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Original Research

Can Machine Learning Identify Patients Who are Appropriate for Outpatient Open Reduction and Internal Fixation of Distal Radius Fractures?

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A R T I C L E I N F O

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Purpose: This study aimed to identify which patients were "unsafe" for outpatient surgery patients and determine the most predictive demographic and clinical factors contributing to postoperative risk following open reduction internal fixation for distal radius fractures.
Methods: Adult patients (aged ≥18 years) who presented with distal radius fracture and underwent open reduction internal fixation were identified using the American College of Surgeons National Surgical Quality Improvement Program database for years 2016 to 2021. Patients who were deemed "unsafe" therefore contraindicated for outpatient open reduction internal fixation of distal radius fracture if they required admission (length of stay of one or more days) or experienced any complication or required readmission within 7 days of the index operation. The model with optimal performance was determined according to area under the curve on the receiver operating characteristic curve and overall accuracy. Additional model metrics were also evaluated, and predictive factors (ie, features) that were most important to model derivation were identified.
Results: A total of 2,020 eligible patients underwent open reduction and internal fixation for distal radius fractures. The majority (78.6%) were women, with a mean age of 57.5 ± 16.0 years. Of these patients, 21.5% experienced short-term adverse events. Gradient boosting was the optimal model for predicting patients who were "unsafe" for outpatient surgery, with key features including International Classification of Diseases, 10th Revision code, preoperative white blood cell count, age, body mass index, and Hispanic ethnicity.
Conclusions: Using machine learning techniques, a predictive model was developed, which demonstrated good discrimination and excellent performance in predicting which patients were "unsafe" for outpatient operative fixation of distal radius fracture. Findings of this study highlight the predictive value of artificial intelligence and machine learning for the purposes of preoperative risk stratification as well as its potential to better inform shared decision making and guide personalized fracture care.
Level of evidence/type of study: Prognostic IV.

Distal radius fractures (DRFs) are one of the most common orthopedic injuries, accounting for approximately 17.5% of all fractures and occurring most often in older adults via low-energy mechanisms.[1] Although extra-articular and minimally displaced injuries may be managed with closed reduction and immobilization, surgical intervention with open reduction and internal fixation (ORIF) is often required to effectively address more unstable or displaced fractures. In addition to mode of treatment,[2] numerous factors influence patient outcomes following surgical management of DRFs, including patient characteristics such as age,[3] sex,[4] comorbidities,[5] and fracture complexity.[6] Moreover, patients with multiple comorbidities may be more susceptible to delayed

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recovery, leading to prolonged hospitalizations and a greater risk of complication.[7–9] A recent study by Schick et al[10] Determined that congestive heart failure (CHF), hypertension (HTN), American Society of Anesthesiologist (ASA) class ≥3, and dependent functional status were each independent risk factors for complication within 30 days of DRF surgery, with complication rates measuring 1% and 10% following outpatient and inpatient surgery, respectively. As the United States population ages and the incidence of DRFs rises accordingly, it is crucial to identify patients at higher risk for complications and develop tailored treatment strategies aiming to optimize outcomes following surgical treatment.

In recent years, a growing emphasis on establishing value-based care models and improving clinical efficiency has heralded a transition toward greater utilization of outpatient surgery. Accurate risk stratification is therefore becoming increasingly important to determine appropriate patient selection, manage patient expectations, and guide clinical decision making. Methods for predicting postoperative risk have traditionally relied on inferential statistical models that are best suited for generalization across populations rather than for application to individual patient cases. In response to some of these limitations, the field of machine learning (ML) has emerged as a promising avenue for improving predictive accuracy and clinical utility.[11] Machine learning constitutes a branch of artificial intelligence that enhances its performance through experience, rather than relying solely on explicitly programmed instructions by humans. The realm of ML encompasses a wide spectrum of techniques, including highly intricate mathematical algorithms. These algorithms are trained using external data to perform tasks such as forecasting the risk of postoperative readmission based on baseline radiographs. Subsequently, these trained algorithms undergo testing against supplementary "test" data sets to assess their broader applicability. Recent studies have leveraged these more advanced ML algorithms to identify factors influencing outcomes following a variety of orthopedic conditions, including DRFs. Bluthgen et al[12] developed an ML algorithm that detected and localized wrist fractures with performance comparable with radiologists, whereas another model produced by Liu et al[13] was used to design effective DRF hand therapy programs based on fracture healing stage. However, prior previous studies have not leveraged ML techniques to identify patients at risk for adverse events following surgical management of DRF. Surgeons rather rely on a combination of clinical judgment and traditional risk stratification assessments (eg, ASA class and comorbidity indices) to guide decisions about the suitability of patients for outpatient surgery. Application of ML predictive analytics, encompassing predictive risk models ranging from regression-based approaches to sophisticated artificial intelligence-based network models, could provide valuable insights into distinguishing appropriate outpatient surgical candidates from those at greater risk of adverse events in the early postoperative period.

The purpose of this study was to develop and compare risk prediction models aiming (1) to identify patients at risk for short-term adverse events including overnight admission, early complication, or early readmission, and therefore likely to benefit from a short inpatient admission following surgery and (2) to determine the most predictive demographic and clinical factors contributing to postoperative risk following ORIF for DRF.

Methods

Study design and patient population

This retrospective cohort study used the American College of Surgeons National Surgical Quality Improvement Program (ACS-NSQIP) database. The American College of Surgeons National Surgical Quality Improvement Program was selected as the primary data source for this study because of its comprehensive nature and inclusion of data from various types of medical centers. Because all data in the ACS-NSQIP database are deidentified and publicly available, this study was considered exempt from formal institutional review board review. The design and reporting of this study followed the Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis guidelines and the Journal of Medical Internet Research Guidelines for Developing and Reporting Machine Learning Predictive Models in Biomedical Research.[14,15] These guidelines were followed to ensure transparency and quality in the design, analysis, and reporting of the study's findings.

Adult patients (aged ≥18 years) who presented with DRFs and underwent ORIF between 2016 and 2021 were identified using current procedural terminology codes for open treatment of distal radial extra-articular fracture or epiphyseal separation, with internal fixation (25607); open treatment of distal radial intra-articular fracture or epiphyseal separation, with internal fixation of two fragments (25608); and open treatment of distal radial intra-articular fracture or epiphyseal separation, with internal fixation of three or more fragments (25609). Surgery performed in cases of polytrauma or malignancy was excluded using current procedural terminology codes.[16]

Definition of groups

Patients who were deemed "unsafe" therefore contraindicated for outpatient open reduction internal fixation of distal radius fracture if they required admission (length of stay of one or more days) or experienced any complication or required readmission within 7 days of the index operation.[17]

Target outcome and candidate predictive features

Predictive models were developed with the aim of identifying patients more suitable for inpatient ORIF for DRF because of the risk of experiencing short-term adverse events including overnight admission, complication within 7 days of surgery, or readmission within 7 days of surgery. Specifically, complications included death, reoperation, respiratory complications (unplanned intubation, mechanical ventilation >48 hours), pneumonia, cardiac complications (cardiac arrest, myocardial infarction), renal complications (progressive renal insufficiency, acute renal failure), thromboembolic complications (deep vein thrombosis/thrombophlebitis, pulmonary embolism), deep wound complications (deep incisional surgical site infection, organ space infection, wound dehiscence), sepsis, superficial surgical site infection, and urinary tract infection. Model development included consideration of various factors potentially contributing to adverse event risk, including demographic (age, sex, body mass index [BMI], race, ethnicity, smoking status, and financial status) and clinical (International Classification of Diseases, 10th Revision [ICD-10], ASA class, diabetes mellitus, steroid use for chronic condition, severe chronic obstructive pulmonary disease [COPD], CHF, HTN requiring medication, functional status, bleeding disorders, past transfusion, wound class, preoperative sodium, blood urea nitrogen [BUN], creatinine, albumin, bilirubin, serum glutamic-oxaloacetic transaminase [SGOT], alkaline phosphatase, white blood cell count, hematocrit, platelets, partial thromboplastin time [PTT], prothrombin time, and international normalized ratio [INR]) variables. Surgical time and anesthesia type were also recorded.

Data Pre-processing

Variables with <20% missing data were imputed as categorical or continuous variables using the variable mode or variable mean strategies, respectively. Variables with >20% missing data were excluded from model development.

Statistical analyses, predictive modeling, and validation

Categorical variables were reported as frequencies and percentages, whereas continuous variables were presented as mean ± standard deviation (SD). Group differences for categorical variables were assessed using chi-square or Fischer exact tests depending on the variable count. For continuous variables, parametric data were analyzed using Student *t* tests, whereas nonparametric data were analyzed using Mann-Whitney U tests. Odds ratios and 95% confidence intervals (95% CI) were calculated for each binomial variable. All *P* values were two-tailed, and statistical significance was set at $P < .05$.

Machine learning predictive models were developed using Python version 3.8.5 (Python Software Foundation). Patients were first divided into training (70%) and testing (30%) cohorts. The training cohort was used to develop models predicting short-term adverse events using support vector machine (SVM), random forest, logistic regression, gradient boosting, and extreme gradient boosting methods. Models were subsequently applied to the testing cohort to validate their predictive efficacy.

To identify the optimal predictive model, the performance of each model was assessed using various metrics. The area under the curve (AUC) on the receiver operating curve (ROC) and model accuracy were used as primary evaluation measures. Additionally, several supplementary metrics including precision, recall, F1-score, and Brier score were employed. The F1-score, ranging from 0.0 to 1.0, was used as a measure of the harmonic mean of model precision and recall, providing a balanced assessment of the model's ability to correctly identify positive cases while minimizing false positives and false negatives. The Brier score represents an additional indicator of overall model performance, assigning a score of zero for perfect prediction and a score of one for the poorest prediction. By considering the squared differences between predicted probabilities and actual outcomes, the Brier score provides a comprehensive evaluation of the model's calibration and accuracy.

Table 1
Summary of Patient Demographic and Clinical Characteristics

Demographics	$n = 2{,}020$
	Count (%)
Sex (F)	1,587 (78.6 %)
Race (White)	1,392 (68.9%)
Age (y)	57.5 ± 16.0
BMI	27.7 ± 6.7
Diabetes (YES)	145 (7.2%)
Smoker (YES)	403 (20.0%)
Functionally Independent (YES)	1,956 (96.8%)
ASA Class (1—No Disturb)	279 (13.8%)
COPD (YES)	80 (4.0%)
CHF (YES)	8 (0.4%)
Hypertension on Medication (YES)	653 (32.3%)
Dialysis (YES)	4 (0.2%)
Steroid (YES)	48 (2.4%)
Bleeding Disorder (YES)	42 (2.1%)
Transfusion (YES)	4 (0.2%)
Preoperative Laboratories	Mean ± SD
Sodium	138.8 ± 3.1
BUN	15.8 ± 7.2
Creatinine	0.9 ± 0.5
Albumin	4 ± 0.5
Bilirubin	0.6 ± 0.9
SGOT	27.4 ± 25.9
Alkaline Phosphatase	84.6 ± 30.8
WBC	8.1 ± 3
Hematocrit	39.3 ± 4.4
Platelet Count	255.5 ± 74.5
PTT	29.1 ± 6.1
INR	1.1 ± 0.3

Results

A total of 2,020 eligible patients underwent ORIF for DRF during the study period. The majority of the patients were women, accounting for 78.6% of the total sample, and the mean age of the patients was 57.5 ± 16.0 years. Overall, 435 (21.5%) experienced a short-term adverse event, with 420 (20.8%) instances of overnight admission, 9 (0.5%) instances of complication within 7 days of surgery, and 21 (1.0%) instances of readmission within 7 days of surgery. Compared with those who underwent uncomplicated outpatient surgery, patients experiencing a short-term adverse event were significantly older (61.6 ± 17.1 years vs 56.4 ± 15.5 years, $P < .001$) and were more commonly women (82.8% vs 77.4%, $P = .016$). They also exhibited significantly higher rates of ASA class ≥3 (5.0% vs 1.4%, $P < .001$), HTN requiring medication (38.9% vs 30.5%, $P = .018$), bleeding disorder (3.7% vs 1.6%, $P < .001$), preoperative sepsis (3.2% vs 0.9%, $P < .001$), and a history of requiring a transfusion (0.7% vs 0.06%, $P < .001$). Furthermore, several preoperative laboratory values differed between patients who experienced short-term adverse events and those who did not. Patients experiencing short-term adverse events had lower preoperative levels of sodium (138.3 ± 3.4 vs 139.0 ± 3.0; $P = .002$), albumin (3.8 ± 0.6 vs 4.2 ± 0.5; $P < .001$), hematocrit (38.1 ± 4.9 vs 39.8 ± 4.1; $P < .001$), and platelets (241.4 ± 69.5 vs 261.7 ± 75.8; $P < .001$). However, average preoperative white blood cell counts were higher than among patients undergoing uncomplicated outpatient surgery (8.5 ± 2.9 vs 7.9 ± 3.0; $P = .003$). Surgical time was also found to be longer among patients who experienced short-term adverse events, with a mean duration of 73.1 ± 36.1 minutes compared with 68.1 ± 34.7 minutes ($P = .015$). A complete summary of demographic, clinical, and surgical characteristics for each group is provided in Tables 1 and 2.

Relative frequencies of included procedures significantly differed between patients who did and did not experience a short-term adverse event ($P < .001$). The incidence of short-term adverse events was highest among patients undergoing ORIF for intra-articular fracture with three fragments (34.9%), followed by ORIF for intra-articular fracture with two fragments (30.0%) and ORIF for extra-articular fracture (17.9%).

Model performance and feature importance

Area under the curve values ranged from 0.653 to 0.830, and Brier scores ranged from 0.176 to 0.205 among all algorithms developed. Measures of accuracy were between 0.795 and 0.824, precision values were between 0.532 and 0.750, recall values were between 0.230 and 0.356, and F1-scores were between 0.126 and 0.466 (Table 3). Gradient boosting was found to produce the optimal model for predicting short-term adverse events following ORIF for DRF, achieving an AUC of 0.830 (Fig. 1) and a Brier score of 0.176. Measures of accuracy (0.824), precision (0.674), recall (0.356), and F1-score (0.466) also indicated fair to food discrimination. The features determined by the model to be most important in contributing to short-term adverse event risk included ICD-10 code, preoperative white blood cell count, age, BMI, and ethnicity (Hispanic; Fig. 2).

Table 2
Summary of Patient Demographic and Clinical Characteristics Stratified by Those Deemed Unsuitable for Outpatient Versus Those Suitable for Outpatient Surgery

	Unsafe for Outpatient Surgery ($n = 435$)	Safe for Outpatient Surgery ($n = 1,585$)	*P* Value	95% CI		
				Odds Ratio	Lower Limit	Upper Limit
Sex (F)	360	1,227	.016*	0.714	0.542	0.94
Race (White)	226	1,166	.724	0.919	0.573	1.472
Diabetes (YES)	38	107	.155	1.322	0.898	1.946
Smoker (YES)	90	313	.663	1.06	0.815	1.379
Functionally independent (YES)	410	1,546	<.001*	0.414	0.247	0.692
Anesthesia (Yes)	405	1,422	.033*	1.547	1.032	2.319
ASA Class (>=3)	22	22	<.001*	3.785	2.075	6.901
COPD (YES)	33	47	<.001*	2.686	1.698	4.249
CHF (YES)†	3	5	.271	2.194	0.522	9.219
Hypertension on medication (YES)	169	484	.001*	1.445	1.159	1.802
Dialysis (YES)†	1	3	1	1.215	0.023	15.172
Steroid (YES)	13	35	.344	1.364	0.715	2.602
Bleeding disorder (YES)	16	26	.008*	2.29	1.217	4.308
Transfusion (YES)†	3	1	.033*	10.98	0.879	575.816
Preoperative sepsis (YES)	14	15	<.001*	3.481	1.667	7.268
Age (y)‡	61.6 ± 17.1	56.4 ± 15.5	<.001*			
BMI	28.0 ± 7.4	27.6 ± 6.6	.31			
Sodium‡	138.3 ± 3.4	139.0 ± 3.0	.002*			
BUN‡	16.4 ± 7.9	15.6 ± 6.9	.297			
Creatinine	0.8 ± 0.3	0.9 ± 0.6	.272			
Albumin‡	3.8 ± 0.6	4.2 ± 0.5	<.001*			
Bilirubin‡	0.8 ± 1.3	0.6 ± 0.6	.215			
SGOT	30.7± 38.3	25.9 ± 17.8	.056			
Alkaline phosphatase	87.6 ± 35.9	83.2 ± 28.2	.14			
WBC	8.5 ± 2.9	7.9 ± 3.0	.003*			
Hematocrit‡	38.1 ± 4.9	39.8 ± 4.1	<.001*			
Platelet count‡	241.4 ± 69.5	261.7 ± 75.8	<.001*			
INR	29.5 ± 6.5	28.78 ± 5.7	.321			
PTT	1.01 ± 0.2	1.1 ± 0.3	.464			
Operative time‡	73.1 ± 36.1	68.1 ± 34.7	.015			

* Significant results are indicated in bold font.
† Fisher Exact test.
‡ Mann-Whitney test.

Table 3
Comparative Analysis of ML Models Predicting Short-Term Adverse Events Following Open Reduction Internal Fixation of Distal Radius Fracture

Model	SVM	Random Forest	Logistic Regression	Decision Tree	Gradient Boosting
AUC	0.795	0.817	0.795	0.797	0.824
Brier Score	0.755	0.823	0.768	0.653	0.830
Accuracy	0.750	0.644	0.556	0.532	0.674
Precision	0.069	0.333	0.230	0.471	0.356
Recall	0.126	0.439	0.325	0.500	0.466
F1-score	0.205	0.183	0.205	0.203	0.176

Discussion

This retrospective investigation used predictive modeling and ML methods to create innovative tools to assist health care professionals in their clinical decision making process regarding the eligibility of patients for outpatient ORIF following DRF. The resulting computational model, incorporating various preoperative demographic and clinical factors, demonstrated fair to good discrimination and excellent overall performance. The five features identified as most important in determining short-term adverse event risk were ICD-10 code, preoperative white blood cell count, age, BMI, and ethnicity (Hispanic). This study establishes a predictive model aiming to identify patients suitable for outpatient ORIF of DRF. These findings underscore the potential of ML techniques to enhance predictive accuracy and offer valuable insights for patient selection and preoperative counseling.

The current study identified postoperative ICD-10 code as the single most important feature in determining prediction of patients likely to experience a short-term adverse event following ORIF for DRF. International Classification of Diseases-10 codes are a standardized system of alphanumeric codes used worldwide for classifying diseases, medical conditions, and various health-related issues. Although there is limited research surrounding ICD-10 code and outcomes after DRF, the codes do provide fundamental initial injury details that the resulting algorithm may have used a surrogate for overall fracture severity. Recent studies have highlighted the impact of initial fracture position, presence of comminution, and intra-articular involvement on postoperative outcomes.[18] A study by Wadsten et al[18] of 406 patients noted worsened patient-reported outcomes as well as range of motion in patients with greater initial fracture displacement. Unfortunately, radiographic data are not included in the ACS-NSQIP database, thus precluding assessment of fracture severity to be included in these analyses. Furthermore, Wei and colleagues used the ACS-NSQIP database to conduct a retrospective analysis of 11,272 patients and determined that that prolonged operation times were linked to an elevated risk of reoperation following DRF repair.[19] In many cases, prolonged operative times are a result of greater difficulty in achieving adequate fracture visualization, reduction, and fixation of more complex fractures, which itself may also increase the likelihood of

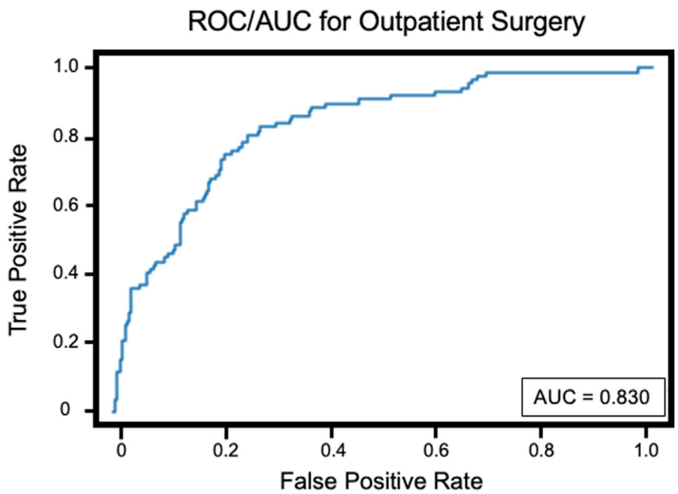

Figure 1. Overall logistic regression model performance as measured by AUC on the ROC curve. Area under the curve indicates the ability of the model to discriminate between patients who did and did not experience a short-term adverse event following ORIF for DRF.

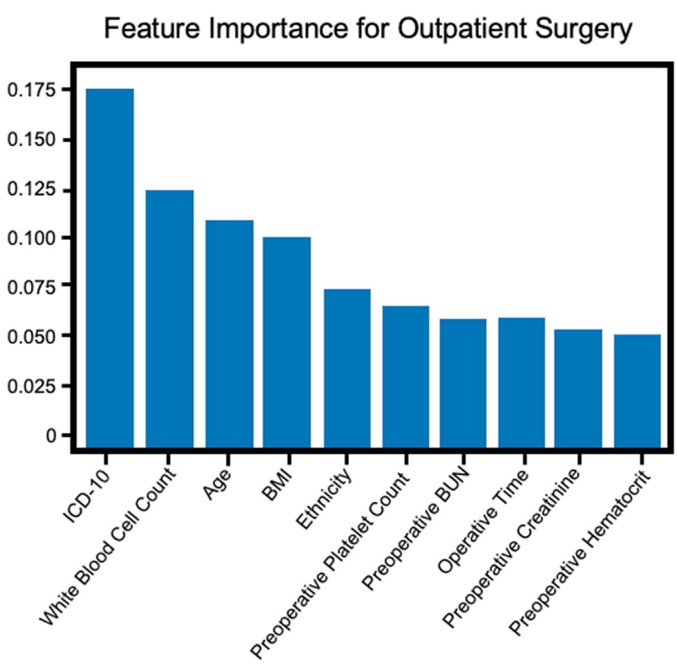

Figure 2. Feature importance calculated according to usefulness within the logistic regression model for predicting incidence of short-term adverse events following ORIF for DRF.

reoperation. Additional research investigating the correlation between DRF and the complexity of surgical procedures would enhance surgeons' decision making and help in setting realistic patient expectations.

Perhaps unsurprisingly, those who experienced short-term adverse events demonstrated elevated white blood cells compared with their counterparts. Initial elevation of white blood cell count is often part of the normal physiological stress response to injury.[20] Moreover, a recent study by Chisalita et al[21] noted that in a cohort of 38 women with DRF, fracture healing, as measured by the Hammer et al[22] classification of fracture healing on serial radiographs, was associated with initial leukocytosis and a lower thrombocyte count, suggesting that inflammation and thrombocytes are important components in fracture healing. However, it can be difficult to determine whether the leukocytosis is secondary to a post-traumatic inflammatory response, which may be favorable for DRF healing or if it is a consequence of infection, bacteremia, or sepsis. Ninety-two patients exhibited an elevated white blood cell count (greater than 12,000) and fulfilled the criteria for experiencing a short-term adverse event, rendering them "unsuitable" for outpatient surgery according to the parameters established in this study. This was likely due to these patients being scheduled for surgery as inpatients to better address concurrent infection. Nevertheless, elevated preoperative white blood cell count may represent a future research avenue to potentially establish a theoretical cutoff differentiating normal physiologic responses that are beneficial to fracture healing from levels that ultimately affect surgical outcomes.

Patient age was identified as the third most important factor for identifying those who were at risk of short-term adverse event following ORIF for DRF. Historically, a study by Lafontaine and colleagues noted that age, specifically age greater than 60 years, was associated with instability, and as such these fractures should be treated operatively[23] despite multiple studies demonstrating that outcomes and self-reported disability are not correlated with radiographic appearance or malunion.[24–26] Past studies across various surgical specialties have highlighted that elderly patients have multiple risk factors, including their general condition, comorbidities, and pathophysiological changes, that may result in more adverse outcomes after surgery.[27] Mosenthal et al[28] reiterated these sentiments in a study of 155,353 DRFs, demonstrating that the prevalence of comorbidities tended to correlate with age in patients with DRF. Interestingly, our findings diverge from more recent literature, as both Mosenthal et al[28] and Navarro et al[29] reported decreased complications and no appreciably greater risk for reoperation with increasing patient age, respectively. In contrast, in a study of complications after DRF, Jiang et al[30] noted a trend toward older age ($P = .06$) in patients who developed complications after surgical fixation after DRF; however, this trend was not appreciated in a more recent ACS-NSQIP study investigating complications and reoperations among patients treated for DRF between 2005 and 2020.[31] Moreover, a systematic review by MacIntrye and Dewan[32] noted poorer health outcomes after DRF are associated with older age, further convoluting the impact of age on DRF. In sum, patient age at injury represents a complicated variable in regard to postoperative outcomes. Although age may represent a surrogate measure for fragility and has been associated with increased complications, readmission, and reoperation, this study determined increasing age to increase risk for short-term adverse events following ORIF for DRF and suggests older patients may be more suited to undergo surgery in the inpatient setting.

This study has several limitations that should be considered. First, although the sample size is substantial, it is crucial to acknowledge that the algorithm's development was based solely on patients from the ACS-NSQIP database. Therefore, the generalizability of the findings relies on robust external validation studies conducted using similar databases. The lack of detailed breakdowns within the ACS-NSQIP data set hindered the ability to analyze specific factors such as radiographic findings (eg, fracture pattern or severity), which have been shown to alter postoperative outcomes after DRF, thus limiting the current model. Although certain modifiable risk factors like BMI, WBC, or platelet count were identified, it is important to note that many of the predictive factors are nonmodifiable; as such, there is limited potential to intervene on these factors to possibly improve outcomes. In addition, the ACS-NSQIP database captures data only for patients treated in a hospital setting (both inpatient and outpatient) and excludes patients who were treated at an ambulatory surgery center. Furthermore, when using a comprehensive database like the ACS-NSQIP, it is essential to acknowledge certain limitations, including coding errors, missing data points, and inaccuracies within the provided information. The presence of sample bias implies that the predictions of the ML model are only as reliable as the training data set. To address this, in our analysis, we opted to use imputation techniques as numerous studies in the literature have shown the advantages of multiple imputations over complete case analysis. Complete case analysis can result in inefficient utilization of data, potentially exacerbating existing health care disparities, and producing biased models. To enhance the robustness of the algorithm, future investigations should focus on externally validating this model using distinct populations, which would provide further insights into its performance and generalizability.

Conflicts of Interest

No benefits in any form have been received or will be received related directly to this article.

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