it is essential to recognize the study's limitations, demonstrated by the bed-to-nurse ratio. Depending on the occupancy rate of beds in a healthcare institution, the deviation from actual nurse staffing levels increases. If specific patterns exist in nurse staffing and patient outcomes across the excluded medical institutions, they could affect the findings of this study.

This study possesses multiple drawbacks that warrant acknowledgment. The analysis was performed using data from a single public teaching hospital in Iran, thereby limiting the generalizability of the findings to other institutions with varying patient demographics, clinical processes, or resource availability. Subsequent studies should examine the proposed models across various institutions and healthcare environments to assess external validity. Secondly, while the CHIMS system offers comprehensive encounter-level data, many potentially significant elements, including extensive comorbidity history, laboratory biomarkers, and physiological monitoring information, were absent from the retrieved dataset. The inclusion of these clinical factors enhances predictive accuracy and model interpretability. Third, the study relies on retrospective observational data; hence, the results should not be construed as evidence of causation. The predictive models can assist in personnel and capacity planning decisions. Nonetheless, the impact of these decisions on patient flow and duration of stay necessitates prospective assessment or supervised implementation studies. While this increases real-world relevance, it may also introduce noise into the model inputs. Further efforts should concentrate on data harmonization and feature standardization to enhance model resilience.

The hybrid ANN–RL framework demonstrated significant improvements in a simulation-based optimization context, reducing the anticipated LOS and nurse overtime under realistic demand conditions. The results indicate that RL may efficiently convert length-of-stay forecasts

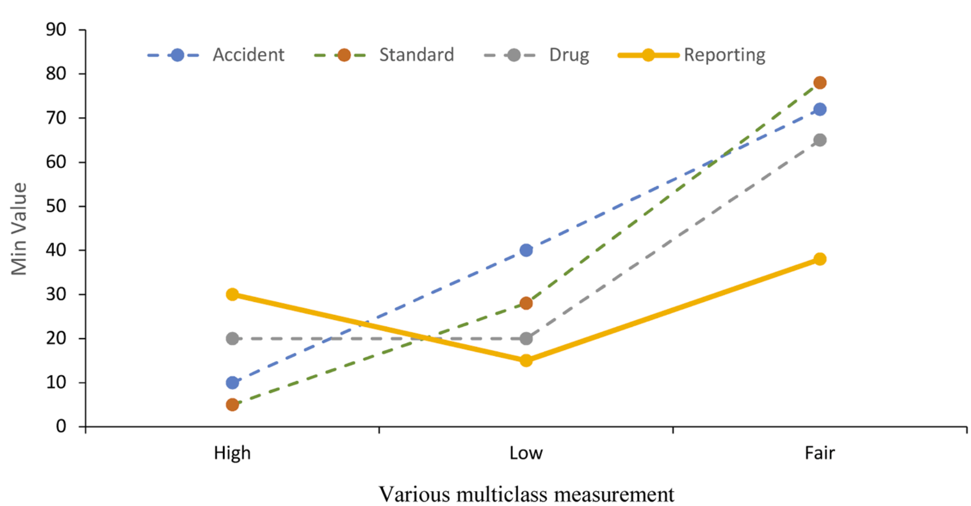

Fig. 14. Factors of influence degree on LOS.

into operational decision support for nursing allocation. The reported reductions indicate prospective enhancements resulting from the model's optimization behavior rather than actual outcomes from real-world implementation. The actual implementation necessitates interaction with hospital scheduling systems and a prospective study to assess workflow impacts and staff acceptance.

The current hybrid framework was developed and evaluated using data that reflects standard hospital operations. As a result, its forecasts and optimization functions cannot be guaranteed to remain accurate during rare, catastrophic, or highly non-stationary events, such as pandemics, earthquakes, or extensive system outages. In these circumstances, the fundamental data distribution, patient rates, and staffing limitations may diverge significantly from historical trends, thereby diminishing model trustworthiness.

Future improvements should focus on resilient, adaptable learning, integrating methods for anomaly or domain-shift detection, online retraining, and scenario-driven RL to continuously re-optimize policies in crises. Enhancing these features would improve the model's resilience and its use for emergency planning and surge control in healthcare.

Predictive models developed using extensive operational datasets may inadvertently capture misleading correlations stemming from data-entry practices, system configurations, or temporal anomalies rather than genuine causal factors. This danger is especially pertinent in healthcare analytics, where variables may possess implicit contextual or semantic significance. To address these difficulties, subsequent research must integrate semantic validation, expert evaluation of feature definitions, and cross-source verification to confirm that identified associations reflect genuine clinical or operational realities rather than dataset-specific biases. Incorporating these precautions would enhance the reliability and interpretability of LOS prediction algorithms in intricate healthcare settings. The present study focused on predictive modeling using ML and deep learning methods, rather than on inferential or causal estimation. This phase excluded classical statistical methodologies, hence constraining the direct interpretability of model parameters. Subsequent research will thus include direct comparisons with conventional regression-based techniques to reconcile predictive accuracy with clinical clarity and guarantee comprehensibility for end users.

6. Conclusions

The research designed a two-stage approach based on ML for predicting the LOS of patients on the surgical ward and generating adaptable nurse schedules from these predictions. With a dataset containing information about 137,145 hospital patients, the study compared the predictive power of four models, which resulted in the selection of the RF with $R^2 = 0.84$ and RMSE = 1.63 h being superior to the second runner-up model (Gradient Boosting) with $R^2 \sim 0.83$, third (Decision Tree), which had almost similar accuracy, and MLP with $R^2 = 0.63$. The forecasted LOS states were used to train an RL algorithm for adjusting staffing and conducting early discharge reviews based on demand conditions. In comparison to the traditional scheduling method, our proposed approach brought about a significant reduction in average LOS to 4.82 days from 6.12 days, weekly nurse overtime to 22.7h from 42.5h, an almost 47% decrease, increased staff usage efficiency to 84.3% from 69.1%, and finally reduced the rate of readmission by 8.3% to 6.1%, with all improvements significant at $p < 0.001$. Association rule mining further identified the factors most strongly associated with extended LOS intervals, including age, surgical status, and department, and the weekday analysis showed the highest extended-stay workload on Monday and Sunday. Together, these results show that coupling continuous LOS prediction with reinforcement-learning scheduling produces measurable operational gains rather than prediction alone.

The main contributions of this work are the formulation of nursing LOS as a continuous variable in the understudied surgical ward, the comparison of four models selected by measured error, the conversion of predicted LOS into a daily nursing schedule, and the integration of forecasting with reinforcement-learning-based resource optimization within a single framework.

Limitations of our study include its dependence on retrospective data from only one teaching hospital. The operational improvements reported were realized in simulation, not actual implementation, and not all clinically relevant variables were available at the time of modeling, including history of comorbidities and lab-based variables. In future work, we will validate our framework in multiple institutions, benchmark against classical survival and regression methods to enhance clinical interpretability, and model. Scholars may use RL or deep learning algorithms and models to predict nursing LOS. Future work will also include determining the statistically best ways to identify cost-based solutions. By shortening the LOS through better nursing workflow and care, hospitals can work to decrease patient stay and outcomes while increasing the overall healthcare experience.

CRediT authorship contribution statement

Mahdi Yousefi Nejad Attari: Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Akbar Abbaspour Ghadim:** Writing – review & editing, Writing – original draft, Visualization, Software, Investigation, Formal analysis, Data curation. **Ali Ala:** Writing – review & editing, Writing – original draft, Visualization, Validation, Investigation, Formal analysis, Data curation. **Vladimir Simic:** Writing – review & editing, Writing – original draft, Visualization, Validation, Project administration, Investigation, Formal analysis. **Domonkos Tinka:** Writing – review & editing, Writing – original draft, Validation, Resources, Funding acquisition. **Dragan Pamucar:** Writing – review & editing, Writing – original draft.

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.

Appendix

Table A.1.

Table A.1
Results of various LOS intervals for men and women nurses during the week.

Monday					
	dept_women_surgery	emergency_dept	men_internal	ICU	dept_men_surgery
LOS≤1	0	37	0	0	0
1<LOS<4	2	53	0	0	0
4≤LOS<8	1	8	0	0	0

(*continued on next page*)

Table A.1 (*continued*)

Monday					
	dept_women_surgery	emergency_dept	men_internal	ICU	dept_men_surgery
LOS≥8	41	10	10	16	27
Tuesday					
	dept_women_surgery	**emergency_dept**	**men_internal**	**ICU**	**dept_men_surgery**
LOS≤1	0	30	0	0	0
1<LOS<4	1	45	0	0	0
4≤LOS<8	1	9	0	0	1
LOS≥8	23	3	17	15	27
Wednesday					
	dept_women_surgery	**emergency_dept**	**men_internal**	**ICU**	**dept_men_surgery**
1≤LOS	0	33	0	0	0
1<LOS<4	1	64	0	0	0
4≤LOS<8	0	8	0	0	0
LOS≥8	16	5	20	22	21
Thursday					
	dept_women_surgery	**emergency_dept**	**men_internal**	**ICU**	**dept_men_surgery**
LOS≤1	0	30	0	0	0
1<LOS<4	1	53	0	0	0
4≤LOS<8	1	4	1	0	0
LOS≥8	22	4	21	8	19
Friday					
	dept_women_surgery	**emergency_dept**	**men_internal**	**ICU**	**dept_men_surgery**
LOS≤1	0	12	0	0	0
1<LOS<4	0	37	0	0	0
4≤LOS<8	0	14	0	0	0
LOS≥8	10	4	9	7	5
Saturday					
	dept_women_surgery	**emergency_dept**	**men_internal**	**ICU**	**dept_men_surgery**
LOS≤1	0	21	0	0	0
1<LOS<4	1	46	0	0	1
4≤LOS<8	0	9	0	0	3
LOS≥8	21	6	15	11	25
Sunday					
	dept_women_surgery	**emergency_dept**	**men_internal**	**ICU**	**dept_men_surgery**
LOS≤1	0	25	1	0	0
1<LOS<4	1	45	0	0	0
4≤LOS<8	1	11	0	0	1
LOS≥8	35	5	22	19	30

Data availability

Data will be made available on request.

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