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ORIGINAL RESEARCH

Predictive Factors of Length of Stay in Intensive Care Unit after Coronary Artery Bypass Graft Surgery based on Machine Learning Methods

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Abstract: **Introduction:** Coronary artery bypass grafting (CABG) surgery requires an extended length of stay (LOS) in the intensive care unit (ICU). This study aimed to predict the factors affecting LOS in the ICU after CABG surgery using machine learning methods. **Methods:** In this study, after extracting factors affecting the LOS of patients in the ICU after CABG surgery from the literature and confirming these factors by experts, the medical records of 605 patients at Farshchian Specialized Heart Hospital were reviewed between April 20 and August 9, 2024. Four machine learning models were trained and tested to predict the most desired factors, and finally, the performance of the models was evaluated based on the relevant criteria. **Results:** The most important predictors of the LOS of CABG patients in the ICU were the length of intubation, body mass index (BMI), age, duration of surgery, and the number of postoperative transfusions of packed cells. The Random Forest model also performed best in predicting the effective factors (Mean square Error = 1.64, Mean absolute error = 0.93, and R2 = 0.28). **Conclusion:** The insights gained from the mashine learning model highlight the significance of demographic and clinical variables in predicting LOS in ICU. By understanding these predictors, healthcare professionals can better identify patients at higher risk for prolonged ICU stays.

Keywords: Coronary Artery Bypass; Length of Stay; Machine Learning; Intensive Care Units; Random Forest

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1. Introduction

Cardiovascular diseases have become a leading cause of death worldwide, particularly in low and middle-income countries, with approximately one-third of global deaths attributed to them (1-3). Coronary artery disease is one of the most prevalent cardiovascular diseases, making its treatment and management of influencing factors vital for healthcare systems (4).

When less invasive methods, such as percutaneous coronary intervention (PCI), are contraindicated or have failed in treating patients, coronary artery bypass grafting (CABG) surgery becomes the most suitable option for coronary artery disease. Due to its positive outcomes, this surgery is performed widely around the world, with nearly a million CABG surgeries conducted in the past decade (4-8). In Iran, CABG surgery represents approximately 60% of all open-heart surgeries (9). Due to the potential for both short and long-term complications, all patients undergo post-operative care in the intensive care unit (ICU) following this surgery (10).

Cardiac ICUs are units that provide specialized care to critically ill heart patients after surgery (11). The extended LOS in the ICU depends on various factors, including the individual characteristics of patients, preoperative and intraoperative care, the presence or absence of complications, and hospital policies. A prolonged LOS in the ICU can lead to adverse outcomes and increase the risk of mortality for patients. In conclusion, while providing care in the ICU can significantly aid patient recovery, an extended stay may also result in complications. The limited number of beds in the ICU and the increase in the LOS in this unit can expose patients to various complications and, on the other hand, increase the waiting time of patients for heart surgery (10).

Artificial intelligence, an emerging technological phenomenon, was introduced in 1950. Fifty years later, in 2000, the limitations of this technology were addressed with the advent of deep learning (12, 13). Artificial intelligence has rapidly entered clinical medicine, showcasing impressive capabilities. It can predict the likelihood of patient survival following kidney transplants and has demonstrated its po-

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tential for early diagnosis, especially during the COVID-19 pandemic (14, 15).

Machine learning is a branch of artificial intelligence that focuses on developing algorithms that enable computers to learn from past experiences. This field, which is closely related to statistics, allows systems to analyze and understand input data and make informed decisions based on that information (16-18).

Currently, machine learning is utilized to examine extensive biomedical data. This technology is applied in diagnosing liver diseases, skin lesions, cancer classification, and assessing the risk of cardiovascular disease (19). The use of machine learning in diagnosing cardiovascular diseases is growing. This technology enhances diagnostic accuracy and optimizes treatment processes, significantly improving the overall quality of care in this field (20, 21).

Machine learning algorithms can use predictive analytics to reveal hidden relationships and patterns within large volumes of historical data (22). Data prediction results from the training and testing phases. Models can be trained on a data set to respond to new data or values (23, 24). Today, despite the growing amount of patient-related data, predictive analytical techniques can be employed to forecast various events. These techniques can help predict risks, such as the likelihood of a heart attack or the chances of hospital readmission. In addition to being a promising approach for enhancing clinical applications, these methods can also identify patients who are at high risk for complications after surgery (25, 26). This study aimed to predict the factors affecting LOS in the ICU after CABG surgery using machine learning methods.

2. Methods

2.1. Study design and setting

This study aimed to identify the key factors influencing LOS in the ICU following CABG surgery using machine learning models. Additionally, it seeks to compare the accuracy and precision of various machine learning models in predicting the LOS. The research was conducted in three primary steps: data understanding, preprocessing, and modeling and evaluation, which will be explained in detail below.

2.2. Data Understanding

The first step involved identifying and confirming the factors affecting ICU LOS in patients undergoing CABG surgery. To determine these factors, the researchers thoroughly reviewed relevant literature. They searched four databases: PubMed, Web of Science, Scopus, and Institute of Electrical and Electronics Engineers (IEEE) Xplore. In collaboration with cardiovascular surgeons, the researchers selected the most relevant articles for review and extracted the related factors based on their findings. After identifying the relevant factors, the content validity of these factors was evaluated by a cardiac surgeon, two expert nurses in the cardiac intensive care unit, and three faculty members from the operating room technology department.

In the second step, a researcher-developed questionnaire was created to validate the extracted factors. This questionnaire consisted of three sections: the first section gathered demographic information, the second assessed the importance of the identified factors, and the final section invited respondents to suggest additional factors deemed necessary by experts but not included in the initial list. To ensure content and face validity, the questionnaire was reviewed by a cardiac surgeon, two expert nurses from the open-heart intensive care unit, and three faculty members from the operating room technology department again. Finally, the relevant questionnaire was distributed to cardiac surgeons, anesthesiologists in the Open Heart ICU, nurses in the Open Heart ICU, and expert nurses in cardiovascular operating rooms. The experts were instructed to rate the importance of each parameter using a 5-point Likert scale, where 1 represents "strongly disagree," 2 signifies "disagree," 3 denotes "neutral," 4 means "agree," and 5 indicates "strongly agree." Only the factors with an average score above 3.80 were selected as the final factors. In addition, a test-retest (at 10-day intervals) was done to evaluate the reliability of the questionnaire.

After the selected invoices were approved, a form included the patient file numbers and the desired invoices. Once the Ethical Code and the letter of introduction were obtained, the researchers visited the Health Information Technology Unit at Farshchian Specialized Heart Hospital to extract the necessary information from the files of patients who had undergone coronary CABG surgery in 2023. Required data were collected between April 20, 2024, and August 9, 2024.

The researchers defined specific criteria for selecting patients' medical records, ensuring that CABG surgery was not performed simultaneously with other procedures, such as valve surgeries, and that the on-pump method was used for the CABG surgery. In the final step of this phase, all collected data were entered into an Excel file.

2.3. Preprocessing

After collecting the data, it was organized and managed according to type. Patient names were confidentially coded for inclusion in the database. Records with missing values exceeding 85% were excluded from the study. The data was then prepared for preprocessing. Missing values were addressed by replacing them with the average for numerical features and the most frequent value for nominal features. Noisy or abnormal values, errors, duplicates, and irrelevant data were reviewed by the authors (AJ and SS) in collaboration with the cardiac surgeon (AS). A dimension reduction step was implemented before training the models to prevent overfitting due to the large number of features. This process involved removing unnecessary features and those with minimal correlation to the target variable. The f_regression method was employed for this dimension reduction, selecting 25 features that strongly correlate with the target variable. Additionally, the features were standardized before training the network to enhance efficiency and speed up convergence.

2.4. Modeling and evaluation

Similar studies in this field were reviewed in this stage to choose the appropriate machine-learning model (27-31). The most suitable models for analysis were selected based on the studies and the data type available. The models included Random Forest, Linear Regression, Support Vector Regressor (SVR), and XGBoost, all built and evaluated using Python version 3.8. Building and evaluating these models involved feature selection and optimizing model parameters during the training phase, followed by evaluation with test data in the testing phase. 80% of the data was utilized for model training, while the remaining 20% was used for testing.

Evaluating model performance is a crucial step in developing an effective machine-learning model. Mean Square Error (MSE), Mean Absolute Error (MAE), and R-squared (R^2) were utilized to evaluate the performance of predictive models. Mean Square Error (MSE) is essential for assessing predictive models' performance. It measures the average of the squared differences between the predicted values and the actual target values in a dataset. Mean Absolute Error (MAE) refers to the average magnitude of the differences between predicted values and observations' actual values without considering the errors' direction. R-squared (R^2), or the coefficient of determination, is a statistical measure used in regression models that indicates the proportion of variance in the dependent variable that the independent variable can explain.

Finally, the MSE, MAE, and R^2 were reported for each selected model. The model that yielded better results than the others was identified as the best model for predicting the factors affecting LOS in ICU in patients undergoing CABG surgery.

2.5. Ethical considerations

To conduct this study, the code of ethics with the number IR.UMSHA.REC.1402.630 was obtained from the ethics committee of Hamadan University of Medical Sciences. The specialist physicians participated voluntarily and could leave the study at any time and without any consequences. The research team confidentially collected all patients' data without registering their identity data. These data were not made available to individuals outside the research team. Furthermore, according to the research type, using data did not pose any risk to patients.

3. Results

The research findings are organized into three phases, each reflecting the different steps of the research process:

3.1. Data understanding

After conducting a thorough search in the specified databases and selecting the most relevant articles regarding the factors affecting the LOS in ICU in patients undergoing CABG, 48 significant factors were identified. The insights of a cardiac surgeon, two expert nurses from the cardiothoracic ICU, and three faculty members from the operating room technology department were gathered to evaluate the content validity of these factors. Table 1 presents the factors extracted from the relevant articles in this field. Finally, the final questionnaire was distributed to 49 people according to the mentioned inclusion criteria. The demographic information of these people is specified in Table 2. After the questionnaires were distributed and filled out by knowledgeable and experienced individuals, the filled-in information was entered into SPSS software. Factors whose average was less than 3.8 were eliminated (Table 1). Of course, duration of surgery (h), Number of grafts, preoperative Partial Thromboplastin Time (S), Preoperative hemoglobin level, intrahospital Postoperative Complications, General history of patients, cardiopulmonary bypass time (CPB) time, elective or emergency and Opioid consumption were some of the factors suggested by experts, which were not among the factors we extracted but were finally added to the factors. The final selected factors are listed in Table 3.

The source of extraction of all variables mentioned in Table 3 was nursing reports, surgical report sheets, patient tests, and perfusionist report sheets available in the patient's medical records. After considering the final factors, a data collection form was designed. Subsequently, 668 patient files of those who underwent CABG surgery in 2023 were reviewed based on the established inclusion and exclusion criteria. Finally, the information related to these files was entered into Excel.

3.2. Preprocessing

63 files that were selected based on the inclusion and exclusion criteria were excluded from the study due to more than 85% incomplete information. Finally, 605 files were reviewed. The number of missing data for each factor and the results of its descriptive statistics are shown in Tables 4 and 5. The average age of the patients who underwent this surgery was 62.3 ± 13.8 years. Of these patients, 22.8% were female, and 77.2% were male. Additionally, 16.2% of the surgeries were performed as emergencies, while 83.8% were elective CABG procedures. The average LOS for patients after CABG surgery was 6.43 ± 1.75 days.

3.3. Modeling and evaluation

After collecting the data, linear regression, random forest, SVR, and XGboost models were selected for analysis. According to the MSE, MAE, and R2 criteria, the model evaluation results showed that the lowest MSE value was related to the random forest model and the highest to the SVR model. Also, the random forest model had the lowest value for the MAE criterion, and the XG boost model had the highest value. About the R2 criterion, the highest value was related to the random forest, and the lowest was related to the SVR (Table 6). According to the results of the model evaluation, it was determined that the random forest model had the best performance compared to other models used in this study in predicting factors affecting patients' LOS in the ICU, so the selection of feature importance was made based on this model. Intubation time, BMI, age, surgery duration, and the number of postoperative transfusions of packed cells (Bag) were the most influential factors in predicting patients' LOS in the ICU after CABG surgery (Figure 1).

4. Discussion

This study utilized machine learning methods to predict the factors influencing patients' LOS in the ICU following CABG surgery. Four different machine learning models were tested, and the results indicated that the Random Forest method outperformed the others in predicting these influencing factors. According to the findings from this model, the most significant factors affecting patients' LOS in the ICU were the length of intubation, BMI, age, surgery duration, and the number of postoperative transfusions of packed cells (Bags).
Our study's results revealed that, according to the Random Forest model, the most significant factor affecting the LOS in the ICU is the Length of intubation. Prolonged intubation after cardiac surgeries, such as CABG, can increase the risk of mortality. The Society of Thoracic Surgeons defines prolonged intubation as when patients are intubated for more than 24 hours. Using a cardiopulmonary bypass pump (CPB) is a major contributor to the increased length of intubation. The CPB pump can trigger the release of inflammatory factors into the bloodstream, which may ultimately decrease lung compliance and extend the duration of intubation (32). Previous studies suggest that the length of intubation can influence patient mortality after CABG surgery (33). The results of a study by Zhang et al. in 2021 also showed that the length of intubation, according to a regression model, can increase or decrease the LOS in the ICU after cardiac surgeries (34). The results of a study by Triana et al. in 2021 also showed that the length of intubation, along with factors such as age, preoperative creatinine, and packed red blood cell transfusions, are among the factors that affect the LOS of patients in the ICU (31).
Age is a significant factor in postoperative recovery. Generally, older individuals face a higher risk of complications after surgery. Consequently, their survival rates tend to be lower compared to younger patients (35). A study by Almashrafi et al. (2016) investigated the factors that influence LOS in the ICU after cardiac surgery. The results indicated that age is a significant factor affecting LOS (36).
A higher BMI is linked to obesity, a condition that is increasingly prevalent around the globe, as reported by the World Health Organization. Obesity poses risks for conditions such as diabetes and heart failure, and it can negatively impact recovery for patients following heart surgery. Research has also indicated that obesity may influence the duration for which patients need to be intubated (37). Even the result of the study by Shi et al. 2020 shows a significant relationship between obesity and the incidence of acute kidney injury after cardiac surgery, which can also affect the LOS in ICU (38). The meta-analysis conducted by Akinnusi et al. in 2008 showed that obesity significantly affected the postoperative length of intubation and prolonged LOS in the ICU. (39).
As is evident from Figure 1, the duration of the surgery, Postoperative transfusion of packed cells given to the patient, complications, intraoperative transfusion of platelets, and the number of grafts are among the other influential factors.
Regular patient assessment programs can be designed before surgery by considering the factors that affect the increase or decrease of the LOS of patients in the ICU. Programs that can help improve postoperative care programs while evaluating high-risk patients based on the factors extracted from our study. Identifying these patients, in addition to identifying high-risk patients for surgeons and nurses, can also help hospital managers manage financial resources and limited beds in the ICU.
The discussion surrounding the long-term education of patients on how to manage modifiable factors, such as BMI, is crucial in preventing adverse health events. Education in this area should not be confined to patients alone; educating nurses in the care of high-risk patients, particularly those who require prolonged intubation, is equally important.
This study is one of the few conducted in Iran to predict the factors affecting the LOS of patients in the ICU after CABG surgery. While it is considered the most essential factor, it also faces some limitations. One of our most important problems in this study was the single-center nature of this study and our small sample size, which affected the reliability of our results. Additionally, the retrospective nature of the study introduced potential confounding biases. Since the primary source of data collection was the patients' medical records, certain factors could not be extracted, leading to their exclusion at the outset of the study.

5. Limitations

To address these limitations, future research should aim for larger sample sizes and compare factors affecting ICU LOS after on-pump and off-pump CABG surgeries. Moreover, incorporating additional laboratory factors, such as pre- and postoperative creatinine levels, would enhance the comprehensiveness of future studies.

6. Conclusions

This study successfully identified key factors that influence the LOS for patients undergoing CABG in the ICU using machine learning techniques. The insights gained from this analysis emphasize the importance of clinical variables such as intubation duration, body mass index, age, duration of surgery, and the number of postoperative transfusions of packed cells in predicting the LOS in ICU after CABG. By understanding these predictors, healthcare professionals can better identify patients at higher risk for extended ICU stays, which can lead to the development of targeted perioperative care strategies. These strategies aimed at improving patient outcomes can also help optimize resource allocation within the hospital.

7. Declarations

7.1. Acknowledgments

This study has been adapted from an MSc thesis at Hamadan University of Medical Sciences. We extend our heartfelt gratitude to our colleagues in the Clinical Research Development Unit at Farshchian Specialized Heart Hospital.

7.2. Author Contribution

All contributors to this work have substantially participated in its development, encompassing the concept formation, study design, implementation, data collection, data analysis, and interpretation. Each author has been involved in the drafting and revising, providing critical feedback on the manuscript. They have unanimously approved the final version for publication, concurred on the choice of journal for submission, and collectively accepted responsibility for the integrity of all aspects of the work.

7.3. Funding/Support

The study was funded by the Vice-Chancellor for Research and Technology, Hamadan University of Medical Sciences (No. 140210128969).

7.4. Conflict of interest

The authors have declared no conflict of interest

7.5. Data Availability

The datasets used and/or analyzed during the current study are available from the corresponding author upon reasonable request.

7.6. Using Artificial Intelligence Chatbots

None.

7.7. Ethical Considerations

To conduct this study, the code of ethics with the number IR.UMSHA.REC.1402.630 was obtained from the ethics committee of Hamadan University of Medical Sciences. The specialist physicians participated voluntarily and could leave the study at any time and without any consequences. The research team confidentially collected all patients' data without registering their identity data. These data were not made available to individuals outside the research team. Furthermore, according to the research type, using data did not pose any risk to patients

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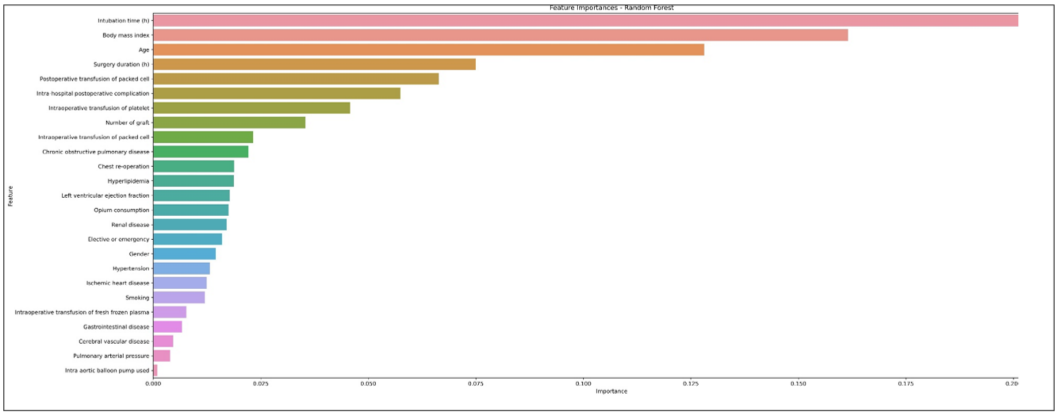

Figure 1: Analysis of factors affecting length of stay in ICU after coronary artery bypass graft using the Random Forest model.

Table 1: Factors affecting the length of stay (LOS) in intensive care unit (ICU) patients undergoing CABG and their mean score out of 5

Predictor	Score	Predictor	Score
Left ventricular ejection fraction	4.6	Age	4.6
History of cerebrovascular accident	4.34	Gender	3.97
Peripheral vascular disease	4.16	Height	3.6
Having more than two chest tubes	3.12	Infection	4.57
Occurrence of atelectasis	3.51	Body mass index (BMI)	4.42
Intra-aortic balloon pump used	4.57	Angina class	2.97
Pulmonary artery systolic Pressure	2.97	Diabetes	4.55
Complications during operation	3.6	Logistic Euroscore	3.51
Recent potent antiplatelet use	2.97	Smoking	4.4
Critical preoperative state	3.69	Fluid balance	2.97
Preoperative anxiety	3.51	Inotropes	3.75
Mechanical ventilation for > 24 hours	3.75	Low cardiac output	3.6
Chest re-operation	4.65	Atrial fibrillation	3.51
Surgeon category	3.6	Poor mobility	2.97
pulmonary artery pressure (PAP)	3.9	NYHA class	3.75
Administration of catecholamines	3.69	Depression scores	3.6
Comorbid illness	4.2	Income	2.97
Presence of arrhythmias	4.36	Use of statins	3.40
Intubation time (h)	4.40	COPD	4.44
Early hemodynamic instability	3.6	Hypertension	4.18
Aortic cross-clamp time (min)	4.46	Prior surgery	4.18
Blood transfusions	3.91	Disease severity	2.97
Myocardial Infarction	3.12	Parsonnet score	3.6
Postoperative Bleeding	4.30		

COPD: Chronic Obstructive Pulmonary Disease. CABG: coronary artery bypass graft.

Table 2: Demographic information of the study expert panel

Variables	N (%)
Age (year)	
28-40	25 (51.0)
41-63	23 (46.9)
Sex	
Male	25 (51.0)
Female	24 (49.0)
Type of specialty	
Cardiac surgeon	3 (6.0)
Anesthesiologist	5 (10.0)
OH-ICU nurse	25 (51.0)
OR nurse	16 (16.0)
Employment history (year)	
5-10	9 (18.4)
11-15	14 (28.6)
16-20	15 (30.6)
21-25	6 (12.2)
26-30	5 (10.2)

OH-ICU= open-heart intensive care unit. OR: operating room.

Table 3: Potential factors affecting the length of stay (LOS) in intensive care unit (ICU) in patients undergoing coronary artery bypass graft, which was selected based on literature review and expert panel opinion

#	Factors	#	Factors
1	Age	16	Comorbid illness
2	Gender	17	Prior surgery
3	Left ventricular ejection fraction	18	Presence of arrhythmia
4	Infection	19	Intubation time (h)
5	Body mass insex (BMI)	20	Aortic cross-clamp time (min)
6	Diabetes	21	Blood transfusion
7	Smoking	22	Postoperative bleeding
8	History of cerebral vascular accident	23	surgery duration (h)
9	Peripheral vascular disease	24	Number of graft
10	Intra aortic balloon pump used	25	Preoperative Partial Thromboplastin Time (s)
11	Chronic Obstructive Pulmonary Disease	26	Preoperative hemoglobin level
12	Hypertension	27	Intra-hospital postoperative complication
13	Chest re-operation	28	General History of Patients
14	Elective or emergency	29	Cardiopulmonary bypass Time (min)
15	Pulmonary Arterial Pressure (mm Hg)	30	Opium consumption

Table 4: Descriptive information of patients (quantitative variables affecting the length of stay (LOS) in the intensive care unit (ICU) after coronary artery bypass graft)

Variables	**N**	**Mean ± SD**
Age (year)	605	62.27 ±8.13
Body mass index (BMI)	604	26.4605 ±4.01
Intubation time*	604	11.2619 ±7.31
Aortic Cross Clamp Time (min)	583	30.25 ±14.95
Cardiopulmonary bypass Time (min)	585	53.55 ±22.53
Blood transfusion (bag)		
Intraoperative transfusion of platelet	605	7.76 ±2.15
Intraoperative transfusion of FFP	604	2.72 ±0.99
Intraoperative transfusion of packed cell	605	0.27 ±0.58
postoperative transfusion of platelet	605	0.43 ±1.50
Postoperative transfusion of FFP	605	0.52 ±1.39
Postoperative transfusion of packed cell	605	1.28 ±1.37
surgery duration (h)	605	3.5560 ±0.61
Number of graft	604	2.83 ±0.75
Preoperative PPT (S)#	587	32.156 ±12.77
Preoperative hemoglobin level#	594	14.8239 ±7.88

SD: standard deviation; FFP: Fresh frozen plasma; PPT: Partial Thromboplastin Time.*: Time from start of surgery to extubation in ICU; #: Based on The patient's last recorded test before surgery.

Table 5: Descriptive information of patients (qualitative variables affecting the length of stay (LOS) in the intensive care unit (ICU) after coronary artery bypass graft

Variable	**n**	**(%)**
Sex		
Female	138	22.8
Male	467	77.2
Intra-aortic balloon pump used*		
No	594	98.2
Yes	11	1.8
Intra-hospital postoperative complication#		
No	334	55.2
Yes	271	44.8
Comorbidity		
Smoking	172	28.4
Opium consumption	173	28.6
Hyperlipidemia	123	20.3
Diabetes	192	31.7
Hypertension	309	51.1
Chronic Obstructive Pulmonary Disease	24	4.0
Other	42	6.9
General History of Patients		
Renal Disease	58	9.6
Thyroid Disease	35	5.8
Gastrointestinal disease	80	13.2
Trauma	26	4.3
Accident	26	4.3
Benign Prostatic Hyperplasia	43	7.1
Ischemic Heart Disease	95	15.7
cerebral vascular accident	19	3.1
prior surgery	256	42.3
Chest re-operation	25	4.1
Surgery type		
Elective	507	83.8
Emergency	98	16.2
Left ventricular Ejection Fraction		
Normal (≥ 50%)	278	46.7
Abnormal (≤ 49%)	317	53.3
Pulmonary Arterial Pressure (mm Hg)		
Normal (≤20)	5	0.9
Abnormal (≥ 21)	556	99.1

*: Patients using the pump before, during, or after surgery; #: What we considered as complications included death, sternal wound infection, arrhythmia, postoperative bleeding based on the amount of chest tube drainage, and acute kidney injury based on the RIFLE criteria.

Table 6: Comparing model performance for the length of stay (LOS) in the intensive care unit (ICU) after coronary artery bypass graft

	Linear Regression	**Random Forest**	**SVR**	**XGBoost**
MSE (95% CI)	1.97 (1.90, 2.30)	1.64 (1.59, 2.19)	2.2 (2.08, 2.44)	2.03 (1.76, 2.60)
MAE (95% CI)	0.98 (0.96, 1.09)	0.93 (0.91, 1.06)	1.02 (0.98, 1.10)	1.04 (0.99, 1.21)
R2 (95% CI)	0.14 (0.00, 0.17)	0.28 (0.04, 0.30)	0.02 (0.00, 0.09)	0.11 (0.00, 0.23)

MSE = Mean Square Error; MAE= mean absolute error; SVR= Support Vector Regressor; CI= confidence interval.