

# Prevalence and Predictors of Unplanned Readmission After Outpatient Breast Cancer Surgery: A Retrospective Cohort Study of 191,559 Patients

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## Article

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# Abstract

Outpatient breast surgery has become increasingly common, yet contemporary national data on unplanned readmission after same-day discharge remain limited. Using the American College of Surgeons National Surgical Quality Improvement Program (2011–2023), we performed a retrospective cohort study of adult women undergoing elective outpatient breast cancer surgery, with 30-day unplanned readmission as the primary outcome. Multivariable logistic regression identified independent predictors, a nomogram was developed for individualized risk estimation, and machine learning models (LASSO, XGBoost, random forest) were applied for validation. Among 191,559 patients, the overall readmission rate was 1.82%, rising from partial (1.36%) to total (2.83%) and radical mastectomy (3.34%). Despite a roughly seven-fold increase in outpatient volume, readmission declined from 2.8% in 2011 to 1.6% in recent years. The strongest independent predictors were functional dependence, congestive heart failure, dialysis, operative time exceeding 120 minutes, bleeding disorders, and ASA class  $\geq 3$ . The nomogram identified high-risk patients with excellent calibration and discriminated comparably to machine learning models. Outpatient breast cancer surgery carries low overall readmission risk that varies substantially by procedure type and comorbidity, with functional dependence and cardiovascular disease outweighing cancer-specific factors. The proposed nomogram offers a practical tool for individualized risk stratification and surgical planning.

## 1. BACKGROUND

Approximately one in eight women will develop breast cancer during their lifetime, and its global burden continues to rise due to population aging and improved detection.<sup>1–5</sup> As the incidence of breast cancer is projected to increase further,<sup>3–5</sup> optimizing the safety, efficiency, and value of surgical care has become priority. Surgery remains the cornerstone of curative treatment, and improvements in perioperative outcomes may translate into meaningful benefits for a large and growing patient population.<sup>6–8</sup>

In recent years, outpatient breast surgery has emerged as an increasingly adopted surgical strategy, driven by advances in surgical technique, anesthesia, perioperative pain management, and enhanced recovery protocols.<sup>9–11</sup> Same-day discharge offers several potential advantages, including improved patient satisfaction, reduced healthcare costs, and decreased utilization of inpatient resources.<sup>12–14</sup> However, these benefits must be carefully balanced against the risk of unplanned hospital readmission, a quality metric that reflects postoperative complications, inadequate perioperative support, and gaps in discharge planning.<sup>15</sup> Unplanned readmissions are associated with substantial clinical and economic consequences, including increased morbidity, psychological distress, delayed adjuvant therapy, and significant financial burden for both patients and healthcare systems.<sup>16–18</sup>

Despite the growing prevalence of outpatient procedures, the true incidence and determinants of unplanned readmission following same-day discharge remain incompletely understood.<sup>19,20</sup> Patients

undergoing surgery for breast cancer may represent a vulnerable surgical population; beyond the physiological stress of surgery, cancer has been associated with systemic immune and metabolic alterations that could influence postoperative outcomes.<sup>21,22</sup> Moreover, neoadjuvant and adjuvant treatments can further impair wound healing and recovery.<sup>22–24</sup> While wound-related complications typically manifest weeks postoperatively, the outpatient setting eliminates the early observation window. This shift places a greater burden on patient self-monitoring and may increase the likelihood of readmission for acute early concerns that may otherwise have been managed during a brief inpatient stay.

Unplanned readmission after outpatient breast cancer surgery not only undermines the intended benefits of same-day discharge but also raises concerns regarding patient selection, perioperative optimization, and post-discharge support.<sup>25,26</sup> Identifying patients at elevated risk for readmission is therefore essential to ensure safe implementation of outpatient pathways. However, existing evidence on readmission after breast cancer surgery is limited.<sup>19,20,27</sup> Prior studies are often restricted to single-center experiences or small retrospective cohorts, frequently combining inpatient and outpatient procedures, and thus lack the granularity required to specifically evaluate same-day discharge.<sup>19,27,28</sup> Additionally, heterogeneity in definitions, follow-up intervals, and reporting standards has hindered meaningful comparison across studies.

To address these limitations, we conducted a large-scale, multicenter analysis using data from the American College of Surgeons National Surgical Quality Improvement Program (ACS-NSQIP), a well-established database capturing standardized perioperative outcomes.<sup>29–31</sup> Leveraging this robust dataset, we sought to determine the prevalence of unplanned readmission following outpatient breast cancer surgery and to identify patient-, procedure-, and perioperative factors associated with increased readmission risk.

## 2. METHODS

### 2.1 Data Source

We performed a retrospective analysis of the ACS-NSQIP database, a well-validated, risk-adjusted surgical quality improvement registry that aggregates outcomes data from nearly 700 participating hospitals worldwide. The database has been widely used in breast surgery research and provides standardized information on more than 150 preoperative, intraoperative, and 30-day postoperative variables.<sup>32–38</sup> Data are collected and abstracted by specially trained clinical reviewers using standardized definitions and protocols, ensuring high data fidelity and reproducibility. All data were accessed through an NSQIP-participating institution and were fully de-identified. All methods were carried out in accordance with relevant guidelines and regulations, including the ethical principles of the Declaration of Helsinki. The study was reviewed by Mass General Brigham Human Research Affairs and was granted a formal exemption by the Mass General Brigham Institutional Review Board (IRB), which

determined that the analysis did not constitute human subjects research under Mass General Brigham IRB policies and the U.S. Department of Health and Human Services regulations set forth in 45 CFR 46, as it did not involve identifiable private information (determination ID 4495). Because the study was based exclusively on fully de-identified, retrospective registry data and posed no more than minimal risk, the Mass General Brigham Institutional Review Board waived the requirement for informed consent.

## 2.2 Patient Selection

ACS-NSQIP datasets from 2011 to 2023 were analyzed to identify female patients with breast cancer undergoing outpatient surgery. The study period began in 2011, as the primary outcome was first systematically captured in the NSQIP database that year; earlier cases were therefore excluded. At the time of analysis, no datasets beyond 2023 were available through the ACS. The cohort was restricted to patients undergoing breast surgery for oncologic indications and was identified using International Classification of Diseases, Ninth and Tenth Revision, Clinical Modification (ICD-9-CM and ICD-10-CM) diagnostic codes, including ICD-9-CM 174 ("Malignant neoplasm of female breast") and 233.0 ("Carcinoma in situ of breast"), as well as ICD-10-CM C50 ("Malignant neoplasm of breast") and D05 ("Carcinoma in situ of breast"). Surgical procedures were identified using Current Procedural Terminology (CPT) codes and subsequently categorized into partial mastectomy (CPT codes 19160, 19162, 19301, and 19302), total mastectomy (CPT codes 19180 and 19303), or radical (modified) mastectomy (CPT codes 19200, 19220, 19248, 19305, 19306, and 19307). All cases involving reconstructive procedures, as well as those coded with CPT 19304, were excluded from the analysis because these procedures may be subject to inconsistent or inaccurate coding.<sup>39</sup> Because the NSQIP database captures only adult surgical cases, pediatric patients were excluded by design. The cohort was further restricted to female patients to ensure clinical homogeneity. Eligible cases included elective outpatient procedures performed by general or plastic surgery services under general anesthesia or monitored anesthesia care (MAC); urgent and emergency procedures were excluded. Patients with missing key outcome data, including unplanned readmission status, were also excluded to ensure complete outcome ascertainment. These criteria yielded a well-defined, clinically homogeneous cohort of adult women undergoing elective outpatient breast surgery for oncologic indications.

## 2.3 Variable Extraction

All variables were obtained from the ACS-NSQIP Participant Use Data File (PUF) and were defined according to standardized ACS-NSQIP criteria, as specified in the ACS-NSQIP PUF User Guide. The use of these uniformly defined variables ensured methodological consistency across the study period. Preoperative variables included patient demographics (age, body mass index [BMI], and race), baseline comorbidities (obesity, diabetes mellitus, current smoking, chronic obstructive pulmonary disease [COPD], congestive heart failure, hypertension requiring medication, renal failure, dialysis dependence, chronic steroid use, bleeding disorder, preoperative blood transfusion, history of sepsis, and disseminated cancer), American Society of Anesthesiologists (ASA) physical status classification, and functional status (independent, partially dependent, or totally dependent). Operative characteristics comprised anesthesia type and operative time. The primary outcome was 30-day unplanned hospital

readmission. Secondary outcomes included any postoperative complication, reoperation, and specific surgical complications (superficial surgical site infection [SSI], deep SSI, organ/space SSI, and wound dehiscence) as well as medical complications (pneumonia, unplanned reintubation, pulmonary embolism, prolonged ventilator dependence > 48 hours, myocardial infarction, cardiac arrest requiring cardiopulmonary resuscitation, deep vein thrombosis, urinary tract infection, sepsis, and septic shock).

## 2.4 Statistical Analysis

Baseline characteristics were compared across mastectomy types (partial, total, and radical) using one-way analysis of variance (ANOVA) for continuous variables and chi-square tests or Fisher's exact tests, as appropriate, for categorical variables (the latter applied when expected cell counts were < 5). Continuous variables are reported as mean  $\pm$  standard deviation, and categorical variables as frequencies with corresponding percentages. Univariable logistic regression analyses were first performed to identify candidate predictors of 30-day unplanned readmission. Variables demonstrating both clinical relevance and statistical significance ( $p < 0.05$ ) on univariable analysis were subsequently entered into a multivariable logistic regression model. The final model comprised 15 independent predictors: functional dependence, congestive heart failure, dialysis dependence, operative time > 120 minutes, bleeding disorder, ASA physical status classification  $\geq 3$ , disseminated cancer, COPD, diabetes mellitus, chronic steroid use, current smoking, use of general anesthesia, obesity (BMI  $\geq 30$  kg/m<sup>2</sup>), Black race, and age. A nomogram was developed based on the multivariable logistic regression model to facilitate individualized estimation of readmission risk. Model discrimination was quantified using the area under the receiver operating characteristic curve (AUC), while calibration was assessed using calibration plots generated with 200 bootstrap resamples. Agreement between predicted and observed probabilities was summarized using the mean absolute error (MAE). To assess the robustness of predictor selection and model performance, artificial intelligence-based machine learning approaches were applied using the same set of 15 predictors. The dataset was randomly partitioned into training (80%) and testing (20%) cohorts. Four models were evaluated and compared: standard logistic regression, least absolute shrinkage and selection operator (LASSO) regression, extreme gradient boosting (XGBoost), and random forest. Discriminatory performance was compared using paired AUCs and the DeLong test. Variable importance was quantified using absolute LASSO coefficients and gain-based importance metrics derived from the XGBoost model. An exploratory analysis using LASSO regression was additionally performed on an expanded set of 26 potential variables, comprising the 15 primary variables, five additional comorbidities, and six laboratory parameters, to identify potentially overlooked risk factors. Furthermore, interaction analyses were conducted to evaluate whether associations between predictors and readmission differed by mastectomy type. Interaction effects were classified as strong (> 50% effect modification), moderate (25–50%), or weak (< 25%). Temporal trends in 30-day readmission rates over the study period were examined using linear regression. Multiple regression analyses were restricted to patients with complete covariate data. A two-sided  $p$ -value < 0.05 was considered statistically significant. Statistical analyses were performed using R version 4.3.1 (R Foundation for Statistical Computing, Vienna, Austria), employing the rms package for nomogram

construction, glmnet for LASSO regression, xgboost for gradient boosting, randomForest for random forest modeling, and pROC for receiver operating characteristic analyses and DeLong test.

## 3. RESULTS

### 3.1 Patient Demographics and Preoperative Characteristics

A total of 191,559 female patients undergoing outpatient breast surgery between 2011 and 2023 met the inclusion criteria. Of these, 136,437 (71.2%) underwent partial mastectomy, 40,021 (20.9%) total mastectomy, and 15,101 (7.9%) radical mastectomy (Table 1). The mean age of the cohort was  $63.1 \pm 12.2$  years, and the mean body mass index (BMI) was  $29.7 \pm 7.6$  kg/m<sup>2</sup>; 42.2% of patients met criteria for obesity (BMI  $\geq 30$  kg/m<sup>2</sup>). The cohort was predominantly White (71.4%), followed by Black (11.0%), Asian (5.2%), and other or unknown race (12.4%). The most prevalent comorbidities were hypertension (39.2%), diabetes mellitus (15.2%), current smoking (9.0%), and chronic obstructive pulmonary disease (COPD; 2.7%). An American Society of Anesthesiologists (ASA) physical status classification  $\geq 3$  was present in 43.8%, while 1.9% of patients were functionally dependent. The proportion of invasive breast cancer increased stepwise from partial (77.0%) to total (81.1%) and radical mastectomy (93.2%;  $p < 0.001$ ). Patients undergoing total and radical mastectomy exhibited a higher burden of clinical risk factors compared with those undergoing partial mastectomy. In particular, patients undergoing radical mastectomy were younger ( $61.5 \pm 13.5$  years) and had higher rates of current smoking (12.8% vs 8.6%), ASA class  $\geq 3$  (53.8% vs 41.2%), metastatic cancer (4.3% vs 0.9%), and chronic steroid use (3.3% vs 1.9%) compared with partial mastectomy patients (all  $p < 0.001$ ).

### 3.2 Surgical Characteristics and Postoperative Outcomes

Operative characteristics and postoperative outcomes are summarized in Table 2. The mean operative time was  $86.6 \pm 57.0$  minutes overall, with substantially longer durations for total ( $126.9 \pm 71.1$  minutes) and radical ( $130.2 \pm 65.3$  minutes) mastectomy compared with partial mastectomy ( $69.9 \pm 40.5$  minutes,  $p < 0.001$ ). Operative time exceeded 120 minutes in 19.3% of cases overall, ranging from 9.2% in partial to 47.8% in radical mastectomy. General anesthesia was used in 90.0% of procedures. Overall, 3,493 patients (1.8%) experienced an unplanned readmission within 30 days. Readmission rates differed significantly by procedure type, with the lowest rate observed after partial mastectomy (1.4%), followed by total (2.8%) and radical mastectomy (3.3%,  $p < 0.001$ ). The overall postoperative complication rate was 3.3%, driven primarily by surgical site infections (superficial SSI 2.0%, deep SSI 0.3%, organ/space SSI 0.4%). Reoperation occurred in 1.4% of patients.

### 3.3 Temporal Trends

The annual volume of outpatient procedures increased markedly over the study period, from 2,746 cases in 2011 to 18,628 cases in 2022, representing an approximately seven-fold increase. Over the same period, the 30-day unplanned readmission rate declined from 2.8% in 2011 to approximately 1.6% in recent years (Figure 1). This downward trend was consistent across all procedure types, although radical mastectomy persistently demonstrated the highest readmission rates throughout the study period.

### **3.4 Risk Factors for Unplanned Readmission**

On univariable analysis, multiple preoperative and operative variables were significantly associated with unplanned readmission (Supplementary Table 1). The strongest associations were observed for congestive heart failure (OR 5.22, 95% CI 4.14–6.49), functional dependence (OR 4.87, 95% CI 4.07–5.78), dialysis dependence (OR 4.00, 95% CI 2.69–5.72), and bleeding disorder (OR 2.76, 95% CI 2.32–3.26). Multivariable logistic regression was performed in 154,210 patients with complete data. Fourteen of the 15 candidate predictors demonstrated independent associations with readmission, while Black race showed a borderline association (aOR 1.11, 95% CI 1.00–1.23,  $p=0.053$ ) (Table 3). The strongest independent predictors were functional dependence (aOR 3.03, 95% CI 2.49–3.65), congestive heart failure (aOR 2.77, 95% CI 2.16–3.50), dialysis (aOR 2.20, 95% CI 1.46–3.19), operative time >120 minutes (aOR 1.94, 95% CI 1.80–2.10), bleeding disorder (aOR 1.93, 95% CI 1.61–2.30), and ASA class  $\geq 3$  (aOR 1.80, 95% CI 1.67–1.95). Additional significant predictors included disseminated cancer (aOR 1.74), COPD (aOR 1.61), diabetes (aOR 1.32), steroid use (aOR 1.27), current smoking (aOR 1.15), general anesthesia (aOR 1.15), and obesity (aOR 1.12) (Table 3).

### **3.5 Nomogram Development and Validation**

A nomogram incorporating all 15 predictors was developed to estimate individualized 30-day readmission risk (Figure 2). The model demonstrated acceptable discrimination, with an AUC of 0.666 (95% CI 0.654–0.678) (Figure 3). Calibration analysis using 200 bootstrap resamples showed excellent agreement between predicted and observed probabilities, with a mean absolute error of 0.001 (Supplementary Figure 1).

### **3.6 Machine Learning Validation**

Machine learning models were applied to validate predictor selection and assess potential performance gains (Table S1). Using the same 15 predictors, LASSO regression achieved an AUC of 0.647 (95% CI 0.632–0.662), logistic regression 0.646 (95% CI 0.631–0.661), and XGBoost 0.638 (95% CI 0.623–0.653) (Figure 3; Table 4). Random forest performed poorly (AUC 0.546), likely reflecting class imbalance due to the low event rate. DeLong testing demonstrated no clinically meaningful improvement over logistic regression (LR vs LASSO  $p=0.041$ ; LR vs XGBoost  $p=0.507$ ). Variable importance analyses were concordant across methods. LASSO prioritized functional dependence, dialysis, bleeding disorder, congestive heart failure, and COPD (Supplementary Table 3), whereas XGBoost emphasized age, ASA class  $\geq 3$ , and operative time, reflecting non-linear effects. Exploratory LASSO analysis of 26 candidate variables identified preoperative ventilator dependence (OR 10.9,  $p=0.019$ ) and ascites (OR 8.5,  $p=0.0005$ ) as additional predictors. However, both were exceedingly rare (<0.05%) and clinically incompatible with outpatient mastectomy. The expanded model yielded a statistically significant but clinically marginal AUC increase to 0.659 ( $\Delta$ AUC 0.012,  $p<0.001$ ).

### **3.7 Interaction Analysis**

Interaction analyses demonstrated that the effect of selected risk factors varied by procedure type (Supplementary Figure 2, Supplementary Table 2). The strongest interaction was observed for chronic steroid use ( $p=0.001$ , strong magnitude): steroid use doubled readmission risk following partial

mastectomy (1.6% to 3.2%) and substantially increased risk after radical mastectomy (3.7% to 5.1%), but had no effect after total mastectomy (3.8% vs 3.8%). Metastatic cancer also exhibited a significant interaction ( $p=0.015$ , moderate magnitude), with the largest relative effect in partial mastectomy patients (readmission 1.6% to 4.0%). Additional statistically significant but weaker interactions were observed for operative time  $>120$  minutes ( $p<0.001$ ), obesity ( $p=0.016$ ), and ASA class  $\geq 3$  ( $p=0.030$ ). Stratified multivariable analyses confirmed procedure-specific effects (Table 3). Dialysis was an independent predictor following partial mastectomy (aOR 2.66, 95% CI 1.55–4.28) but not after total or radical mastectomy. In contrast, COPD was consistently associated with readmission across all procedure types, with the strongest effect observed in radical mastectomy (aOR 1.93, 95% CI 1.36–2.68).

## 4. DISCUSSION

In this big data real-world analysis, we demonstrate that same-day discharge after outpatient breast cancer surgery is associated with a low overall rate of 30-day unplanned readmission. However, this aggregate safety signal masks important heterogeneity across procedure types, patient characteristics, and perioperative factors. In the present study, the 30-day readmission rate was 1.8%, and the 30-day reoperation rate was 1.4%. These findings are consistent with previously published data, which report 30-day readmission rates of 3.1%–3.3% among patients undergoing outpatient total mastectomy and 7-day reoperation rates of approximately 1.6%.<sup>25,40,41</sup> In studies not limited to outpatient procedures, reported 30-day readmission rates range from 1.7% to 2.2% for partial mastectomy and from 4.9% to 5.6% for total mastectomy.<sup>19,20,27,42</sup> Collectively, these data suggest that outpatient breast surgery has not been restricted to a narrowly selected low-risk patient population; rather, the outpatient setting appears to have been applied broadly to patients with an indication for surgery, without an associated increase in short-term adverse outcomes.

Importantly, the low readmission rate observed in this cohort should be interpreted within the context of patient selection inherent to outpatient surgical practice. Patients deemed suitable for same-day discharge likely represent a lower-risk subset of all patients undergoing breast cancer surgery, as surgeons and anesthesiologists apply clinical judgment to exclude patients with significant comorbidities or anticipated postoperative needs from outpatient pathways. The absence of an inpatient comparator cohort in this study precludes definitive conclusions about the safety of outpatient management relative to inpatient care. Rather, our findings characterize the risk profile and readmission patterns among patients already selected for outpatient surgery, providing a pragmatic framework for identifying those within this population who may benefit from enhanced postoperative surveillance or transitional care protocols.

### Procedure-Specific Risk Profiles and Implications for Patient Selection

Although the overall readmission rate was low (1.82%), we observed a stepwise increase in readmission risk with increasing procedural extent, from partial to total to radical mastectomy. This gradient may suggest that operative complexity and surgical burden remain central determinants of postoperative

vulnerability, even more so within an outpatient framework.<sup>25,40</sup> Radical mastectomy patients exhibited not only the highest readmission rates but also a greater prevalence of high-risk clinical features, including advanced disease, higher ASA class, smoking, and steroid use. These findings underscore that outpatient feasibility is not solely a function of discharge timing but is intimately linked to the extent of the procedure and the patient comorbidities. Importantly, the observed differences in readmission risk across mastectomy types argue against a uniform outpatient strategy. Instead, procedure-specific pathways that account for expected surgical stress, recovery trajectory, and complication profiles may be more appropriate.<sup>10,43</sup> For example, partial mastectomy appears highly amenable to same-day discharge across a broad patient population, the presence of additive risk factors, such as a radical mastectomy in a patient with significant comorbidities, may define a clinical threshold where outpatient surgery is no longer advisable. This would necessitate planned inpatient observation to mitigate readmission risk.

### **Frailty and Cardiovascular Reserve as Dominant Drivers of Readmission**

Among all evaluated predictors, functional dependence and congestive heart failure emerged as the most powerful independent risk factors for unplanned readmission. These findings indicate that global physiologic reserve and frailty, rather than demographic or disease-specific variables, appear to be the principal drivers of early postoperative instability in the outpatient setting.<sup>44–46</sup> Functional dependence likely reflects a convergence of impaired mobility, reduced self-care capacity, and limited physiologic adaptability, all of which may compromise recovery after early discharge. Similarly, congestive heart failure represents a marker of diminished cardiovascular reserve and vulnerability to perioperative fluid shifts, anesthesia-related stress, and postoperative decompensation.<sup>47,48</sup> The strong and consistent association between cardiac comorbidity and readmission underscores the importance of careful cardiovascular assessment and optimization when considering outpatient surgery. Together, these results align with a growing body of surgical outcomes literature highlighting frailty and cardiopulmonary function as key determinants of short-term postoperative outcomes across surgical disciplines.<sup>27,44,45</sup> While several of these predictors – including functional dependence, congestive heart failure, and dialysis dependence – are well-established risk factors across general surgical populations, their quantification in the specific context of outpatient mastectomy is clinically relevant, as outpatient pathways rely heavily on accurate preoperative risk stratification to guide discharge planning. Furthermore, the identification of operative time and procedure type as independent predictors highlights surgical complexity as a potentially modifiable target for reducing readmission risk through optimized case selection and operative efficiency in ambulatory surgery centers.

### **Temporal Improvements Reflect Maturation of Outpatient Pathways**

One of the most striking findings of this study was the substantial decline in readmission rates over time, from 2.8% in 2011 to approximately 1.6% in recent years, with a concurrent nearly seven-fold increase in outpatient procedure volume. This temporal trend strongly suggests that improvements in perioperative care have successfully expanded the safety margin of same-day discharge. Several factors likely

contribute to this evolution, including advances in anesthesia techniques, multimodal analgesia, minimally invasive surgical approaches, standardized enhanced recovery protocols, and improved patient education and discharge planning.<sup>10,49–51</sup> Growing institutional experience with outpatient breast surgery may have also refined patient selection and post-discharge support structures.<sup>9,11</sup> These data provide reassurance that outpatient breast surgery can be performed safely when embedded within well-developed perioperative systems.

### **Predictive Modeling and the Role of Machine Learning**

From a methodological standpoint, our study demonstrates that current advanced machine learning approaches do not meaningfully outperform traditional logistic regression in predicting unplanned readmission after outpatient mastectomy.<sup>52</sup> Although machine learning models such as LASSO and XGBoost may capture complex relationships and non-linear effects, their discriminatory performance was comparable to that of standard regression, and random forest models performed poorly due to class imbalance. These findings have important translational implications. In clinical settings, interpretability, transparency, and ease of implementation are critical for adoption.<sup>52–54</sup> The logistic regression-based nomogram offers these advantages without sacrificing predictive accuracy, making it a more practical tool for preoperative risk stratification. Our results support the principle that model complexity alone does not guarantee superior clinical utility, particularly when outcome events are rare, and predictors are largely clinical in nature.<sup>52,55</sup> Future improvements in predictive performance may depend on shifting toward more granular data sources, such as utilizing natural language processing to analyze unstructured clinical notes or incorporating real-time physiological data from post-discharge wearable technology.

### **Heterogeneous Effects of Risk Factors Across Breast Surgery Types**

A novel contribution of this study is the demonstration that the impact of certain risk factors varies substantially by type of procedure. Chronic steroid use, for example, markedly increased readmission risk after partial and radical mastectomy but had no discernible effect following total mastectomy. Similarly, metastatic cancer exerted its strongest relative effect in less extensive procedures. At first glance, these patterns appear clinically counterintuitive, as the biological effects of systemic factors including chronic steroid exposure would be expected to influence outcomes across procedure types. Several explanations may account for this finding. Differences in baseline procedural risk may attenuate the relative contribution of individual comorbidities in more extensive operations, whereas in lower-risk procedures smaller absolute effects may translate into larger relative risk estimates. In addition, procedure-specific patient selection and unmeasured confounding, such as differences in oncologic stage, perioperative management, or steroid indication, may contribute to these patterns. Consequently, these results should be interpreted cautiously. Nonetheless, the observed heterogeneity underscores the possibility that the relative importance of patient-level risk factors may vary across surgical contexts and highlights limitations of uniform “one-size-fits-all” risk models for breast surgery.<sup>20</sup>

## Clinical Implications and Future Directions

Taken together, our findings have important implications for clinical practice and health system planning. Outpatient breast cancer surgery is broadly safe, but optimal outcomes depend on careful patient selection, particularly with respect to functional status and cardiovascular health.<sup>9,10,12,14,25</sup> Procedure type should be explicitly considered when determining suitability for same-day discharge. For high-risk patients, specifically those presenting with multiple risk factors, such as a radical mastectomy in a medically complex patient, planned inpatient admission or overnight observation should be recommended as the clinical standard rather than the exception.<sup>25</sup> In instances where outpatient surgery is pursued for these individuals, enhanced postoperative surveillance should be performed at minimum. From a system perspective, reducing unplanned readmissions is central to value-based care.<sup>15,16,56</sup> By identifying modifiable and non-modifiable risk factors, this study provides a foundation for targeted interventions aimed at preserving the benefits of outpatient surgery while minimizing downstream utilization. The proposed nomogram offers a pragmatic tool to support shared decision-making and individualized care planning.

Future studies should focus on prospective validation of the proposed risk model and explore integration with additional clinical, oncologic, and social determinants of health not captured in NSQIP. Incorporating patient-reported outcomes, pain trajectories, and post-discharge support mechanisms may further refine risk prediction and enhance patient-centered care. Ultimately, such efforts are essential to ensuring that the continued expansion of outpatient breast surgery remains both safe and sustainable.

## 5. LIMITATIONS

This study is subject to several limitations. First, its retrospective observational design precludes causal inference, and residual confounding may persist despite extensive multivariable adjustment, interaction analyses, and machine learning validation.<sup>57</sup> Although NSQIP uses standardized data collection, the analysis remains dependent on administrative coding accuracy, introducing potential misclassification of diagnoses, procedures, and outcomes.<sup>58</sup> Second, NSQIP captures outcomes only within a 30-day postoperative period. Consequently, late complications, delayed readmissions, and longer-term outcomes relevant to breast cancer surgery could not be assessed.<sup>59</sup> Moreover, the database does not provide information on the timing, cause, or preventability of readmissions, limiting mechanistic interpretation. Readmission as a quality metric is further influenced by institutional admission thresholds, geographic access to emergency care, patient health literacy, and social support systems, none of which are captured in NSQIP. It is also possible that some patients presented to non-index hospitals, leading to potential underascertainment of readmission events. Third, several clinically important variables are not available in NSQIP, including indication for steroid use, tumor stage and biology, neoadjuvant or adjuvant therapies, pain management strategies, drain management, social support, and socioeconomic factors.<sup>60</sup> These unmeasured factors may have influenced readmission risk and likely contributed to the modest discriminatory performance of the prediction model. Furthermore,

while predictive models were internally validated with a large number of patients, external validation is required for proof-of-concept. Finally, outpatient designation reflects institutional reporting and does not capture variability in perioperative pathways, discharge criteria, post-discharge support, surgeon experience, or hospital-level characteristics, which may confound outcomes.<sup>61</sup> Additionally, while the large sample size increases statistical power, it also raises the possibility that small effect sizes reached statistical significance without clear clinical relevance.<sup>62</sup>

## 6. CONCLUSIONS

In this multi-institutional data analysis of outpatient breast cancer surgery, same-day discharge was associated with a low overall rate of 30-day unplanned readmission, supporting its safety in appropriately selected patients. However, readmission risk varied substantially by procedure type, patient functional status, and comorbidity burden, underscoring that outpatient breast surgery is not uniformly low risk. Frailty and cardiovascular disease, particularly functional dependence and congestive heart failure, emerged as the strongest predictors of readmission, outweighing cancer-specific factors and emphasizing the importance of physiologic reserve in the outpatient setting. Notably, readmission rates declined markedly over time despite rapid expansion of outpatient mastectomy. Advanced machine learning approaches did not meaningfully outperform traditional regression, highlighting the clinical value of transparent, interpretable risk models. Based on these findings, we recommend that outpatient breast cancer surgery be primarily reserved for patients with low-risk clinical profiles, defined by low procedural complexity and an absence of significant systemic comorbidities. Our results support a highly selective approach to same-day discharge that explicitly integrates functional assessment, comorbidity burden, and operative complexity into preoperative decision-making. Procedure-specific pathways tailored to expected surgical stress and recovery trajectories are more appropriate for individualized care. To this end, the proposed predictive model provides a pragmatic tool to facilitate individualized risk stratification, patient counseling, and targeted perioperative planning. Future prospective studies incorporating oncologic, social, and patient-reported factors are needed to further refine outpatient pathways and ensure their continued safety and sustainability.

## Declarations

### Synopsis

This study of 191,559 outpatient breast cancer surgery patients from ACS-NSQIP (2011–2023) identifies 15 predictors of 30-day unplanned readmission and presents a validated nomogram, demonstrating that machine learning models do not outperform conventional logistic regression.

### Conflicts of Interest:

Sarah Bishop - Integra Round Table \$1770 Sept 2024 one time; MMI Speaker \$1300 one time Sept 2024; BG Course one time May 2025 \$7500

## Competing Interests

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Artificial intelligence tools (Claude, Anthropic) were used to assist with statistical code generation and manuscript formatting. All outputs were critically reviewed and verified by the authors, who bear full responsibility for the content.

## Author Contribution

S.A.K. and R.D. conceived and designed the study. S.A.K. and J.M.W. acquired and curated the data, performed the statistical analysis, developed and validated the nomogram and machine learning models, and interpreted the results. S.A.K. and J.M.W. wrote the main manuscript text and prepared Figures 1–3 and Tables 1–4. G.M., E.A.K., C.E., C.T., and M.H. contributed to clinical interpretation and methodological guidance. V.K., D.P., A.F., S.R., P.M., H.K., J.J., F.A.G.P. contributed to data interpretation and critical revision of the manuscript for important intellectual content. F.A.G.P., S.N.B and R.D. supervised the project. All authors reviewed the manuscript.

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## Data Availability

The data that support the findings of this study were obtained from the American College of Surgeons National Surgical Quality Improvement Program (ACS-NSQIP) under an institutional Data Use Agreement. Restrictions apply to the availability of these data, which are proprietary to the American College of Surgeons and were used under licence for the current study; they are therefore not publicly available. De-identified ACS-NSQIP Participant Use Data Files can be obtained by investigators at participating institutions through the American College of Surgeons upon execution of a Data Use

Agreement (<https://www.facs.org/quality-programs/data-and-registries/acs-nsqip/>). The aggregated data underlying the results presented here are available from the corresponding author upon reasonable request.

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Tables

**TABLE 1.** Patient demographics and comorbidities stratified by mastectomy type. Values are mean ± SD or n (%).

| Variable                                     | Overall<br>N =<br>191,559 | Partial<br>N =<br>136,437 | Total<br>N =<br>40,021 | Radical<br>N = 15,101 | P-<br>value |
|----------------------------------------------|---------------------------|---------------------------|------------------------|-----------------------|-------------|
| <b>Demographics</b>                          |                           |                           |                        |                       |             |
| Age (years), mean $\pm$ SD                   | 63.1 $\pm$ 12.2           | 63.4 $\pm$ 11.8           | 62.6 $\pm$ 13.1        | 61.5 $\pm$ 13.5       | <0.001      |
| BMI (kg/m <sup>2</sup> ), mean $\pm$ SD      | 29.7 $\pm$ 7.6            | 29.8 $\pm$ 7.6            | 29.1 $\pm$ 7.5         | 29.8 $\pm$ 7.6        | <0.001      |
| <b>Race, n (%)</b>                           |                           |                           |                        |                       |             |
| └ White                                      | 136,679<br>(71.4)         | 97,447<br>(71.4)          | 28,733<br>(71.8)       | 10,499<br>(69.5)      |             |
| └ Black                                      | 21,019<br>(11.0)          | 14,660<br>(10.7)          | 4,381<br>(10.9)        | 1,978<br>(13.1)       |             |
| └ Asian                                      | 10,021 (5.2)              | 6,275 (4.6)               | 2,947 (7.4)            | 799 (5.3)             |             |
| └ Other / Unknown                            | 23,840<br>(12.4)          | 18,055<br>(13.2)          | 3,960 (9.9)            | 1,825<br>(12.1)       | <0.001      |
| <b>Preoperative Comorbidities,<br/>n (%)</b> |                           |                           |                        |                       |             |
| Obesity (BMI $\geq$ 30 kg/m <sup>2</sup> )   | 80,900<br>(42.2)          | 58,754<br>(43.1)          | 15,640<br>(39.1)       | 6,506<br>(43.1)       | <0.001      |
| Diabetes                                     | 29,207<br>(15.2)          | 20,241<br>(14.8)          | 6,338<br>(15.8)        | 2,628<br>(17.4)       | <0.001      |
| Current smoker                               | 17,185 (9.0)              | 11,696 (8.6)              | 3,553 (8.9)            | 1,936<br>(12.8)       | <0.001      |
| Ventilator dependence                        | 12 (<0.1)                 | 6 (<0.1)                  | 3 (<0.1)               | 3 (<0.1)              | 0.068       |
| COPD                                         | 5,232 (2.7)               | 3,548 (2.6)               | 1,165 (2.9)            | 519 (3.4)             | <0.001      |
| Ascites                                      | 36 (<0.1)                 | 22 (<0.1)                 | 9 (<0.1)               | 5 (<0.1)              | 0.293       |
| Congestive heart failure                     | 795 (0.4)                 | 531 (0.4)                 | 173 (0.4)              | 91 (0.6)              | <0.001      |
| Hypertension                                 | 75,058<br>(39.2)          | 53,974<br>(39.6)          | 14,557<br>(36.4)       | 6,527<br>(43.2)       | <0.001      |
| Renal failure                                | 31 (<0.1)                 | 16 (<0.1)                 | 9 (<0.1)               | 6 (<0.1)              | 0.020       |
| Dialysis                                     | 357 (0.2)                 | 221 (0.2)                 | 92 (0.2)               | 44 (0.3)              | <0.001      |
| Chronic steroid use                          | 3,954 (2.1)               | 2,592 (1.9)               | 859 (2.1)              | 503 (3.3)             | <0.001      |
| Bleeding disorder                            | 2,502 (1.3)               | 1,734 (1.3)               | 505 (1.3)              | 263 (1.7)             | <0.001      |
| Preoperative transfusion                     | 37 (<0.1)                 | 14 (<0.1)                 | 10 (<0.1)              | 13 (<0.1)             | <0.001      |
| History of sepsis                            | 361 (0.2)                 | 207 (0.2)                 | 89 (0.2)               | 65 (0.4)              | <0.001      |

|                                 |                   |                   |                  |                  |        |
|---------------------------------|-------------------|-------------------|------------------|------------------|--------|
| Disseminated cancer             | 2,434 (1.3)       | 1,205 (0.9)       | 586 (1.5)        | 643 (4.3)        | <0.001 |
| <b>Cancer Type, n (%)</b>       |                   |                   |                  |                  | <0.001 |
| └ Malignant                     | 151,552<br>(79.1) | 105,027<br>(77.0) | 32,454<br>(81.1) | 14,071<br>(93.2) |        |
| └ In situ                       | 40,007<br>(20.9)  | 31,410<br>(23.0)  | 7,567<br>(18.9)  | 1,030 (6.8)      |        |
| <b>ASA Class, n (%)</b>         |                   |                   |                  |                  |        |
| └ ASA I                         | 6,794 (3.5)       | 5,484 (4.0)       | 990 (2.5)        | 320 (2.1)        |        |
| └ ASA II                        | 100,688<br>(52.6) | 74,632<br>(54.7)  | 19,414<br>(48.5) | 6,642<br>(44.0)  |        |
| └ ASA III                       | 80,715<br>(42.1)  | 54,154<br>(39.7)  | 18,827<br>(47.0) | 7,734<br>(51.2)  |        |
| └ ASA ≥ IV                      | 3,177 (1.7)       | 2,012 (1.5)       | 772 (1.9)        | 393 (2.6)        | <0.001 |
| <b>Functional Status, n (%)</b> |                   |                   |                  |                  |        |
| └ Independent                   | 187,894<br>(98.1) | 134,066<br>(98.3) | 39,129<br>(97.8) | 14,699<br>(97.3) |        |
| └ Partially dependent           | 1,588 (0.8)       | 874 (0.6)         | 477 (1.2)        | 237 (1.6)        |        |
| └ Totally dependent             | 200 (0.1)         | 98 (<0.1)         | 57 (0.1)         | 45 (0.3)         | <0.001 |

**TABLE 2.** Surgical characteristics and postoperative outcomes stratified by mastectomy type. Values are mean ± SD or n (%). P-value: Chi-square/Fisher's exact for categorical; ANOVA for continuous. Abbreviations: SSI, surgical site infection; DVT, deep vein thrombosis; CPR, cardiopulmonary resuscitation

| Variable                             | Overall<br>N = 191,559 | Partial<br>N = 136,437 | Total<br>N = 40,021 | Radical<br>N = 15,101 | P-<br>value |
|--------------------------------------|------------------------|------------------------|---------------------|-----------------------|-------------|
| <b>Surgical Characteristics</b>      |                        |                        |                     |                       |             |
| Operative time (min), mean $\pm$ SD  | 86.6 $\pm$ 57.0        | 69.9 $\pm$ 40.5        | 126.9 $\pm$ 71.1    | 130.2 $\pm$ 65.3      | <0.001      |
| Operative time >120 min              | 36,987 (19.3)          | 12,490 (9.2)           | 17,284 (43.2)       | 7,213 (47.8)          | <0.001      |
| General anesthesia                   | 172,489 (90.0)         | 117,858 (86.4)         | 39,599 (98.9)       | 15,032 (99.5)         | <0.001      |
| Laterality, n (%)                    |                        |                        |                     |                       | <0.001      |
| └ Unilateral                         | 180,307 (94.1)         | 134,752 (98.8)         | 33,672 (84.1)       | 11,883 (78.7)         |             |
| └ Bilateral                          | 11,251 (5.9)           | 1,685 (1.2)            | 6,349 (15.9)        | 3,218 (21.3)          |             |
| <b>Postoperative Outcomes, n (%)</b> |                        |                        |                     |                       |             |
| Any complication                     | 6,259 (3.3)            | 3,450 (2.5)            | 1,980 (4.9)         | 829 (5.5)             | <0.001      |
| Any readmission                      | 4,168 (2.2)            | 2,548 (1.9)            | 1,087 (2.7)         | 533 (3.5)             | <0.001      |
| Unplanned readmission                | 3,493 (1.8)            | 1,857 (1.4)            | 1,131 (2.8)         | 505 (3.3)             | <0.001      |
| Reoperation                          | 2,653 (1.4)            | 1,556 (1.1)            | 750 (1.9)           | 347 (2.3)             | <0.001      |
| <b>Surgical Complications, n (%)</b> |                        |                        |                     |                       |             |
| └ Superficial SSI                    | 3,748 (2.0)            | 2,114 (1.5)            | 1,137 (2.8)         | 497 (3.3)             | <0.001      |
| └ Deep SSI                           | 509 (0.3)              | 253 (0.2)              | 167 (0.4)           | 89 (0.6)              | <0.001      |
| └ Organ/space SSI                    | 724 (0.4)              | 323 (0.2)              | 305 (0.8)           | 96 (0.6)              | <0.001      |
| └ Wound dehiscence                   | 401 (0.2)              | 178 (0.1)              | 152 (0.4)           | 71 (0.5)              | <0.001      |
| <b>Medical Complications, n (%)</b>  |                        |                        |                     |                       |             |
| └ Pneumonia                          | 159 (<0.1)             | 96 (<0.1)              | 47 (0.1)            | 16 (0.1)              | 0.010       |
| └ Reintubation                       | 47 (<0.1)              | 19 (<0.1)              | 22 (<0.1)           | 6 (<0.1)              | <0.001      |
| └ Pulmonary embolism                 | 26 (<0.1)              | 9 (<0.1)               | 16 (<0.1)           | 1 (<0.1)              | <0.001      |
| └ Ventilator >48 h                   | 22 (<0.1)              | 9 (<0.1)               | 11 (<0.1)           | 2 (<0.1)              | 0.005       |
| └ Myocardial infarction              | 15 (<0.1)              | 10 (<0.1)              | 3 (<0.1)            | 2 (<0.1)              | 0.621       |

| Variable                       | Overall<br>N = 191,559 | Partial<br>N = 136,437 | Total<br>N = 40,021 | Radical<br>N = 15,101 | P-<br>value |
|--------------------------------|------------------------|------------------------|---------------------|-----------------------|-------------|
| ↳ Cardiac arrest requiring CPR | 9 (<0.1)               | 6 (<0.1)               | 3 (<0.1)            | 0 (0.0)               | 0.511       |
| ↳ Deep vein thrombosis         | 179 (<0.1)             | 80 (<0.1)              | 73 (0.2)            | 26 (0.2)              | <0.001      |
| ↳ Urinary tract infection      | 641 (0.3)              | 427 (0.3)              | 151 (0.4)           | 63 (0.4)              | 0.027       |
| ↳ Sepsis                       | 306 (0.2)              | 107 (<0.1)             | 139 (0.3)           | 60 (0.4)              | <0.001      |
| ↳ Septic shock                 | 47 (<0.1)              | 15 (<0.1)              | 23 (<0.1)           | 9 (<0.1)              | <0.001      |

**TABLE 3.** Multivariable logistic regression analysis overall and stratified by mastectomy type

|                                      | <b>Overall<br/>N = 154,210</b> | <b>Partial<br/>N = 112,014</b> | <b>Total<br/>N = 29,016</b> | <b>Radical<br/>N = 13,180</b> |
|--------------------------------------|--------------------------------|--------------------------------|-----------------------------|-------------------------------|
| <b>Variable</b>                      | <b>aOR (95% CI)</b>            | <b>aOR (95% CI)</b>            | <b>aOR (95% CI)</b>         | <b>aOR (95% CI)</b>           |
| Functional dependence                | 3.03* (2.49–3.65)              | 3.30* (2.46–4.33)              | 2.46* (1.73–3.41)           | 2.47* (1.59–3.69)             |
| Congestive heart failure             | 2.77* (2.16–3.50)              | 2.87* (2.05–3.93)              | 2.80* (1.76–4.29)           | 2.33* (1.23–4.15)             |
| Dialysis                             | 2.20* (1.46–3.19)              | 2.66* (1.55–4.28)              | 1.32 (0.54–2.75)            | 2.17 (0.73–5.22)              |
| Bleeding disorder                    | 1.93* (1.61–2.30)              | 2.02* (1.58–2.54)              | 1.96* (1.39–2.69)           | 1.54 (0.93–2.41)              |
| Disseminated cancer                  | 1.74* (1.42–2.10)              | 2.19* (1.61–2.91)              | 1.15 (0.76–1.66)            | 1.51* (1.05–2.12)             |
| COPD                                 | 1.61* (1.40–1.85)              | 1.56* (1.29–1.88)              | 1.49* (1.15–1.91)           | 1.93* (1.36–2.68)             |
| ASA class ≥ III                      | 1.80* (1.67–1.95)              | 1.84* (1.65–2.05)              | 1.63* (1.42–1.86)           | 1.55* (1.26–1.92)             |
| Operative time >120 min              | 1.94* (1.80–2.10)              | 1.37* (1.18–1.59)              | 1.68* (1.47–1.90)           | 1.22* (1.01–1.48)             |
| Chronic steroid use                  | 1.27* (1.06–1.50)              | 1.59* (1.25–1.98)              | 0.79 (0.54–1.12)            | 1.27 (0.82–1.88)              |
| Diabetes mellitus                    | 1.32* (1.21–1.44)              | 1.36* (1.20–1.53)              | 1.22* (1.04–1.43)           | 1.31* (1.05–1.64)             |
| Current smoker                       | 1.15* (1.04–1.27)              | 1.11 (0.96–1.29)               | 1.10 (0.92–1.31)            | 1.22 (0.95–1.56)              |
| Obesity (BMI ≥30 kg/m <sup>2</sup> ) | 1.12* (1.05–1.21)              | 1.05 (0.95–1.16)               | 1.30* (1.15–1.48)           | 1.40* (1.15–1.69)             |
| General anesthesia                   | 1.14* (1.00–1.31)              | 0.99 (0.86–1.14)               | -                           | -                             |
| Black race                           | 1.11 (1.00–1.23)               | 1.07 (0.92–1.23)               | 1.20* (1.00–1.43)           | 1.18 (0.91–1.51)              |
| Age (per year increase)              | 1.00* (1.00–1.01)              | 1.01* (1.00–1.01)              | 1.00 (1.00–1.01)            | 1.01 (1.00–1.01)              |

\*p<0.05. Multivariable analysis restricted to patients with complete data on all 15 covariates (N=154,210; 80.5% of total cohort). Missing data were primarily due to incomplete recording of body mass index and laboratory values. Stratified estimates for general anesthesia not reported for total and radical mastectomy due to insufficient variation (>98% general anesthesia use).

**TABLE 4.** Model discrimination performance using 15 preselected clinical predictors. Machine learning models were compared with traditional logistic regression–based approaches for prediction of 30-day readmission using 15 preselected clinical predictors. \*Random Forest performed poorly due to class imbalance (1.81% event rate)

| Model                | Test AUC | 95% Confidence Interval | Model Type       |
|----------------------|----------|-------------------------|------------------|
| Nomogram (full data) | 0.666    | 0.654–0.678             | Traditional      |
| Logistic regression  | 0.646    | 0.631–0.661             | Traditional      |
| LASSO regression     | 0.647    | 0.632–0.662             | Machine learning |
| XGBoost              | 0.638    | 0.623–0.653             | Machine learning |
| Random forest*       | 0.546    | 0.531–0.561             | Machine learning |

Figures

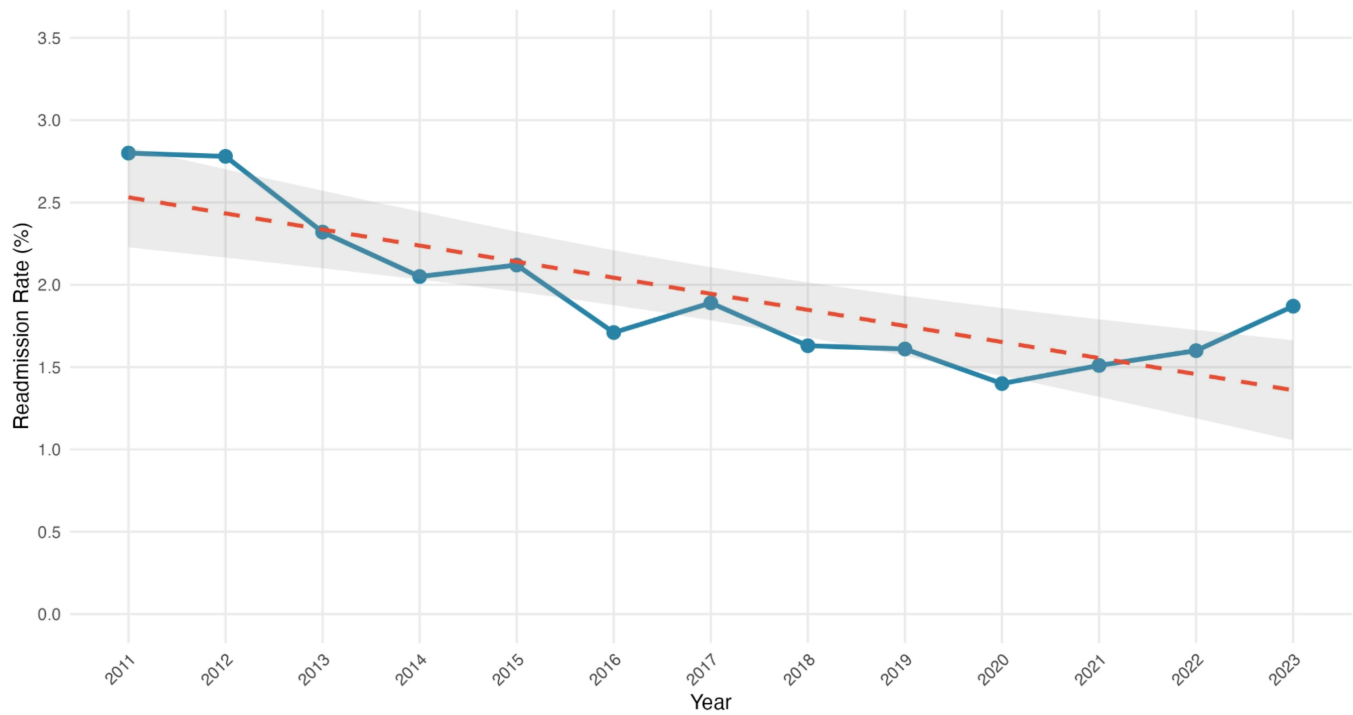


Figure 1

Temporal trend in 30-day unplanned readmission rate after outpatient mastectomy (2011–2023). Dashed line indicates linear trend.

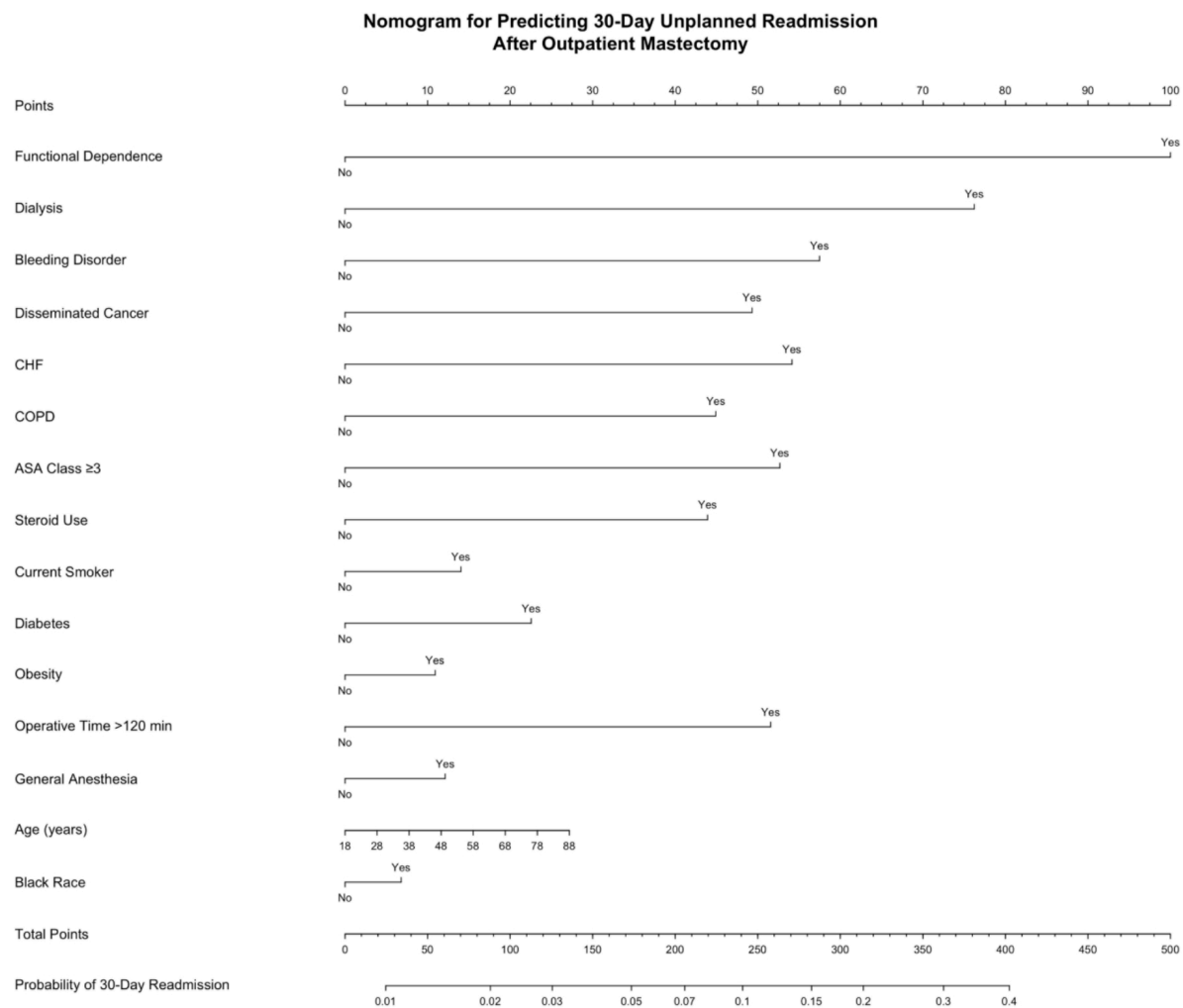


**Figure 2**

Nomogram for predicting 30-day unplanned readmission after outpatient mastectomy.

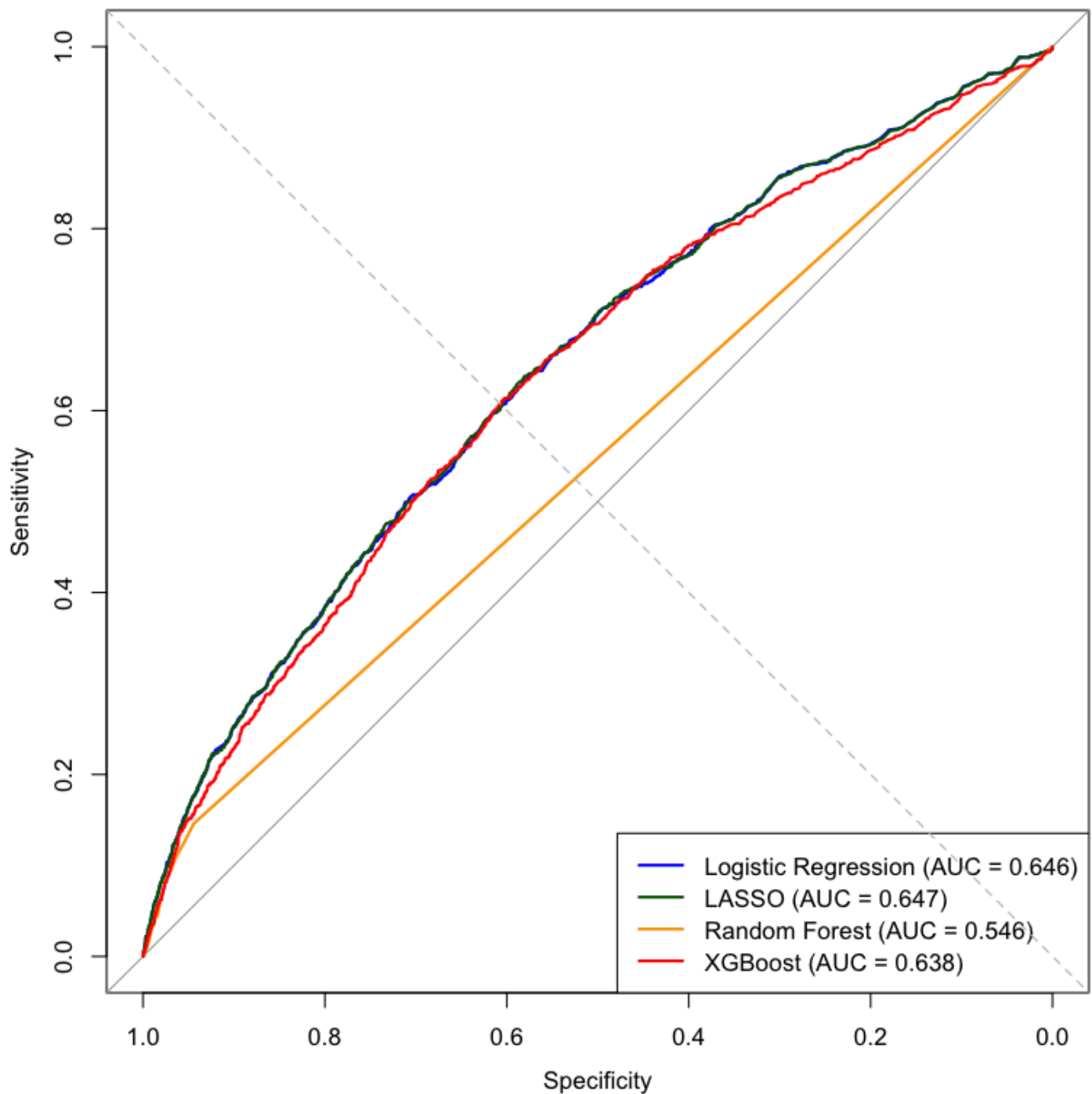


**Figure 3**

Comparison of receiver operating characteristic (ROC) curves for machine learning models versus logistic regression. Receiver operating characteristic (ROC) curve comparison of machine learning models versus logistic regression. AUCs: Logistic Regression 0.646, LASSO 0.647, XGBoost 0.638, Random Forest 0.546.

## Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [Supplementarymaterial.docx](#)