JAMA Surgery | Original Investigation

Using Smartphones to Capture Novel Recovery Metrics After Cancer Surgery

Nikhil Panda, MD; Ian Solsky, MD, MPH; Emily J. Huang, PhD; Stuart Lipsitz, ScD; Jason C. Pradarelli, MD; Megan Delisle, MD; James C. Cusack, MD; Michele A. Gadd, MD; Carrie C. Lubitz, MD, MPH; John T. Mullen, MD; Motaz Qadan, MD, PhD; Barbara L. Smith, MD, PhD; Michelle Specht, MD; Antonia E. Stephen, MD; Kenneth K. Tanabe, MD; Atul A. Gawande, MD, MPH; Jukka-Pekka Onnela, DSc; Alex B. Haynes, MD, MPH

Invited Commentary page 130

Supplemental content

IMPORTANCE Patient-generated health data captured from smartphone sensors have the potential to better quantify the physical outcomes of surgery. The ability of these data to discriminate between postoperative trends in physical activity remains unknown.

OBJECTIVE To assess whether physical activity captured from smartphone accelerometer data can be used to describe postoperative recovery among patients undergoing cancer operations.

DESIGN, SETTING, AND PARTICIPANTS This prospective observational cohort study was conducted from July 2017 to April 2019 in a single academic tertiary care hospital in the United States. Preoperatively, adults (age ≥18 years) who spoke English and were undergoing elective operations for skin, soft tissue, head, neck, and abdominal cancers were approached. Patients were excluded if they did not own a smartphone.

EXPOSURES Study participants downloaded an application that collected smartphone accelerometer data continuously for 1 week preoperatively and 6 months postoperatively.

MAIN OUTCOMES AND MEASURES The primary end points were trends in daily exertional activity and the ability to achieve at least 60 minutes of daily exertional activity after surgery among patients with vs without a clinically significant postoperative event. Postoperative events were defined as complications, emergency department presentations, readmissions, reoperations, and mortality.

RESULTS A total of 139 individuals were approached. In the 62 enrolled patients, who were followed up for a median (interquartile range [IQR]) of 147 (77-179) days, there were no preprocedural differences between patients with vs without a postoperative event. Seventeen patients (27%) experienced a postoperative event. These patients had longer operations than those without a postoperative event (median [IQR], 225 [152-402] minutes vs 107 [68-174] minutes; $P < .001$), as well as greater blood loss (median [IQR], 200 [35-515] mL vs 25 [5-100] mL; $P = .006$) and more follow-up visits (median [IQR], 2 [2-4] visits vs 1 [1-2] visits; $P = .002$). Compared with mean baseline daily exertional activity, patients with a postoperative event had lower activity at week 1 (difference, −41.6 [95% CI, −75.1 to −8.0] minutes; $P = .02$), week 3 (difference, −40.0 [95% CI, −72.3 to −3.6] minutes; $P = .03$), week 5 (difference, −39.6 [95% CI, −69.1 to −10.1] minutes; $P = .01$), and week 6 (difference, −36.2 [95% CI, −64.5 to −7.8] minutes; $P = .01$) postoperatively. Fewer of these patients were able to achieve 60 minutes of daily exertional activity in the 6 weeks postoperatively (proportions: week 1, 0.40 [95% CI, 0.31-0.49]; $P < .001$; week 2, 0.49 [95% CI, 0.40-0.58]; $P = .003$; week 3, 0.39 [95% CI, 0.30-0.48]; $P < .001$; week 4, 0.47 [95% CI, 0.38-0.57]; $P < .001$; week 5, 0.51 [95% CI, 0.42-0.60]; $P < .001$; week 6, 0.73 [95% CI, 0.68-0.79] vs 0.43 [95% CI, 0.33-0.52]; $P < .001$).

CONCLUSIONS AND RELEVANCE Smartphone accelerometer data can describe differences in postoperative physical activity among patients with vs without a postoperative event. These data help objectively quantify patient-centered surgical recovery, which have the potential to improve and promote shared decision-making, recovery monitoring, and patient engagement.

JAMA Surg. 2020;155(2):123-129. doi:10.1001/jamasurg.2019.4702
Published online October 28, 2019.

Author Affiliations: Ariadne Labs, Brigham and Women's Hospital, Harvard T. H. Chan School of Public Health, Boston, Massachusetts (Panda, Solsky, Lipsitz, Pradarelli, Delisle, Gawande, Onnela, Haynes); Department of Surgery, Massachusetts General Hospital, Boston (Panda, Cusack, Gadd, Lubitz, Mullen, Qadan, Smith, Specht, Stephen, Tanabe, Haynes); Montefiore Medical Center, Department of Surgery, Albert Einstein College of Medicine, Bronx, New York (Solsky); Department of Biostatistics, Harvard T. H. Chan School of Public Health, Boston, Massachusetts (Huang, Onnela); Department of Surgery, Brigham and Women's Hospital, Boston, Massachusetts (Pradarelli, Gawande).

Corresponding Author: Nikhil Panda, MD, Department of Surgery, Massachusetts General Hospital, 55 Fruit St, GRB-425, Boston, MA 02114 (nikhil.panda@mgh.harvard.edu).

Patients undergoing surgery are often faced with complex treatment decisions without sufficient information regarding the association of these choices with outcomes that matter most to them. This is especially true for patients with cancer, for whom multidisciplinary treatment makes it difficult to appreciate the association of each therapy with changes in patient quality of life. Traditional surgical outcome measures, such as postoperative complications and readmission rates, are often imprecise measures of the association of cancer surgery with patient quality of life.

The demand for high-frequency patient-centered outcome measures after oncologic surgery has led to novel methods of collecting not only patient-reported outcome measures (PROMs) but also other forms of patient-generated health data. As a result, there have been a growing number of investigations describing the use of wearable digital activity-trackers to quantify patient activity around the time of a health care event.[1,2] In 2016, Torous et al introduced digital phenotyping as "moment-by-moment quantification of the individual-level human phenotype in-situ using data from smartphones and other personal digital devices."[3(pe16)] Unlike wearable digital activity-trackers, digital phenotyping harnesses data from smartphone sensors (eg, global positioning systems, accelerometer, gyroscope, etc) and logs (eg, communication logs, screen-activity logs) without additional active participation from the user. This effectively capitalizes on hardware already in the hands of patients rather than introducing additional devices.[4] By coupling digital phenotyping with high-frequency, digitally collected PROMs, this method can be used to analyze behavioral patterns, social interactions, physical mobility, gross motor activity, and cognitive function, all of which may inform patient quality of life.[5]

Therefore, the objective of this proof-of-principle study was to demonstrate the feasibility and efficacy of quantifying physical activity from smartphone accelerometer data to describe physical recovery among patients after cancer operations. We hypothesized that metrics derived from smartphone accelerometer data could be used to demonstrate differences in physical recovery among patients with vs without clinically significant postoperative events. If so, this methodology has the potential to provide patients and surgeons with a novel and scalable approach to quantify recovery after surgery, which may better inform shared decision-making, improve recovery monitoring, and promote patient engagement.

Key Points

Question Can metrics derived from smartphone accelerometer data capture differences in physical recovery among patients after surgery?

Findings In this cohort study, smartphone accelerometer data captured decreases in daily exertional activity in patients with a postoperative event (eg, complication, reoperation) compared with baseline at up to 6 weeks after surgery. Similarly, these data demonstrated that fewer of these patients achieved at least 60 minutes of daily exertional activity in the first 6 weeks after surgery compared with patients without a postoperative event.

Meaning Physical activity measured passively through smartphone accelerometer data can be used to quantify differential recovery trends after surgery.

Methods

Patient Selection

This study was approved by the Partners Human Research Committee institutional review board. The written consent requirement was waived in favor of documented verbal consent. Adults (age ≥18 years) who spoke English, had a cancer diagnosis, and were scheduled for surgery between July 2017 and April 2019 were approached for inclusion. Patients were excluded if they did not own a smartphone with an Android or iOS operating system. Patients were eligible if they were scheduled to undergo an operation for breast, melanoma, extremity, or truncal sarcoma; thyroid or parathyroid tumors (skin, soft tissue, head, and neck tumors); or any gastric, colorectal, adrenal, retroperitoneal, hepatic, or peritoneal tumors (abdominal tumors).

After giving verbal consent, patients downloaded the Beiwe smartphone application, which is the front-end component of the open-source Beiwe research platform created by our research team.[3] In this study, Beiwe prospectively and passively collected raw smartphone accelerometer data continuously preoperatively and for 6 months postoperatively.

Collection of Clinical Data

The following variables were extracted from the medical records of enrolled patients to understand the diverse perspective of patients engaging with this tool: age, sex, self-reported race, American Society of Anesthesiology classification, type of surgery, prior chemotherapy or radiation, operative time, blood loss, hospital length of stay, discharge location, opioid prescriptions, number of follow-up visits with the operating surgeon, perioperative complications, mortality, emergency department admissions, readmissions, and scheduled or unplanned reoperations. All data were stored on Research Electronic Data Capture (REDCap).

Collection of Smartphone Sensor Data

The Beiwe application passively and continuously collected raw accelerometer data from patients' smartphones through the entirety of the 6-fmonth study period. Accelerometer data were sampled identically for each patient, alternating between a 10-second on-cycle and a 10-second off-cycle. During on-cycles, the smartphone's triaxial accelerometers were sampled, capturing acceleration in a 3-dimensional orthogonal coordinate system. This sampling design yielded dense temporal data without causing extensive phone battery drainage, an issue that the research team has studied.[6-8]

Accelerometer data captured the smartphone's movement and were used as a surrogate of individual patient activity patterns.[3] Smartphone accelerometers have been tested against industrial accelerometers used in clinical research and have found to be reliable in capturing and distinguishing between exertional and nonexertional activity.[9,10]

All newly collected data were immediately encrypted on the smartphone. The smartphone application attempted a data upload every 3600 seconds (1 hour); if successful, the data were deleted from the devices. Uploads occurred through wifi rather than cellular networks to avoid costs for patients. Once uploaded, data were received by an Amazon Elastic Compute Cloud (EC2) server and re-encrypted. The data were then stored in Amazon Simple Storage Service (S3) industry-standard secure storage, in compliance with the Health Insurance Portability and Accountability Act.

Exposure and Outcome Measures

Raw measured accelerometer data were processed to determine a summary statistic called *daily exertional activity* for individual patients; this was defined as the number of minutes each day when the sum of smartphone accelerometer variances exceeded a threshold selected a priori, normalized by the number of minutes when accelerometer data were collected that day (eMethods in the Supplement). The predetermined activity threshold of $0.15g^2$ ($1\ g = 9.807\ m/s^2$) was determined by identifying an accelerometer variance level that correlated with exertional activity each minute. Exertional movements (ie, the activity above the threshold level) included going up or down stairs and vigorous walking. Nonexertional (or stationary) activity included standing, sitting, or lying down. Distinguishing between these exertional and nonexertional activities was clinically meaningful because they correspond with patient functional status and metabolic equivalents assessed by surgeons before an operation.

To determine the ability of accelerometer data to demonstrate differential activity patterns after surgery, trends in daily exertional activity were determined among patients with vs without a clinically significant postoperative event and compared with mean preoperative baseline daily exertional activity. In this study, a postoperative event included any perioperative complications, mortality, emergency department presentations, readmissions, and scheduled or unplanned reoperations. Scheduled reoperations included completion of resections in staged surgery (eg, primary colectomy followed by hepatic metastasectomy) or reconstructive procedures (eg, an implant reconstruction after mastectomy). Although these reoperations do not represent a complication of an initial surgery, they were included because a second operation may delay recovery, as would a complication. To demonstrate potential clinical uses for patient-level data, we also identified select patients with postoperative complications to illustrate unique activity patterns that emerged.

The primary end points were trends in daily exertional activity and the ability to achieve at least 60 minutes of daily exertional activity after surgery among patients with vs without a clinically significant postoperative event. Sensitivity analyses at 30 and 90 minutes of daily exertional activity, representing milder and more vigorous activity thresholds, respectively, were performed to test alternative thresholds.

Statistical Analysis

Data were summarized using mean with SDs or median with interquartile ranges (IQRs) for continuous measures and frequency with percentages for categorical variables. To determine significant covariates among patients with vs without a clinically significant postoperative event, bivariate analysis was performed using 2-sample *t* tests for continuous variables and χ^2 tests for categorical variables. Trends in daily exertional activity compared with baseline were determined using unadjusted restricted cubic spline regression with prespecified knots at each enrollment week (eg, days 7, 14, 21, 28, 35, 42, and 49). Generalized estimating equations under naive independence were used to estimate the spline regression parameters. These analytic methods were selected because they protect against biases associated with differences in the distribution of missing data among patients with vs without a postoperative event.[11] Tests on the equality of proportions were used to determine unadjusted differences in the number of patients able to achieve at least 60 minutes of daily exertional activity. All statistical analyses were performed using Stata software version 15.1 (StataCorp). Statistical significance was defined as a 2-sided *P* value less than .05.

Results

Patient Recruitment and Data Volume

Of the 139 patients contacted preoperatively, 9 were unable to be reached, and 18 were ineligible because they lacked a smartphone or had technical issues using a smartphone. Of the 112 eligible patients, 64 patients (57.1%) downloaded the Beiwe application, and accelerometer data were available for 62 patients for final analysis (**Figure 1**). Among these 62 patients, the mean (SD) age was 65.7 (13.0) years; 39 were female (63%). Accelerometer data from the 62 patients who participated were available for a median (IQR) of 5 (2-12) days preoperatively and a median (IQR) of 147 (77-179) days postoperatively. These were fewer than the number of days each patient was enrolled in the study (**Table**), representing a median (IQR) of 22.2% (4.5%-58.4%) of days with missing accelerometer data.

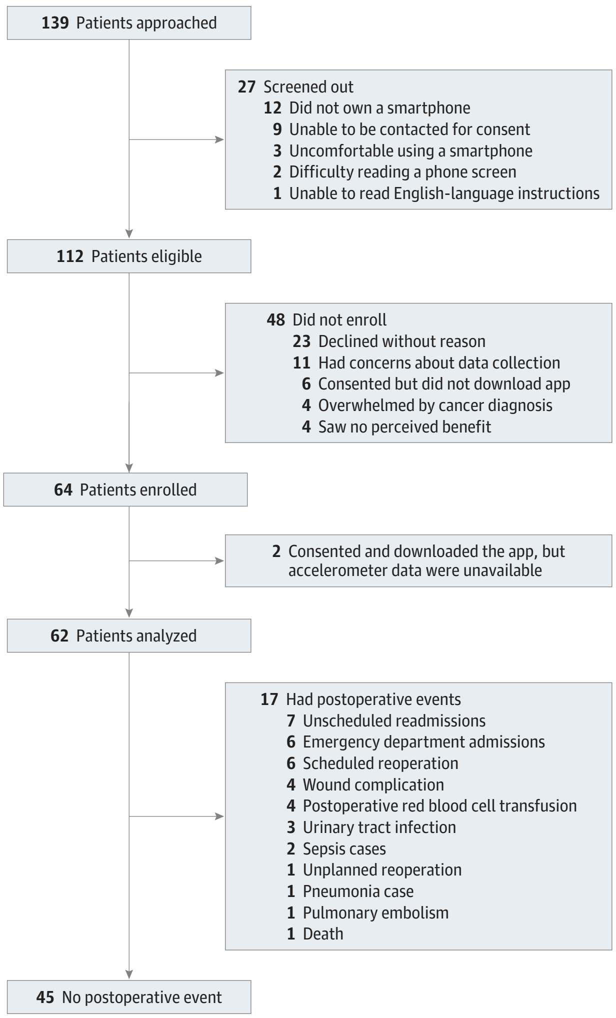
Clinical Outcomes

Among the 62 patients included, 45 patients (73%) experienced no clinically significant postoperative events, while 17 (27%) experienced 1 or more event (Figure 1; Table). Events occurred at a median (IQR) enrollment of 23 (8-40) days. Patients with a postoperative event had a longer operative time (median [IQR], 225 [152-402] minutes vs 107 [68-174] minutes; $P < .001$) with greater estimated blood loss (median [IQR], 200 [35-515] mL vs 25 [5-100] mL; $P = .006$). These patients had a longer hospital stay (median [IQR], 5 [2-9] days vs 2 [0-4] days; $P = .007$), were more likely to be discharged with visiting nursing services (31 of 45 participants [69%] vs 5 of 17 participants [31%]; $P = .009$), and had a greater number of follow-up clinic visits with the operating surgeon (median [IQR], 2 [2-4] visits vs 1 [1-2] visits; $P = .002$).

Trends in Exertional Activity

Figure 2 shows the estimates of daily exertional activity during the first 6 postoperative weeks for patients with vs with-

Figure 1. Recruitment of Patients for Study Participation, Including Screening for Eligibility and Reasons for Refusing Participation



Thirty-six postoperative events are described for 17 patients because 8 of 17 patients experienced more than 1 event.

out a clinically significant postoperative event. Compared with mean baseline daily exertional activity (99.3 minutes), there appeared to be an increase in daily exertional activity peaking 3 weeks postoperatively (at enrollment day 28) among patients without a postoperative event (19.9 [95% CI, −5.0 to 44.8] minutes; *P* = .12; Figure 2A). In contrast, patients with a postoperative event had a decrease in daily exertional activity compared with baseline (104.7 minutes) at week 1 (difference, −41.6 [95% CI, −75.1 to −8.0] minutes; *P* = .02), week 3 (difference, −40.0 [95% CI, −72.3 to −3.6] minutes; *P* = .03), week 5 (difference, −39.6 [95% CI, −69.1 to −10.1] minutes; *P* = .01), and week 6 (difference, −36.2 [95% CI, −64.5 to −7.8] minutes; *P* = .01) postoperatively (Figure 2B). Among patients with a clinically significant postoperative event, 2 patients who underwent abdominal surgery were selected to illustrate the potential of patient-level trend analysis (eAppendix and eFigure in the Supplement).

Table. Baseline Demographic, Procedural, Postprocedural Information, and Smartphone Data Information Among Patients With vs Without a Postoperative Event[a]

Characteristic	Patients, No. (%) Without a Postoperative Event	Patients, No. (%) With a Postoperative Event	*P* Value
Total	45 (73)	17 (27)	NA
Demographics			
Age, mean (SD), y	54.5 (12.9)	54.9 (13.7)	.92
Female	28 (62)	11 (65)	.86
Race/ethnicity			
White	44 (98)	14 (82)	.07
Black	0	0	
Hispanic	0	1 (6)	
Asian	0	0	
Other/unknown	1 (2)	2 (12)	
Type of surgery			
Skin, soft tissue, or head and neck	25 (56)	7 (41)	.31
Abdominal	20 (44)	10 (59)	
Prior chemotherapy			
None or >6 mo preoperatively	36 (80)	11 (65)	.21
<6 mo Preoperatively	9 (20)	6 (35)	
Prior radiation			
None or >6 mo preoperatively	41 (91)	14 (82)	.33
<6 mo Preoperatively	4 (9)	3 (18)	
Procedure details			
American Society of Anesthesiologists classification, median (IQR)	2 (2.0-2.5)	2.0 (2.0-3.0)	>.99
Operative time, median (IQR), min	107 (68-174)	225 (152-402)	<.001
Blood loss, median (IQR), mL	25 (5-100)	200 (35-515)	.006
Postprocedure information			
Hospital length of stay, median (IQR), d	2 (0-4)	5 (2-9)	.007
Discharge location			.009
Home	31 (69)	5 (31)	
Home with visiting nursing	14 (31)	11 (69)	
No of opioid tablets at discharge, median (IQR)	15 (5-25)	20 (12-20)	.34
Follow-up visits with surgeon, median (IQR)	1 (1-2)	2 (2-4)	.002
Smartphones, enrollment, and data			
Smartphone operating system			
iOS	34 (78)	14 (82)	.57
Android	11 (24)	3 (18)	
Time enrolled, median (IQR), d	187 (184-195)	189 (185-193)	.99
Time with accelerometer data, median (IQR), d	136 (63-179)	172 (123-177)	.21
Time with missing accelerometer data, median (IQR), d	31 (3.7-65.5)	10.3 (5.4-30.4)	.21

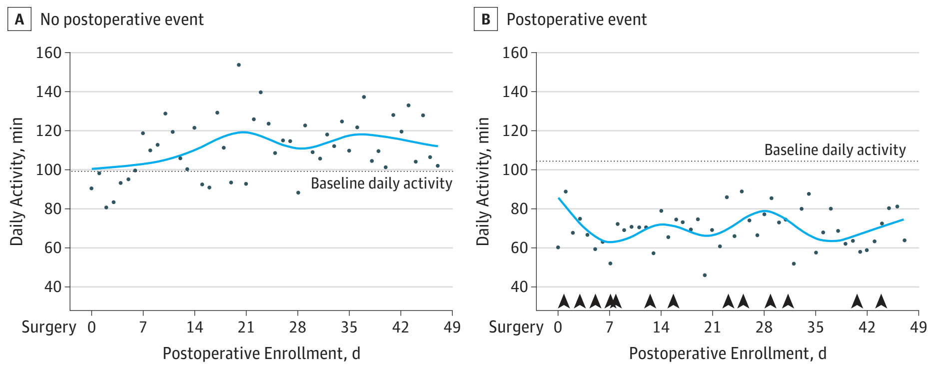
Abbreviations: IQR, interquartile range; NA, not applicable.

[a] A postoperative event was defined as any perioperative complications, mortality, emergency department presentations, readmissions, and scheduled or unplanned reoperations.

Differential Exertional Activity Levels

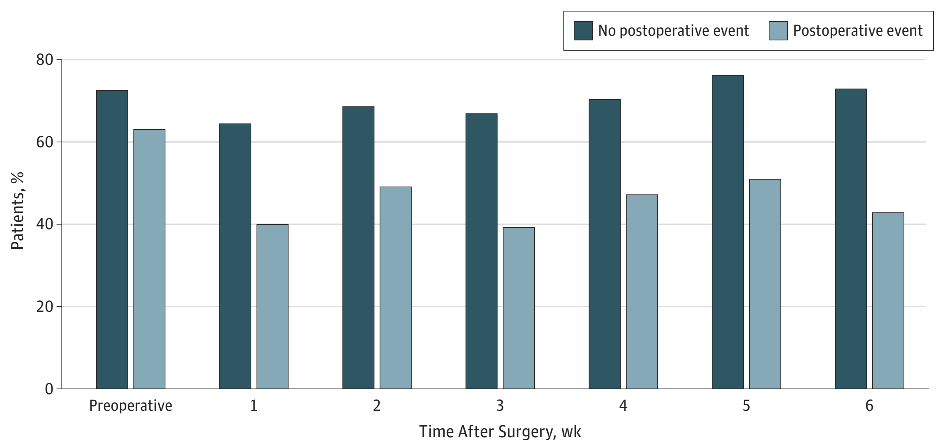
The proportion of patients with vs without a clinically significant postoperative event who were able to achieve at least

Figure 2. Trends in Daily Exertional Activity Compared With Mean Preoperative Baselines Among Patients



Patients without (A) vs with (B) a clinically significant postoperative event. Solid circles for each trend represent mean daily exertional activity. Solid arrowheads along the x-axis indicate the timing of postoperative events. Absolute differences for those with postoperative events varied significantly from baseline (104.7 minutes) in week 1 (difference, −41.6 [95% CI, −75.1 to −8.0] minutes; *P* = .02), week 3 (difference, −40.0 [95% CI, −72.3 to 3.6] minutes; *P* = .03), week 5 (difference, −39.6 [−69.1 to −10.1] minutes; *P* = .01), and week 6 (difference, −36.2 [−64.5 to −7.8] minutes; *P* = .01).

Figure 3. Proportion of Patients With 60 or More Minutes of Daily Exertional Activity in the First 6 Weeks of Study Period



No differences existed at baseline (patients with a postoperative event, 0.63 [95% CI, 0.53-0.73] vs patients without a postoperative event, 0.71 [95% CI, 0.65-0.77]; *P* = .15). Fewer patients with a postoperative event achieved 60 minutes of daily exertional activity than those without a postoperative event (week 1, 0.65 [95% CI, 0.58-0.70] vs 0.40 [95% CI, 0.31-0.49]; *P* < .001; week 2, 0.69 [95% CI, 0.63-0.74] vs 0.49 [95% CI, 0.40-0.58]; *P* = .003; week 3, 0.67 [95% CI, 0.61-0.73] vs 0.39 [95% CI, 0.30-0.48]; *P* < .001; week 4, 0.70 [95% CI, 0.65-0.76] vs 0.47 [95% CI, 0.38-0.57]; *P* < .001; week 5, 0.76 [95% CI, 0.71-0.81] vs 0.51 [95% CI, 0.42-0.60]; *P* < .001; week 6, 0.73 [95% CI, 0.68-0.79] vs 0.43 [95% CI, 0.33-0.52]; *P* < .001).

60 minutes of daily exertional activity in the first 6 weeks after surgery are shown in **Figure 3**. There were no differences between cohorts at baseline (proportion: 0.71 [95% CI, 0.65-0.77] vs 0.63 [95% CI, 0.53-0.73]; *P* = .15). However, in each subsequent week after surgery, there was a lower proportion of patients with a postoperative event who were able to achieve a minimal daily exertional activity of 60 minutes (proportions: week 1, 0.40 [95% CI, 0.31-0.49]; *P* < .001; week 2, 0.49 [95% CI, 0.40-0.58]; *P* = .003; week 3, 0.39 [95% CI, 0.30-0.48]; *P* < .001; week 4, 0.47 [95% CI, 0.38-0.57]; *P* < .001; week 5, 0.51 [95% CI, 0.42-0.60]; *P* < .001; week 6, 0.73 [95% CI, 0.68-0.79] vs 0.43 [95% CI, 0.33-0.52]; *P* < .001). Sensitivity analyses for daily exertional activity levels of 30 minutes (eTable 1 in the Supplement) and 90 minutes (eTable 2 in the Supplement) demonstrated similar results. The exception was an absence of a significant difference in the proportion of individuals those with vs without a clinically significant postoperative event who achieved 30 minutes of daily exertional activity in week 3.

Discussion

The results of this study show that physical activity measured passively through smartphone accelerometer data was associated with differential recovery trends after surgery. Prior studies have suggested that patient-generated health data, such as PROMs, should be incorporated alongside traditional surgical outcome measures to create the recovery metrics that matter most to patients.[12] Many of these studies have specifically examined the utility of patient-generated health data from wearable digital activity-trackers around the time of surgery.

Our results similarly describe how longitudinal analysis of physical activity reflected by smartphone accelerometer data may become clinically actionable. Furthermore, a digital phenotyping methodology, as applied in this study, offered several unique insights and potential advantages for collecting patient-centered outcomes.[13]

Patients may be hesitant to actively report their own quality of life or behavioral activity. In a study by Pevnick et al,[14] nearly 66 000 patients were invited to upload their activity data from Apple HealthKit,[15] Fitbit,[16] and Withings[17] platforms. Fewer than 500 patients (0.8%) uploaded data. Concerns regarding data privacy may contribute to hesitation. In this study, for example, 11 patients expressed similar concerns during recruitment. In addition, active participation may represent an additional burden to patients, especially among those coping with a new cancer diagnosis or facing complex multimodal treatment. Wearable devices are similarly associated with poor long-term compliance,[18,19] potentially associated with user error or cost.[20,21] A digital phenotyping approach as applied in this study may alleviate this burden by capturing data passively without the introduction of a new data-generating tool. Our results underscored this yield, with only 22.2% of physical activity data missing in a 25-week period.

Beyond robust data collection, smartphone accelerometer data were analyzed to generate a novel patient-centered outcome measure of physical functioning: daily exertional activity. Additionally, smartphone accelerometer data were collected at high frequency (10-second on-cycles and off-cycles) to generate this outcome. As a result, momentary differences in daily exertional activity among patients with vs without postoperative events were determined, providing a more frequent and durable assessment of recovery, as well as a better description of the physical manifestations of postoperative events.

There are few studies of patient recovery from oncologic surgery using passive collection of patient-generated health data, which use predetermined metrics of physical functioning (eg, step counts, sleep duration).[22] Relying on these proprietary algorithms, rather than an individual's raw activity data, limits the potential to generate personalized outcomes and pool data across patients or long follow-up periods.[23] The threshold for daily activity in this study was selected a priori to distinguish between exertional and nonexertional physical activity, but this can be tailored to study outcomes among different patient groups (eg, elderly individuals), disease processes (eg, claudication), or procedures (eg, minimally invasive techniques).

Future Considerations: Recovery Monitoring, Patient Engagement, and Shared Decision-making

It was impossible to determine if the changes in physical activity observed among patients with postoperative events were predictive of or attributable to the effect of the event on physical activity. While both interpretations are plausible, they have different potential clinical value. If an indicator of a potential adverse event, these data, when analyzed in near-real time, may prove valuable for recovery monitoring. Especially with the prevalence of early discharge and enhanced recovery programs, most patients undergoing surgery recover outside of a clinical setting.[24] A digital phenotyping approach may serve as future tool for surgeons, where subtle changes in passively collected patient data in an otherwise unmonitored environment could trigger contact with the patient and escalate care if needed. From the patient perspective, the ability to monitor one's progress during recovery improves engagement.[25,26] Patients could access these data to evaluate recovery compared with their own baseline or standardized trajectories. These types of recovery data could be shared with family members or caregivers to promote engagement, bolster social support, and foster communication beyond the direct patient-clinician interactions.

If these data, however, represented only the outcomes of certain postoperative events on physical functioning, they may be incorporated into decision tools at the time of surgical consultation to enhance shared decision-making.[5] Surgeons may harness these data to describe the differential outcome of different treatments using metrics that are more meaningful to patients (eg, likelihood of returning to baseline exercise or activity patterns after surgery). This is especially valuable in fields similar to surgical oncology, where the multidisciplinary management of cancer makes describing the physical outcomes of not only cancer surgery but also chemotherapy and/or radiation challenging for clinicians.

Limitations

These findings must be interpreted in the context of the study design. First, inclusion required ownership of a smartphone. While potentially limiting generalizability, it should be noted that more than 81% of US adults own a smartphone, with relatively equal ownership among different age, sex, racial/ethnicity, and socioeconomic groups.[4] Second, the computation of daily exertional activity assumes that physical activity during the portion of each day when accelerometer data were collected is a true representation of activity that day and did not account for differential phone usage patterns. Third, there were fewer days of preoperative accelerometer data compared with days during recovery; therefore, estimates of baseline activity relied on fewer data. This is associated with the short time interval between initial surgical consultations and the date of surgery procedures. Fourth, included patients underwent a variety of procedures with different levels of acuity and, likewise, the clinically significant postoperative events were heterogenous. Our relatively small sample size limited any adjusted or subset analyses. Our research group continues to enroll patients from multiple surgical centers to adequately power subsequent adjusted and procedure-specific analyses.

Conclusions

We demonstrate that analysis of smartphone sensor data is an effective method to provide insight into the recovery of patients after cancer surgery. Our future work will focus on studying the signals in other smartphone data streams captured through digital phenotyping. Ultimately, providing these data in a patient-facing and clinician-facing tool at the time of consultation may allow for considerable advances in shared decision-making, recovery monitoring, and patient engagement.

ARTICLE INFORMATION

Accepted for Publication: August 31, 2019.

Published Online: October 28, 2019. doi:10.1001/jamasurg.2019.4702

Author Contributions: Drs Haynes and Onnela had full access to all of the data in the study and take responsibility for the integrity of the data and the accuracy of the data analysis. Drs Panda and Solsky contributed equally as co–first authors. Drs Onnela and Haynes contributed equally as co–senior authors.
Concept and design: Panda, Solsky, Gadd, Qadan, Specht, Stephen, Gawande, Onnela, Haynes.
Acquisition, analysis, or interpretation of data: Panda, Solsky, Huang, Lipsitz, Pradarelli, Delisle, Cusack, Lubitz, Mullen, Smith, Tanabe, Gawande, Onnela, Haynes.
Drafting of the manuscript: Panda, Solsky, Huang, Lipsitz, Cusack, Onnela, Haynes.
Critical revision of the manuscript for important intellectual content: All authors.
Statistical analysis: Panda, Solsky, Huang, Lipsitz, Delisle, Cusack, Onnela, Haynes.
Obtained funding: Panda, Gawande, Onnela, Haynes.
Administrative, technical, or material support: Panda, Solsky, Mullen, Stephen, Onnela, Haynes.
Supervision: Gadd, Lubitz, Qadan, Specht, Stephen, Gawande, Onnela, Haynes.

Conflict of Interest Disclosures: Dr Onnela receives additional research funding from Harvard University, Otsuka Pharmaceutical Co Ltd, and Mindstrong Health (unrestricted gift for methods development in digital phenotyping). Dr Pradarelli receives funding through a research contract with Johnson & Johnson Medical Devices and Global Diagnostic Services as a coinvestigator for projects on new surgical device safety and grants from Risk Management Foundation of the Harvard Medical Institutions outside the submitted work. Dr Qadan reported personal fees from Olympus outside the submitted work. Dr Gawande reported receiving a salary as the chief executive officer from Haven, a health care venture founded by Amazon, Berkshire Hathaway, and JPMorgan Chase, outside the submitted work. No other disclosures were reported.

Funding/Support: This study was supported by a National Institutes of Health Research Training in Alimentary Tract Surgery grant (grant T32 DK007754-18 [Dr Panda]), an Ariadne Labs Spark Grant funded by the Paul G. Allen Family foundation (Drs Panda, Solsky, Onnela, and Haynes), and the National Institutes of Health/National Institute of Mental Health (grant 1DP2MH103909 [Drs Onnela and Huang]).

Role of the Funder/Sponsor: The funders had no role in the design and conduct of the study; collection, management, analysis, and interpretation of the data; preparation, review, or approval of the manuscript; and decision to submit the manuscript for publication.

Meeting Presentation: This paper was presented at the American College of Surgeons Clinical Congress; October 28, 2019; San Francisco, California.

REFERENCES

1. Daskivich TJ, Houman J, Lopez M, et al. Association of wearable activity monitors with assessment of daily ambulation and length of stay among patients undergoing major surgery. *JAMA Netw Open*. 2019;2(2):e187673-e187673. doi:10.1001/jamanetworkopen.2018.7673

2. Krummel TM. The rise of wearable technology in health care. *JAMA Netw Open*. 2019;2(2):e187672-e187672. doi:10.1001/jamanetworkopen.2018.7672

3. Torous J, Kiang MV, Lorme J, Onnela J-P. New tools for new research in psychiatry: a scalable and customizable platform to empower data driven smartphone research. *JMIR Ment Health*. 2016;3(2):e16. doi:10.2196/mental.5165

4. Smith A. US smartphone use in 2015. https://www.pewinternet.org/2015/04/01/us-smartphone-use-in-2015/. Published April 1, 2015. Accessed October 14, 2019.

5. Panda N, Solsky I, Haynes AB. Redefining shared decision-making in the digital era. *Eur J Surg Oncol*. 2019;(July):S0748-7983(19)30583-9. doi:10.1016/j.ejso.2019.07.025

6. Barnett I, Onnela J-P. Inferring mobility measures from GPS traces with missing data [published online October 26, 2018]. *Biostatistics*. doi:10.1093/biostatistics/kxy059

7. Barnett I, Torous J, Staples P, Keshavan M, Onnela J-P. Beyond smartphones and sensors: choosing appropriate statistical methods for the analysis of longitudinal data. *J Am Med Inform Assoc*. 2018;25(12):1669-1674. doi:10.1093/jamia/ocy121

8. Torous J, Staples P, Barnett I, Sandoval LR, Keshavan M, Onnela J-P. Characterizing the clinical relevance of digital phenotyping data quality with applications to a cohort with schizophrenia. *NPJ Digit Med*. 2018;1(1):15. doi:10.1038/s41746-018-0022-8

9. Wannenburg J, Malekian R. Physical activity recognition from smartphone accelerometer data for user context awareness sensing. *IEEE Trans Syst Man Cybern Syst*. 2017;47(12):3142-3149. doi:10.1109/TSMC.2016.2562509

10. Mourcou Q, Fleury A, Franco C, Klopcic F, Vuillerme N. Performance evaluation of smartphone inertial sensors measurement for range of motion. *Sensors (Basel)*. 2015;15(9):23168-23187. doi:10.3390/s150923168

11. Lipsitz SR, Fitzmaurice GM, Ibrahim JG, Gelber R, Lipshultz S. Parameter estimation in longitudinal studies with outcome-dependent follow-up. *Biometrics*. 2002;58(3):621-630. doi:10.1111/j.0006-341X.2002.00621.x

12. Fry BT, Campbell DA Jr, Englesbe MJ, Vu JV. Using patient-reported outcomes to enhance appropriateness in low-risk elective general surgery. *Ann Surg*. 2019;269(1):41-42. doi:10.1097/SLA.0000000000002864

13. de Arriba-Pérez F, Caeiro-Rodríguez M, Santos-Gago JM. Collection and processing of data from wrist wearable devices in heterogeneous and multiple-user scenarios. *Sensors (Basel)*. 2016;16(9):E1538. doi:10.3390/s16091538

14. Pevnick JM, Fuller G, Duncan R, Spiegel BMR. A large-scale initiative inviting patients to share personal fitness tracker data with their providers: initial results. *PLoS One*. 2016;11(11):e0165908. doi:10.1371/journal.pone.0165908

15. Developer A. About the healthkit framework. https://developer.apple.com/documentation/healthkit/about_the_healthkit_framework. Published 2019. Accessed October 16, 2019.

16. Fitbit Health Solutions. Better health research. https://healthsolutions.fitbit.com/researchers/. Accessed October 16, 2019.

17. Withings Health Institute. Our vision of health. https://www.withings.com/us/en/health-institute. Accessed October 16, 2019.

18. Rosenberg D, Kadokura EA, Bouldin ED, Miyawaki CE, Higano CS, Hartzler AL. Acceptability of fitbit for physical activity tracking within clinical care among men with prostate cancer. *AMIA Annu Symp Proc*. 2017;2016:1050-1059.

19. Hermsen S, Moons J, Kerkhof P, Wiekens C, De Groot M. Determinants for sustained use of an activity tracker: observational study. *JMIR Mhealth Uhealth*. 2017;5(10):e164. doi:10.2196/mhealth.7311

20. Gresham G, Hendifar AE, Spiegel B, et al. Wearable activity monitors to assess performance status and predict clinical outcomes in advanced cancer patients. *NPJ Digit Med*. 2018;1(1):27. doi:10.1038/s41746-018-0032-6

21. Mercer K, Giangregorio L, Schneider E, Chilana P, Li M, Grindrod K. Acceptance of commercially available wearable activity trackers among adults aged over 50 and with chronic illness: a mixed-methods evaluation. *JMIR Mhealth Uhealth*. 2016;4(1):e7. doi:10.2196/mhealth.4225

22. Low CA, Bovbjerg DH, Ahrendt S, et al. Fitbit step counts during inpatient recovery from cancer surgery as a predictor of readmission. *Ann Behav Med*. 2018;52(1):88-92. doi:10.1093/abm/kax022

23. Tudor-Locke C, Craig CL, Aoyagi Y, et al. How many steps/day are enough? For older adults and special populations. *Int J Behav Nutr Phys Act*. 2011;8:80. doi:10.1186/1479-5868-8-80

24. Vandrevala T, Senior V, Spring L, Kelliher L, Jones C. 'Am I really ready to go home?': a qualitative study of patients' experience of early discharge following an enhanced recovery programme for liver resection surgery. *Support Care Cancer*. 2016;24(8):3447-3454. doi:10.1007/s00520-016-3158-6

25. Weinstock DE. Can wearable technology boost patient engagement? https://www.eclinicalworks.com/wp-content/uploads/2017/05/Can-Wearable-Technology-Boost-Patient-Engagement-by-Weinstock-3-30-17.pdf. Published March 16, 2017. Accessed October 14, 2019.

26. Schrager JD, Shayne P, Wolf S, et al. Assessing the influence of a fitbit physical activity monitor on the exercise practices of emergency medicine residents: a pilot study. *JMIR Mhealth Uhealth*. 2017;5(1):e2. doi:10.2196/mhealth.6239