Using Passively Collected Sedentary Behavior to Predict Hospital Readmission

Sangwon Bae
Carnegie Mellon University
Pittsburgh, PA
gracebae@andrew.cmu.edu

Anind K. Dey
Carnegie Mellon University
Pittsburgh, PA
anind@cs.cmu.edu

Carissa A. Low
University of Pittsburgh
Pittsburgh, PA
lowca@upmc.edu

ABSTRACT
Hospital readmissions are a major problem facing health care systems today, costing Medicare alone US$26 billion each year. Being readmitted is associated with significantly shorter survival, and is often preventable. Predictors of readmission are still not well understood, particularly those under the patient's control: behavioral risk factors. Our work evaluates the ability of behavioral risk factors, specifically Fitbit-assessed behavior, to predict readmission for 25 postsurgical cancer inpatients. Our results show that sum of steps, maximum sedentary bouts, frequency, and low breaks in sedentary times during waking hours are strong predictors of readmission. We built two models for predicting readmissions: Steps-only and Behavioral model that adds information about sedentary behaviors. The Behavioral model (88.3%) outperforms the Steps-only model (67.1%), illustrating the value of passively collected information about sedentary behaviors. Indeed, passive monitoring of behavior data, i.e., mobility, after major surgery creates an opportunity for early risk assessment and timely interventions.

Author Keywords
Colorectal cancer surgery; wearable tracker; sedentary behavior; physical activity; healthcare outcomes

ACM Classification Keywords
H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous.

INTRODUCTION
Hospital readmissions are a significant problem facing health care systems. 1 in 7 surgery patients are readmitted within 30 days of discharge [20], and many of these are preventable [15]. Readmissions cost Medicare alone US$26 billion dollars annually, of which US$17 billion is considered to be preventable. Preventable readmissions are associated with increased health care costs, significantly shorter survival, and patient and family stress and suffering. Previous research has identified medical predictors of readmission [2][6], but behavioral factors including inadequate levels of activity in the hospital may also play an important and relatively unexplored role [11]. In this paper, we identify some behavioral factors that can both serve as predictors of readmission and targets for patient and provider interventions to improve hospital discharge decisions and postoperative recovery.

In particular, we analyzed the physical activity data from a Fitbit Flex wearable tracker worn by 25 post-surgical cancer patients during their in-hospital recovery. We then built a behavior-based machine-learning model that can identify with an 88.3% accuracy which patients were readmitted to the hospital within 30 days of discharge. The contribution of our paper is a demonstration of the value of passively sensed behavioral data in predicting readmissions, and a discussion of how our predictive model highlights opportunities for patient interventions during postoperative recovery.

In the next section, we describe previous work predicting hospital readmissions and highlight the need to focus on behavioral factors, and sedentary behavior in particular, as predictors. We describe our data collection and data analysis approach for predicting readmissions. We identify which behavioral factors strongly differentiate the readmitted from non-readmitted patients and then describe our machine-learning model that can predict these two classes. We end with a discussion of the limitations of our model, how the model could be used to support patient interventions, and finally identify opportunities for future work on how our model could be extended to other clinical populations. In the future, such models can be used to identify readmission risk behaviors in real time and to provide just-in-time intervention with patients to encourage a change in physical activity patterns.

RISK BEHAVIOR FOR HOSPITAL READMISSION
Post-hospital syndrome, a generalized physiological vulnerability caused by prolonged hospitalization, has been identified as a contributing factor to 30-day readmissions [11]. During hospitalization and recovery from surgery, patients commonly experience sleep disruption and deprivation and become physically weak and deconditioned by long periods of sedentary behavior and inadequate physical activity. Off-the-shelf Fitbits and similar wearable

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devices permit simple, low-cost, objective, and passive quantification of sedentary behavior and physical activity, but whether these passively-sensed data can predict clinically important outcomes remains unclear. Previous research with a non-cancer surgical population suggests that Fitbit-assessed steps during hospitalization are associated with shorter lengths of stay [5]. Low step counts have also been associated with higher readmission risk after cardiac surgery [19] and in older hospitalized non-cancer patients [9]. More recently, we replicated this result with post-surgical cancer patients, with readmitted patients taking significantly fewer steps than non-readmitted patients [13][14].

Despite the promise of these findings, this past work simply uses 'step counts' to measure mobility. While step counts are a good predictor to assess one's functionality and risk of readmissions, we argue that daily step counts are not sufficient. First, step measurements only capture vertical movements when patients walk so they do not capture all activity in which patients engage as part of their postoperative recovery. Second, aggregated step counts may provide inadequate information to *predict* readmission risk. Considering a broader spectrum of behavioral risk factors could identify novel targets for interventions to reduce readmissions.

SEDENTARY BEHAVIOR AS A RISK FACTOR

Research has suggested that sedentary behavior is a significant health risk [3]. Prolonged sitting poses health risks even for those who meet the physical activity recommendations. Past work has critically reviewed current evidence on the association between sedentary behavior and cardiometabolic health [4], and found that high degrees of sedentary behavior increase the risk of diabetes, heart disease and strokes. Others have investigated the impact of sedentary behaviors on cystic fibrosis (CF) and rheumatoid arthritis patients [1]. The health risks due to sedentary behavior likely extend to cancer patients as well [16], although the risks of sedentary behavior after cancer surgery have not yet been studied.

Sedentary behaviors are performed in a seated or reclining posture and involve very low energy expenditure ($\leq$ 1.5 metabolic equivalents) [10]. Previous research has shown that cancer patients spend over two-thirds of their waking hours engaged in sedentary behaviors [16][17]. Sedentary behavior increases profoundly immediately after surgery [7], and the association of sedentary behavior with readmission risk has not yet been examined. Sedentary behavior can be assessed passively, with minimal burden to patients and clinical staff, and objectively, without reporting bias, and at low cost, but its predictive value has not been tested in previous research.

Therefore, in this work, we first identify which behavioral factors are predictive of hospital readmissions for post-surgical cancer patients. We then build a machine-learning based model that predicts hospital readmissions, and evaluate the value of using the following behavioral factors in the model: steps taken and sedentary behaviors.

METHOD

We recruited 30 patients diagnosed with metastatic peritoneal cancer during their preoperative clinic visits. All were scheduled for curative surgical resection. After surgery and upon transfer from the intensive care unit (ICU) to the surgical oncology floor (median postoperative ICU stay = 2 days), patients were given a Fitbit Flex wearable fitness tracker to wear on their non-dominant wrist for the duration of their inpatient recovery (median length of stay = 13 days).

Data Measures

Here we describe how we collected each of the behavioral and health measures considered in our analyses.

Steps and sedentary time, bouts and breaks

To analyze patient behavior patterns, we used the Fitbit API and collected both per-minute and daily totals of *steps*, and distance traveled. We also calculate a number of metrics about sedentary behaviors. A *sedentary bout* refers to a time period where no steps are taken during estimated waking hours. A *sedentary break* is defined as an interruption in a sedentary bout when the step count rate exceeds 1 per minute. *Sedentary time* refers to time in which the step count is less than 100 steps/minute [21]. However, upon discussion with clinicians, this threshold of 100 steps/minute was deemed to be too high for our target population. Therefore, we established the following thresholds: 67-99 steps, 34-66 steps, and 1-33 steps, and used these to define low, medium and high sedentary times. Sedentary breaks are periods of time that follow period of 0 steps. Low, medium and high breaks in sedentary behavior are defined as taking 1-33 steps/minute, 34-46 and 67+, respectively.

Readmission data

Readmission was defined as admission to any hospital within 30 days of discharge following surgery. Readmission data were obtained by reviewing electronic medical records.

Dataset and pre-processing

We collected 199 days of activity and sedentary data from the Fitbit API. As some of our measures were based on waking hours, we needed to estimate this. Wakeup time was inferred as the time when a patient took his/her first steps after 7am. Sleep time was set to the start time of the first sedentary bout after 7pm that had a duration of at least 2 hours. To determine whether patients were wearing the Fitbit, we examined the calorie data. If the calorie count did not change for 2 hours, we assumed the Fitbit had been taken off, and removed this data, total of 215.11 hours (or 64.82 minutes daily) across all patients, from our analysis.

In our analysis, we only included patients who were involved in data collection for at least 7 days. We then discarded the first and last days of data as the Fitbit data included data collected by the research team when they took the Fitbit Flex to and from the hospital for patients to use. Based on this, we excluded five patients from our analysis. P25 stayed in the hospital for only 5 days, as her surgery was slightly less invasive than others. P37 only wore the Fitbit for 1 day and P38 for 2 days. P39 had significant fluid retention after surgery, so the Fitbit would not fit on his wrist until he was close to discharge. P40 was excluded, as he stopped wearing the Fitbit due to interfering medical procedures early in his month-long stay. This left us with 11 readmitted patients and 14 non-readmitted patients.

We extracted a total of 89 features (Table 1) from the Fitbit data and medical records. We created datasets from the Fitbit data related to behavioral patterns in two categories: Fibit Steps-Only, and Fitbit Behavioral, which included sedentary behaviors plus steps. While some data from the Fitbit (*e.g.*, steps) can be used directly as a feature, we computed other features (*i.e.*, sedentary time, bouts and breaks) based on definitions provided earlier. By using sliding windows of different sizes (5, 10, 30 and 60 minutes) that overlapped by 1, 5 and 10 minutes, we explored different time windows to see which one best captures patient activity.

Data analysis

To establish the validity of using the behavioral data to predict readmissions, we compared this data across our readmitted and non-readmitted patient groups. We performed an independent-samples Student t-test to compare the independent and unbalanced samples, and identify factors that were significantly different between the two populations.

We then created two different models:

- Model 1 (Steps-only model): This baseline model only uses the daily step count from the Fitbit Flex.
- Model 2 (Behavioral model): This model includes steps, distance traveled, the sedentary bouts, times and breaks.

By comparing the accuracy of these models in predicting patient readmissions, we can better understand the predictive value of passively collected sedentary data.

We used Weka 3.6.13 to build and train a Random Forest classifier for each model, in which we used a threshold of 0.5 to differentiate between our 2 classes (non- and readmitted patients), and performed feature selection (using InfoGainAttributeEval and Ranker). We evaluated the models using a leave-one day-out cross validation for subjects with 5, 10 and 15 days of valid data (not including the first and last days of data collection, as described earlier).

Source	Features
Fitbit Steps Only	{Sum, Min., Med., Max. Avg., Std., 1Q, 3Q} of step counts, number of minutes that steps were taken, distances, daily sum of steps
Fitbit Behavioral	Low, medium and high level of {Length, Count (sedentary breaks & bouts), Min., Med., Max. Avg., Std., 1Q, 3Q} minutes of sedentary time, sedentary breaks, sedentary bouts, daily sedentary time, step counts, number of minutes that steps were taken, distances
Medical records	Days after surgery, length of stay

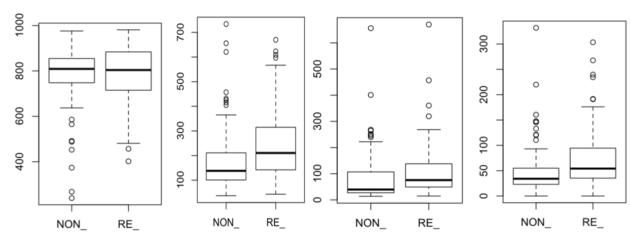
Table 1: Features used in characterizing patients' behaviors for readmissions

RESULTS

Based on the 30-day readmission report, we divided the remaining 25 patients into two groups: readmitted (11) and non-readmitted (14). We first looked at differences in the physical and sedentary behaviors between the two groups, and then built our classification models.

Readmitted Patients Group Has Longer Sedentary Bouts

Contrary to our expectations, there was no significant difference between the two groups in terms of the total number of sedentary bouts (Figure 1a): readmitted (M= 782, SD= 131) and non-readmitted (M= 783, SD= 132); t (189)=0.04, p=. 48266. Both groups had an equivalent number of sedentary bouts, likely indicating the need to sit or lie down to recover from the surgery.



(a) SedBout_Sum ***(n.s.)*** (b)SedBout_Max (c)SedBout_Avg (d)SedBout_Std

Figure 1. Minutes of sedentary bouts (='zero' step) during waking hours between non- and readmitted patient groups

However, there are significant differences in *the maximum duration of sedentary bouts* (1b): readmitted (M=248, SD=139) and non-readmitted (M=183, SD=129); t(189)=3.32, p=.000541, in *the average duration of sedentary bouts*(1c): readmitted (M=108, SD=99) and non-readmitted (M=81, SD=94); t (189)=1.87, p= .031323., and in *standard deviation of sedentary bouts*(1d): readmitted (M=73, SD=58.6) and non-readmitted (M=48.59, SD=48); t(189)=3.18, p= .000.

These results indicate that the longest sedentary bout for readmitted patients was an hour longer than that of non-readmitted patients. While both groups had the same number of sedentary bouts, those of readmitted patients' lasted longer (by 27 minutes).

Readmitted Patient Group Breaks in Sedentary Times Less Frequently During Waking Hours

The readmitted patient group has fewer periods with minimal activity than the non-readmitted group. There was a significant difference in the high sedentary time (between 1-33 steps): readmitted (M= 25.01 SD=30.38) and non-readmitted (M=47.38 SD=41.8); t(189)=4.18 p=.000021, medium sedentary time (between 34-66 steps): readmitted (M= 1.75 SD=2.8) and non- readmitted (M=4.99 SD=5.69); t(189)=4.92, p< .00001, and low sedentary time (between 67-99 steps): readmitted (M=2.42 SD=4.78) and non-readmitted (M=5.97 SD=12.08); t(189)=2.62 p=.004672.

There was a significant difference in low breaks in sedentary time (between 1-33 steps): readmitted (M=1.8 minutes, SD=2.8) and non-readmitted (M=4.99 SD=5.69); t(189)=4.92, p=.00001, breaks in medium sedentary time (between 34-66 steps): readmitted (M= 2.42 SD=4.78) and non-readmitted (M=5.97, SD=12.08); t(189)=2.62, p=.004672, and breaks in high sedentary time (between 67-99 steps): readmitted (M=0.78 SD=2.1) and non-readmitted (M=0.27, SD=1.12); t(189)= 2.11, p=.017881. These results suggest that non-readmitted patients broke up their sedentary time with low and medium step rates more than the readmitted group. However, the readmitted group broke up their sedentary time with high step rates more than the non-readmitted group, although the difference is small. This more intense activity by the readmitted group could be a risky behavior and deserves more exploration. Collectively, these results provide initial evidence that passively-sensed sedentary behavior during the recovery period could be good predictors of readmissions.

Readmitted Patients Have Fewer Daily Steps

As previously reported, patients in the readmitted group have significantly fewer daily steps than those in the non-readmitted group: readmitted (M= 652, SD= 782) and non-readmitted (M=1299, SD=1352); t (189)=3.99, p= .000047. This was true also when looking at only 5 days of data from all 22 patients: readmitted (M=387.7, SD=574.77) and non-readmitted (M=726.94, SD=690.3); t(189)=1.84, p=.035595; 10 days of data from 12 patients (remaining 10 patients did not have data for 10 days): readmitted (M=617.53, SD=727.72) and non-readmitted (M=966.94, SD=835.17); t(189)=2.44, p= .008028; and 15 days of data from 5 patients: readmitted (M=706.54, SD= 817.37) and non-readmitted (M=1329.63, SD=1318); t(189)=3.65, p=.000175.

To further understand the daily impact of step counts, we looked to identify whether there was a particular window in which monitoring step counts was particularly predictive of readmission. Going from a window of 1 day up to a window of 15 days, we found that the daily step counts for a 3-day time window were significant at the p<.05 level, between the two groups. We further found that monitoring steps at Days 5-7 (p < .01.), and Days 7-9 (p < .01.) could be predictive of admissions. These results suggest that monitoring steps in these periods and intervening when too few steps are being taken has the potential to decrease readmissions.

Building Behavioral Machine Learning Models for 30-day readmissions

With evidence that sedentary behavior could be predictive of readmissions, we created a set of two models that predict whether a patient will be readmitted or not. We evaluated the performance of our two models (Steps-only, Behavioral), using a leave-one-day-out cross-validation for performance evaluation. We ran each model three times on data from those patients with 5, 10 and 15 days of data. Figure 2 shows the evaluation results.

Comparison of Model Accuracy

The Steps-only model (Model 1) had lower performance overall than the Behavioral model (Model 2), with similar performance for 5, 10 and 15 days of data. The accuracy of Model 2 in predicting readmissions is 83.6%, 83.9% and 88.3% for data collections of 5, 10 and 15 days, respectively, compared to the Model 1 accuracy of 66.7%, 66.9% and 67.1%. The Steps-only model performed better than the Zero-R model (a naïve model that just predicts the most frequent class). There are different accuracies for the 3 Zero-R models (50.2%, 48% and 46.2%) for 5, 10, and 15 days of data, as there were different numbers of patients that had that many days of data. The relatively poor performance of the Steps-only model compared to the Behavioral model confirms our earlier assumption that means daily steps alone is not an adequate predictor of readmissions.

As shown in Figure 2, our Behavioral model for predicting 30-day readmission with 15 days of data produced the best performance with an average accuracy of 88.3%, where accuracy is the proportion of true results (both readmission or true positives and non-readmission or true negatives) from the total number of cases examined. A little less than half the errors (5.0%) were due to false negatives (predicting non-readmission for those who were readmitted), with the remaining 6.7% being false positives.

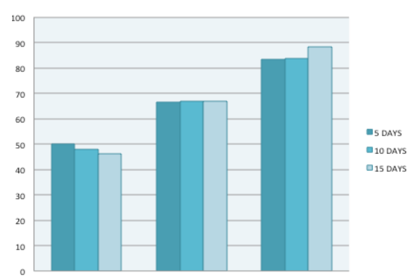


Figure 2. Results of the evaluation of our two models; Fitbit Step Only and Behavioral model for predicting 30-day readmissions, within 5, 10 and 15 days of surgery.

DISCUSSION

In this section, we address how our predictive model highlights opportunities for patient interventions during postoperative recovery by comparing the results achieved with our proposed solution to current clinical approaches for predicting hospital readmissions, limitations of our model, how the model could be utilized to assist patient intervention in the hospital, and finally opportunities for future work on how our model could be extended to other clinical populations.

Applying Behavior Models for Prevent 30-Day Readmissions in Practice

Our model (88.3% accuracy) outperformed existing algorithms that used retrospective clinical administrative data (71%) [11]. Algorithms using clinical data, such as the HOSPITAL score [7], may have limited predictive utility for homogeneous populations (*e.g.*, advanced cancer patients undergoing the same surgical procedure). Indeed, all the patients in our sample had HOSPITAL scores between 6 and 9, with no differences between readmitted (M = 7.81) and nonreadmitted patients (M = 7.42) and predictive accuracy of only 48%.

Leveraging information about patient mobility (steps and sedentary behaviors) before (and ideally after) discharge can help in better estimating the risk of readmissions for clinically homogeneous patient populations, as was the case in our study. In particular, our model can help identify patients in need of additional monitoring or intervention. Daily monitoring of mobility in the inpatient context is important, as there is significant variability across patients – most patients are fairly inactive as they transition out of the ICU but become more active as they approach discharge. In addition, mobility may vary as a result of uncontrolled pain or other symptoms, need for additional surgical procedures, changes in medications, *etc*.

The results of our model can be used to assist both patients and clinicians. By collecting information on physical activity and sedentary behaviors using a wearable fitness tracker, patients can become more aware of whether they are at greater risk for readmissions, for the different time windows during recovery.

While demographic and clinical data (*e.g.*, number of admissions in the past year, discharge from an oncology service) is useful, they are not actionable for patients and clinicians. However, through behavioral interventions, a patient's mobility can be modified. Our results argue for systematic tracking of mobility that can be used to highlight targets for early behavioral interventions: *e.g.*, getting a consult from the physical therapy service or offering more frequent opportunities to walk the halls with patient support staff, or pharmacological interventions to deal with pain.

Opportunities for Generalizing the Behavioral Model

There are a number of health conditions that require prolonged stays in the hospital. We believe that our Behavioral model that includes both step counts and information about sedentary behavior can be applied to predict hospital readmissions for other health conditions. Extending this work to other clinical contexts likely requires identifying appropriate thresholds for sedentary behaviors for different health conditions.

Limitations of Deployment and Future Work

To further generalize the model, we could consider individuals' subjective severity of symptoms, likely a major barrier to activity after surgery. For example, lack of mobility could be due to pain requiring a very different intervention than that due to lack of motivation or lack of knowledge about how important mobility is for the recovery.

One limitation of our work was the relatively small sample size we used that could potentially lead to over-fitting of the model (Random Forests, while known for their accuracy, are subject to overfitting) and lack of generalizability of the results. In the future, we will apply our model to larger clinical, and less homogeneous populations, which will also increase generalizability of the study.

Another limitation of our work is that we are only studying behavioral data collected while a patient recovered in the hospital after surgery. Extending data collection to include the 30 days after discharge is an important future direction for our work, as behavior during this time may be even more predictive of 30-day readmission risk. Broadening the behavioral factors assessed to include such behaviors as medication adherence, diet, and attendance at postoperative follow-up appointments may also shed light on potential targets for interventions to reduce readmissions.

In the future, our model may make it possible to identify behavioral risk factors for readmissions in real time, and to provide interventions to patients in a timely manner to empower a change in physical activity as well as disrupt sedentary behavior.

CONCLUSION

In this paper, we demonstrate for the first time that a machine-learning model using only passively-sensed behavioral data collected from a wearable off-the-shelf fitness tracker accurately predicts 30-day hospital readmissions for postsurgical cancer patients. This model performed significantly better than using step counts alone, which prior work had shown to be quite promising. Our behavioral model was 88.3% accurate at predicting hospital readmissions after 15 days of data collection. Given the relatively low burden and cost of collecting Fitbit and similar data, machine-learning models using such behavioral data could prove useful in predicting readmission risk for other clinical populations and in identifying at-risk patients who might benefit from additional postoperative support or monitoring.

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