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RESEARCH

# Integrating Machine Learning and Dynamic Digital Follow-up for Enhanced Prediction of Postoperative Complications in Bariatric Surgery

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## Abstract

**Background** Traditional risk models, such as POSSUM and OS-MS, have limited accuracy in predicting complications after bariatric surgery. Machine learning (ML) offers new opportunities for personalized risk assessment by incorporating artificial intelligence (AI). This study aimed to develop and evaluate two ML-based models: one using preoperative clinical data and another integrating postoperative data from a mobile application.

**Methods** A prospective study was conducted on 104 bariatric surgery patients at Saint-Pierre University Hospital (September 2022–July 2023). Patients used the "Care4Today" mobile app for real-time postoperative monitoring. Data were analyzed using ML algorithms, with performance evaluated via cross-validation, accuracy, $F1$ scores, and AUC. A preoperative model used demographic and surgical data, while a postoperative model incorporated symptoms and mobile app-generated alerts.

**Results** A total of 104 patients were included. The preoperative model, utilizing Extreme linear discriminant analysis, achieved an accuracy of 75% and an AUC of 64.7%. The postoperative model, using supervised logistic regression with six selected features, demonstrated improved performance with an accuracy of 77.4% and an AUC of 71.5%. A user interface was developed for clinical implementation.

**Conclusions** ML-based predictive models, particularly those integrating dynamic postoperative data, improve risk stratification in bariatric surgery. Real-time mobile health monitoring enhances early complication detection, offering a personalized, adaptable approach beyond traditional static risk models. Future validation with larger datasets is necessary to confirm generalizability.

**Keywords** Bariatric surgery · Machine learning · Risk prediction · Complications · Mobile health monitoring

## Introduction

Several risk score–based models, such as the physiological and operative severity score for the enumeration of morbidity and mortality (POSSUM) and the obesity surgical mortality risk (OS-MS), have been used to predict complications after bariatric surgery [1, 2]. At the present, however, their predictive accuracy remains limited, with AUC values of 0.66 and 0.62, respectively [3], justifying the need to develop improved models.

Artificial intelligence (AI) now offers new solutions in this setting by enabling personalized risk assessments through machine learning (ML) and artificial neural networks (ANN). These models have shown effectiveness in predicting early postoperative complications in bariatric surgery [4, 5]. However, existing AI models in bariatric surgery often rely on static preoperative data, which limits their ability to adapt to dynamic postoperative changes in patient conditions. Despite this, their modular nature allows integration with other technologies, like smartphone applications, for real-time monitoring and dynamic patient-physician

**Key Points**

- Machine learning models can improve risk prediction in bariatric surgery by integrating clinical and real-time postoperative data.
- Postoperative mobile app follow-up enhances complication detection, allowing for timely interventions and personalized patient management.
- The preoperative model provides moderate predictive accuracy but lacks adaptability compared to dynamic, app-based risk assessment.

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interactions [6], potentially enabling enhanced and rapid risk assessment as well as personalized interventions.

The objective of this study was to develop and to evaluate two distinct ML-based risk assessment models relying on (1) preoperative parameters, using standard clinical and demographic data, and (2) postoperative parameters by incorporating patient's data collected through a mobile application follow-up.

## Materials and Methods

### Study Design and Patient Selection

Consecutive adult patients undergoing bariatric surgery at Saint-Pierre University Hospital from September 2022 to July 2023 were considered eligible for inclusion in this study. After signing a written informed consent form, patients who agreed to participate were instructed to download the "Care4 Today" mobile application, which enables real-time remote patient follow-up during the perioperative period. The indications for bariatric surgery were a BMI greater than 40, or greater than 35 in the presence of obesity-related comorbidities. Exclusion criteria included unwillingness to participate, incomplete follow-up (less than 60 days), lack of a mobile phone, or linguistic barriers that precluded the use of the mobile application.

This study was approved by the institutional ethics committee.

### Mobile Application Follow-up

Postoperative remote digital follow-up was performed using the "Care4 Today monitoring" mobile application, developed by Q1.6, in addition to standard office-based consultations. This application enables remote postoperative follow-up by asking patients a set of predefined questions centered around various aspects of postoperative patient care, such as nutrition, wound care, pain management, and patient well-being, starting from one day preoperatively to 60 days postoperatively. The application itself utilizes a questionnaire framework that was designed by five local expert bariatric surgeons and is formatted as a decision tree (Supplementary material). In case of worrisome patient responses, an alert may be generated and transmitted via daily emails, direct email, or directly to the healthcare provider dashboard, depending on the severity of the patients' symptoms. The alerts were further subdivided into three tiers, depending on severity: orange alerts (mild symptoms and complaints), red alerts (symptoms with significant health implications), and red + alerts (symptoms that warrant immediate medical attention. Median office–based patient follow-up was 63 days (range 28 to 369 days).

### Database Creation and Variables of Interest

Clinical details of patients were prospectively collected and entered into a standardized database for further tabulation. Pertinent clinical data included comprehensive information on each patient's medical history and specific details related to their bariatric surgery. This encompassed patient demographics; preoperative BMI; details of prior surgeries, presence of obesity-related comorbidities, type of surgical intervention; Roux-en-Y gastric bypass (RYGB); single anastomosis stomach-ileal bypass with sleeve gastrectomy (SASI-S); or conversion to RYGB following previous bariatric procedures, as well as any complications and postoperative symptoms reported during follow-up visits or via the mobile application. Furthermore, real-time data were collected through the mobile application dashboard, capturing responses to predefined questions, frequency, and types of alerts generated per patient per day.

### Statistical Analysis and Machine Learning Algorithms

To facilitate data handling and processing, raw data from the project database were transformed in preparation for analysis. Null and missing values were imputed by replacing numerical values with the mean and categorical values with the mode, ensuring data robustness. Additionally, ordinal and categorical data were converted into numerical representations using the "one-hot encoding" technique [7].

Following data analysis, cleaning, and preprocessing, a comparative analysis of machine learning (ML) models was conducted for predicting postoperative complications according to pre- and postoperative collected variables. The first provides a general tool to assess the global surgical risk, while the second aims to quantify the specific surgical risk.

To validate the predictive model, a cross-validation approach was used. This technique is essential for evaluating the model's performance on different partitions of the training data, thus ensuring a robust evaluation of the model's performance [8]. The synthetic minority oversampling technique (SMOTE) algorithm was also used, which serves to increase the number of observations of the minority class with synthetic examples [9, 10]. This approach aimed to address the class imbalances observed in the complication outcome data.

A comparison between 15 ML classification models was launched (Table 1). These models were specifically selected for the present study, as they are easy to train with limited data. The Pycaret tool, a Python v 2.3 library that enables training and evaluation, was utilized to provide a reusable pipeline for deploying the best-found model.

**Table 1** Descriptive table of the machine learning models used in the comparisons

| Model | Description |
|---|---|
| Extreme gradient boosting (XGBoost) | Supervised learning algorithm based on decision trees, optimized for performance and speed. Uses gradient boosting to improve accuracy |
| K-neighbors classifier (KNN) | Classifier based on supervised learning that assigns to a data point the most frequent class among its K nearest neighbors |
| Random forest classifier | A set of decision trees used for classification, reducing variance by bagging compared to a single decision tree |
| Dummy classifier | A simple classifier that does not perform any real learning and serves as a reference point for comparing other models |
| Light gradient boosting machine (LightGBM) | A fast and efficient version of gradient boosting, using a histogram-based algorithm to process large data sets |
| Logistic regression | A regression model used for binary classification, estimating the probability that a feature belongs to a specific class |
| Gradient boosting classifier | A boosting algorithm that sequentially builds a set of weak decision trees to improve accuracy |
| Extra trees classifier | A variant of random forest that uses random divisions to reduce variance |
| Decision tree classifier | A predictive tree model that associates observations with conclusions about the target value |
| AdaBoost classifier | A boosting technique that adjusts the weights of learning instances to focus on difficult cases |
| Ridge classifier | A variant of linear regression with L2 regularization, adapted to correlated explanatory variables |
| Quadratic discriminant analysis (QDA) | A classifier that assumes a Gaussian distribution and estimates the variances for each class |
| Linear discriminant analysis (LDA) | A dimension reduction and classification technique that maximizes class separability |
| Linear kernel (used in support vector machines) | A linear method for calculating similarity in support vector machines, suitable for large datasets |
| Naive Bayes | A class of probabilistic classifiers based on Bayes'theorem, with an assumption of naive dependence between features |

The predictive performance of the 15 ML models investigated was assessed based on metrics such as cross-validation accuracy, precision, and recall (measured as cross-validation $F1$ scores), as well as cross-validation area under the curve (AUC), and the total number of input parameters (variables and possible values for each one). In the case of a large number of input features, dimensionality reduction was performed to allow for a model that is easier to manipulate and use. To achieve this, the "SelectKBest" feature selection method from the scikit-learn python library, with principal component analysis (PCA) for dimensionality reduction, was used [11]. Furthermore, the *t*-distributed stochastic neighbor embedding (T-SNE) method was employed to illustrate model classification data on a 2-dimensional diagram after dimensionality reduction, to verify the accuracy and correctness of the final models.

## Results

Overall, 104 patients were included in the study sample, of whom 85 (81.7%) were female and 19 (18.5%) were male, with an average age of 35.6 ± 12 years (Table 2). The median preoperative BMI was 41.5 (21.4–64.8) kg/m$^2$. Fifteen patients (14.4%) reported a smoking history, 18 (17.3%) had a history of gastroesophageal reflux disease, and 71 (68.3%) exhibited obesity-related comorbidities such as hypertension ($n = 6$, 5.8%), sleep apnea ($n = 24$, 23.1%), and diabetes ($n = 41$, 39.4%). Previous surgical history was noted in a minority of these patients ($n = 36$, 34.6%), with the majority undergoing RYGB ($n = 67$, 64.4%), followed by sleeve gastrectomy ($n = 20$, 19.2%).

The total number of patients reporting postoperative symptoms was 52 (64.2% of the entire cohort), among whom pain was the chief complaint (45.7% of patients), followed by vomiting (8.6%), constipation (6.2%), and other isolated complaints including generalized malaise, odynophagia, nausea, or dyspnea. The morbidity rate in the cohort was 20.2%, with six cases of intractable vomiting requiring hospitalization (either readmission or prolongation of initial stay) for intravenous fluid replacement, three cases of postoperative dysphagia lasting longer than 30 days, two cases of anastomotic strictures, three cases of severe pain requiring in-hospital pain management, two cases of dumping syndrome, one case of pancreatitis, one internal hernia, one biliary fistula, one pulmonary embolism, and one case of surgical site infection. No deaths were reported, with three patients (3.7%) requiring readmission.

Global morbidity rate according to Clavien-Dindo (CD) classification [12] was 20.2%, with a total of 141 alerts transmitted by the application during the follow-up period (supplementary material). Complications were minor (CD < III)

**Table 2** Patient-related characteristics utilized as input features in each of the evaluated complication risk assessment models

| Input features | Number of patients n, (%) |
|---|---|
| **Age** (years) | 35.6 ± 12 |
| **Gender** | |
| *Male* | 19 (18.3) |
| *Female* | 85 (81.7) |
| **BMI** (kg/m$^2$) | 41.5 (21.4–64.8)* |
| **Comorbidities** | |
| *Smoking* | 15 (14.4) |
| *Hypertension* | 6 (5.8) |
| *Sleep apnea* | 24 (23.1) |
| *Diabetes* | 41 (39.4) |
| *Gastroesophageal reflux* | 18 (17.3) |
| **Previous surgical history** | 36 (34.6) |
| **Type of intervention** | |
| *Sleeve gastrectomy* | 20 (19.2) |
| *RYGB* | 67 (64.4) |
| *SASI-S* | 7 (6.7) |
| *RYGB conversion* | 10 (9.7) |
| **Total number of alerts** | 1119 |
| *Orange alerts* | 1027 (91.8) |
| *Red alerts* | 74 (6.6) |
| *Red + alerts* | 18 (1.6) |
| **Postoperative complications** | |
| *Postoperative pain* | 3 (2.9) |
| *Postoperative vomiting* | 7 (6.7) |
| *Dysphagia* | 3 (2.9) |
| *Anastomotic stricture* | 2 (1.9) |
| *Other* | 6 (5.8) |
| **Postoperative morbidity** | 21 (20.2) |

*ED* emergency department

*Value represents median (range)

in 16 (76.2%) patients and major (CD ≥ III) in five (23.8%). Out of a total of 19,325 questions sent out by the application during the 60-day postoperative period, 13,049 responses were received, resulting in an overall response rate of 67.5%. Accordingly, a total of 1119 alerts were transmitted during the follow-up period, the majority being orange alerts ($n$ = 1027, 91.8%), followed by red alerts ($n$ = 74, 6.6%), and red + alerts ($n$ = 18, 1.6%).

The total patient cohort was divided into a training ($n$ = 72, 70%) and a validation ($n$ = 32, 30%) cohort. Cross-validation across fivefolds verified the predictive capacity of the final models.

## Model for Preoperative Prediction of Complications

After the training of the models, the best-adapted predictive model used the extreme linear discriminant analysis model, with inputs being patient demographics (age, gender, BMI, comorbidities), the type of scheduled bariatric operation, and the previous history of abdominal surgery. The model displayed an accuracy of 75%, an $F1$ score of 43%, and an AUC of 64.7% (Table 3).

## Model for Postoperative Prediction of Complications

The model applied in this setting initially incorporated all available input variables (namely, answers to mobile application questions and generated alerts), utilizing the supervised logistic regression method and displaying an accuracy of 83.8%, an $F1$ score of 46.1%, and an AUC of 62.7% (Table 3). This $F1$ score indicates a moderate balance between precision and recall, suggesting that while the model is reasonably accurate, it may miss some true positive cases of complications or generate false positives.

However, this model was found to be cumbersome and difficult to deploy due to its large number of input features. To address this, we employed the "SelectKBest" feature selection method from sklearn with principal component analysis (PCA) for dimensionality reduction. We found that the optimal tradeoff between usability and predictive accuracy was achieved with only six features (presence and type of symptoms, answer to smartphone application questions "do you have vomiting," "do you have abdominal pain," "do you have pain while eating," "how much did you drink today," total number of orange and red alerts), using supervised logistic regression, and achieving an accuracy of 77.4%, an $F1$ score of 46.2%, and an AUC of 71.5% (Fig. 1). The attained $F1$ score reflects a similar trade-off between precision and recall, highlighting the challenge of accurately identifying complications in a heterogeneous patient population.

## Model Deployment and User Interface

A graphical user interface was constructed to facilitate the use of the predictive models (Fig. 2). This interface allows

**Table 3** Summary presentation of the performance metrics of each model

| | Model name | Accuracy | AUC | Recall | Precision | $F1$ score | Sensitivity | Specificity |
|---|---|---|---|---|---|---|---|---|
| Pre-operative model | Linear discriminant analysis | 0.75 | 0.65 | 0.5 | 0.375 | 0.429 | 0.5 | 0.81 |
| Post-operative model | Logistic regression | 0.77 | 0.72 | 0.6 | 0.38 | 0.462 | 0.6 | 0.81 |

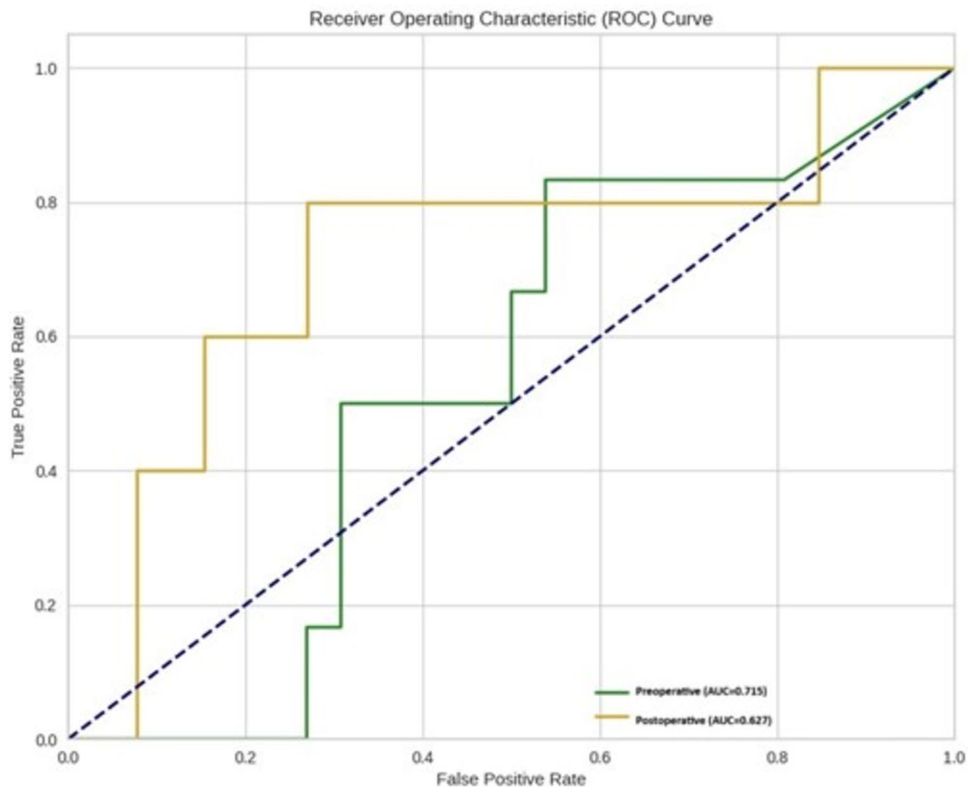


**Fig. 1** Receiver operator curves for the predictive efficacy of each of the two trained models in the postoperative setting

for a choice between the preoperative or postoperative models, with each one utilizing different input features to output a distinct probability associated with the likelihood of postoperative complications. A prototype is deployed in the English language and is available for review on https://barisk.deepilia.com/.

## Discussion

This study demonstrates the potential of an integrated AI-driven approach to risk assessment in bariatric surgery, combining baseline clinical data with dynamic postoperative follow-up data from a mobile application. By leveraging ML, our approach enables a more personalized and adaptable risk prediction, reflecting real-time changes in a patient's postoperative status. Unlike traditional static models, this dynamic risk assessment adapts to postoperative progression, enabling timely interventions.

The obtained AUC values for the preoperative and postoperative models, while acceptable, indicate room for improvement in predictive performance. This could conceivably be achieved by expanding the training datasets and incorporating additional data sources, such as wearable devices or biochemical markers, to enhance model robustness. This is also reflected in the observed $F1$ scores, which were below $< 0.5$, indicating that these prediction models may have limited impact in clinical decision-making but do show a potential for improvement over traditional risk scores. Despite this shortcoming, the performance of our models appears to be on par with results reported from other AI-driven predictive models utilized in different surgical disciplines [13]. Similar studies in abdominal surgery have reported AUC values ranging from 57 to 95% for ML models predicting postoperative complications, indicating high variability [14]. This suggests that our approach, while not yet optimal, is competitive with existing benchmarks and provides a foundation for further refinement.

Complications following bariatric surgery have been identified to occur at any time point during the postoperative course of patients. Mierzwa et al. [15] in a retrospective study of 316,314 patients registered in the Metabolic and Bariatric Surgery Accreditation and Quality Improvement Program (MBSAQIP) database, demonstrated that a large number of septic complications occur at a time point that is beyond the second postoperative week, during which patients have likely been discharged home. Considering that the time period immediately after discharge is a period of limited surveillance, the addition of a remote follow-up by mobile application can enhance the detection of deviations from the normal postoperative course [6]. This process can further be refined by incorporating generated data in a ML model for further risk stratification.

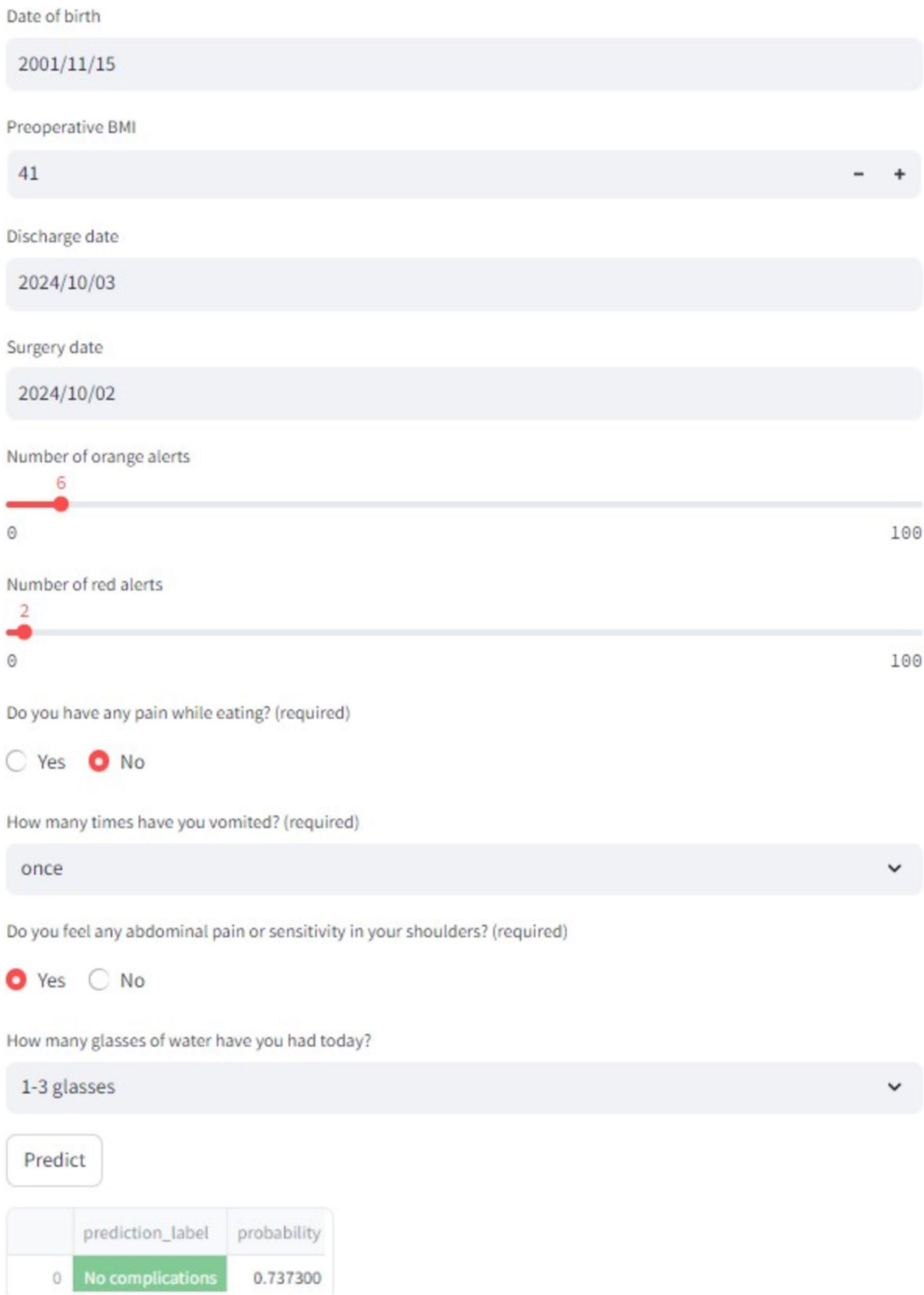


**Fig. 2** Illustration of the deployment of the models through a pilot web–based user interface

The preoperative model evaluated in this study, using only traditional demographic and clinical data, showed a predictive performance associated with an accuracy of 75%. While simpler and potentially useful for generalist physicians in preoperative patient counseling, this model lacks the adaptability and precision offered by a dynamic, app-based follow-up. Similar studies have achieved higher accuracy through more complex models. For instance, Sheikhtaheri et al. [4]

applied an ANN model to predict complications following one-anastomosis gastric bypass, achieving 90.9% accuracy by augmenting baseline clinical features with biochemical, sonographic, endoscopic, and intra-operative data, implying that more extensive data inputs could improve predictive power in specific clinical settings, an observation reproduced in another more recent study [16]. Findings from the present study suggest that the primary limitation of the preoperative model is its tendency to generate false negatives, likely due to limited training and dataset diversity. Ensuring a diverse training dataset is crucial for enhancing the model's generalizability.

In contrast, the postoperative model, which incorporates data from the "Care4 Today" application, proved to be more robust than the preoperative model, achieving an accuracy of 77.4% and an AUC of 71.5% even after dimensionality reduction. This highlights the enhanced predictive accuracy that comes with incorporating dynamic data from patient monitoring. Such a model potentially offers tangible clinical benefits, allowing for a continuous, patient-centered follow-up that specialist physicians can use to reassess the complication risk throughout the postoperative period. This feature is particularly valuable in bariatric surgery, where complications may evolve over time and require early detection to prevent escalation.

Postoperative complications can have a severe impact on bariatric patients' well-being, with bleeding, anastomotic leak, and venous thromboembolism in particular being linked to increased mortality rates and the requirement for intensive care unit hospitalization or reoperation [17]. Moreover, they are associated with a long-lasting negative impact on patients' quality of life, especially when not managed suitably [18]. Despite the focus on severe complications, even minor complications can have significant consequences. Bariatric patients are particularly susceptible to nausea and vomiting [19], a condition that does not permit adequate patient hydration, thus creating the need for an extension of hospital stay or readmission [20]. Similarly, transient dysphagia (not attributable to mechanical obstruction such as kinking or strictures) can endanger patient hydration and nutritional status. Active surveillance against such occurrences and the implementation of management protocols can further improve patient rehabilitation.

The present study has some notable limitations that need to be acknowledged. First, the relatively small sample size of 104 patients, determined by the available cohort during the study period (September 2022–July 2023) as defined by the local ethics committee, may impact the generalizability of the predictive models due to issues relating to overfitting or limited variability in training data. A formal power analysis was not conducted, as the sample size was based on practical constraints rather than statistical calculations. Expanding the dataset through multi-center studies would help improve model robustness and enhance external validation. Additionally, the dataset used in this study was institution-specific, meaning that patient characteristics and postoperative management may not fully reflect practices at other centers. Furthermore, the potential for patient self-reporting bias, such as underreporting or misinterpretation of symptoms, cannot be fully accounted for. External validation in different bariatric surgery populations will be necessary to confirm the model's applicability across various clinical settings.

Another consideration is the dataset's inherent imbalance, which necessitated the use of SMOTE to address class distribution. While this method improves model training by augmenting underrepresented data, it may introduce synthetic patterns that do not fully represent real-world variability. Finally, the model currently provides a general prediction of postoperative risk without distinguishing between specific types or severities of complications. Future refinements could incorporate more granular classification to enhance clinical utility and guide tailored interventions. Despite these limitations, this study demonstrates the potential of integrating artificial intelligence with real-time mobile health monitoring to enhance postoperative risk prediction. Further validation with larger and more diverse datasets will be essential to fully realize the clinical benefits of this approach.

In conclusion, our study demonstrates that the integration of dynamic postoperative follow-up data from a mobile application significantly enhances prognostication compared to a preoperative model relying solely on static clinical data. The postoperative model, with its ability to incorporate real-time patient-reported symptoms and alerts, achieved an AUC of 71.5%, outperforming the preoperative model (AUC 64.7%). This highlights the added value of continuous, patient-centered monitoring in identifying complications and adapting risk assessments over time. While further research is needed to optimize and validate these models, the integration of mobile health technology with AI represents a promising advancement in personalized risk prediction for bariatric surgery patients.

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**Data Availability** The study dataset will be made available by the corresponding author upon reasonable request.

## Declarations

**Competing interests** The authors declare no competing interests.

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