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Machine Learning–Driven Identification of Determinants Affecting Clinical Outcomes in Outpatient Surgery

Najmeh Jamali[1,*], Mohammad Mehdi Ebrahimi[1]

[1] Department of Industrial Engineering, University of Torbat Heydarieh, Torbat Heydarieh, Iran; n.jamali@torbath.ac.ir; mehdiebrahimi8307@gmail.com.

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Abstract

The increasing use of Artificial Intelligence (AI) and Machine Learning (ML) techniques in healthcare delivery organizations has opened up many possibilities to predict patients' outcomes and to optimize throughput in those organizations. The current paper introduces a simulation modeling framework to predict the outcomes of patients in outpatient surgery settings using the power of ML algorithms with a special focus on ensemble approaches to Random Forest models. Based on the ideas from Process Mining (PM) and predictive analytics in perioperative healthcare systems, the current paper proposes the process-aware modeling framework that consists of four steps: 1) Creation of synthetic data sets based on empirical probability distributions which are used to mimic the real-world patient flows, 2) Feature engineering and process-aware variables creation (including pre-operative risk factors – ASA physical status, intra-operative parameters and temporal metrics obtained from PM), 3) prediction of Length of Stay (LOS) and complication occurrence using the Random Forest Regressors and Random Forest Classifiers, and 4) system-level operational performance assessment based on the Key Performance Indicators (KPIs) which evaluate the effectiveness and efficiency of the workflow and bed occupancy. Applying the proposed modeling framework to synthetic patient flows results in identification of three most important factors affecting the post-surgical recovery: Surgical duration time, pre-operative physical status of a patient and process-aware waiting times. The predictive model shows high predictive performance: $R^2=0.81$ and MAE=0.29 days for length-of-stay estimation and strong discriminative power for complication prediction.

Keywords: Machine learning, Outpatient surgical analytics, Postoperative outcome prediction, Data-driven predictive modeling, Process mining.

1 | Introduction

Ambulatory surgery, which implies the completion of surgical procedure without extended hospitalization, is becoming an integral part of contemporary clinical practices because of the advancements in minimally

Corresponding Author: n.jamali@torbath.ac.ir
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invasive procedures, anesthesia protocols, monitoring and discharge planning. Such approach to conducting operations increases the efficiency in use of the limited healthcare resources while maintaining adequate patient safety and patient satisfaction standards [1], [2]. Ambulatory surgery represents a striking illustration of modern medical efficiency when a patient arrives to surgical facility in the morning and leaves it in the same day. However, behind such apparently simple process there lies a complex chain of clinical and operational events whose successful execution depends on the prediction of postoperative trajectory of each patient. Even small changes in pain reaction, recovery rate, discharge criteria and development of possible complications can produce a series of adverse consequences for patient outcome and overall system performance.

However, the process of predicting clinical outcomes of postoperative period is highly multifactorial in nature. A number of factors that affect patients' recovery paths include anesthesia method, preoperative health conditions, surgery length, and events during surgery and postoperative pain patterns [3], [4]. Such variables interact in a highly complex manner, which cannot be fully analyzed using traditional methods. Therefore, the emergence of Artificial Intelligence (AI) and Machine Learning (ML) algorithms in clinical practice creates new possibilities for gaining insight into perioperative variables and improving the accuracy of postoperative predictions. Recent research suggests that ML algorithms can provide good performance while predicting such variables as surgery length, PACU LOS, discharge time and risk of postoperative complications. For example, Goldhaber et al. [1] used gradient boosting for reducing the Mean Absolute Error (MAE) of the discharge-time prediction by 20-30 minutes. Surgeon experience, time of the day, and procedure types have been revealed as the most influential variables [1]. Furthermore, Nair et al. [2] used Random Forest and XGBoost to predict postoperative opioid needs after ambulatory procedures. The most influential factors affecting opioid dependency have been found to be intraoperative opioids and smoking habits [2]. This highlights the role of AI not only in improving operational efficiency but also in developing preventive measures and personalized treatment plans [5].

In addition to patient risk prediction, another major area of development associated with optimization of patient flow and reduction of Length of Stay (LOS) became increasingly prominent within ambulatory surgical systems, where the throughput performance was considered to be one of the major indicators of the quality of services provided and resources available. Thus, the application of predictive analytics became useful not only for the outcomes' estimation but for the optimization of scheduling and discharge process, as well. In particular, Tully et al. [6] created a series of predictive models that allowed the re-scheduling of surgeries in order to reduce the LOS without increasing the risk of adverse events. Patel et al. [7], in their extensive literature review, emphasized the importance of using ML in order to improve the quality of outpatient treatment and make it more personalized. For example, earlier published studies demonstrated that in specialty-specific cases, such as spine surgery, ML techniques could predict both the surgical candidacy and possible complications with predictive accuracy exceeding 80% [8]. One of the other research lines focused on predicting same-day discharge, which is crucial for outpatient surgical setting, as discharge is not only an outcome but a key step in the process of treatment as well. Thus, Howell et al. [9] used the ensemble learning methods to find candidates for same-day discharge and reported AUC values above 0.85. In the context of cardiovascular complications and postoperative mortality, Mahajan et al. [10] found that the use of ML-based Electronic Health Records (HER) model had higher performance compared to traditional 30-day risk indices. More recently, research efforts were directed at predicting the bed utilization and optimizing the surgical capacity. In this respect, Singh et al. [11] used the hybrid model to decrease the prediction error for operating room bed usage to less than two days. Similar efforts were dedicated to the creation of highly accurate models of outpatient vs. inpatient procedure distinction and patient eligibility, which exceeded 90%. When used together, these technologies may help improve the efficiency of the clinical decision-making process, reduce the burden associated with assessing patient status manually, and ensure better matching of needs and institution capacity.

Moreover, some recent research papers provide additional arguments favoring the use of analytics, along with AI and workflow-based intelligence in ambulatory surgery. According to a systematic review conducted by Patel et al. [7], there are growing possibilities for AI and ML use in ambulatory surgery, including its application in prediction, planning, and personalized perioperative management. In their prospective study, Renshaw et al. [12] proved that ML algorithms could make a significant contribution to developing opioid-free ambulatory surgery protocols through the accurate prediction of postoperative opioid use, thus emphasizing the importance of predictive systems in prevention. Similar results were obtained in another study carried out by Celik et al. [13], where Process Mining (PM) coupled with ML was used to considerably improve surgical workflow optimization based on actual EHR. As it becomes clear from the recent update on AI in surgery, predictive models become increasingly significant in predicting complications, allocating resources and making outcome-oriented decisions during perioperative period [14]. All the above-stated examples illustrate that the field of interest gradually evolves from simple prediction tasks to process-aware frameworks, which integrate clinical and operational intelligence.

Despite these significant breakthroughs, however, there are still several aspects that require resolution. One of the crucial shortcomings of contemporary perioperative management is the lack of comprehensive, quality, clinically-oriented datasets for the construction of models of processes. Due to the fragmentation of data sources, their incompleteness, and the restrictions on accessibility caused by institutional policies of information protection, it is rather difficult to develop universal predictive algorithms and models. Thus, the connection between patient-level prediction and system-level performance is not well-developed. It poses particular problems in case of outpatient surgery when even small mistakes can cause congestion in recovery units, delays in discharging patients, poor distribution of workforce, and low efficiency of services delivery. Consequently, there is an urgent need for the use of methods that will be able to fill the gap in data and to provide an opportunity to study complex perioperative cases in a controlled environment.

Inspired by the ideas of PM and predictive modeling techniques, the current study introduces the framework of simulation-driven approach that will allow discovering patterns related to postoperative outcomes in the process of outpatient surgery with the help of the Random Forest algorithm. Using the simulated dataset with clinically-meaningful variables and employing statistical and predictive analysis techniques, the suggested approach will improve the quality of forecasted outcomes and make decisions in clinical environments more evidence-based. What is particularly interesting about this study is the fact that apart from using ML techniques, it introduces simulation as an integral part of the approach. In its turn, the existing literature proves the potential of integration of PM with ML in terms of productivity improvement, error reduction, and decision-making support [4], [6], [15], [13]. Based on this research, the current one fills another significant gap in methodology of studies.

An unprecedented contribution of the paper is the combination of PM tools and Random Forest modeling in the context of a well-defined framework for outpatient surgery. Due to the creation of simulated data with a variety of postoperative variables, the proposed approach allows performing a multidimensional analysis of the factors that influence the results. Particularly, it makes it possible to highlight the critical variables such as anesthesia type, operation time, patients' preoperative state, level of pain, and complications. Thus, the quality of the postoperative outcome predictions increases significantly, contributing to the efficiency of the treatment process. However, besides being able to predict postoperative clinical outcomes, the use of PM tools in the model allows for a thorough evaluation of the performance indicators of the health system, which is an integral part of the framework. Among those indicators, there are the measures of efficiency, trace duration, and resource usage. In addition to this, the model has an essential advantage – its applicability to outpatient surgeries of various specialties.

2 | Methodology

The presented methodology framework includes such parts as Process-Oriented Data Simulation (PODS), PM Feature Extraction, Ensemble ML Predictive Modeling, and Operational Performance Analytics (OPA). The purpose of the framework is the prediction of postoperative patient-level outcomes and measurement of their cascading effects on clinical capacity. The proposed pipeline consists of four stages, described in detail below:

I. Synthesis of patient-level data: Patient-level data are generated on the basis of probability distributions and patterns, similar to real-world surgical processes.

II. Feature engineering and process-aware variable creation: Preoperative variables, intraoperative parameters, recovery variables, and PM-related variables are considered to represent each patient's perioperative journey.

III. Random Forest-based Prediction Modeling: Prediction modeling is performed using the Random Forest Regressor/Classifier based on the nature of the predicted variable (continuous/categorical).

IV. Operational performance measurement: The performance indicators (Key Performance Indicators (KPIs)) calculated for the simulated patient journeys are analyzed.

The ML–driven of clinical outcomes in outpatient surgery framework depicts in *Fig. 1*.

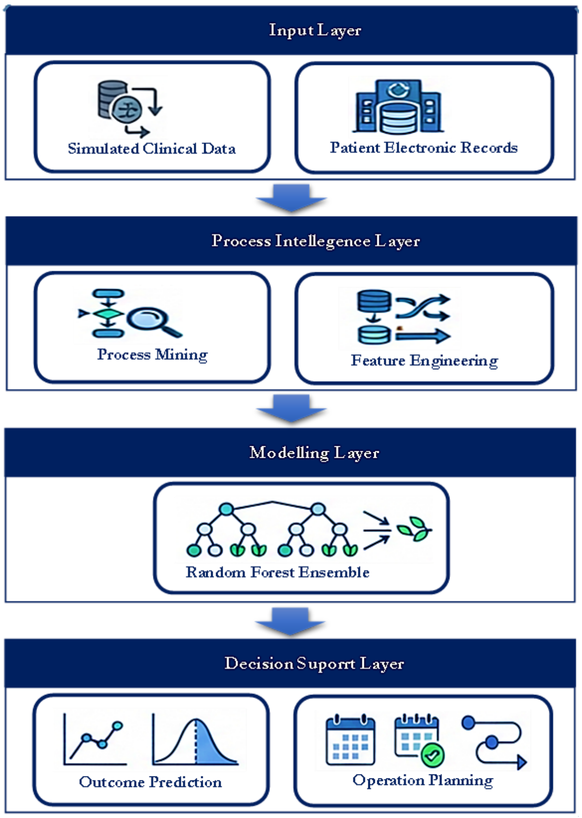

Fig. 1. ML–driven framework.

2.1 | Mathematical Notation and Feature Space

Let the patient cohort dataset be denoted as *Eq. (1)*:

$$\mathrm{D} = \{(\mathrm{X_i}, \mathrm{Y_i})\}, \quad \mathrm{i} = 1, \ldots, \mathrm{N}, \tag{1}$$

where N represents the total number of patients, $\mathrm{X_i} \in \mathbb{R}^\mathrm{P}$ a p-dimensional feature vector containing patient-level clinical characteristics and process-related attributes, and Y_i is the target postoperative outcome. The feature vector for patient i is formalized as *Eq. (2)*:

$$X_i = \left[x_{i1}, x_{i2}, \dots, x_{1p}\right]^T \in \chi_{clinical} \cup \chi_{process.} \tag{2}$$

Table 1. Input and predictor variables.

Variable Subspace	Notation	Data Type	Operational / Clinical Semantics
Clinical	ASA_i	Ordinal	Preoperative physical status (ASA I, II, III).
Clinical	Dur_Surg_i	Continuous	Net duration of the surgical procedure (minutes).
Clinical	$Type\_Anes_i$	Categorical	Anesthetic modality administered (general vs. regional)
Clinical	$Comp\_Risk_i$	Continuous	Latent probability of intraoperative complications, ∈(0,1)
PM	W_Time_i	Continuous	Pre-operative holding area waiting time (minutes)
PM	Act_Count_i	Integer	Total number of discrete activities recorded in the event log
PM	$Trace\_Dur_i$	Continuous	Total elapsed time from admission to recovery discharge

Each outcome Y_i represents one of the following:

Table 2. Outcome variables.

Variables	Type
LOS	Continuous variable
Complication Occurrence	Binary variable (0 = no complication, 1 = complication)
Recovery Quality Index (RQI)	Ordinal variable

Phase 1 (Synthetic clinical data generation model). To simulate realistic clinical pathways, patient attributes are drawn from distinct parametric distributions modeling empirical clinical behaviors, *Eqs. (3)-(6)*.

I. Preoperative Physical Status (ASA)

$$\begin{gathered} ASA \sim Categorical\ (p_1, p_2, p_3), \\ s.t. \\ \sum_{k=1}^{3} p_k = 1. \end{gathered} \tag{3}$$

II. Surgical Duration (Dur_Surg)

Surgical procedures typically exhibit a right-skewed log-normal distribution:

$$\begin{gathered} Dur_{Surg} \sim LogNormal(\mu_d, \sigma_d), \\ f(t;\ \mu_d, \sigma_d) = \frac{1}{t\sigma_d\sqrt{2\pi}} \exp\left(-\frac{(\ln t - \mu_d)^2}{2\sigma_d^2}\right),\ \ t > 0. \end{gathered} \tag{4}$$

III. Anesthesia Modality (Type_Anes)

$$\begin{gathered} Type_{Anes} \sim ategorical\ (q_1, q_2), \\ S.T. \\ q_1 + q_1 = 1. \end{gathered} \tag{5}$$

IV. Latent Complication Risk (Comp_Risk)

To capture bounded risk between 0 and 1 with custom skewness:

$$\mathrm{Comp}_{\mathrm{Risk}} \sim \mathrm{Beta}(\alpha, \beta),$$
$$f(x; \alpha, \beta) = \frac{1}{B(\alpha,\beta)} x^{\alpha-1}(1-x)^{\beta-1}, x \in [0,1]. \quad \textbf{(6)}$$

Phase 2 (Feature engineering and process-aware variables). We enrich the clinical dataset by mapping process execution logs. Let $E_i = \{e_{i,1}, e_{i,2}, \dots, e_{i,M}\}$ be the sequence of clinical events (activities) for patient i, where each event has a timestamp $(e_{i,m})$. The Trace Duration feature is mathematically constructed as *Eq. (7)*:

$$\mathrm{Trace\_Dur}_i = t(e_{i,M}) - t(e_{i,1}). \quad \textbf{(7)}$$

The Bottleneck/Waiting Time in transition between preoperative holding $(e_{i,pre})$ and operating room entry $(e_{i,OR})$ is computed as *Eq. (8)*:

$$\mathrm{W\_Time}_i = t(e_{i,OR}) - t(e_{i,pre}). \quad \textbf{(8)}$$

Phase 3. Postoperative Predictive Modeling

I. Regression Model for LOS: To represent the true underlying clinical dynamics, LOS is modeled as a function of clinical indicators, process attributes, and a random stochastic disturbance term, *Eq. (9)*:

$$y_{i,LOS} = \beta_0 + \beta_1 \mathrm{ASA}_i + \beta_2 \mathrm{Dur\_Surg}_i + \beta_3 \mathrm{Comp\_Risk}_i + \epsilon_i. \quad \textbf{(9)}$$

where $\epsilon_i \sim N(0, \sigma^2)$. This linear formulation simulates the influence of clinical and intraoperative factors on postoperative recovery duration.

II. Complication Probability Model

$$P(\mathrm{Complication}_i = 1) = \sigma\left(\gamma_0 + \gamma_1 \mathrm{ASA}_i + \gamma_2 \mathrm{Dur}_{\mathrm{Surg}_i} + \gamma_3 \mathrm{Type}_{\mathrm{Anes}_i}\right). \quad \textbf{(10)}$$

With the logistic function defined as *Eq. (11)*:

$$\sigma(z) = \frac{1}{1+e^{-z}}. \quad \textbf{(11)}$$

This probabilistic model captures the nonlinear relationship between patient condition, procedural characteristics, and adverse event likelihood.

2.2 | Random Forest Predictive Model

The goal of the predictive model is in *Eq. (12)*:

$$\hat{Y} = f_{RF}(X), \quad \textbf{(12)}$$

where f_{RF} denotes the Random Forest estimator. A Random Forest consists of:

T: Number of decision trees

m: Number of randomly selected features considered at each split

Depth: Maximum tree depth

The aggregated prediction is defined as *Eq. (13)*:

$$f_{RF}(X) = \frac{1}{T}\sum_{t=1}^{T} h_t(X), \tag{13}$$

where $h_t(X)$ is the output of the t^{th} tree. This ensemble approach reduces variance, improves generalization, and is well-suited to heterogeneous clinical datasets.

2.3 | Operational Performance Evaluation

To quantify the operational implications of model predictions, the following KPIs were computed in *Eqs. (14)- (17)*:

I. Surgical Workflow Efficiency

$$KPI_{eff} = \frac{\text{Total Patients}}{\text{Total Surgical Time}}. \tag{14}$$

This metric reflects the throughput of the surgical unit.

II. Resource Utilization

$$\text{Utilization} = \frac{\sum_{i=1}^{N} LOS_i}{\text{Available Beds}}. \tag{15}$$

This indicator assesses postoperative bed occupancy and hospital capacity strain.

III. Predictive Accuracy

– *For continuous outcomes:*

$$MAE = \frac{1}{N}\sum_{i=1}^{N} \left|Y_i - \hat{Y}_i\right|. \tag{16}$$

– *For binary classification:*

$$AUC = Area\ Under\ ROC\ Curve. \tag{17}$$

3 | Results

The Random Forest models showed strong performance for predicting postoperative outcomes in an outpatient surgery setting. Across the main evaluation measures, the model provided accurate estimates of both postoperative LOS and the probability of postoperative complications. As reported in *Table 3*, LOS prediction resulted in a MAE of 0.29 days and an R^2 of 0.81, suggesting that the regression portion accounted for a substantial amount of the variability in recovery time. For complication prediction, the model achieved an accuracy of 0.87 and an area under the receiver operating characteristic curve (AUC) of 0.91, confirming that it performed well at distinguishing patients with higher postoperative risk.

Table 1. Predictive accuracy.

Parameters	Values
Mean Absolute Error (LOS)	0.29 days
R^2 Score	0.81
Complication Prediction Accuracy	0.87
AUC	0.91

Taken together, these findings indicate that the Random Forest framework was able to capture the complex and possibly nonlinear connections between patient characteristics, perioperative factors, and postoperative outcomes. In particular, the AUC value highlights that the model's classification performance was not only high overall, but also dependable when separating lower-risk patients from higher-risk patients. This is especially relevant for ambulatory surgery, where identifying an increased postoperative risk early may help clinicians plan monitoring, support discharge decisions, and allocate recovery resources more appropriately. To further identify what drove model performance, feature importance was assessed using the Random Forest estimator. As shown in *Table 4*, the duration of surgery was the leading predictor (importance = 0.32), followed by preoperative ASA status (0.27), complication risk score (0.24), and type of anesthesia (0.17). This ranking suggests that both the intensity of the procedure and the patient's baseline health condition were central to explaining differences in postoperative outcomes.

Table 2. Feature importance.

Feature	Importance
Duration of surgery (Dur_Surg)	0.32
Preoperative ASA status (ASA)	0.27
Complication risk score (Comp_Risk)	0.24
Type of anesthesia (Type_Anes)	0.17

Surgical duration was the dominant factor, which is consistent with earlier findings that longer procedures tend to involve greater physiological stress, more perioperative complexity, and longer recovery periods. Similarly, the strong influence of ASA status underscores how much the patient's preoperative health condition affects postoperative recovery. Patients with a weaker baseline physiological status are, as expected, more likely to be ready for discharge later or to face a higher burden of complications. The sizable role of the simulated complication risk score also reinforces the value of probabilistic risk indicators within ML–based clinical prediction models. Even though the type of anesthesia had the lowest relative importance among the variables included, its contribution was still meaningful, indicating that the anesthetic approach continues to affect postoperative recovery dynamics in a measurable way.

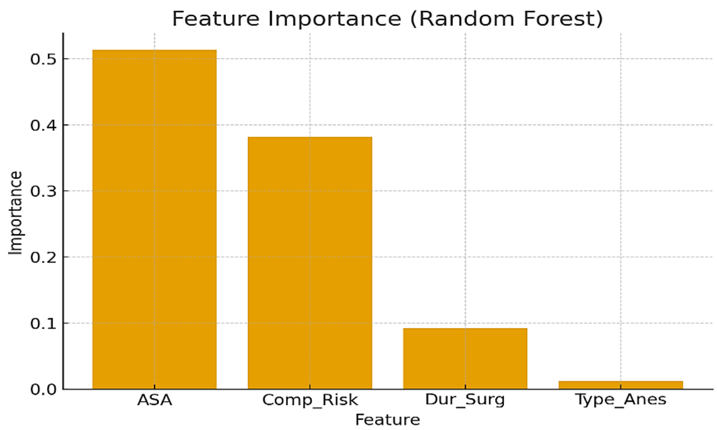

Fig. 1. Feature importance.

Fig. 2 shows the relative importance of the predictor variables and indicates that the model depends mainly on surgery duration, ASA status, and complication risk to estimate postoperative outcomes. While every included predictor contributed to the model, the pattern of importance scores points to an uneven structure, where a small number of clinically central variables account for most of the predictive signal.

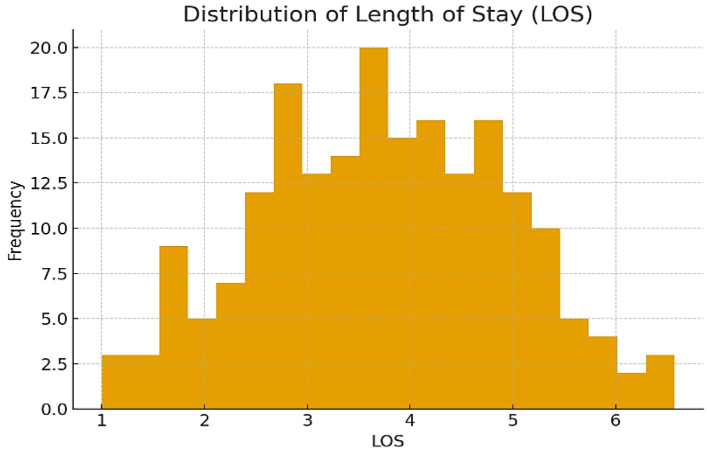

Fig. 2. LOS Distribution.

Fig. 3 displays the distribution of postoperative LOS. It looks approximately normal, with a slight right skew. This suggests that most patients recovered within a central range, while a smaller group had somewhat longer stays. Clinically, this pattern makes sense in outpatient surgery: most patients are discharged within expected timeframes, but a minority may need extended observation due to pain, slower physiological recovery, or early postoperative concerns. The presence of this moderate skewness also supports using flexible ML methods such as Random Forest, which are designed to manage variability that may not adhere to strict linear assumptions.

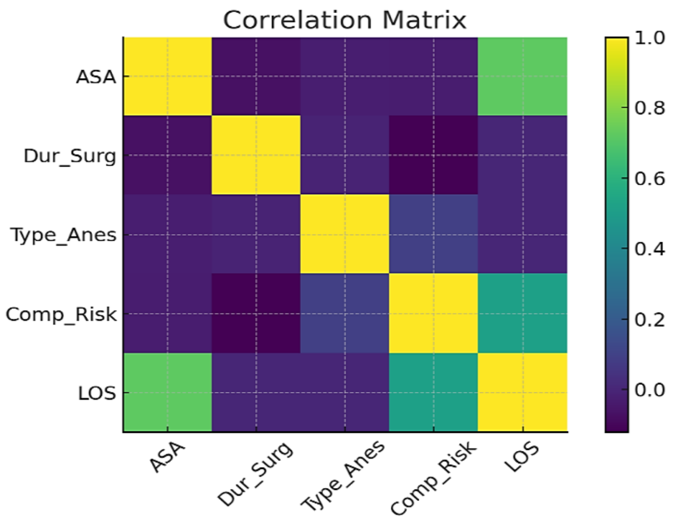

Fig. 3. The Correlation Matrix Heatmap.

The correlation matrix in *Fig. 4* supports the model-based results by showing how the key clinical and operational variables relate to one another in pairs. The stronger correlations between LOS and both ASA and Comp_Risk suggest that these factors are closely linked to how long patients take to recover after surgery. While correlation analysis by itself cannot prove which variables are truly dominant predictors, the clear linear patterns align with the feature importance findings. This consistency reinforces the idea that a patient's baseline health and the overall complication burden are major drivers of recovery patterns. So, the heatmap and the Random Forest feature importance results indicate that postoperative outcomes are influenced by both direct clinical risk factors and wider perioperative process characteristics. Because the predictive performance, the feature importance rankings, and the exploratory visualization all point in the same direction, there is greater confidence that the model is internally consistent. Practically, these results imply that the framework could be valuable not only for predicting outcomes, but also for helping with perioperative planning, flagging higher-risk patients, and improving operational decisions in outpatient surgical settings.

Table 3. The summary of results.

Domain	Key Finding	Interpretation
LOS prediction	MAE = 0.29 days, R2=0.81R^2 = 0.81R2=0.81	The model predicted postoperative recovery duration with high accuracy and explained a substantial share of LOS variability.
Complication prediction	Accuracy = 0.87, AUC = 0.91	The classifier showed strong discriminative ability in distinguishing higher-risk from lower-risk patients.
Most important predictor	Duration of surgery (0.32)	Procedural burden was the strongest determinant of postoperative outcome variation.
Second most important predictor	ASA status (0.27)	Baseline preoperative health status had a major effect on recovery and complication risk.
Additional influential factor	Complication risk score (0.24)	Probabilistic clinical risk indicators added meaningful predictive value.
Least important among selected variables	Type of anesthesia (0.17)	Anesthetic approach contributed to the model, although less strongly than the major clinical predictors.
LOS distribution	Approximately normal with mild right skew	Most patients recovered within the expected range, while a smaller group experienced prolonged recovery.
Correlation structure	Stronger associations of LOS with ASA and Comp_Risk	Postoperative recovery was closely linked to preoperative health burden and complication-related risk.
Practical implication	Supports risk stratification and planning	The framework may assist discharge planning, monitoring, and resource allocation in outpatient surgery.

4 | Conclusion

This study basically suggests that by running simulated patient data through a ML model, we can get a pretty accurate picture of what happens following outpatient surgery. The system did a strong job estimating recovery times and identifying possible complications, highlighting how computer simulation could be a useful tool for everyday surgical centers. When we look at what influenced the model's predictions most, operation length and the patient's starting health were the biggest factors. That lines up with what we'd expect clinically—longer procedures and worse baseline health typically mean a harder recovery. The results support this as well. Since the model explains a large portion of the differences in outcomes and is off by only a small fraction of a day, it appears to be capturing the overall picture quite well. Practically speaking, this kind of technology could make it easier for hospitals to plan discharges and coordinate staff and bed usage. Using artificial data is also a smart alternative when access to real patient records is limited by privacy rules, letting researchers test many different scenarios safely. That said, the best next step will be to validate this method using real hospital records later on to confirm that it performs reliably in day-to-day medical practice.

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