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A Pilot Study Using Machine Learning Algorithms and Wearable Technology for the Early Detection of Postoperative Complications After Cardiothoracic Surgery

Authors: Jorind Beqari* MD[1], Joseph Powell* MS[2], Jacob Hurd BS[1], Alexandra L. Potter BS[1], Meghan McCarthy BS[1], Deepti Srinivasan BS[1], Danny Wang MD[1], James Cranor BS[1], Lizi Zhang BS[2], Kyle Webster BS[2], Joshua Kim[1], Allison Rosenstein[1], Zeyuan Zheng BS[1], Tung Ho Lin MS[2], Jing Li PhD[2], Zhengyu Fang BS[2], Yuhang Zhang BS MS[2], Alex Anderson[1], James Madsen BS[1], Jacob Anderson BS[1], Anne Clark BS[1], Margaret E. Yang BS[1], Andrea Nurko[1], Areej R. El-Jawahri MD[3], Thoralf M. Sundt MD[1], Serguei Melnitchouk MD, MPH[1], Arminder S. Jassar MBBS[1], David D'Alessandro MD[1], Nikhil Panda MD[1], Lana Y. Schumacher-Beal MD[1], Cameron D. Wright MD[1], Hugh G. Auchincloss MD[1], Uma M. Sachdeva MD, PhD[1], Michael Lanuti MD[1], Yolonda L. Colson MD, PhD[1], Nathaniel Langer MD[1], Asishana Osho MD, PhD[1], Chi-Fu Jeffrey Yang** MD[1], Xiao Li** PhD[2]

*Co-First Authors
**Co-Senior Authors

Affiliations:

[1]Department of Surgery, Massachusetts General Hospital, Boston, MA
[2]Department of Computer and Data Sciences, Case Western Reserve University, Cleveland, OH
[3]Department of Medicine, Massachusetts General Hospital, Boston, MA

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WEARABLE DETECTION OF COMPLICATIONS

Corresponding Author:

Jorind Beqari MD
Massachusetts General Hospital
Austen 7 Rm 733A
55 Fruit Street
Boston, MA 02114
Email: jbeqari@mgh.harvard.edu
Phone: 781-414-1773

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STRUCTURED ABSTRACT

Objective:

To evaluate whether a machine learning algorithm (i.e. the "NightSignal" algorithm) can be used for the detection of postoperative complications prior to symptom onset after cardiothoracic surgery.

Summary Background Data:

Methods that enable the early detection of postoperative complications after cardiothoracic surgery are needed.

Methods:

This was a prospective observational cohort study conducted from July 2021 to February 2023 at a single academic tertiary care hospital. Patients aged 18 years or older scheduled to undergo cardiothoracic surgery were recruited. Study participants wore a Fitbit watch continuously for at least 1 week preoperatively and up to 90-days postoperatively. The ability of the NightSignal algorithm—which was previously developed for the early detection of Covid-19—to detect postoperative complications was evaluated. The primary outcomes were algorithm sensitivity and specificity for postoperative event detection.

Results

A total of 56 patients undergoing cardiothoracic surgery met inclusion criteria, of which 24 (42.9%) underwent thoracic operations and 32 (57.1%) underwent cardiac operations. The median age was 62 (IQR: 51-68) years and 30 (53.6%) patients were female. The NightSignal algorithm detected 17 of the 21 postoperative events a median of 2 (IQR: 1-3) days prior to symptom onset, representing a sensitivity of 81%. The specificity, negative predictive value, and positive predictive value of the algorithm for the detection of postoperative events were 75%, 97%, and 28%, respectively.

Conclusions:

Machine learning analysis of biometric data collected from wearable devices has the potential to detect postoperative complications—prior to symptom onset—after cardiothoracic surgery.

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INTRODUCTION

Every year over 500,000 patients undergo operations for heart and lung diseases in the United States.[1] After cardiothoracic surgery, up to 32% of patients develop postoperative complications,[2-7] which often occur in the outpatient setting and lead to unplanned hospital readmission.[7-12] Currently, there is a large gap in patient monitoring after discharge during which the patient has minimal interaction with their healthcare team for several weeks until the first postoperative visit. This gap in monitoring can cause delays in the detection of complications, thereby contributing to more severe complications and unplanned hospital readmission. While several interventions, such as telemedicine appointments and home health visits, have been explored as strategies to improve the earlier identification of complications, these interventions collect low-resolution data, are often expensive, and have not been shown to decrease complication rates.[13-16]

Accurate and easy-to-implement methods to detect complications before symptom onset after cardiothoracic surgery are needed. Wearable devices, such as smart watches, enable the collection of high-resolution physiologic data and can be used for patient monitoring during the postoperative period. Our previous research[17-20] has demonstrated the effectiveness of machine learning analysis of wearable data in detecting abnormal physiological events—often before symptom onset—including Covid-19 and other respiratory illnesses. By analyzing high-resolution biometric data obtained from wearables, machine learning has the potential to allow for the prediction of and earlier identification of postoperative complications, possibly leading to reductions in the frequency or severity of postoperative complications after cardiothoracic surgery.

The objective of this pilot study was to evaluate whether a machine learning algorithm—previously shown to enable the early detection of abnormal physiologic events, including Covid-19 and other infections[17]—could be extended to the early detection of postoperative complications after cardiothoracic surgery. We hypothesized that machine learning analysis of patients' resting heart rate (RHR) data collected by wearable devices could be used to predict postoperative complications prior to symptom onset after cardiothoracic surgery.

METHODS

Patient Selection

This study was approved by the Massachusetts General Brigham Institutional Review Board (IRB Protocol #:2020P002984; Clinical Trial #: NCT04824066). Patients aged 18 years or older scheduled to undergo cardiothoracic surgery from July 2021 to October 2022 were eligible to participate in the study. Exclusion criteria included individuals with mental incapacity and/or cognitive impairment that would preclude adequate understanding of, or cooperation with the study protocol, pregnant individuals, and past medical history of severe irreversible pulmonary hypertension, congenital heart disease, chronic renal insufficiency, and liver cirrhosis. Additionally, patients who did not own a smartphone with an Android or iOS operating system or who did not have an electronic mailing address were excluded.

After obtaining verbal consent, patients were asked to download the Fitbit (Fitbit, Inc) mobile application onto their smartphone and were provided with a Fitbit Charge 4/5. Patients wore the Fitbit device for at least 1 week prior to their surgery and up to 90 days postoperatively.

Collection of Wearable Data

A unique Fitbit application identification was requested prior to study initiation to gain access to Fitbit's developer application programming interface (API). Participants were assigned a unique username and password corresponding to a deidentified Fitbit account. A pipeline was used to collect participant data from the Fitbit API through automated scripts written in Python (Python Software Foundation, v3.9.1). Deidentified data was stored in a secure network drive on the Case Western Reserve University High Performance Computing Cluster. For the present analysis, we obtained raw heart rate data collected from wearables and applied our pre-processing workflow we previously developed[17,19,20] to calculate nighttime resting heart rate. Data audits were conducted on a weekly basis to ensure high-quality data collection.

Collection of Clinical Data

Participant demographics as well as pre-, peri- and post-operative data were collected from the electronic medical record (EMR) and securely stored on Research Electronic Data Capture (REDCap). Data collected from the electronic medical record included: age, sex, self-reported race and ethnicity, body mass index, smoking history, allergies, medications, preoperative symptoms, receipt of chemotherapy, immunotherapy, or radiation, American Society of Anesthesiology (ASA) classification, Eastern Cooperative Oncology Group (ECOG) functional

status, pulmonary function test data, major comorbidities, operative details, and postoperative data (length of hospital stay, chest tube days, routine clinic follow-up, postoperative events, readmission).

Definition of Postoperative Events

For the purposes of this analysis, any clinical note documenting a postoperative complication after discharge, presentation to the emergency department, unplanned readmission, or mortality was defined as a postoperative event. Patient-reported symptoms requiring an intervention that were documented in outpatient postoperative visits or telephone encounters were also included as a postoperative event. Postoperative complications that occurred prior to discharge were not considered to be postoperative events. The date of each postoperative event was considered to be the date on which symptoms related to that postoperative event were first documented in the EMR.

NightSignal Machine Learning Algorithm

For the present study, we tested whether the NightSignal algorithm—a machine learning algorithm that was previously shown to identify physiologic aberrations preceding Covid-19[17]—could be extended to the detection of postoperative events after cardiothoracic surgery. The details of the NightSignal algorithm have been described in depth in a previous publication.[17] Briefly, the NightSignal algorithm uses a deterministic finite state machine (FSM) based on overnight RHR to detect abnormal increases in RHR. For each night the patient wears the watch, the patient's average RHR for that night is calculated and compared to the median of averages of

RHR of all preceding nights that the patient wore the watch (here on out referred to as "baseline RHR"). If the patient's average RHR for that night is similar (e.g., within 3 beats per minute) compared to their baseline RHR, the algorithm issues a "green state." Alternatively, if the patient's average RHR for that night is sufficiently elevated compared to their baseline RHR, the algorithm issues a "yellow state" (if RHR is >3 and <4 beats per minute higher compared to their baseline RHR) or a "red state" (if RHR is > 4 beats per minute higher compared to their baseline RHR). If the algorithm issues two consecutive yellow states or two consecutive red states, a yellow or red alert is triggered, respectively. In the present study, a postoperative event is detected when a red alert is triggered.

Data Analysis and Statistical Analysis

Baseline patient demographics were summarized using median and interquartile ranges for continuous data and frequencies for categorical data. The algorithm was applied to a dataset comprising patients' overnight RHR data collected from the Fitbit devices during the pre- and postoperative periods. Overnight RHR data included RHR data collected between 12:00 AM and 8:00 AM. To avoid including RHR data collected while the patient was awake during these hours, we excluded all RHR data collected while the patient was walking. Patients who experienced a postoperative complication prior to discharge were not included in this dataset. To evaluate the algorithm's ability to detect postoperative events, we defined an analysis period for each patient using the methodology described below.

Start Date of the Analysis Period

The start date of the analysis period was the date of discharge if (1) the patient was discharged after POD 10 or (2) the patient experienced a postoperative event after discharge and before postoperative day 10 (POD 10). For all other patients (including patients who experienced a postoperative event after POD 10 and patients who never experienced a postoperative event), the start date of the analysis period was POD 10. The rationale for selecting POD 10 as the start date for the analysis period for these patients was because, during the days immediately after surgery, many patients experienced an increase in RHR due to physiologic stress from the operation, and not from a complication. To avoid classifying these red alerts as false positives, we chose POD 10 as the start date for the analysis period. We selected this cutoff because it would allow patients to recover from the immediate stress of the operation, whilst still allowing our algorithm to analyze a large window of time (POD 10 and beyond) where postoperative complications commonly occur. Indeed, 81% of complications in our cohort that occurred after discharge occurred after POD 10.

End Date of the Analysis Period

For patients who experienced a postoperative event, the end of the analysis period was 7 days after the date of their postoperative event. For patients who did not experience a postoperative event, the end of the analysis period was either the date in which the patient completed the study or the date in which the patient experienced one of the following events: additional operations, medication changes known to cause major changes in patients' heart rate, or other events unrelated to the index operation.

Defining Intervals in the Analysis Period

We then grouped patients' physiologic data collected during the analysis period into distinct intervals. Among patients who experienced a postoperative event, data were categorized into 14-day intervals beginning from the start of the analysis period to up to 7 days before the postoperative event; the days between the end date of the last interval and the date of the complication and the 7 days after the postoperative event were then grouped into a separate interval, marking the final interval in that patient's analysis period. Among patients who did not experience a postoperative event, data were categorized into 14-day intervals beginning from the start of the analysis period until the end date of the analysis period.

Evaluation of Algorithm Performance for the Detection of Postoperative Events

We then evaluated the algorithm's detection of postoperative events by classifying each interval as a true positive, true negative, false positive, or false negative. A *true positive (TP)* is defined as an interval in which a patient experienced a postoperative event and in which a red alert was triggered. A *true negative (TN)* is defined as an interval in which a patient did not experience a postoperative event and in which there were no red alerts triggered. A *false positive (FP)* is defined as an interval in which a patient did not experience a postoperative event but there was one or more red alerts triggered in that interval. A *false negative (FN)* is defined as an interval in which the patient experienced a postoperative event but there were no red alerts triggered in that interval. Based on these definitions, we calculated the sensitivity, specificity, positive predictive value, and negative predictive value of the algorithm for the detection of postoperative events.

Differences in the proportion of red alerts during the first 30 days after surgery between patients who had a postoperative event and patients who did not have a postoperative event were analyzed using the Wilcoxon Rank Sum Test. All statistical analyses were performed using R statistical software version 4.0.2 (R Core Team). Statistical significance was defined as a 2-sided alpha less than 0.05.

RESULTS

Of the 299 eligible cardiothoracic surgical patients who were recruited to participate in the study, 195 patients (65.2%) enrolled in the study. Among the 195 patients who enrolled, 4 patients (2.1%) did not undergo surgery, 51 patients (26.2%) withdrew early from the study, and 11 (5.6%) patients had fewer than 90-days of postoperative follow-up data. Among the 129 patients who underwent surgery and completed the 90-day postoperative course, a total of 56 patients (43.1%) were included for analysis; 73 patients (56.6%) were excluded from the analysis because they experienced a postoperative complication prior to discharge (n=27) or because they had insufficient biometric data for analysis (n=46) (**Figure 1**). Of the 46 patients who were excluded from the analysis because they had insufficient biometric data, the majority only wore the watch intermittently after surgery. The baseline characteristics of patients who completed the 90-day postoperative course and were included versus excluded from the analysis are shown in Supplemental Table 1, Supplemental Digital Content 1, http://links.lww.com/SLA/F40**.**

Baseline Characteristics of Patients Who Completed the Study

Patient characteristics are listed in **Table 1**. Of the 56 patients in the study cohort, 24 patients (42.9%) underwent thoracic surgery, and 32 patients (57.1%) underwent cardiac surgery. The median age was 62 years (IQR: 51-68) and the cohort was predominately female (53.6%, n=30). Lobectomy was the most common operation among thoracic surgery patients (54.2%, n=13), and valve replacement was the most common operation among cardiac surgery patients (43.8%, n=14). All thoracic surgery patients underwent minimally invasive surgery (100%, n=24) while open surgery was the predominant approach among cardiac surgery patients (68.8%, n=22).

Performance of the NightSignal Algorithm for Postoperative Event Detection

Of the 56 patients in the study cohort, 20 patients (35.7%) experienced a total of 21 postoperative events during the 90 days after surgery. The NightSignal algorithm detected 17 out of 21 (81.0%) postoperative events. **Figure 2A** is an example of a true positive for a patient undergoing minimally invasive mitral valve repair who developed shortness of breath beginning on POD 30 (which was considered to be the date in which the postoperative event began) and then developed bilateral pulmonary emboli on POD 33. Prior to the patient's postoperative event on POD 30, a yellow alert was noted on POD 28 and a red alert was noted on POD 29.

Figure 2B is an example of a true negative for a patient undergoing a video-assisted thoracoscopic right middle lobectomy. The patient was discharged home on POD 2 without any inpatient issues. Red alerts up to POD 2 were considered normal postoperative recovery. No other red alerts were appreciated from that point onward. There were also no documented postoperative events from the chart review.

The NightSignal algorithm had a sensitivity of 81%, a specificity of 75%, a negative predictive value of 97%, and a positive predictive value of 28% for the detection of postoperative events (**Figure 3A**). Details of the postoperative events in our cohort are listed in **Table 2**. When compared to patients who did not experience a postoperative event, patients who did experience a postoperative event had a significantly higher proportion of red alerts issued by the NightSignal algorithm during the first 30 days after surgery (0.325 vs. 0.063; $p<0.05$) (Supplemental Figure 1, Supplemental Digital Content 1, http://links.lww.com/SLA/F40).

The NightSignal algorithm detected postoperative events a median of 2 (IQR: 1 to 3 days) prior to the onset of symptoms. In a subgroup analysis by surgery type (cardiac vs. thoracic), the algorithm detected postoperative events a median of 2 (IQR: 1 to 3.5) days and 1.5 (IQR: 0.25 to 2.75) days prior to symptom onset among cardiac and thoracic patients, respectively (**Figure 3B**). Of the 17 postoperative events detected by the NightSignal algorithm, 15 (88.2%) were detected before the documented postoperative event date and 2 (11.8%) were detected after the postoperative event date (considered to be "delayed detections"). Notably, the 2 patients who had a delayed detection of a postoperative event only wore their watch intermittently during the interval surrounding their complication, which reduced the resolution of the RHR data collected during that interval.

DISCUSSION

In this pilot study of 56 patients who underwent cardiothoracic surgery, the NightSignal algorithm detected 17 out of 21 postoperative events a median of 2 days prior to the onset of symptoms related to that postoperative event. The sensitivity and specificity of the algorithm for postoperative event detection were 81% and 75%, respectively.

Using smart technology (e.g., smart watches, iPhones) to collect patient biometrics before and after surgery is emerging as a promising strategy to improve patient monitoring during the perioperative period. Thus far, most studies investigating the use of smart technology among surgical patients have focused on the use of these devices to track patients' postoperative recovery after surgery.[21-24] For example, a previous study by Panda and colleagues[25] used patients' smartphone accelerometer data collected during the postoperative period to identify different recovery patterns among patients undergoing major cancer operations. However, to date, no study has evaluated the use of wearable devices to enable the early detection of postoperative complications after cardiothoracic surgery.

In the present study, we evaluated whether machine learning analysis of high-resolution biometric data collected from wearable devices during the postoperative period could successfully predict postoperative complications and other clinically relevant postoperative events. We extended the NightSignal algorithm—a machine learning algorithm previously developed for the early detection of Covid-19[17]—to the detection of postoperative complications after cardiothoracic surgery. Importantly, we found that the NightSignal algorithm had a sensitivity of 81% for the detection of postoperative events, which compares favorably to the

previously reported sensitivity of the algorithm for the detection of Covid-19 (sensitivity of 80%).[17]

The specificity of the algorithm for the detection of postoperative events in our cohort was 75%, which is lower compared to the previously reported specificity of the algorithm for the detection of Covid-19 (specificity of 87.7%).[17] It is important to note that the algorithm used in this study has not yet been optimized for the detection of postoperative complications after cardiothoracic surgery. Cardiothoracic surgery is itself a major stressor resulting in notable changes in patients' physiologic signals during recovery, regardless of whether they experience a postoperative event. Further refinement of the algorithm will likely improve the algorithm's ability to differentiate between changes in physiologic signals characteristic of normal recovery after an operation versus changes in physiologic signals preceding a postoperative complication. As such, we anticipate that—after optimizing the algorithm for the detection of postoperative events among cardiothoracic surgery patients—the algorithm will achieve much higher specificity than that observed in this pilot study.

It is worth noting that, for the present study, we chose to use a broad definition of postoperative events and included a range of events with varying degrees of clinical significance. Our rationale in including these events was that many clinically significant postoperative events, even if they are not considered to be major postoperative complications, can still lead to hospital readmission, increased healthcare costs, and poorer quality of life for patients.[26-28] As such, we felt that patients would still likely benefit from earlier identification of these postoperative events, as it

would potentially prevent the development of more severe symptoms and could allow patients to avoid hospital readmission and additional healthcare costs. For example, earlier identification of a patient experiencing a significant anxiety episode can allow for earlier intervention (i.e., supportive care and/or treatment) and potentially improved care and quality of life. A key focus of our research moving forward is to not only detect postoperative events in general but to revise the algorithm such that it can distinguish less critical postoperative events from those that are potentially life-threatening. Ultimately, we aim to refine the algorithm to be able to detect specific postoperative events (e.g., pulmonary embolism versus pneumonia versus atrial fibrillation).

It is also worth considering how the proposed machine learning algorithm can be optimally implemented into clinical practice. In the future, we aim to develop a real-time monitoring system that combines wearable technology and our machine learning algorithm to enable the real-time, early detection of postoperative events. When a red alert is issued by the machine learning algorithm, the monitoring system will notify the healthcare team. Once notified, the healthcare team can closely monitor the patient for early signs of complications, potentially leading to the earlier diagnosis and treatment of complications.

Importantly, the majority of postoperative events in the present study—if identified early—have associated treatments that can be provided in the outpatient setting and can reduce the severity of the event and the risk of hospitalization from that event. For example, pneumonia can be treated with antibiotics, pulmonary embolism can be treated with oral anticoagulants, and atrial

fibrillation can be treated with beta blockers, calcium channel blockers, or amiodarone; each of these treatments can be provided in the outpatient setting, potentially reducing the severity of the complication and allowing the patient to avoid hospital readmission.

This study has several limitations. First, this pilot study was conducted among patients undergoing cardiothoracic surgery at a single academic institution, and the findings may not be generalizable to patients undergoing cardiothoracic surgery at other institutions or patients undergoing non-cardiothoracic operations. Importantly, the findings of this pilot study will directly inform the development of a multi-institutional clinical trial to evaluate whether machine learning analysis of high-resolution biometrics collected from wearable devices can reduce the frequency and/or severity of postoperative complications after cardiothoracic surgery. Additionally, the findings of this pilot study can provide the framework to extend this technology to other surgical specialties. Second, a patient's ability to participate in this study was contingent upon internet access, possession of a smartphone and having a basic understanding of wearable device functionality. Great efforts were made to provide substantial technical support to our participants in order to alleviate any anxiety related to technology used in this study. Third, our current algorithm was based on biometric data collected at night while a patient was presumed to be sleeping. Postoperative recovery for patients can be difficult and can greatly influence their circadian rhythm and sleeping habits. With continued algorithm development, patient-specific factors such as sleeping patterns will be incorporated into the algorithm and will allow for more accurate postoperative event detection. Fourth, given the pilot nature of this study, our sample size was small, and the findings of this study should be interpreted in the context of this small sample size. Fifth, for patients who either had no postoperative event or who had a postoperative

event after POD 10, we selected POD 10 as the start date for the analysis period to avoid classifying red alerts immediately after the operation as false positives. As a result, we did not fully evaluate the algorithm's performance in detecting postoperative events that occur after discharge but prior to POD 10. We believe this is an important area of future research and we are actively studying how we can optimize our algorithm to detect these early outpatient postoperative events. Sixth, there are many factors that can cause fluctuations in RHR that were not accounted for in this pilot study, and likely contributed to the notable proportion of false positives observed in this pilot study. A key future direction of our research is to incorporate baseline comorbidities, the initiation and cessation of medications (e.g., beta blockers), and other important factors known to affect heart rate into our machine learning algorithm to reduce false positives. Seventh, of the 129 patients enrolled in the study who completed the 90-day postoperative course, only 56 were included in the final analysis. Insufficient biometric data was the primary reason patients were excluded from the analysis. Since completion of this pilot study, we have identified several strategies to increase patient adherence to wearing the watch and have found that these strategies have greatly improved adherence. Developing strategies to promote patient adherence to wearing the watch was an important part of the learning process during this pilot study, and we anticipate much higher adherence in our future analyses. Lastly, all information about postoperative events for participants was collected directly from the EMR. Clinical information, such as the timing of symptoms and complications, is completely dependent on appropriate documentation by the healthcare team.

CONCLUSION

In this pilot study of 56 patients undergoing major cardiothoracic operations, we found that machine learning analysis of high-resolution RHR data passively collected by wearable devices could detect 81% of postoperative events, most of which were major postoperative complications. Importantly, most of these complications were identified several days prior to the onset of symptoms related to that complication. These results highlight the possibility of using machine learning analysis of high-resolution biometric data collected from wearable devices for the early detection of postoperative complications—prior to symptom onset—after cardiothoracic surgery.

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Figure 1. Consort Diagram of Study Participants

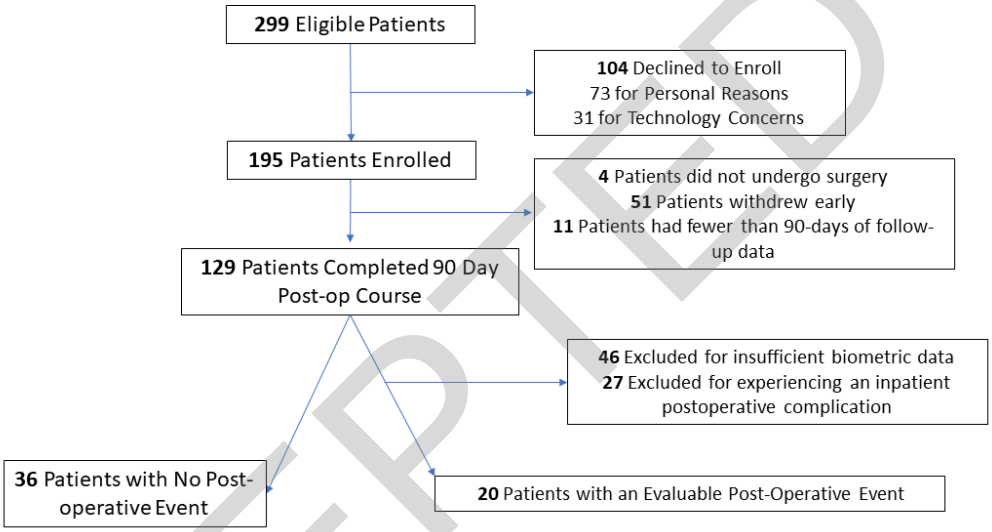

Figure 2. Time series of patients' resting heart rates collected during the pre- and postoperative periods. Each panel represents a single patient's resting heart rate. **Figure 2A** is an example of a true positive for a patient who underwent minimally invasive mitral valve repair and was discharged on POD 7. He reported shortness of breath for 3 days and presented to the emergency department with bilateral pulmonary emboli on POD 33. The date of symptom onset is indicated by the red circle (POD 30). The NightSignal algorithm first detected the postoperative clinical event on POD 29, as indicated by the red alert on POD 29. The gray-shaded region of the graph indicates postoperative days that were excluded from the analysis as they occurred more than 7 days after the date of the postoperative event. **Figure 2B** is an example of a true negative for a patient who underwent video-assisted thoracoscopic right middle lobectomy, was discharged on POD 2, and had no postoperative events. In both **Figure 2A** and **2B**, POD 0 indicates the date of surgery. The green, yellow, and red dashed lines represent the different thresholds of the NightSignal algorithm. The solid black represents the patient's average daily resting heart rate. Solid vertical yellow and red lines correspond to yellow and red alerts issued by the NightSignal algorithm. Red alerts during the immediate postoperative period were considered to reflect physiologic changes characteristic of normal recovery from the operation.

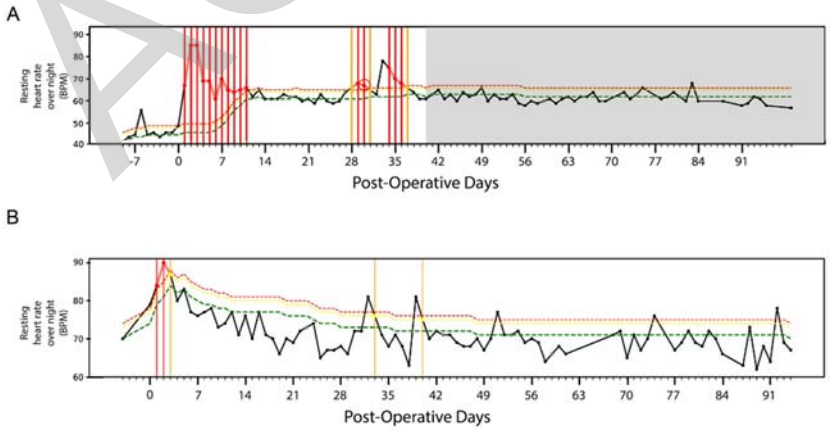

Figure 3. Analysis of the performance of the NightSignal algorithm for postoperative event detection (A) and the time between the date the NightSignal algorithm first detected the postoperative event and the documented date of the postoperative event.

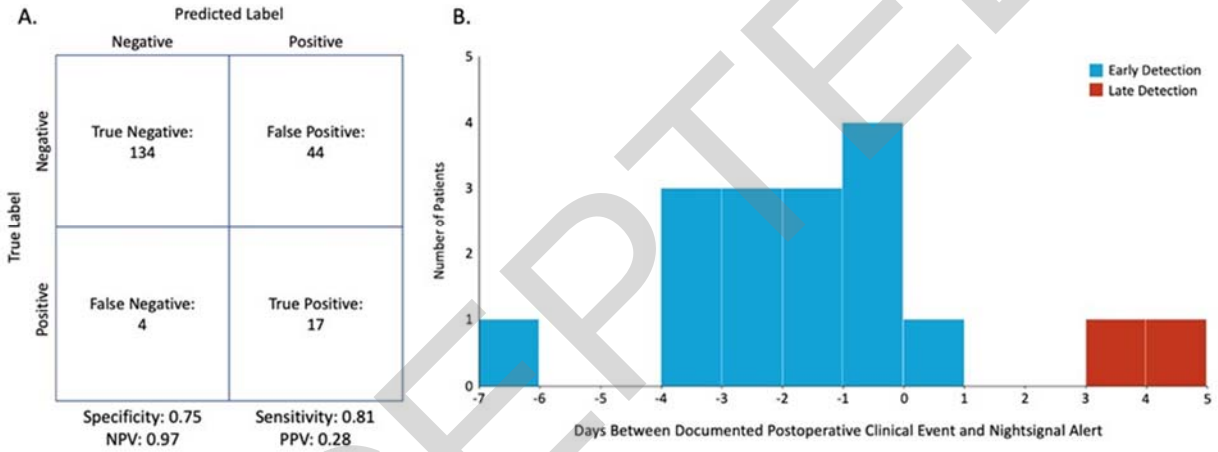

Table 1. Baseline Characteristics and Perioperative Data

Patient Characteristics	Thoracic (N=24)	Cardiac (N=32)	Total (N=56)
Baseline Characteristics			
Age, (years), median (IQR)	65 (63, 73)	58 (43, 65)	62 (51, 68)
Female, n (%)	18 (75.0%)	12 (37.5%)	30 (53.6%)
Race & Ethnicity, n (%)			
White	23 (95.8%)	29 (90.6%)	52 (92.9%)
Black	-	1 (3.1%)	1 (1.8%)
Asian	-	1 (3.1%)	1 (1.8%)
Hispanic	1 (4.2%)	1 (3.1%)	2 (3.6%)
Comorbidities			
Diabetes, n (%)	4 (16.7%)	2 (6.3%)	6 (10.7%)
Hypertension, n (%)	12 (50.0%)	6 (18.8%)	18 (32.1%)
Congestive Heart Failure, n (%)	-	3 (9.4%)	3 (5.4%)
COPD, n (%)	5 (20.8%)	-	5 (8.9%)
Chronic Kidney Disease, n (%)	1 (4.2%)	1 (3.1%)	2 (3.6%)
Obesity, n (%)	6 (25.5%)	8 (25.0%)	14 (25.0%)
Disseminated Cancer, n (%)	1 (4.2%)	-	1 (1.8%)
Immunocompromised, n (%)	4 (16.7%)	3 (9.4%)	7 (12.5%)
Arrhythmia, n (%)	2 (8.3%)	8 (25.0%)	10 (17.9%)
Other Comorbidities, n (%)	4 (16.7%)	8 (25.0%)	12 (21.4%)
Diabetes, n (%)	10 (41.7%)	13 (40.6%)	23 (41.1%)
Preoperative Data			
Pulmonary Function Test, n (%)[1]	22 (91.7%)	-	-
Predicted FEV1, median (IQR)	93 (77, 100)	-	-
Predicted DLCO, median (IQR)	75 (60, 87)	-	-
Ejection Fraction, median (IQR)[1]	-	65 (59, 68)	-
Non-Malignant Diagnosis, n (%)	6 (25.0%)	-	6 (10.7%)
Pathologic Lung Cancer Stage, n (%)[2]			
Stage IA1	8 (44.4%)	-	-
Stage IA2	4 (22.2%)	-	-
Stage IA3	0 (0.0%)	-	-
Stage IB	2 (11.1%)	-	-
Stage IIB	3 (16.7%)	-	-

Stage IIIA	1 (5.6%)	-	-
Peri- & Post-Operative Data			
Operation, n (%)			
VATS Lobectomy	7 (29.2%)	-	7 (12.5%)
Robotic Lobectomy	6 (25.0%)	-	6 (10.7%)
VATS Wedge Resection	3 (12.5%)	-	3 (5.4%)
Robotic Wedge Resection	2 (8.3%)	-	2 (3.6%)
VATS Segmentectomy	2 (8.3%)	-	2 (3.6%)
Robotic Segmentectomy	4 (16.7%)	-	4 (7.1%)
Aortic Arch Repair	-	2 (6.3%)	2 (3.6%)
Coronary Artery Bypass Graft	-	1 (3.1%)	1 (1.8%)
Open Valve Repair	-	5 (15.6%)	5 (8.9%)
Non-robotic Minimally Invasive Valve Repair	-	7 (21.9%)	7 (12.5%)
Robotic Valve Repair	-	1 (3.1%)	1 (1.8%)
Open Valve Replacement	-	12 (37.5%)	12 (21.4%)
Non-robotic Minimally Invasive Valve Replacement	-	2 (6.3%)	2 (3.6%)
Other	-	2 (6.3%)	2 (3.6%)
Surgical Approach, n (%)			
Open	-	22 (68.8%)	22 (39.3%)
Non-robotic Minimally Invasive	12 (50.0%)	9 (28.1%)	21 (37.5%)
Robotic	12 (50.0%)	1 (3.1%)	13 (23.2%)
Length of Hospital Stay, (days), median (IQR)	3 (2, 4)	5 (5, 7)	5 (3, 7)
Chest Tube Duration, (days), median (IQR)	2 (1, 3)	3 (2, 4)	3 (2, 4)

[1]Data that were specific to thoracic patients (e.g., pulmonary function tests, pathologic stage) and cardiac patients (e.g., ejection fraction) were not reported for the overall cohort.

[2]Calculated using the total number of patients diagnosed with lung cancer as the denominator (n=18)

Table 2. Postoperative Events in the Study Cohort

Postoperative Event	Surgery Type	Time between NightSignal Alert and Symptom Onset Related to the Postoperative Event (Days)
Anxiety Episodes	VATS Lobectomy	-1
Atrial Fibrillation	Minimally Invasive Valve Repair	-4
Atrial Fibrillation	Minimally Invasive Valve Replacement	-7
Dermatitis	Open Valve Replacement	-2
Diarrhea	Robotic Segmentectomy	4*
Diarrhea	Open Valve Replacement	-1
Endocarditis	Minimally Invasive Valve Repair	-3
Pleural Effusion	Robotic Segmentectomy	0
Pleural Effusion	Open Valve Repair	-1
Pleural Effusion	VATS Wedge Resection	-4
Pleural Effusion**	Open Valve Replacement	-
Pneumonia	Robotic Segmentectomy	-2
Pulmonary Embolism	Minimally Invasive Valve Repair	-1
Severe Postoperative Pain	Robotic Valve Repair	-4
Severe Postoperative Pain**	Minimally Invasive Valve Repair	-
Thrombophlebitis	Open Valve Replacement	-3
Transient Ischemic Attack	Open Valve Repair	3*
Worsened Sleep Apnea	Aortic Arch Repair	-2
Wound Infection	Robotic Lobectomy	-3
Wound Infection**	Robotic Segmentectomy	-
Wound Infection**	VATS Wedge Resection	-

*Among 17 true positive postoperative events, 2 were detected by the NightSignal algorithm after the documented postoperative event date.
**4 postoperative events were not detected by the NightSignal algorithm