Modeling Biobehavioral Rhythms with Passive Sensing in the Wild: A Case Study to Predict Readmission Risk after Pancreatic Surgery

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Biobehavioral rhythms are associated with numerous health and life outcomes. We study the feasibility of detecting rhythms in data that is passively collected from Fitbit devices and using the obtained model parameters to predict readmission risk after pancreatic surgery. We analyze data from 49 patients who were tracked before surgery, in hospital, and after discharge. Our analysis produces a model of individual patients' rhythms for each stage of treatment that is predictive of readmission. All of the rhythm-based models outperform the traditional approaches to readmission risk stratification that uses administrative data.

CCS Concepts: • **Human-centered computing → Ubiquitous and mobile computing**; • **Applied computing → Life and medical sciences**.

Additional Key Words and Phrases: Mobile and Wearable Sensing, Data Processing, Feature Extraction, Machine Learning, Circadian Rhythm, Patient Readmission, Cancer

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1 INTRODUCTION

Biobehavioral rhythms, including patterns of activity and rest as well as physiology such as heart rate, may provide important insights into health. The proliferation of consumer activity monitors and other mobile devices offers new opportunities for monitoring biobehavioral rhythms [2]. The goal of our research is to 1) detect and model biobehavioral rhythms from passively collected mobile and wearable data in the wild, and 2) demonstrate the value of rhythm modeling in predicting clinical health outcomes. In this paper, we explore the potential of detecting biobehavioral rhythmicity in passively collected data from patients undergoing pancreatic surgery to further predict readmission risk after discharge.

Hospital readmissions cost the US healthcare system billions of dollars annually; are associated with high mortality rates and listed as the source of stress and suffering for both patients and family members [6,34]. Readmissions after abdominal cancer surgery such as pancreatic surgery are very common, with up to 50% of

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patients experiencing an unplanned readmission to a hospital within 30 days of postoperative discharge [50]. It is estimated that up to 82% of readmissions after cancer resections are potentially preventable [55], so more accurate and earlier prediction of readmission risk could enable management of emerging postoperative complications before they escalate into readmissions. However, it is challenging to predict who will be readmitted to the hospital following pancreatic surgery ahead of time. Traditional approaches to readmission risk stratification rely on static administrative and medical record data and generally classify all surgical oncology patients at high-risk [12,28].

Patient behavioral factors, including rest-activity rhythms, are a novel and dynamic set of risk factors that could improve readmission prediction accuracy and could also highlight potentially modifiable targets for behavioral intervention. [30] suggests that behavioral and environmental changes endemic to hospitalization may place patients at generalized risk for negative outcomes independent of the disease causing their hospital stay. These include experiences common in prolonged hospital stays such as physical inactivity, disturbed sleep, poor nutrition, and physical and mental stress, all of which may contribute to what he has termed 'post-hospital syndrome'. Disrupted biobehavioral rhythms may represent a core feature of post-hospital syndrome that may adversely affect short- and long-term outcomes following hospitalization, including readmissions. On the other hand, research also shows that interventions aimed at preserving patients circadian rhythms through strategies like reduction of nighttime noise, delay of routine blood draws, use of red-enriching light after sunset, and use of bright light therapy help expedite recovery and effectively reduce readmission rates [36,40]. Given the value of these interventions in reducing the prevalence of readmissions, in this paper we focus on who should be the target of these interventions by determining who is most at risk for readmissions.

We use passively collected biobehavioral data from consumer wearable devices to detect instability in biobehavioral rhythms before surgery, in hospital, and after discharge. We observe significant differences in rhythms within- and between-patients across those three stages. We also use rhythm metrics extracted from sensor data in a machine learning pipeline to predict readmission risk in those patients. Our results show the potential of biobehavioral rhythm features in predicting readmission. The paper makes the following contributions to mobile health and medical informatics:

(1) We provide evidence for the feasibility of detecting and modeling rhythmicity in biobehavioral data passively collected from consumer wearable devices in the wild and using it to predict readmission risk.
(2) We demonstrate irregularity in biobehavioral rhythms related to hospitalization and show that these irregularities are more profound in readmitted patients.
(3) We use features obtained from the rhythm models in a machine learning analysis to predict readmission within 90 days of discharge and demonstrate significant differences in those features between readmitted and non-readmitted patients as well as superiority of our rhythms-based model over traditional clinical approaches. Our results also suggest that with this approach, the readmission risk can be predicted as early as during hospitalization.

In the following sections, we first present the background for this work and discuss existing research using mobile and wearable devices to understand patterns in human behavior such as sleep cycles and alertness, and to estimate readmission risk from passively collected data. We point out how our work extends existing research in human behavior modeling with passive sensing and in readmission prediction in the wild. We then describe the methods we use to model and describe the rhythms of our subject population, to identify rhythm disruptions in each stage of treatment, and to predict readmission risk in our study population. Our analysis and results will demonstrate the potential of rhythm modeling with passive data to identify and describe behavior and to predict health outcomes (*i.e.*, readmission risks in this work).

2 BACKGROUND AND RELATED WORK

Our research on biobehavioral rhythms is informed by significant research on related constructs such as circadian rhythms, diurnal rhythms, ultradian rhythms, and infradian rhythms. The body's normal functions, including performance, behavior, sleep and endocrine cycles are regulated by a biological clock (a distinct group of cells found within the hypothalamus) in the brain. The clock responds to periodic changes in environmental conditions linked to the earth's rotation on its axis and revolutions around the sun [44] by synchronizing internal cycles with external stimuli called zeitgebers (from the German meaning 'time givers'). Zeitgebers include environmental time cues such as light, food, noise, or social interaction, which help to reset the biological clock to a 24-hour day [11,14]. The clock translates environmental information on day length, social contact, and seasonal changes into hormonal messages that are sent throughout the body to set the clock of other organs [11,17]. Secretion of melatonin (a hormone that induces sleep) is highest at night and falls during the day [5,25]. Even when light cues are absent, melatonin is still released in a cyclic manner.

As such, environmental conditions, lifestyle, and circumstances such as travels across time zones and shift work cause disruptions in biobehavioral rhythms. Continuous disruptions in one's rhythms can lead to chronic health problems such as cardiovascular disease, cancer, diabetes, and mental illness [9,15,19,22,23,29,48,49]. Rhythms can also affect the daily life and productivity of individuals, inducing so-called social jetlag [18,45,53] which refers to a misalignment between one's biological clock and social obligations, and can provide cues about the state of health and wellbeing in individuals.

A vast literature documents the relevance of rhythm disruption for cancer specifically [51]. Epidemiologic studies highlight circadian rhythm disruption (*e.g.*, due to shift work) as a robust risk factor for cancer incidence [23]. Cancer treatment has been shown to lead to circadian dysregulation, with chemotherapy patients exhibiting progressively worsening disruptions as characterized via research grade wrist actigraphy [24,47] and cancer inpatients exhibiting profound dampening of amplitude of activity, lower mean level of activity, and phase advancement, *i.e.*, activity shifted earlier [41]. Circadian disruption in cancer patients has been associated with a high severity of symptoms such as fatigue and anorexia [26] and is also a robust predictor of survival in metastatic colorectal cancer patients [32]. To date, researchers have not used data from smartphone sensors or consumer activity monitors to estimate biobehavioral rhythm disruption during cancer treatment, and no studies have examined links between biobehavioral rhythm disruption and readmission risk in cancer or other clinical populations.

2.1 Using Mobile and Wearable Technology to Understand Biobehavioral Rhythms

Research-grade actigraphy devices have been used extensively in Chronobiology, medicine and health to understand circadian rhythms, sleep-wake cycles or rest-activity patterns and their associations with health outcomes [4,8,27,33,42]. For example, the analysis of data collected from such devices in [16] showed different circadian behavior such as sleep, amplitude fluctuations, and daytime hyperactivity in children with bipolar disorder, ADHD, and normal children. Research using actigraphic monitoring in [46] showed temporal interrelationships among fatigue, circadian rhythm and depression in breast cancer patients undergoing chemotherapy treatment. A similar study of circadian locomotor activity in schizophrenic patients with acute neuroleptic-induced akathisia [43] demonstrated persistent higher daytime motor activity during mid-day and evening hours in those patients compared to the control group. [20] investigated the relationship between actigraphic measurement of circadian organization and self-reported subjective sleep quality among patients with advanced lung cancer. Another study [52] demonstrated the effect of indirect bright light in regulating circadian rhythm disturbances in patients with dementia. Overall, research has demonstrated actigraphy to be a 'reliable and useful adjunct to routine clinical evaluation of insomnia, circadian-rhythm disorders, and excessive sleepiness' and 'useful in characterizing

and monitoring circadian rhythm patterns or disturbances in certain special populations (*e.g.*, children, demented individuals)' [33].

Advancements in personal mobile and wearable devices have provided the possibility to study human rhythms more broadly in the wild, giving rise to the emergence of circadian computing [1]. Mobile and wearable devices have been used to understand sleep patterns and quality [37,38], and commercial devices such as Fitbits are now able to infer sleep duration and quality reasonably accurately. Two brief studies with healthy young adults have used activity data from Fitbit devices to quantify rest-activity rhythms and found that rhythm measurement compared well relative to research-grade actigraphy [7,31]. Studies in [54] and [35] have also explored the capability of personal tracking devices to measure sleep compared to gold standards such as polysomnography. We are unaware of studies that have examined the rhythmicity of Fitbit-assessed heart rate.

Abdullah et al. [1] explored the patterns of mobile device use to illustrate differences in the sleep behavior of early and late chronotypes. Other studies from this research group used the same type of data to understand daily cognitive cycles, more specifically daily alertness patterns [3,39]. Their study with 20 students over 40 days showed that time and body clock as well as hours slept and stimulant intake can influence alertness oscillation. However, in addition to the underlying assumption of, and a focus on, a 24-hour cycle, these studies have primarily looked at the daily variations in mobile use behavior and compared it to ground truth data on alertness level rather than modeling the actual rhythm. In contrast, we use the data to 1) detect cycles and their periods in our study population and 2) model the cyclic biobehavioral rhythms from passive data and use these features to predict readmission, a clinically significant outcome.

2.2 Using Mobile and Wearable Technology to Predict Readmission

Low et al. [34] and Bae et al. [6] have explored the potential of activity data collected from Fitbits to infer readmission risk among cancer patients. Both analyses have demonstrated that low activity measured by step counts [34] and sedentary behavior [6] during in-hospital recovery contributes to early readmission. Our study extends the existing research in readmissions in three ways:

- We model biobehavioral rhythms of cancer patients, including rest-activity and heart rate rhythms, in all three stages of treatment, namely before surgery, in-hospital, and after discharge.
- We illustrate the biobehavioral rhythm disruption in each stage and its association with readmission status.
- Using features obtained from the rhythm models at each stage, we predict readmission within 90 days of discharge and demonstrate the impact of biobehavioral rhythms features in each stage on predicting readmission. To our knowledge this is the first study to objectively study the relations between readmission and rhythm disruption in patients.

The following sections describe our approach to rhythm modeling and using those models to predict readmissions in our patient population.

3 METHODS

To support these contributions and study the role of rhythms in understanding and predicting health outcomes, we conducted a data collection study with oncological patients, followed by a rhythm-based data analysis. We now describe our data collection.

3.1 Study Procedure

Potential study participants were identified for the study by their surgical oncology team. Men and women aged 18 years and above who were scheduled for pancreatic surgery at [anon] Cancer Center were eligible and were enrolled at their preoperative clinic visit.

Table 1. List of features extracted from Fitbit steps and heart rate

Category	Features
Steps	Sum and max steps
	Min, average, and max length of active bouts
	Min, average, and max length of sedentary bouts
	Min, average, and max number of steps in active bouts
	Number of active bouts
	Number of sedentary bouts
Heart rate	Min, max, mean of heart rate
	Min, max, mean of absolute change
	Min, max, mean of negative change
	Min, max, mean of positive change
	Number of no change

If eligible, participants were provided with a Fitbit Charge2 device to wear for the duration of the data collection, which they were invited to keep after the study completion. The Fitbit device collected data including information about activity (approximately every minute) and heart rate (approximately every second). Participants' electronic medical records were reviewed to extract information on whether participants were readmitted to any inpatient facility within 90 days of postoperative discharge.

A total of 60 patients enrolled in the study between March 2017 and February 2018. Surgery was canceled for four patients, and three patients withdrew from the study, leaving 53 patients in our analytic sample (mean age 65 years, range 40-82, 43% female, 94% White, 78% married/living as married). Most patients were undergoing surgery for pancreatic cancer (83%), with the remainder undergoing surgery for benign conditions (*e.g.*, pancreatic cysts), and the average length of inpatient stay following surgery was 7 days (range 2-22). One-third of patients (34%, n = 18) were readmitted within 90 days of discharge. Readmission to outside facilities was determined by outside hospital records and/or direct patient or caregiver reporting documented in the electronic medical record. There were no significant differences between readmitted and non-readmitted patients with regard to age ($p = .72$), gender ($p = .38$), preoperative body mass index ($p = .40$), comorbidity ($p = .88$), estimated blood loss during surgery ($p = .20$), tumor size ($p = 1.00$), or length of hospital stay ($p = .06$).

3.2 Data Processing

3.2.1 Feature Extraction. Our approach for identifying relevant features is exploratory and based on previous research. We have developed a generic and flexible Feature Extraction Component (FEC) to extract as many features as possible from passive data streams and then use correlation-based feature selection to choose the most relevant and least redundant ones. This data-driven approach reduces redundancy while preserving valuable features. FEC computes features from timestamped streams of data in specified time windows ranging from 1 minute to several months. From the data streams, FEC extracts a set of common statistical features such as min, median, mean, max, and standard deviation, as well as more complex behavioral features such as circadian movement and travel distance. For this analysis, we extracted features on an hourly basis to capture more variations. The features extracted from Fitbit steps (Table 1) include sum and max steps; min, average, and max

Table 2. The list of rhythmic features extracted per wearable feature listed in Table 1

Rhythm Parameter	Description
Mean activity	Arithmetic mean of activity counts per hour balanced across 24-hours
Mean diurnal activity	Arithmetic mean of activity counts from rise time to bedtime
Mean nocturnal activity	Arithmetic mean of activity counts from bedtime to rise time
Percentage of nocturnal activity	Sum of nocturnal activity divided by total sum of activity, with total sum based on full 24-hour periods
Diurnal skew	The skewness of the distribution of one hour activity epochs from rise time to bedtime
Time dependent coefficient of variation	Variability from one hour to the next from rise time to bedtime
Interdaily stability	The extent to which the overall pattern of activity across days remains consistent over the monitoring period
Intradaily stability	The Frequency and extent of transitions between rest and activity from hour epoch to hour epoch (24-hour basis)
Mean 10 most active hours	Mean of the 10 most active hours each day (diurnal activity) calculated without reference to bed and rise times
Mean 5 least active hours	Mean of the 5 least active hours each day (nocturnal activity) calculated without reference to bed and rise times
Relative amplitude	The difference between M10 and L5 using the formula: RA = (M10 - L5) / (M10 + L5)
Circadian variance	Percent of variance in the activity profile that can be accounted for by a circadian rhythm
Total sleep time	Number of minutes designated as sleep from bedtime to rise time
Sleep efficiency	Percent of minutes from bedtime to rise time scored as sleep
Cosinor fit	Fit of a cosinor model to the data in one hour epochs as indicated by the correlation coefficient
Cosinor acrophase	Phase of the circadian rest-activity cycle as indicated by the time when the fit rhythm reaches its maximal value
Cosinor amplitude	The extent to which the rhythm rises above or falls below the mesor
Cosinor mesor	An overall estimate of mean daily activity
Cosinor relative amplitude	Amplitude of the circadian rhythm model divided by the mesor

length of active bouts; min, average, and max length of sedentary bouts; min, average, and max number of steps in active bouts; and number of active and sedentary bouts whereas heart rate features include min, max, and mean heart rate; min, max, and mean of positive, negative, and absolute change as well as number of no change in heart rate (in each time window, here hourly). We consider a bout to be a continuous period of time (here more than 5 minutes) where a dominant activity takes place. For example, if the patient is sedentary for 2 hours and then starts walking for more than 5 minutes, s/he switches from sedentary to active.

From the hourly features in Table 1, we further extract rhythm features following the list in [16]. We adjust some of those features such as mean diurnal activity and extract their daily value instead of values across all days as suggested in [16]. We also use rise time to bedtime duration that was extracted from Fitbit sleep. Table 2 summarizes the list of these parameters.

3.3 Detection of Rhythmicity

Our first question is whether we can detect rhythmicity in the passively collected biobehavioral data. Different methods have been used for rhythmicity detection such as ANOVA, Fourier analysis, cosinor, periodograms, autocorrelation, and cross-correlation. Given the equidistant nature of our time series data (hourly intervals), all of these methods can be used to model rhythmicity in our data. We use cosinor for our analysis as it provides the means to estimate and quantify parameters of a rhythm with an assumed period and use those parameters as features in our machine learning analysis for readmission prediction. We also use autocorrelation and Fourier periodograms to further observe rhythmicity and to detect existing periods in the data other than the assumed 24-hour period. Our goal is to detect, understand, and observe the extent to which a patient's biobehavioral rhythms are affected by surgery as well as the extent to which rhythm variation in different stages of hospitalization predicts possible readmission.

3.3.1 Cosinor. Cosinor, first developed by Halberg et al. [21], comprises a set of regression-based parametric methods for rhythms assessment and is able to model both equidistant and non-equidistant data. For a specified period, *e.g.*, 24 hours, cosinor fits one or more cosine curves to the data to minimize the sum of squares of the differences between the actual measurements and the fitted model. The model outputs several rhythmic parameters (see Figures 1 and 6) including MESOR (the rhythm adjusted mean), amplitude (the distance between

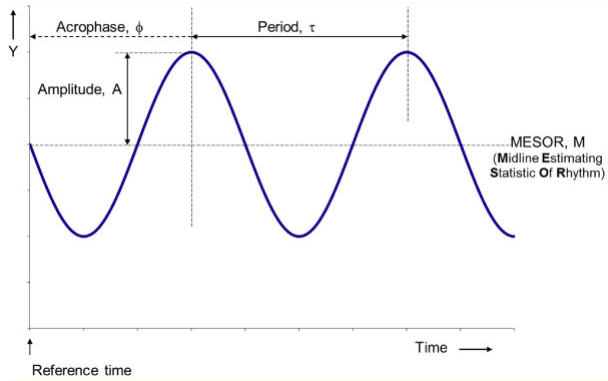


Fig. 1. The parameters or attributes of a sinusoidal rhythm presented in [10].

the oscillation peak and the MESOR), and acrophase (distance from the reference time to the crest time). It also measures the statistical significance of the period, *i.e.*, whether or not a rhythm exists in data and reports the proportion of variance in the model as percentage rhythm (see *e.g.* Figure 6).

We build individual cosinors where we use data from each patient to model their biobehavioral rhythms. We then build population-mean cosinors using data from readmitted and non-readmitted populations to identify similarities and differences between the two patient groups. This analysis may provide evidence for or against using the rhythm model of the population as a baseline to compare to individual rhythms to identify the patients at risk of readmission at each state of the treatment process. We also use the estimated cosinor parameters as features (also listed in Table 2 in our machine learning analysis that is described in the next section.

3.3.2 Autocorrelation. Autocorrelation is a statistical method which has been shown to reliably identify periodicity in biological data [13]. Autocorrelation calculates the correlation coefficient by comparing the time series data to itself from start to end. In each round, the two time series are shifted by one point and the process is repeated until one third of data (N/3) is parsed. The resulting coefficient values (r) create an autocorrelation plot, or correlogram, that provides the possibility of observing rhythms in data. If the data is rhythmic, the r values increase and decrease in regular intervals (see *e.g.*, Figure 2a). The significance of peaks in a 95% confidence interval (the dashed blue lines in Figure 2a) are given at 2/sqrt(N). Repeated peaks above the confidence interval indicate strong periodicity in the data and rapid decay in the amplitude of peaks shows variation between cycles in data.

3.3.3 Periodogram. Periodogram is another method that finds periodicity in data. Unlike cosinor to which the period should be known, the periodogram uses a Fourier analysis at specific intervals going from N to 2 (N, N/2, N/3, ..., 2) to identify significant periods observed in the data where N is the number of equidistant data points. Each waveform is represented by a spectral line at the fundamental frequency, the lowest frequency of the waveform with additional smaller peaks. For example, in Figure 2a, the longest spectral line is the 24-hour period indicating the dominant rhythm followed by approximately 6- and 3-hour periods. This method, in addition to identifying circadian disruptions, helps detect other existing cycles in the data that were not evident before.

3.4 Machine Learning Analysis

We use the features listed in Table 2 including cosinor parameters to predict readmission in cancer patients after surgery. We define readmission prediction as a binary classification problem (readmitted or not) where rhythmic

features of passive data at each stage of hospitalization are used to predict whether or not the patient is at risk of readmission. The predictions are compared to the ground truth labels acquired from patients' hospitalization records to measure the accuracy of prediction.

3.4.1 Dimensionality Reduction. We remove patients with no or very few data points (less than 10%) which leave us with 49 patients out of which 17 were readmitted. One readmitted patient was among the removed ones. We also exclude features with zero variation or missing values. Although we include only features from steps and heart rate, more than 500 features are still left, which is too many for the amount of data we have. We therefore perform a correlation analysis on the feature set to identify features that are highly correlated with each other and therefore redundant with no extra discriminative power to infer the readmission class. We only keep those features that are least correlated ($|r| \leq 0.7$) and remove the rest. This leave us with the following hourly features: Average length of active bouts, number of sedentary bouts, number of no change, mean heart rate, and absolute change in heart rate. We then extract rhythmic parameters for these feature values as listed in Table 2, which in total provides 95 rhythmic features to be used for modeling.

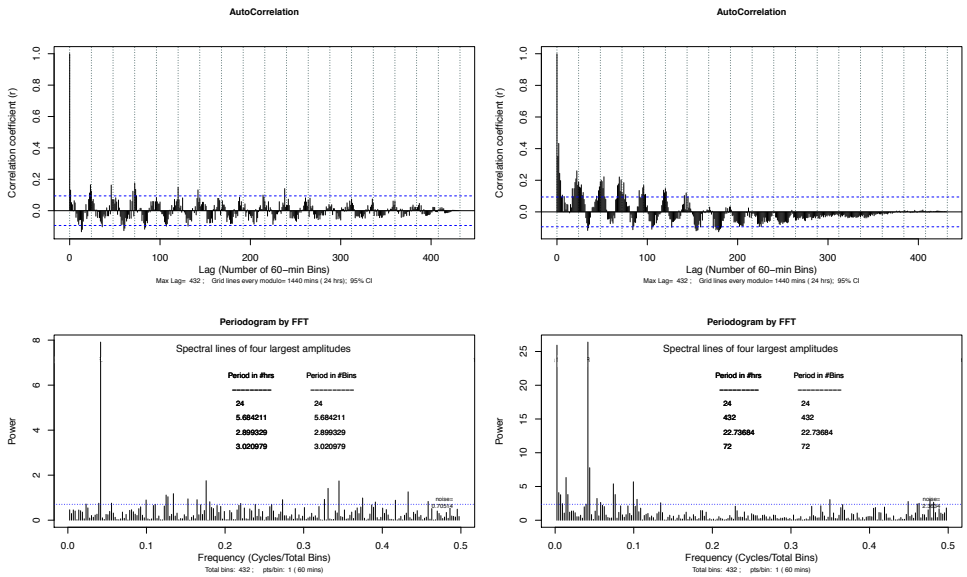
3.4.2 Classification. Our process of choosing the learning algorithms is an exploratory task with trials and tests of multiple off-the-shelf meta algorithms and choosing the best performing ones. We evaluate the performance of Random Forest, Logistic Regression, Support Vector Machine, Bayesian Network, and Boosted Logistic Regression. Boosted Logistic Regression with Linear Regression or Decision Stump as base learners provides the best performance according to our evaluation criteria explained below. We compare our classification results with two widely-used clinical approaches to readmission risk stratification, namely LACE (which includes data about Length of stay, Acuity of admission, Comorbidity, ER visits in past 6 months) and HOSPITAL (which includes data about Hemoglobin at discharge, discharged from Oncology service, Sodium at discharge, Procedure during hospitalization, Index admission Type (emergent or planned), number of Admissions in the past year, and Length of stay). Both of these measures use the administrative and medical record data available at the time of hospital discharge to stratify patients into low vs. high risk for readmission groups. We use the rhythm model features in three stages to predict readmission 1) before surgery, 2) during the inpatient hospital stay, and 3) after discharge.

3.4.3 Validation. We use leave-one-patient-out cross-validation (LOPO) on our dataset to evaluate the power of rhythmic features in predicting readmission. The LOPO will provide an overall performance of the classification and show how a classifier may perform when the distribution of training data is different in each run. In other words, given that the generated model in each fold is tested on one patient's data, we examine how well other patients' data used as training set (even if very different from the test patient) can predict the readmission status of the test patient. We evaluate the performance of the classifier by looking at the overall accuracy, precision and recall for each class value (here readmitted vs. non-readmitted), and F1 measure. We are especially interested in optimizing the recall for the readmitted class label which is maximizing the number of accurately classified readmitted patients (true positives) and minimizing the number of misclassifications (false negatives). This is important because the cost of misclassifying the readmitted patients as non-readmitted is higher than misclassifying the non-readmitted patients as readmitted.

4 ANALYSIS AND RESULTS

Our analysis is two-fold: First, we explore the potential of modeling and detecting rhythmicity in passively collected data from consumer-level wearable devices. Then we use the built rhythm models and parameters to infer and predict readmission in cancer patients after surgery. Specifically, we are interested in the following questions:

(1) Can we detect and observe biobehavioral rhythmicity in patients' passive time series data?



(a) Non-readmitted patient - Before surgery (b) Readmitted patient - Before surgery

Fig. 2. The correlograms and periodograms of data from two sample patients before surgery. The regularity of rhythms in both patients is decreased as they get close to surgery dates but the 24-hour rhythm period is still observed (see the longest spectral line in the periodograms).

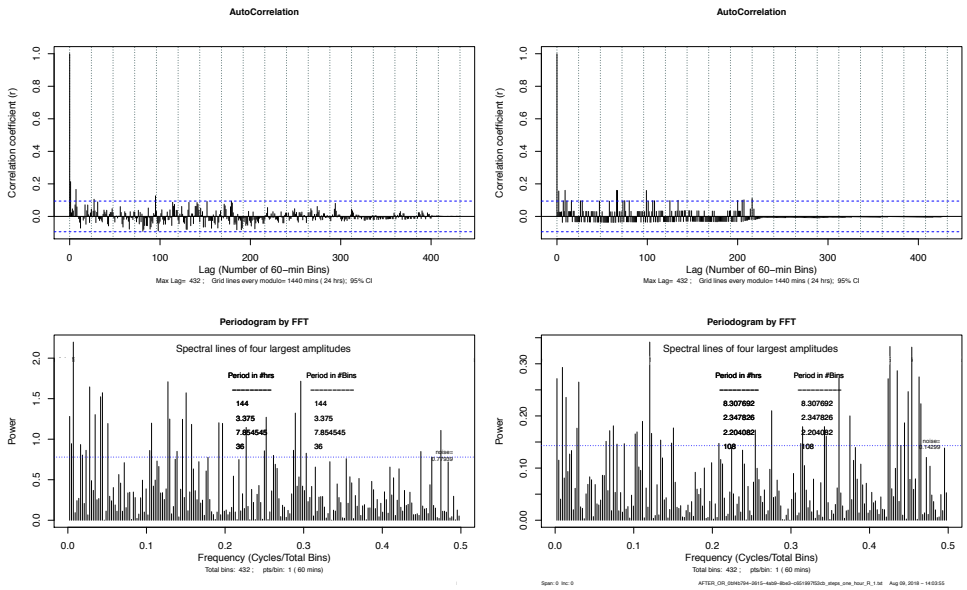
(2) If so, do we observe rhythm variation in different stages of hospitalization? And how do those variations relate to patients' readmission status?
(3) Are individual biobehavioral rhythms and their variations predictive of readmission?

We explore these questions in the following sections.

4.1 Modeling and Detecting Biobehavioral Rhythms with Passive Data

We use autocorrelation, periodogram, and cosinor to model patient rhythms in three main time segments namely before surgery, in hospital, and after discharge for each selected mobile feature. All three methods provide visual interpretation of rhythms in the data. In addition to periodic representation of data, cosinor outputs rhythmic parameters such as MESOR, phase, and amplitude (as described in the Methods section) for a given period (*e.g.*, 24 hours). Unlike cosinor that needs to have specific periods or rhythms specified, periodogram detects all significant periods in the time series.

Figures 2, 3, and 4 show correlograms (generated by autocorrelations) and periodograms, respectively, of two sample patients in the three stages that represent rhythmicity in data. The regularity of rhythms in both patients before surgery is decreased as they get close to surgery dates (Figures 2a and 2b) but the 24-hour rhythm period is still observed before surgery (see the longest spectral line in the periodograms). Great irregularity appears during the hospitalization (Figures 3a and 3b) in both patients where the 24-hour period no longer exists. The irregularity is more visible in the readmitted patient. A clear difference between the rhythms of the two patients is observed in the after discharge period (Figures 4a and 4b). The rhythm analysis of the non-readmitted patient



(a) Non-readmitted patient - In hospital

(b) Readmitted patient - In hospital

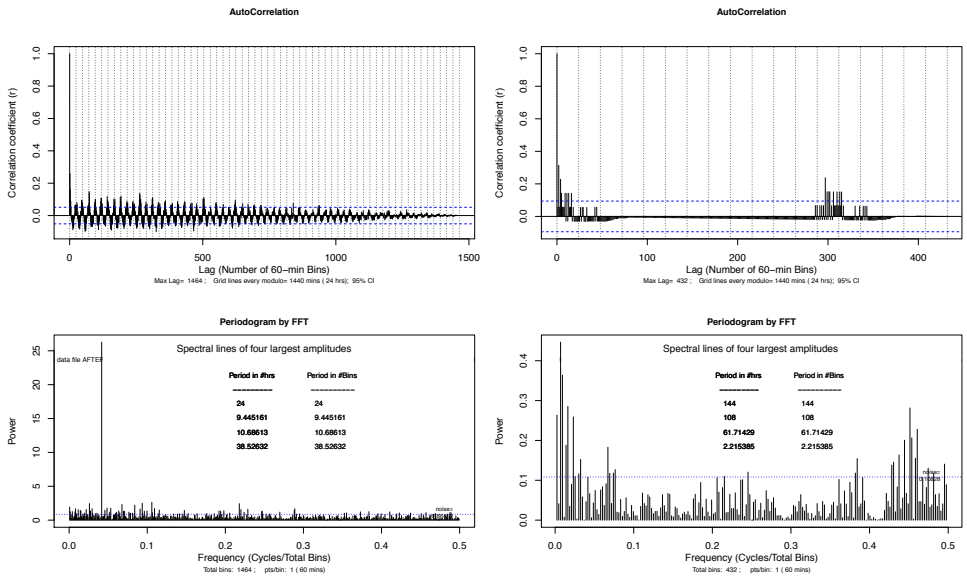
Fig. 3. The correlograms and periodograms of data from the two sample patients in hospital. Great irregularity appears during the hospitalization in both patients where the 24-hour period no longer exists. The irregularity is more visible in the readmitted patient.

shows a return to a regular rhythm of 24 hours after discharge, but this pattern is not observed in the readmitted patient. These observations clearly show a relationship between rhythm disruption and readmission risk despite its unclear direction, *i.e.*, whether rhythm disruption contributes to readmission or it is a solely an indicator of readmission risk.

Table 3 describes the overall statistics of rhythm detection that resulted from applying periodogram on the activity bouts in readmitted and not-readmitted patients. According to our analysis, the majority of the patients have 24-hour activity rhythms before surgery (N = 39) and after discharge (N = 43) out of which 35 have regular rhythms in both stages. In contrast, only a few patients (N = 7) amongst the not-readmitted patients retain a regular activity rhythm in all three stages, while none of the readmitted patients keeps their normal rhythm in the hospital. This observation 1) confirms existing evidence of disrupted biobehavioral rhythms during hospitalization[30] and 2) introduces the lack of a 24-hour rhythm during hospitalization as a potentially important and discriminative feature for inferring readmission risk.

4.2 The Role of Rhythms Variation in Patient Readmission

Disruption of biobehavioral rhythms can both be a sign of readmission or it can contribute to the risk of readmission. We are curious to understand 1) how different biobehavioral rhythms of each patient are in the three stages of treatment, 2) how different the rhythms of the readmitted group is from the not-readmitted group, and 3) what rhythm parameters are significantly different in each stage and between the two populations. We therefore first calculate changes between rhythm parameters at each stage, *e.g.*, the difference between the mesor of active bouts rhythm before surgery and after discharge. We then calculate the averages of those parameters in



(a) Non-readmitted patient - After discharge (b) Readmitted patient - After discharge

Fig. 4. The correlograms and periodograms of data from the two sample patients after discharge. The non-readmitted patient shows a return to a regular rhythm of 24 hours after discharge, but this pattern is not observed in the readmitted patient.

Table 3. Number of patients with 24-hour rhythms

	R (N=17)	NR (N=32)	Total (N=49)
Before surgery	15	24	39
In hospital	0	11	11
After discharge	14	29	43
Before surgery & in hospital	0	7	7
Before surgery & after discharge	13	22	35
In hospital & after discharge	0	11	11
All 3 stages	0	7	7

each readmission group (re-admitted and not-readmitted) and repeat the process of calculating differences. We observe differences at each stage per patient as well as among the two groups.

Table 4 lists the parameters that are significantly different between the two groups using a t-test ($p \leq 0.05$). More and larger differences are observed between feature values when comparing the after discharge period to before surgery. The highest difference is in the mean of heart rate during the least 5 active hours between the two groups (diff = 6.57) where the mean heart rate of the readmitted patients is highly different after discharge compared to before surgery (value = 5.95) showing an increase in heart rate in these patients after discharge. In contrast, the same value in non-readmitted patients is -0.63 showing only a slight decrease in heart rate after

Table 4. Differences in rhythmic features between readmitted and non-readmitted patients across three stages of treatment

Stage 1 - Stage 2	Fitbit feature	Rhythm feature	NR	R	Diff. (p<0.05)
After discharge - before surgery	Heart rate - average absolute change	Mean 10 most active hours	-0.73	-2.12	-1.38
		Mean activity	-0.65	-1.80	-1.15
		Mean diurnal activity	-0.62	-1.33	-0.71
		Mean nocturnal activity	-0.65	-2.39	-1.74
	Steps - average length active bouts	Circadian variance	-0.12	-0.21	-0.10
		Cosinor amplitude	-0.09	-0.19	-0.10
		Cosinor mesor	-0.08	-0.17	-0.10
		Cosinor relative amplitude	0.04	0.27	0.24
		Diurnal skew	0.10	0.77	0.66
		Intradaily variability	0.06	0.24	0.18
		Mean 10 most active hours	-0.24	-0.55	-0.31
		Mean activity	-0.08	-0.17	-0.10
		Mean diurnal activity	-0.14	-0.27	-0.12
		Relative amplitude	-0.06	-0.25	-0.19
	Mean heart rate	Diurnal skew	-0.01	-0.22	-0.21
		Mean 5 least active hours	-0.63	5.95	6.57
	Heart rate - number of no change hours	Mean 5 least active hours	-0.03	1.30	1.34
		Mean nocturnal activity	0.35	1.46	1.11
	Steps - number of sedentary bouts	Circadian variance	-0.02	-0.05	-0.03
		Cosinor amplitude	-0.02	-0.06	-0.04
		Cosinor mesor	-0.01	-0.05	-0.04
		Cosinor relative amplitude	-0.02	-0.05	-0.03
		Diurnal skew	0.21	0.68	0.47
		Intradaily variability	-0.10	0.06	0.16
		Mean 10 most active hours	-0.07	-0.20	-0.13
		Mean activity	-0.01	-0.05	-0.04
		Mean diurnal activity	-0.02	-0.07	-0.05
		Relative amplitude	-0.04	-0.09	-0.05
After discharge - in hospital	Steps - number of sedentary bouts	Cosinor acrophase	0.13	-0.02	-0.15
In hospital - before surgery	Steps - average length active bouts	Diurnal skew	0.57	1.37	0.79
		Cosinor amplitude	-0.07	-0.11	-0.03
		Cosinor relative amplitude	-0.06	-0.09	-0.03
		Mean diurnal activity	-0.09	-0.13	-0.04

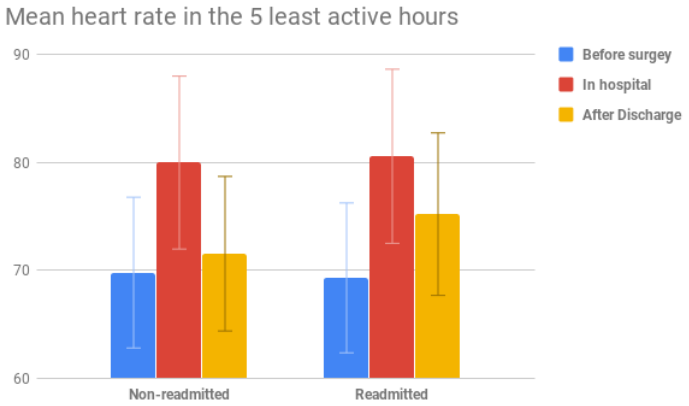


Fig. 5. Comparison of change in mean heart rate during the least 5 active hours between readmitted and non-readmitted patients during different stages of treatment

discharge compared to before surgery. In general, the differences in feature values are higher among readmitted patients in all three stages indicating more variations and irregularity in rhythms in this group. The graph in Figure 5 presents more details of differences in mean activity during the least 5 active hours between the two groups and across the three stages.

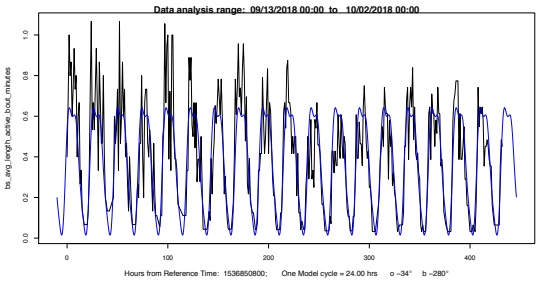
Note that we only list significant differences in feature values between the two groups in Table 4. There are however, many other features that are largely different (but not significant) between readmitted and non-readmitted patients with sleep efficiency as the most notable. Our results show a large decrease in sleep efficiency in readmitted patients after discharge (diff = -5.9) and in hospital (diff = -11.5) compared to before surgery and an increase in sleep efficiency after discharge compared to in hospital (diff = 5.6) whereas non-readmitted patients experience an increase in sleep efficiency after discharge compared to before surgery (diff = 6.6) and compared to the in hospital stay (diff = 10.1) and a decrease in sleep efficiency during the in hospital stay compared to before surgery (diff = -3.5). The highest differences in sleep efficiency and other features during the hospital stays indicate a higher degree of disruptions in patient rhythms during this period of treatment, which is aligned with findings in [30].

4.2.1 Comparison of Population Rhythms. To further understand the role of patients' rhythms in readmission, we also build the population-mean cosinor model of each stage for our readmitted and non-readmitted groups. As mentioned before, the population models may have the potential to be used as baselines to assess the level of rhythm disruption in each patient. The population-mean cosinor uses the average values of patient data to generate the waveform representing the population rhythm (the blue lines in *e.g.*, Figure 6. Given that days of surgery, discharge, and length of stay at the hospital are different from patient to patient, we first create a new dataset where we align patients records based on the universal date of surgery and discharge. More specifically, we create a surgery day index and a discharge day index with index=0 for surgery and discharge date. Days before surgery or discharge are indexed as -1, -2, -3, ... , -n and days after surgery or discharge are indexed as 1, 2, 3, ... , m. We then average the patients' data per index day for each stage of hospitalization (before surgery, in hospital, and after discharge).

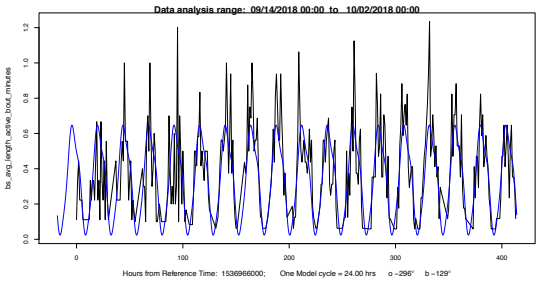
We then build population-mean cosinors with data from the readmitted only group and the not-readmitted only group for all three stages and compare the model parameters. We compare the population-mean cosinor models

Interval	Period	P	PR	Mesor	s.e.	Amp	s.e.	Phi	s.e.
0 – 455.000	24.00	0.000	65.639	0.37518928	0.00752547	0.311468	0.0111524	−78.9735	1.85273
0 – 455.000	12.00	1.59e−08	0.97362	0.37518928	0.00752547	0.0659917	0.0107552	−12.7683	9.02264
0 – 455.000	8.00	0.000714	1.7847	0.37518928	0.00752547	0.0400141	0.0104128	−24.5274	15.1624

Interval	Period	P	PR	Mesor	s.e.	Amp	s.e.	Phi	s.e.
0 – 431.000	24.00	0.000	53.295	0.3416657	0.010553	0.291484	0.0167278	−313.702	2.47444
0 – 431.000	12.00	0.154	−0.79994	0.3416657	0.010553	0.0275963	0.01431	−140.253	30.1253
0 – 431.000	8.00	0.0722	0.83541	0.3416657	0.010553	0.0314751	0.0136841	−143.687	25.5674



(a) Non-readmitted patients - Before surgery

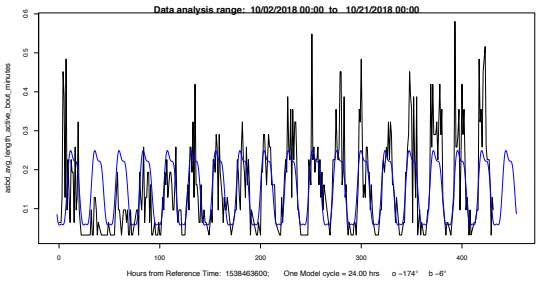


(b) Readmitted patients - Before surgery

Fig. 6. The population-mean cosinor modeling the overall activity rhythms of the non-readmitted and readmitted patient groups before surgery. The dark lines show the raw data and the blue line is the rhythm model built by the cosinor for each patient group. The activities of both groups follow similar waveforms with the exception of slightly lower activity amplitude in the readmitted group compared to the non-readmitted group. The three periods of 24, 12, and 8 hour are significant in the non-readmitted population whereas only the 24 hour period is significant in the readmitted population.

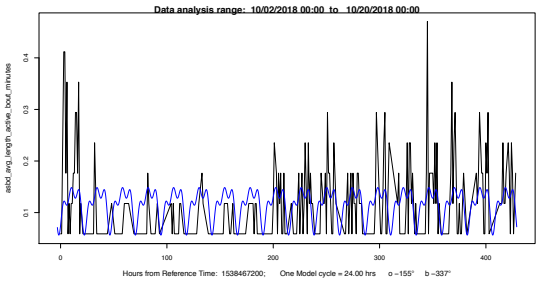
of activity bouts built for the most frequent cycles, namely 24 (circadian), 12 (diurnal), and 8 hour (nocturnal) in Figures 6, 7, and 8. The dark lines show the raw data and the blue line is the rhythm model built by the cosinor for each patient group. As observed in Figures 6a and 6b, the activities of both groups follow similar waveforms with the exception of slightly lower activity amplitude in the readmitted group compared to the non-readmitted group. The three periods of 24, 12, and 8 hour are significant in the non-readmitted population whereas only the 24 hour period is significant in the readmitted population. The rhythms of both groups, however, are disrupted during the hospital stay (Figures 7a and 7b) with a more visible disruption in the readmitted group. This same pattern was observed at the individual level comparing patient to patient as demonstrated in Figure 3. The after discharge models (Figures 8a and 8b) show more stability in both populations especially in the non-readmitted group. These observations confirm common patterns between patients in each group providing evidence for the potential of using population rhythm models as a baseline to measure the degree or severity of readmission risk. For example, a distance measure can be used to compare a patient with an unknown readmission risk level to both the readmitted and non-readmitted population rhythms to infer a readmission risk level, *i.e.*, if the patient's rhythm is closer to the non-readmitted model, the risk of readmission is low and vice versa.

Interval	Period	P	PR	Mesor	s.e.	Amp	s.e.	Phi	s.e.
0 – 455.000	24.00	0.000	35.77	0.14897491	0.00490889	0.101903	0.00723421	−207.403	3.7248
0 – 455.000	12.00	0.440	−0.036894	0.14897491	0.00490889	0.00879956	0.00686217	−297.138	45.2999
0 – 455.000	8.00	0.0291	1.886	0.14897491	0.00490889	0.0184305	0.00689736	−103.144	21.1298



(a) Non-readmitted patients - In hospital

Interval	Period	P	PR	Mesor	s.e.	Amp	s.e.	Phi	s.e.
0 – 431.000	24.00	0.00107	5.5386	0.11673297	0.00557484	0.0307012	0.00823109	−171.466	14.0626
0 – 431.000	12.00	0.200	0.62806	0.11673297	0.00557484	0.0142684	0.00792405	−133.949	30.7536
0 – 431.000	8.00	0.0843	1.8516	0.11673297	0.00557484	0.0168082	0.00752419	−95.5023	24.884



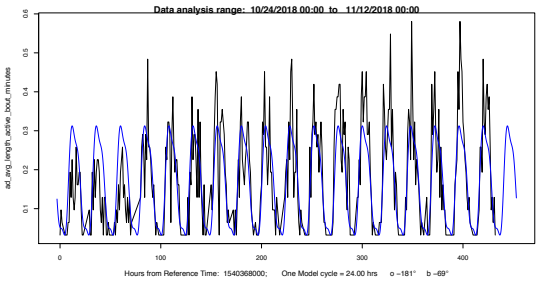
(b) Readmitted patients - In hospital

Fig. 7. The population-mean cosinor modeling the overall activity rhythms of the non-readmitted and readmitted patient groups in hospital. The rhythms of both groups are disrupted during the hospital stay with a more visible disruption in the readmitted group.

4.3 Using Patients' Biobehavioral Rhythms to Predict Readmission after Surgery

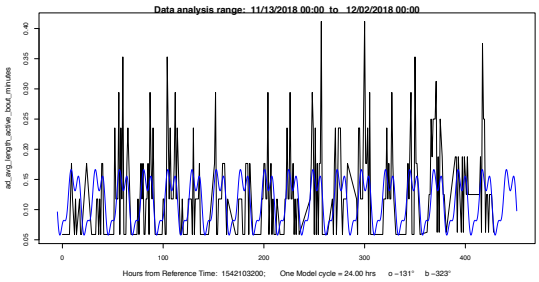
As mentioned in the Methods section, we use Boosted Logistic Regression with Linear Regression or Decision Stump as base learners to predict readmission. We built models of data for each stage and report results of leave-one patient out cross-validation. We calculated the values of our two baselines LACE and HOSPITAL using data available at the time of discharge, through comparison of the probability to a predetermined threshold (50%) and then a comparison to the ground truth (readmission) labels to get the accuracy. We obtain 36.7% and 51.7% accuracy for the LACE and HOSPITAL approaches, respectively. As shown in Table 5 below, our evaluation results in overall accuracies above the baselines in all three stages with the exception of accuracy using data from before surgery (Accuracy = 51%) which is 14.3% above LACE but 0.7% lower than HOSPITAL. The LOPO cross-validation on data during the in-hospital recovery was the most predictive for readmission (Accuracy = 77.5%, F1 = 77.2%) followed by data after discharge (Accuracy = 71.4%, F1 = 71.4%). The recall for accurately labeling the readmission class (R class in Table 5) in both stages is 65% indicating that the classifier is able to accurately label readmitted patients 65% of the time. This value is 28.3% above LACE and 13.3% above HOSPITAL and suggests that readmission risk can be predicted as early as during hospitalization. The least accurate results are obtained from the before surgery dataset (Accuracy = 51%, F1 = 51%) with a recall of 40% for the readmitted class indicating that the rhythms before surgery may be less predictive of the readmission risk. However, as we discussed earlier, these results are still above or at the same level of our two baselines.

Interval	Period	P	PR	Mesor	s.e.	Amp	s.e.	Phi	s.e.
0 – 455.000	24.00	0.000	54.287	0.1634724	0.00462962	0.142057	0.0069971	−210.88	2.42662
0 – 455.000	12.00	0.00877	0.9055	0.1634724	0.00462962	0.0194482	0.00627882	−345.637	19.522
0 – 455.000	8.00	0.00209	2.7401	0.1634724	0.00462962	0.0225257	0.00635703	−111.468	16.0982



(a) Non-readmitted patients - After discharge

Interval	Period	P	PR	Mesor	s.e.	Amp	s.e.	Phi	s.e.
0 – 455.000	24.00	1.16e−06	11.444	0.11459321	0.00536272	0.0456252	0.00855033	−171.494	7.95676
0 – 455.000	12.00	0.388	−0.22692	0.11459321	0.00536272	0.010127	0.00734984	−168.192	40.2617
0 – 455.000	8.00	0.0203	3.8635	0.11459321	0.00536272	0.018246	0.00649138	−19.7527	21.2077



(b) Readmitted patients - After discharge

Fig. 8. The population-mean cosinor modeling the overall activity rhythms of the non-readmitted and readmitted patient groups after discharge. The models show more stability in both populations especially in the non-readmitted group.

Table 5. The results of leave-one-patient-out cross validation to predict readmission in cancer patients

LACE accuracy = 36.7%		LOPO Cross Validation		
HOSPITAL accuracy = 51.7%		Overall	R Class	NR Class
Accuracy	After Discharge	71.4%	-	-
	In hospital	77.5%	-	-
	Before Surgery	51%	-	-
Precision	After Discharge	71.4%	65%	75.9%
	In hospital	77.4%	76.5%	78.1%
	Before Surgery	51%	40%	58.6%
Recall	After Discharge	71.4%	65%	75.9%
	In hospital	77.6%	65%	86.2%
	Before Surgery	51%	40%	58.6%
F1	After Discharge	71.4%	65%	75.9%
	In hospital	77.2%	70.3%	82%
	Before Surgery	51%	40%	58.6%

5 DISCUSSION

We studied the case of predicting readmission in cancer patients through modeling their biobehavioral rhythms before surgery, during inpatient recovery, and after discharge and to determine whether rhythm dysregulation predicts 90-day readmission risk after pancreatic cancer surgery. In a sample of 49 pancreatic surgery patients, we demonstrated that we can capture patients' biobehavioral rhythms across the perioperative period using passively sensed heart rate and activity data from commercial devices. Our analysis provided answers to questions about the potential of detecting rhythmicity in passive mobile data, detecting rhythm disruption in the data from surgical oncology patients, and the feasibility of using the information about biobehavioral rhythm disruption to predict readmission risk in patients. We discuss our results and their medical and technological implications in the following sections.

5.1 Detecting Rhythms from Consumer Device Timeseries Data

Our first question was whether we can model and detect biobehavioral rhythms from passively collected consumer activity monitor data. The modeling of data from pancreatic surgery patients showed we can detect and observe periodicity in patients' time series sensor data. Our study and analysis demonstrated the feasibility of using passively collected activity and heart rate data from consumer devices to model biobehavioral rhythms and show the value of these rhythms in predicting clinical health outcomes.

The lack of rhythms seen at 24-hour periods during different stages of treatment in our patient population points out the importance of rhythm detection as part of a rhythm-aware technology in order to adjust services to the current rhythm of the person without making an assumption of the underlying period being *e.g.*, 24 hours. Our approach to rhythm detection provides the ability to discover human rhythms with longer or shorter periods than 24 hours up to days, months and even years depending on the amount of available data. As technology provides the means for collecting more longitudinal data, detection of human rhythms with different periods provides opportunities to build applications that are more aligned with human needs at particular times and situations.

5.2 Detecting Rhythm Variations in Different Stages of Hospitalization and its Association with Readmission Status

The second question in our analysis was whether we can observe variations in patient rhythms over the course of surgery and recovery and whether those variations relate to readmission risk. Our results highlight the profound disruption in biobehavioral rhythms that occurs in the hospital environment, where patients spend most of their time lying in bed with minimal natural light exposure and where nocturnal rest is frequently disrupted by routine blood draws, noise from other patients, and other interruptions. Moreover, patients who were ultimately readmitted within 90 days of postoperative discharge exhibited greater disruption in the hospital that persists even after patients return home, consistent with Krumholz's concept of post-hospital syndrome [30]. Readmitted patients showed greater disruption in rhythms of both heart rate and activity after hospital discharge, and this disruption was evident across a range of rhythm metrics. This suggests that our findings do not merely reflect lower levels of overall activity or heart rate variability in readmitted patients and that there is a meaningful signal in the pattern of these variables that may account for additional variance in postoperative outcomes.

Although our analyses cannot shed light on whether persistent rhythm dysregulation is a cause or merely a correlate of readmission, they introduce the potential for advancing our understanding of risk factors associated with readmission. The finding that rhythmic factors predict readmission risk highlights several potential avenues for intervention that can be used to lessen the occurrence of readmissions. First, efforts should be made to minimize rhythm disruption in the hospital environment for all patients, particularly those recovering from highly invasive cancer surgeries. A recent study of general medical-surgical patients found that an intervention

aimed at improving inpatient circadian rhythm through strategies like reduction of nighttime noise, delay of routine blood draws, and use of red-enriching light after sunset effectively reduced readmission rates [36]. The use of bright light therapy may also help to preserve rhythms in hospital or to expedite recovery of rhythms after discharge [40]. Behavioral interventions after discharge, including general patient education about how to re-entrain biological rhythms (*e.g.*, morning exposure to natural light, regular wake time, limiting daytime naps, and keeping a consistent schedule of social and physical activities) as well as more personalized just-in-time interventions based on sensed disruptions in an individual patient's rhythms, may prove to be useful in helping patients recover from hospital-induced rhythm disruption.

Our results showed the value of using variation in patients' biobehavioral rhythms to predict readmission risk from all three stages, including before surgery has even occurred. Intervention design and delivery for readmission prevention using data in the wild can therefore benefit from early monitoring of patients' biobehavioral rhythms to estimate early readmission risks. As our results in period detection suggested stable 24-hour periods in the majority of the patients before surgery, this data can provide a baseline to measure the level of rhythm disruption during hospital stay and after discharge and to estimate the readmission risk accordingly.

5.3 Prediction of Readmission through Rhythm Modeling

In the last step of our analysis, we asked a question on how well rhythm-induced features can predict readmission. Our machine learning classifier using only those features was able to differentiate readmitted from non-readmitted patients with an average of 30% and 16% higher accuracy above the traditional clinical risk stratification algorithms using administrative data (*i.e.*, LACE and HOSPITAL). Models built with rhythms features both during hospitalization and after hospital discharge yielded promising results with average recalls of 65% for accurately labeling readmitted patients which are 28.3% above LACE and 13.3% above HOSPITAL baselines. These results highlight that using our approach, the readmission risk can be predicted as early as during hospitalization. Taken together, our findings suggest that modeling biobehavioral rhythms and quantifying their disruption before and after cancer surgery using commercial devices is feasible and that this approach holds promise in stratifying patients on risk for readmission.

5.4 Limitations

Despite the encouraging observations and results, our study has some limitations. First, although we collected data from both smartphones and Fitbits, we only used steps and heart rate data from Fitbit as they, according to existing studies, can more closely capture cyclic behavior. We further eliminated highly correlated features to reduce redundancy and to improve model performance. However, these analysis choices limited the examination of the full feature set and the impact of features extracted from smartphone data streams such as audio and phone usage. Our future work will explore the potential of the full feature set in rhythm modeling and their technological or health related applications.

Our case study of readmission prediction in surgical pancreatic patients provided great evidence for the application of rhythm modeling for predicting health outcomes. However, we have yet to examine the potential of our approach in other domains including mental health, substance use, productivity, and learning. We plan to replicate this approach with data related to mental health in a student population.

Although we had a relatively large patient population participating in our study compared to existing studies, the power and generalizability of our analyses were constrained by the small dataset. We are in the process of designing a much broader data collection from significantly larger patient population.

6 CONCLUSION

We studied the feasibility of detecting biobehavioral rhythms from consumer wearable devices and using rhythms data to predict health outcomes such as readmission risk following pancreatic surgery. Biobehavioral rhythms estimated from wearable device data collected from 49 patients before pancreatic surgery, in hospital, and after discharge were shown to be predictive of readmission risk with accuracies above traditional clinical approaches to readmission risk stratification. Our results demonstrate the feasibility of using passively sensed consumer sensor data to characterize biobehavioral rhythms as well as the potential value of rhythm modeling in predicting health-related outcomes such as readmission risk.

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