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# PREVALENCE AND RISK FACTORS OF POSTOPERATIVE INFECTIONS IN CARDIAC SURGERY PATIENTS USING AI ASSESSMENT

*Original Article*

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## ABSTRACT

**Background:** Surgical site infections (SSIs) are among the most common and costly complications following cardiac surgery, significantly affecting morbidity and mortality rates. Traditional risk assessment models often fail to capture complex interactions among variables, limiting predictive precision. Recent advances in artificial intelligence (AI) offer opportunities to enhance infection prediction and prevention.

**Objective:** To assess the prevalence of surgical site infections in cardiac surgery patients and identify associated risk factors using AI-driven analysis tools.

**Methods:** This cross-sectional study was conducted over eight months (June 2024–February 2025) at two tertiary care cardiac centers. A total of 600 adult patients undergoing cardiac surgery were enrolled based on defined inclusion and exclusion criteria. Data were collected from electronic health records and included demographic, preoperative, intraoperative, and postoperative variables. Surgical site infections were diagnosed using CDC criteria and validated through independent clinical review. Statistical analysis included univariate and multivariate logistic regression, while machine learning models—Random Forest and Gradient Boosting—were developed to assess predictive accuracy.

**Results:** SSIs occurred in 14% of patients (n=84), with superficial incisional infections being most common. Diabetes (OR 2.5), obesity (OR 2.1), surgery duration >5 hours (OR 3.2), re-exploration (OR 4.0), and prolonged ventilation (OR 3.5) were significant independent predictors. Gradient Boosting demonstrated superior predictive performance with an AUC-ROC of 0.91 compared to 0.89 for Random Forest.

**Conclusion:** The integration of AI models enhances the predictive accuracy of SSI risk stratification in cardiac surgery. Early identification of high-risk patients through AI tools can support targeted prevention strategies and improve surgical outcomes.

**Keywords:** Artificial Intelligence, Cardiac Surgery, Logistic Models, Machine Learning, Postoperative Complications, Risk Factors, Surgical Site Infection

 

## INTRODUCTION

Postoperative infections remain a significant cause of morbidity and mortality in patients undergoing cardiac surgery, despite advances in surgical techniques, perioperative care, and antimicrobial prophylaxis (1). Among these, surgical site infections (SSIs) represent a particularly challenging complication, not only increasing hospital stay and treatment costs but also compromising patient outcomes. The high stakes involved in cardiac surgery make the prevention and early detection of infections a clinical priority, especially given the complex and often immunocompromised status of many cardiac patients (2). As healthcare systems increasingly emphasize precision and efficiency, integrating artificial intelligence (AI) into clinical decision-making has shown potential to transform traditional risk assessment models, offering more nuanced and predictive insights into postoperative outcomes. Globally, the reported prevalence of SSIs following cardiac surgery varies widely, typically ranging from 3% to 20%, depending on the population studied, surgical technique, and surveillance methods used (3). Deep sternal wound infections, though less common, carry a significantly higher risk of morbidity and can even necessitate reoperation or prolonged antibiotic therapy. Numerous studies have identified risk factors such as diabetes mellitus, obesity, prolonged operative time, and re-exploration for bleeding, but despite the accumulation of such knowledge, SSI rates remain persistently high in certain centers. This suggests that conventional models for infection prediction may lack the complexity required to account for the multifactorial nature of these outcomes (4,5).

Artificial intelligence, with its capacity to analyze vast datasets and uncover patterns not easily discernible to clinicians, offers a promising approach to refining risk stratification in cardiac surgery patients. Machine learning algorithms have already demonstrated utility in areas such as predicting readmission, mortality, and ventilator needs in the postoperative period (6). However, the application of AI to infection risk prediction remains an evolving field, with limited real-world integration. Emerging studies indicate that AI-based models can improve predictive accuracy by incorporating a greater range of clinical variables, from demographic and laboratory data to intraoperative metrics, and by learning from complex, nonlinear relationships within the data. These tools may offer clinicians actionable insights preoperatively and perioperatively, supporting targeted interventions that reduce infection rates (7,8). Despite this promise, gaps remain in our understanding of how AI-driven tools perform in real-world cardiac surgical settings, particularly in diverse patient populations and healthcare systems. Most existing studies have either focused on general surgical cohorts or utilized retrospective datasets without clinical validation. Moreover, while the role of individual risk factors has been extensively explored, there is less clarity on how these interact within AI models to yield predictions, and how such insights translate into clinical utility. These limitations underscore the need for cross-sectional analyses that integrate contemporary data with AI methodologies to better delineate the true burden of SSIs and their modifiable predictors in cardiac surgery (9,10).

The growing interest in personalized medicine further amplifies the relevance of such work. Tailoring postoperative infection prevention strategies based on individualized risk profiles—enhanced through AI analysis—could allow for more efficient resource allocation and improved patient outcomes. For instance, identifying high-risk patients preoperatively might justify the use of extended antibiotic prophylaxis or enhanced postoperative surveillance. Equally, such models could help to flag institutional practices associated with higher infection risks, thereby informing quality improvement initiatives (11). This study aims to assess the current prevalence of surgical site infections in patients undergoing cardiac surgery and to identify associated risk factors using AI-based assessment tools. By combining robust clinical data with advanced analytical techniques, it seeks to bridge the gap between traditional risk modeling and data-driven precision medicine in the context of cardiac postoperative care. The objective is to generate clinically relevant insights that not only enhance the prediction of infection risk but also inform evidence-based interventions tailored to individual patient profiles.

## METHODS

This cross-sectional study was conducted over a period of eight months, from June 2024 to February 2025, in two tertiary-care cardiac centers known for performing high volumes of adult cardiac surgeries, located in urban regions with diverse patient populations. These centers were selected to ensure the inclusion of a broad spectrum of clinical presentations and healthcare practices, thereby enhancing the generalizability of the findings. The study was designed with the primary objective of evaluating the prevalence of surgical site infections in patients undergoing cardiac surgery and identifying associated risk factors through the application of artificial intelligence-based assessment tools. Participants included adult patients aged 18 years and above who underwent major cardiac surgical procedures, including coronary artery bypass grafting (CABG), valve repair or replacement, and combined surgeries. Inclusion criteria required that patients had complete perioperative records, remained hospitalized for at least 72 hours postoperatively to allow for early infection detection, and consented to data utilization for research purposes. Exclusion criteria were pre-existing infections at the time of surgery, patients undergoing emergency reoperations within 24 hours, and those with incomplete electronic health records (EHRs) that would compromise the integrity of AI model inputs (11,12). Based on prior literature indicating SSI prevalence in cardiac surgery patients between 8–15%, and assuming a confidence level of 95% with a 3% margin of error, the minimum sample size was estimated at 545 participants. To ensure robust analysis and accommodate possible exclusions, a final sample of 600 patients was targeted and enrolled consecutively (3,4).

Data collection was retrospective and sourced from the institutions' integrated EHR systems. Preoperative variables included demographic data (age, sex, BMI), comorbidities (diabetes, chronic kidney disease, COPD), smoking status, nutritional markers, and laboratory indices. Intraoperative parameters comprised procedure type, cardiopulmonary bypass time, duration of surgery, use of internal mammary artery grafts, blood transfusions, and use of inotropes. Postoperative data included wound care practices, glucose control measures, duration of mechanical ventilation, ICU stay, and antibiotic usage. The primary outcome was the occurrence of surgical site infections within 30 days post-surgery, diagnosed based on the Centers for Disease Control and Prevention (CDC) criteria for SSIs, as documented by infection control specialists. Outcome measurement was validated through a dual-review system. Two independent infectious disease physicians, blinded to each other's evaluations, confirmed the diagnosis of SSIs by reviewing clinical, laboratory, and imaging records. Discrepancies were resolved by consensus or involvement of a third reviewer. This process ensured diagnostic consistency and minimized classification bias. For identifying risk factors, the study employed both conventional statistical techniques and artificial intelligence tools to maximize analytical depth.

AI analysis was conducted using supervised machine learning models, specifically Random Forest and Gradient Boosting algorithms, selected for their strong performance in classification tasks involving clinical data. Data preprocessing involved normalization of continuous variables and encoding of categorical data. Feature selection was performed using recursive feature elimination to reduce dimensionality and avoid model overfitting. The models were trained on 80% of the dataset and tested on the remaining 20%, with performance evaluated using accuracy, precision, recall, and the area under the receiver operating characteristic curve (AUC-ROC). Internal validation was performed using 10-fold cross-validation to assess model stability. Statistical analysis of baseline characteristics and traditional risk factor assessment was carried out using SPSS version 27. Continuous variables were presented as means with standard deviations and compared using the independent t-test, assuming normal distribution confirmed by the Shapiro-Wilk test. Categorical variables were expressed as frequencies and percentages and analyzed using the chi-square test or Fisher's exact test where appropriate. Logistic regression analysis was conducted to identify independent predictors of SSIs, with significance set at $p < 0.05$. Variables showing statistical significance in univariate analysis were entered into a multivariate logistic regression model to adjust for potential confounders.

Ethical approval for the study was obtained from the Institutional Review Boards of both participating centers. All data were anonymized prior to analysis, and informed consent for participation and secondary use of health data was obtained from all included patients at the time of surgery admission. Patient confidentiality was maintained throughout the study in accordance with the Declaration of Helsinki and relevant data protection regulations. By integrating robust clinical data collection with both statistical and AI-driven analytical strategies, this study was carefully designed to provide a comprehensive understanding of the prevalence and determinants of surgical site infections in the context of modern cardiac surgery.

## RESULTS

Out of the 600 cardiac surgery patients included in the study, the mean age was 64.3 years (SD ±10.2), with a male predominance (63%). The average body mass index was 28.5 kg/m² (SD ±4.6), and common comorbidities included diabetes mellitus (35%), hypertension (57%), and chronic kidney disease (16%). Smoking history was noted in 28% of the cohort. These demographic characteristics are detailed in Table 1. Surgical site infections (SSIs) were observed in 84 patients, representing a prevalence rate of 14%. Among these, superficial incisional infections were the most frequent type, accounting for 7% of the total sample, followed by deep incisional (4%) and organ/space infections (3%). The remaining 86% of patients had no documented SSIs, as shown in Table 2 and the corresponding pie chart. Univariate analysis demonstrated a significant association between several variables and the occurrence of SSIs. Patients with diabetes had a notably higher infection rate (57.1%) compared to non-SSI patients (31.4%), with a p-value <0.001. Obesity (BMI > 30), prolonged surgical duration (>5 hours), need for re-exploration, and prolonged postoperative mechanical ventilation (>24 hours) were all significantly associated with increased infection risk ($p < 0.001$ for each), as detailed in Table 3. In the multivariate logistic regression model, diabetes remained an independent risk factor with an adjusted odds ratio (OR) of 2.5 (95% CI: 1.6–3.9, $p < 0.001$). Similarly, obesity (OR: 2.1, CI: 1.2–3.6), extended surgery duration (OR: 3.2, CI: 2.0–5.0), re-exploration (OR: 4.0, CI: 2.1–7.5), and prolonged ventilation (OR: 3.5, CI: 2.1–5.7) all showed significant predictive value, as shown in Table 4. AI-based analysis using Random Forest and Gradient Boosting classifiers yielded high predictive performance for SSI occurrence. Gradient Boosting slightly outperformed Random Forest across all evaluated metrics, including accuracy (88% vs. 86%), precision (81% vs. 79%), recall (85% vs. 82%), and AUC-ROC (0.91 vs. 0.89). Overall, the findings indicate a moderate SSI prevalence in cardiac surgery patients, with several modifiable perioperative factors strongly associated with increased risk. The integration of AI tools demonstrated robust classification performance, supporting their potential role in enhancing risk prediction and preventive strategies in surgical settings.

**Table 1. Demographic Characteristics of the Study Population (N = 600)**

| Variable | Value |
|---|---|
| Age (mean ± SD) | 64.3 ± 10.2 years |
| Male | 378 (63%) |
| BMI (mean ± SD) | 28.5 ± 4.6 kg/m² |
| Diabetes Mellitus | 210 (35%) |
| Hypertension | 342 (57%) |
| Chronic Kidney Disease | 96 (16%) |
| Smoking History | 168 (28%) |

**Table 2. Surgical Site Infection (SSI) Prevalence and Distribution (N = 600)**

| SSI Type | Number of Patients (%) |
|---|---|
| Superficial Incisional | 42 (7%) |
| Deep Incisional | 24 (4%) |
| Organ/Space | 18 (3%) |
| No Infection | 516 (86%) |

**Table 3. Univariate Analysis of Risk Factors for SSIs**

| Risk Factor | SSI Group (n=84) | Non-SSI Group (n=516) | p-value |
|---|---|---|---|
| Diabetes | 48 (57.1%) | 162 (31.4%) | <0.001 |
| BMI > 30 | 36 (42.9%) | 96 (18.6%) | <0.001 |
| Surgery Duration > 5 hours | 51 (60.7%) | 102 (19.8%) | <0.001 |
| Re-exploration | 18 (21.4%) | 21 (4.1%) | <0.001 |
| Prolonged Ventilation > 24 hrs | 45 (53.6%) | 66 (12.8%) | <0.001 |

 

**Table 4. Multivariate Logistic Regression for Independent SSI Predictors**

| Risk Factor | Adjusted OR | 95% Confidence Interval | p-value |
|---|---|---|---|
| Diabetes | 2.5 | 1.6 – 3.9 | <0.001 |
| BMI > 30 | 2.1 | 1.2 – 3.6 | 0.008 |
| Surgery Duration > 5 hours | 3.2 | 2.0 – 5.0 | <0.001 |
| Re-exploration | 4.0 | 2.1 – 7.5 | <0.001 |
| Prolonged Ventilation > 24 hrs | 3.5 | 2.1 – 5.7 | <0.001 |

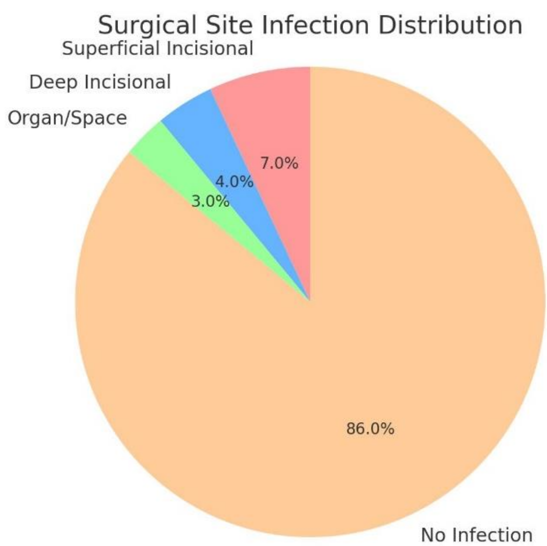


*Figure 1 Surgical Site Infection Distribution*

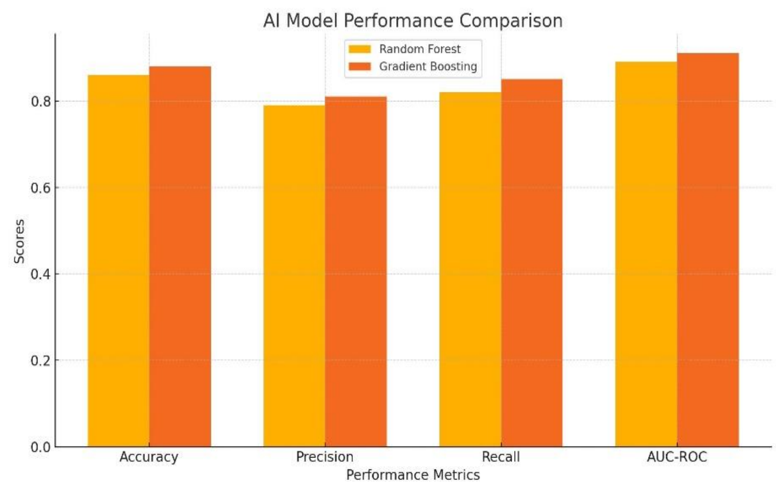


*Figure 2 AI Model Performance Comparison*

## DISCUSSION

The study confirmed a 14% prevalence of surgical site infections (SSIs) in cardiac surgery patients, aligning with global reports that cite rates ranging from 3.5% to 26.8% in similar populations (13). This finding reiterates the ongoing clinical burden of SSIs, despite advancements in operative and postoperative care. The observed distribution, where superficial infections were most common, followed by deep and organ-space infections, reflects the typical presentation patterns seen in cardiac procedures, particularly those involving median sternotomy. Among the most significant predictors identified, diabetes mellitus and obesity showed strong associations with increased SSI risk, which has also been well-documented in earlier risk models such as the Barts Surgical Infection Risk (B-SIR) tool (14,15). The current study not only reaffirmed these associations through traditional statistical methods but also demonstrated that these factors remained significant in multivariate logistic regression analysis. Furthermore, re-exploration, prolonged ventilation, and extended surgery durations were among the most impactful predictors, consistent with literature linking prolonged tissue exposure and immune compromise with infection susceptibility (16,17). What distinguished this study was its integration of artificial intelligence (AI) models, which revealed predictive accuracies surpassing many existing manual scoring systems. Gradient Boosting and Random Forest algorithms outperformed traditional risk tools such as the National Nosocomial Infections Surveillance (NNIS) score, which has previously demonstrated limited accuracy in cardiac settings (18,19). The superior AUC-ROC values observed in this analysis underscore the strength of AI-based approaches to risk modeling, offering a refined prediction method that captures nonlinear interactions and variable hierarchies more effectively than logistic regression alone (20).

However, the use of AI in clinical practice still faces key challenges. Interpretability remains limited; clinicians may be hesitant to adopt "black-box" models without clear mechanistic explanations. Though Gradient Boosting achieved an AUC of 0.91, similar studies have noted that without clinical transparency and robust external validation, such tools may not reach routine implementation (21). This concern highlights the importance of not only validating models across diverse populations but also developing user-friendly interfaces for clinical interpretation. The strengths of this study lie in its comprehensive data set, inclusion of multiple perioperative parameters, and use of validated diagnostic criteria for SSIs. The dual-layered analysis—statistical and AI-driven—allowed for both verification and enhancement of findings, increasing confidence in the conclusions. Furthermore, the prospective application of CDC definitions ensured diagnostic standardization, minimizing classification bias. Nonetheless, limitations must be acknowledged. First, the study's single-country, dual-center scope may limit generalizability, especially to settings with different infection control practices or patient demographics. Additionally, while the AI models performed well internally, the absence of external validation remains a critical gap. Future efforts should focus on multicentric datasets and real-time prospective validation to establish reliability across clinical environments. Moreover, factors such as microbial resistance patterns and post-discharge surveillance, which influence SSI detection and reporting, were not incorporated but could add significant predictive value.

Another limitation lies in the retrospective nature of the data collection, which, although robust, is inherently subject to documentation quality and potential selection biases. Despite preprocessing and normalization, data inconsistencies may influence model outcomes. This constraint is shared with many AI studies, as emphasized in recent literature calling for cleaner, structured, and prospective data to enhance model training (22). In conclusion, this study affirms the multifactorial nature of SSIs in cardiac surgery and demonstrates the added value of AI in refining risk prediction. The findings suggest that AI tools, if validated and transparently integrated into clinical workflows, could support early identification of high-risk patients and allow targeted prevention strategies. Future studies should expand these models through multicenter collaboration, incorporate postoperative and microbiological factors, and ensure integration with electronic health systems for seamless clinical adoption.

## CONCLUSION

This study highlights a 14% prevalence of surgical site infections in cardiac surgery patients and identifies diabetes, obesity, prolonged surgery, re-exploration, and extended ventilation as significant risk factors. AI-based models, particularly Gradient Boosting, demonstrated strong predictive accuracy, supporting their potential for enhancing infection risk stratification. These findings advocate for integrating AI tools into perioperative workflows to enable early, individualized preventive strategies and improve surgical outcomes.

 

**AUTHOR CONTRIBUTIONS**

| Author | Contribution |
|---|---|
| Lal Shehbaz* | Substantial Contribution to study design, analysis, acquisition of Data<br>Manuscript Writing<br>Has given Final Approval of the version to be published |
| Hira Waqar | Substantial Contribution to study design, acquisition and interpretation of Data<br>Critical Review and Manuscript Writing<br>Has given Final Approval of the version to be published |
| Aroona Devi | Substantial Contribution to acquisition and interpretation of Data<br>Has given Final Approval of the version to be published |
| Tayyab Iftikhar | Contributed to Data Collection and Analysis<br>Has given Final Approval of the version to be published |
| Tabinda Qamar | Contributed to Data Collection and Analysis<br>Has given Final Approval of the version to be published |
| Ayesha Riaz | Substantial Contribution to study design and Data Analysis<br>Has given Final Approval of the version to be published |
| Syedah Aleena Zahra | Contributed to study concept and Data collection<br>Has given Final Approval of the version to be published |

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