Engagement with daily symptom reporting, passive smartphone sensing, and wearable device data collection during chemotherapy

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Sean McClaine[1] BS; Jennifer Fedor[1] MS; Christianna Bartel[1] BS; Leeann Chen[1] MPS; Krina C Durica[1] MA; Carissa A Low[1] PhD

[1]University of Pittsburgh Pittsburgh US

Corresponding Author:
Carissa A Low PhD
University of Pittsburgh
5051 Centre Avenue, Suite 5002
Pittsburgh
US

Abstract

Background: Chemotherapy can cause a variety of symptoms that can impair quality of life and functioning. Remote monitoring of daily symptoms and activity during outpatient treatment may enable earlier detection and management of emerging toxicities but requires patients, including older and acutely ill patients, to successfully engage with technology to report symptoms via smartphone and to charge and wear or carry mobile devices.

Objective: The objective of this study was to identify factors that were associated with participant engagement with collecting three data streams over 90 days during chemotherapy: daily patient-reported symptom surveys, passive smartphone sensing, and a wearable Fitbit device.

Methods: We enrolled 162 patients receiving outpatient chemotherapy into a 90-day prospective study. Patients were asked to rate daily symptoms via a smartphone app, to install an application on their smartphones to collect passive sensor data, and to wear a Fitbit device for the duration of the study. Participants completed baseline demographic and quality of life questionnaires, and clinical information was extracted from the electronic medical record. We fit a series of logistic generalized estimating equations to evaluate the association between demographic and clinical factors and daily engagement with each data stream.

Results: Overall engagement was high, with participants completing daily surveys on 61% of days and collecting sufficient smartphone data and wearable sensor data on 73% and 70% of enrolled days, respectively, on average. Relative to White participants, non-White patients demonstrated lower odds of engagement with both the daily symptom surveys and wearable data collection. Patients with Stage IV cancer also exhibited lower odds of engagement with daily symptom reporting than those with earlier stage disease, and patients were less likely to complete symptom ratings on the weekend. Odds of engagement with smartphone and Fitbit data collection were greater the less time had elapsed since the patient's last chemotherapy appointment. Older patients and those who reported better cognitive functioning at study entry were more likely to engage with Fitbit data collection, and patients who reported higher levels of depressive symptoms were less likely to engage with smartphone data collection.

Conclusions: Remote patient monitoring during chemotherapy has the potential to improve clinical management, but only if patients engage with monitoring systems. Results suggest significant associations between demographic and clinical factors and sustained engagement with smartphone and wearable device assessments during chemotherapy, suggesting that non-White participants, those with metastatic cancer, or those with existing cognitive impairment may benefit from additional resources to optimize engagement. Contrary to hypotheses, older adults were more likely than younger adults to engage consistently with wearable device assessments.

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Keywords: Cancer; Chemotherapy; Remote monitoring; Mobile Health; Wearable device

Introduction

Background

Patients with cancer undergoing chemotherapy often experience numerous adverse effects, including fatigue, nausea and vomiting, peripheral neuropathies, and more [1]. These symptoms can have a significant negative impact on the patient's quality of life and can lead to early discontinuation or reduction of treatment.

Growing evidence suggests that patients that used symptom reporting software during chemotherapy continued their treatment for longer, required fewer hospital admissions, and survived longer than those who were not randomized to report symptoms [2-4]. To achieve these potential benefits, patients, including those that are older, acutely ill, or with low digital or health literacy, must engage with technological systems to report symptoms and provide other patient-generated health data for remote monitoring purposes. The goal of this paper is to characterize patient engagement with a system aimed at capturing daily patient-reported symptoms as well as continuous wearable and smartphone sensor data during chemotherapy.

Smartphones and other technologies provide a unique opportunity for remote patient monitoring as they allow patients to record their symptoms and other patient-reported outcomes (PROs) quickly and easily. Providers can benefit from patients electronically recording and sharing their symptoms, as they can use this information to track their patient's symptom progression and identify concerning symptoms in real time. Several studies have investigated patient adherence to daily or weekly symptom surveys on the patient's smartphone or via email [5-9]. Typical adherence rates in the literature have varied depending on the technology used, the frequency and duration of assessments, how adherence is defined, and whether participants were given reminders to answer symptom surveys. A systematic review of 33 different electronic symptom self-reporting systems reported response rates ranging from 45-92% [5].

Wearable devices such as Fitbits and other activity monitors as well as passive data from smartphones may also be useful for patient monitoring, as they allow for the continuous collection of physiological and behavioral data related to sleep, activity, geographic mobility, and more. These data may also be helpful to clinicians, as studies have shown a correlation between lower step counts and negative patient outcomes including greater symptom burden, lower quality of life and performance status, and worse clinical outcomes among oncology patients [10-12]. The growing literature in this area suggests that patient adherence to wearable data collection during cancer treatment has been relatively robust [13,14]. A systematic review of 38 studies that investigated cancer patient adherence to wearable devices reported adherence rates ranging from 60-100% [14]. Collecting data from a wearable device may require less active involvement from participants but does requires the participant to keep the device charged, wear it consistently and correctly, and sync the wearable to an internet connected device. Indeed, there is evidence that patient adherence to wearable devices may be limited when the patient is not given reminders to wear and sync the device [15]. Other barriers to wearable device data collection reported in the literature include limited technical literacy and limited access to a reliable internet connection. Passive smartphone sensor data collection is less common, and to our knowledge, no studies to date have examined patient adherence to passive smartphone sensing during chemotherapy. In addition, there has been little research done on the sociodemographic and medical factors that affect a participant's engagement with these

technology-based monitoring systems during cancer treatment.

Objective

The objective of this study was to identify factors that impacted participant engagement with collecting three data streams over 90 days during chemotherapy: daily patient-reported symptom surveys, passive smartphone sensing, and a wearable Fitbit device.

Methods

Participants

Potential study participants were identified for the study by their medical oncology care team. Men and women aged 18 years or older who were undergoing chemotherapy for any solid tumor at a large academic cancer center, who owned a smartphone, and who had at least two chemotherapy cycles remaining were eligible to participate. Data collection for this prospective cohort study is ongoing; this analysis focuses on 162 patients who had completed (146/162, 90.1%) or withdrawn from (16/162, 9.9%) the 90-day study protocol between March 2020 and June 2023. Participants were enrolled in the study for a grand total of 13,954 days, with an average of 86 days per participant (SD 17, range 8-92).

Study Procedure

Following informed consent, participants had an application installed on their smartphone that delivered a daily and weekly (weekly data not reported) symptom survey. The survey was based on the NCI's Patient Reported Outcome-Common Terminology Criteria for Adverse Events [16] and included the following symptoms: nausea, vomiting, decreased appetite, abdominal pain, constipation, diarrhea, shortness of breath, insomnia, fatigue, rash, dizziness, numbness or tingling in hands/feet, anxiety, sad or unhappy feelings, and "other symptoms." Participants were able to set times for daily notifications to remind them to complete the surveys.

The AWARE application [17] was also installed on participants' Android or iOS smartphones. AWARE runs in the background to record information about movement and location of the phone, screen on and off events, nearby Bluetooth devices and Wi-Fi networks, and metadata about calls and messages exchanged using the smartphone. Finally, participants were provided with a Fitbit Inspire device that recorded the patient's activity, heart rate, and sleep patterns. Participants were asked to wear the Fitbit at all times except when charging (approximately every 10 days).

Data were collected from each participant for three months. Incoming data quality was monitored throughout the study, and participants were contacted via phone, text, email, or in-person if they were missing data for three or more consecutive days.

At baseline, participants completed a demographic questionnaire as well as the PROMIS-29+2 v2.1. Information about participants' cancer and its treatment was extracted from the electronic medical record.

Measures

Demographics. Demographic variables were self-reported by participants in a baseline

questionnaire and included age (in years), gender (male, female, non-binary), race (White/Caucasian, Black/African American, Asian, other, more than one race/ethnicity), highest level of education (less than a high school diploma; high school diploma or equivalent; some college, no degree; Associates of arts or other 2-year degree; Bachelor's degree; Graduate degree). Residential zip code was used to classify participants as rural (yes, no) based on eligible zip code data from the Federal Office of Rural Health Policy [18]. Smartphone model information was recorded by the study team and verified against data collected by AWARE. Phone type was categorized as iOS if the device brand was "iPhone" and as Android otherwise.

Clinical. Insurance plan type was extracted from the electronic medical record (EMR) in June 2023 and categorized by the study team as public; private; mixed public, private, and/or other; or none, if no insurance was listed. Because we were unable to determine if a lack of available insurance information was due to the participant not having insurance coverage, removal of insurance information from the system upon death, or another reason, we subsequently chose to treat no insurance listed as missing. Cancer type (biliary, bone, breast, gastrointestinal (GI), gynecologic, liver, lung, multiple myeloma, pancreas, salivary gland, urogenital), stage (0, 1, 2, 3, 4), and diagnosis date were extracted from the EMR at enrollment. For consistency, cancer diagnosis date was defined as the date listed beside the cancer type in the participant's outpatient progress notes. Time in days since cancer diagnosis at enrollment was calculated by subtracting the cancer diagnosis date from the study enrollment date and was rescaled to time in months for interpretability in analyses.

Quality of life. To assess quality of life, participants completed the PROMIS Profile 29+2 v2.1 [19] as part of the baseline questionnaire. From each participant's item-level responses, we obtained domain-level theta values from the Health Measures Scoring Service [20] and used these values to generate PROMIS preference-based scores [21]. Theta values from the Pain Interference, Cognitive Function, Depression/Sadness, Ability to Participate in Social Roles/Activities, Anxiety/Fear, Fatigue, Physical Function, and Sleep Disturbance domains were used to compute one overall ("PROPr") and seven domain-specific preference-based scores. Possible scores range from 0 (reflecting death) to 1 (reflecting full health).

Time-related. Time-varying, day-level variables included an index for study day (with 0 corresponding to the date of enrollment), an indicator for weekday or weekend days, and the time in days since the participant's last known chemotherapy treatment. Dates on which the participant received chemotherapy treatment were extracted from the EMR. For each participant, available treatment dates were joined with study day dates and the most recent prior treatment date was assigned by carrying forward each known treatment date until the next known treatment date occurred. For each day for each participant, we then computed the number of days that had elapsed since the participant's last known chemotherapy treatment as the difference in days between the study day date and the most recent prior treatment date.

Daily symptom survey completion. To evaluate associations between demographic, clinical, quality of life, and time-related factors and adherence to daily surveys, we created a day-level, binary outcome variable reflecting daily symptom survey completion. For each day for each participant, adherence to daily symptom survey completion was defined as the presence of a recorded survey response that was started at any time on the given day and was at least 50% complete.

Smartphone and Fitbit data collection. To evaluate associations between demographic, clinical, quality of life, and time-related factors and adherence to smartphone and Fitbit data collection, we created separate day-level, binary outcome variables reflecting the presence of at least

8 valid hours of phone or Fitbit data, respectively. We first used our Reproducible Analysis Pipeline for Data Streams (RAPIDS) [22] to extract day-level (24 hours from midnight to midnight) phone and Fitbit data yield features for each participant. Data yield features approximate the proportion of each day during which the device was sensing data from any of the specified sensors. For each day for each participant, adherence to phone data collection was defined as at least 8 valid hours of data from any AWARE sensor (activity recognition, applications crashes, applications foreground, applications notifications, battery, Bluetooth, calls, keyboard, light, locations, messages, screen, WiFi connected, WiFi visible), and adherence to Fitbit data collection was defined as at least 8 valid hours of Fitbit intraday heart rate data. Valid hours were defined as 60-minute windows in which at least one row of raw data from any of the specified sensors was recorded in at least 30 of those minutes.

Statistical Analysis

We first computed descriptive statistics of demographic, clinical, quality of life, and time-related measures to characterize our sample. For continuous variables, Wilcoxon rank sum tests, and for categorical variables, Chi-square or Fisher's exact tests were used to determine if these measures significantly differed between participants who completed the full study protocol and those who withdrew early. Additionally, to characterize overall adherence in our sample, for each participant, we calculated the proportions of days with adherence to daily symptom survey completion, smartphone data collection, and Fitbit data collection as the ratio between the respective number of adherent days and the number of days the participant was enrolled in the study and computed descriptive statistics. For statistical models, we evaluated the day-level, binary outcomes.

For interpretability in analyses, age was centered at the mean age of the sample. Due to low frequencies of some categories, non-binary gender was treated as missing, and race and highest level of education were collapsed into binary variables (respectively, White/Caucasian, not White/Caucasian; less than a college degree, college degree or higher). Additionally, cancer types with frequency <10 were collapsed into a single Other category, and cancer stage was collapsed into a binary variable representing stage 4 cancer (yes, no). Baseline PROMIS preference-based scores were rescaled for interpretability by multiplying each score by 10.

To evaluate the association between each covariate of interest and each binary outcome, we fit a series of univariable logistic generalized estimating equations (GEE) [23] using the *geepack* package for R (v1.3.9) [24]. Due to a small proportion of missing values for some covariates, we analyzed model-wise complete cases. Because phone data yield was systematically lower among participants using Android devices compared to those using iOS devices due to differences in sensor data sampling frequencies across platforms, all models for the phone data yield outcome were additionally adjusted for phone type. GEE is a method for modelling clustered data, such as those from a longitudinal study, where observations within a cluster (i.e., participant) are correlated. Either an exchangeable or first-order autoregressive (ar1) working correlation structure was selected by minimizing the Quasi Information Criterion (QIC). Robust standard errors for parameter estimates were obtained using the sandwich estimator. Estimates were exponentiated to obtain odds ratios (OR) and 95% confidence intervals (CI). Because Likelihood-based methods are not available for GEE, we used a series of Wald tests to conduct single- and multi-parameter inference. We accounted for multiple comparisons for each outcome by controlling for the false discovery rate (FDR) [25] when evaluating global covariate effects across univariable models (*Q* values). An alpha level of .05 was used as a strict cutoff for determining statistical significance.

Finally, for each outcome, we fit a single multivariable GEE containing a purposefully selected subset of covariates which were determined *a priori*. For the sufficient Fitbit data yield outcome, we

defaulted to an independence working correlation structure because unstable and extreme parameter estimates were obtained under both exchangeable and first-order autoregressive correlation structures; a first-order autoregressive correlation structure was selected for all other outcomes based on QIC, with the exception of an exchangeable working correlation structure for the sufficient phone data yield outcome.

All analyses were performed using R (v4.2.3; R Core Team, 2023) [26]. All code for data management and analysis is available [27].

Results

Participant Characteristics

Participant characteristics are summarized in Table 1. Participants were aged 59.47 years on average (SD 11.84, range 28-92), and were mostly female (101/162, 62.3%), White/Caucasian (135/162, 83.3%), had obtained a Bachelor's degree (42/162, 25.9%), did not live in a rural zip code (145/162, 89.5%), and used an iOS smartphone (98/162, 60.5%). Most participants had a private insurance plan (79/162, 48.8%), GI cancer (57/162, 35.2%), stage 4 cancer (103/162, 63.6%), and enrolled in the study 10.88 months after their cancer diagnosis, on average (SD 22.01, range 0-124). With the exception of insurance plan type (P=.02) participant characteristics did not significantly differ between participants who completed the study and those who withdrew early (all P>.08). Day-level characteristics are summarized in Table 2.

Table 1. Participant characteristics

Characteristic	Overall, N = 162	Study completion status		P value[a]
		Completed, n = 146	Withdrawn, n = 16	
Age (years), mean (SD)	59.47 (11.84)	59.97 (11.90)	54.94 (10.54)	.11
Gender, n (%)				.09
Female	101 (62.3%)	87 (59.6%)	14 (87.5%)	
Male	60 (37.0%)	58 (39.7%)	2 (12.5%)	
Non-binary	1 (0.6%)	1 (0.7%)	0 (0%)	
Race, n (%)				.71
White/Caucasian	135 (83.3%)	122 (83.6%)	13 (81.2%)	
Black/African American	21 (13.0%)	18 (12.3%)	3 (18.8%)	
Asian	1 (0.6%)	1 (0.7%)	0 (0%)	
Other	2 (1.2%)	2 (1.4%)	0 (0%)	
More than one race/ethnicity	3 (1.9%)	3 (2.1%)	0 (0%)	
Education, n (%)				.09
Less than a high school diploma	2 (1.2%)	1 (0.7%)	1 (6.2%)	
High school diploma or equivalent	32 (19.8%)	30 (20.5%)	2 (12.5%)	
Some college, no degree	32 (19.8%)	28 (19.2%)	4 (25%)	
Associate of arts or other 2-year degree	15 (9.3%)	13 (8.9%)	2 (12.5%)	
Bachelor's degree	42 (25.9%)	37 (25.3%)	5 (31.2%)	
Graduate degree	37 (22.8%)	36 (24.7%)	1 (6.2%)	
Unknown	2 (1.2%)	1 (0.7%)	1 (6.2%)	
Rural zip code, n (%)				.38
No	145 (89.5%)	132 (90.4%)	13 (81.2%)	
Yes	17 (10.5%)	14 (9.6%)	3 (18.8%)	
Phone type, n (%)				.71
iPhone	98 (60.5%)	89 (61.0%)	9 (56.2%)	
Android	64 (39.5%)	57 (39.0%)	7 (43.8%)	

Characteristic	Overall, N = 162	Study completion status		*P* value[a]
		Completed, n = 146	Withdrawn, n = 16	
Baseline PROMIS preference score, mean (SD)[b]				
PROPr	0.43 (0.23)	0.43 (0.23)	0.38 (0.19)	.51
Cognition	0.83 (0.20)	0.83 (0.20)	0.85 (0.13)	>.99
Depression	0.88 (0.15)	0.89 (0.13)	0.80 (0.28)	.26
Fatigue	0.77 (0.15)	0.76 (0.15)	0.79 (0.12)	.57
Pain	0.85 (0.21)	0.85 (0.21)	0.82 (0.16)	.23
Physical	0.76 (0.18)	0.76 (0.18)	0.77 (0.18)	.63
Sleep	0.77 (0.16)	0.77 (0.16)	0.76 (0.13)	.56
Social	0.79 (0.18)	0.79 (0.18)	0.78 (0.17)	.55
Insurance plan type, n (%)				.02
Private	79 (48.8%)	68 (46.6%)	11 (68.8%)	
Public	51 (31.5%)	49 (33.6%)	2 (12.5%)	
Mixed	21 (13.0%)	21 (14.4%)	0 (0%)	
Unknown	11 (6.8%)	8 (5.5%)	3 (18.8%)	
Cancer type, n (%)				.67
Biliary	7 (4.3%)	7 (4.8%)	0 (0%)	
Bone	1 (0.6%)	1 (0.7%)	0 (0%)	
Breast	24 (14.8%)	23 (15.8%)	1 (6.2%)	
GI	57 (35.2%)	49 (33.6%)	8 (50%)	
Gynecologic	9 (5.6%)	7 (4.8%)	2 (12.5%)	
Liver	2 (1.2%)	2 (1.4%)	0 (0%)	
Lung	6 (3.7%)	6 (4.1%)	0 (0%)	
Multiple myeloma	1 (0.6%)	1 (0.7%)	0 (0%)	
Pancreas	40 (24.7%)	35 (24.0%)	5 (31.2%)	
Salivary gland	1 (0.6%)	1 (0.7%)	0 (0%)	
Urogenital	14 (8.6%)	14 (9.6%)	0 (0%)	

Characteristic	Overall, N = 162	Study completion status		P value[a]
		Completed, n = 146	Withdrawn, n = 16	
Cancer stage, n (%)				.81
0	1 (0.6%)	1 (0.7%)	0 (0%)	
1	10 (6.2%)	10 (6.8%)	0 (0%)	
2	25 (15.4%)	23 (15.8%)	2 (12.5%)	
3	20 (12.3%)	19 (13.0%)	1 (6.2%)	
4	103 (63.6%)	90 (61.6%)	13 (81.2%)	
Unknown	3 (1.9%)	3 (2.1%)	0 (0%)	
Time since diagnosis (months), mean (SD)	10.88 (22.01)	11.69 (23.00)	3.50 (4.62)	.15

[a]Wilcoxon rank sum test; Fisher's exact test; Pearson's Chi-squared test

[b]Data missing for 3/162 participants (1.8%)

Table 2. Day-level characteristics

Characteristic	N = 13,954
Study day, mean (SD) [range]	44.18 (26.28) [0, 91]
Weekend, n (%)	
No	9,976 (71.49%)
Yes	3,978 (28.51%)
Time since last chemotherapy (days), mean (SD) [range][a]	11.21 (12.04) [0, 90]

[a]Data missing for 1257/13954 days (9.01%)

Overall Adherence

We characterized overall adherence for each data stream as the proportion of enrolled days with daily survey, smartphone, or Fitbit adherence for each participant. Overall adherence was higher for passive smartphone and Fitbit data streams than for patient-reported daily symptom surveys (Table 3). On average, participants were adherent to daily survey completion on 60.96% (SD 27.24%, range 0-100%), smartphone data collection on 73.06% (SD 34.94%, range 0-100%) and Fitbit data collection on 70.07% of enrolled days (SD 33.45%, range 0-100%).

Table 3**.** Descriptive statistics of overall adherence

Outcome	N = 162
Daily survey adherence, mean (SD) [range][a]	60.96 (27.24) [0, 100]
Smartphone adherence, mean (SD) [range][a]	73.06 (34.94) [0, 100]
Fitbit adherence, mean (SD) [range][a]	70.07 (33.45) [0, 100]

[a]Percent of enrolled days per participant

Univariable Models

To determine how demographic, quality of life, clinical, and time-related factors may be associated with daily adherence to daily survey completion and smartphone and Fitbit data collection, we first fit a series of univariable GEEs, with each binary, day-level outcome as the dependent variable and, separately, each factor as the independent variable. For the smartphone data collection adherence outcome only, we additionally adjusted for phone type given that smartphone data yield was systematically lower among Android devices relative to iOS devices. Results of these univariable models are summarized in Table 4.

Table 4. Summary of results of univariable GEEs

Covariate[a]	N	Daily survey adherence			Smartphone adherence			Fitbit adherence		
		OR (95% CI)[b]	*P* value[c]	*Q* value[d]	OR (95% CI)[b]	*P* value[c]	*Q* value[d]	OR (95% CI)[b]	*P* value[c]	*Q* value[d]
Age (years, centered at mean)	13,954	1.01 (0.99-1.02)	.34	.51	1.00 (0.97-1.02)	.81	.94	1.02 (1.00-1.05)	.03	.13
Gender	13,863		.55	.67		.32	.51		.92	.95
Female	8,485	*Reference*			*Reference*			*Reference*		
Male	5,378	0.89 (0.62-1.29)	.55		1.35 (0.75-2.42)	.32		1.03 (0.62-1.71)	.92	
Race (collapsed)	13,954		.004	.02		.91	.94		.002	.02
White/Caucasian	11,631	*Reference*			*Reference*			*Reference*		
Not White/Caucasian	2,323	0.48 (0.29-0.80)	.004		1.04 (0.54-2.00)	.91		0.36 (0.19-0.68)	.002	
Education (collapsed)	13,820		.41	.54		.57	.75		.15	.39
College degree or higher	6,883	*Reference*			*Reference*			*Reference*		
Less than college degree	6,937	0.86 (0.61-1.22)	.41		0.85 (0.49-1.48)	.57		0.70 (0.43-1.14)	.15	
Rural zip code	13,954		.80	.88		.94	.94		.88	.95
No	12,510	*Reference*			*Reference*			*Reference*		
Yes	1,444	1.08 (0.61-1.92)	.80		1.02 (0.60-1.73)	.94		0.94 (0.45-2.00)	.88	
Phone type	13,954		.85	.89		<.001	<.001		.10	.30
iPhone	8,433	*Reference*			*Reference*			*Reference*		
Android	5,521	0.96 (0.66-1.40)	.85		0.07 (0.04-0.12)	<.001		0.65 (0.40-1.08)	.10	
Baseline PROMIS, PROPr	13,756	1.08 (1.00-1.17)	.06	.25	1.07 (0.95-1.21)	.28	.49	1.06 (0.94-1.19)	.35	.58
Baseline PROMIS, cognition	13,756	0.98 (0.89-1.06)	.57	.67	0.92 (0.81-1.04)	.18	.49	1.14 (1.00-1.31)	.05	.19
Baseline PROMIS, depression	13,756	1.06 (0.96-1.16)	.25	.41	1.14 (1.00-1.29)	.046	.32	1.11 (0.94-1.31)	.21	.44
Baseline PROMIS, fatigue	13,756	1.07 (0.96-1.19)	.24	.41	1.11 (0.95-1.30)	.19	.49	1.08 (0.91-1.28)	.40	.59
Baseline PROMIS, pain	13,756	1.07 (0.99-1.17)	.10	.34	1.11 (0.98-1.25)	.09	.49	1.06 (0.95-1.19)	.31	.58
Baseline PROMIS, physical	13,756	1.06 (0.96-1.16)	.25	.41	1.09 (0.94-1.26)	.27	.49	1.00 (0.88-1.15)	.95	.95

Covariate[a]	N	Daily survey adherence			Smartphone adherence			Fitbit adherence		
		OR (95% CI)[b]	*P* value[c]	*Q* value[d]	OR (95% CI)[b]	*P* value[c]	*Q* value[d]	OR (95% CI)[b]	*P* value[c]	*Q* value[d]
Baseline PROMIS, sleep	13,756	1.07 (0.97-1.19)	.19	.41	1.04 (0.91-1.20)	.55	.75	0.97 (0.86-1.11)	.70	.86
Baseline PROMIS, social	13,756	1.04 (0.95-1.13)	.41	.54	1.08 (0.92-1.26)	.38	.57	0.94 (0.83-1.07)	.36	.58
Insurance plan type	13,063		.94	.94		.19	.49		.76	.88
Private	6,621	*Reference*			*Reference*			*Reference*		
Mixed	1,911	0.98 (0.63-1.53)	.94		0.55 (0.28-1.08)	.08		1.15 (0.51-2.62)	.73	
Public	4,531	0.93 (0.64-1.36)	.73		0.70 (0.37-1.33)	.28		1.23 (0.70-2.17)	.47	
Cancer type (collapsed)	13,954		.11	.34		.69	.85		.66	.86
GI	4,810	*Reference*			*Reference*			*Reference*		
Pancreas	3,313	0.69 (0.46-1.04)	.08		0.75 (0.33-1.72)	.50		1.24 (0.65-2.36)	.51	
Breast	2,158	1.25 (0.81-1.94)	.31		0.74 (0.36-1.52)	.41		1.54 (0.70-3.37)	.28	
Urogenital	1,275	1.09 (0.59-2.03)	.78		0.48 (0.17-1.31)	.15		0.92 (0.37-2.32)	.87	
Other	2,398	1.20 (0.74-1.95)	.45		0.76 (0.39-1.48)	.42		1.54 (0.75-3.15)	.24	
Cancer stage 4	13,681		.25	.41		.91	.94		.52	.72
No	4,959	*Reference*			*Reference*			*Reference*		
Yes	8,722	0.81 (0.56-1.16)	.25		1.03 (0.62-1.72)	.91		0.84 (0.51-1.41)	.52	
Time since cancer diagnosis (months)	13,954	1.01 (1.00-1.01)	.18	.41	1.01 (0.99-1.02)	.23	.49	1.01 (1.00-1.02)	.21	.44
Study day	13,954	0.99 (0.99-0.99)	<.001	<.001	1.00 (0.99-1.00)	.27	.49	1.00 (0.99-1.00)	.03	.13
Weekend	13,954		<.001	.002		.20	.49		.007	.05
No	9,976	*Reference*			*Reference*			*Reference*		
Yes	3,978	0.89 (0.84-0.95)	<.001		0.94 (0.86-1.03)	.20		0.93 (0.89-0.98)	.007	
Time since last chemotherapy (days)	12,697	0.99 (0.98-0.99)	<.001	<.001	0.98 (0.97-1.00)	.02	.22	0.99 (0.98-0.99)	<.001	.002

[a]For smartphone adherence outcome, adjusted for phone type

Covariate[a]	N	Daily survey adherence				Smartphone adherence				Fitbit adherence			
		OR CI)[b]	(95%	*P* value[c]	*Q* value[d]	OR CI)[b]	(95%	*P* value[c]	*Q* value[d]	OR CI)[b]	(95%	*P* value[c]	*Q* value[d]

[b]OR: odds ratio, CI: confidence interval

[c]Unadjusted Wald test *P* value for single- or multi-parameter inference

[d]Adjusted global Wald test *P* value, corrected for multiple comparisons

For the daily survey adherence outcome, there were statistically significant effects of race, weekends, time in the study, and time since last chemotherapy treatment. The odds of completing a daily survey were significantly lower for non-White/Caucasian participants relative to White/Caucasian participants (odds ratio [OR] 0.48, 95% CI 0.29-0.80, *P*=.004); on weekend days relative to weekday days (OR 0.89, 95% CI 0.84-0.95, *P*<.001); with each additional day in study following enrollment (OR 0.99, 95% CI 0.99-0.99, *P*<.001); and with each additional day since the participant's last chemotherapy treatment (OR 0.99, 95% CI 0.98-0.99, *P*<.001).

For the smartphone adherence outcome, there were statistically significant effects of baseline depression and time since last chemotherapy treatment, after adjusting for phone type. Each 10 percentage-point increase (i.e., an increase of 0.1) in baseline PROMIS preference depression subscale score, reflecting less depression, was associated with higher odds of adherence (OR 1.14, 95% CI 1.00-1.29, *P*=.046), while each additional day since the participant's last chemotherapy treatment was associated with lower odds of adherence to smartphone data collection (OR 0.98, 95% CI 0.97-1.00, *P*=.021). These effects did not survive correction for multiple comparisons (baseline depression *Q*=.32; time since last chemotherapy treatment *Q*=.22).

For the Fitbit adherence outcome, there were statistically significant effects of age, race, weekends, time in the study, and time since last chemotherapy treatment. Odds of adherence to Fitbit data collection increased with each additional year of age relative to the mean age of the sample (OR 1.02, 95% CI 1.00-1.05, *P*=.025). Odds of adherence to Fitbit data collection were significantly lower for non-White/Caucasian participants relative to White/Caucasian participants (OR 0.36, 95% CI 0.19-0.68, *P*=.002); on weekend days relative to weekday days (OR 0.93, 95% CI 0.89-0.98, *P*=.007); with each additional day in study following enrollment (OR 1.00, 95% CI 0.99-1.00, *P*=.03); and with each additional day since the participant's last chemotherapy treatment (OR 0.99, 95% CI 0.98-0.99, *P*<.001). Effects of age (*Q*=.13), weekends (*Q*=.05), and time in the study (*Q*=.13) did not survive correction for multiple comparisons.

Multivariable Models

To determine how a purposeful subset of these covariates were together associated with adherence, we fit a single multivariable GEE, separately for each data stream. Covariates chosen *a priori* included age; gender; race; education; rural zip code; baseline PROMIS preference scores, cognition and depression subscales; stage 4 cancer; study day; weekends; and time since last chemotherapy. As with the univariable models, we additionally adjusted for phone type in the model for the smartphone data collection adherence outcome only.

Results of the multivariable models were generally consistent with those of the univariable models. For the daily survey adherence outcome (Figure 1), we again found that, adjusting for other covariates in the model, non-White/Caucasian participants were less likely to complete a daily

survey relative to White/Caucasian participants (OR 0.49, 95% CI 0.29-0.81, *P*=.006), and participants were less likely to complete surveys on weekend days relative to weekday days (OR 0.90, 95% CI 0.83-0.97, *P*=.008). Additionally, participants with stage 4 cancer were significantly less likely to be adherent to daily survey completion relative to participants with cancer in stages 0-3 (OR 0.69, 95% CI 0.48-1.00, *P*=.048). Controlling for the other covariates in the model, time in the study and time since last chemotherapy treatment were no longer significantly associated with daily survey adherence.

Covariate		N	Odds Ratio (95% CI)	*P* value
Age (years, centered at mean)		12,160	1.01 (0.99-1.03)	.18
Gender	Female	7,666	Reference	
	Male	4,494	0.85 (0.58-1.23)	.39
Race	White/Caucasian	10,207	Reference	
	Not White/Caucasian	1,953	0.49 (0.29-0.81)	.006
Education	College degree or higher	5,914	Reference	
	Less than college degree	6,246	0.85 (0.60-1.21)	.37
Rural zip code	No	10,990	Reference	
	Yes	1,170	1.03 (0.60-1.76)	.92
Baseline PROMIS, Cognition		12,160	0.97 (0.90-1.05)	.46
Baseline PROMIS, Depression		12,160	1.10 (1.00-1.21)	.06
Cancer stage 4	No	4,273	Reference	
	Yes	7,887	0.69 (0.48-1.00)	.048
Study day		12,160	1.00 (0.99-1.00)	.13
Weekend	No	8,702	Reference	
	Yes	3,458	0.90 (0.83-0.97)	.008
Time since last chemotherapy (days)		12,160	1.00 (0.99-1.01)	.94

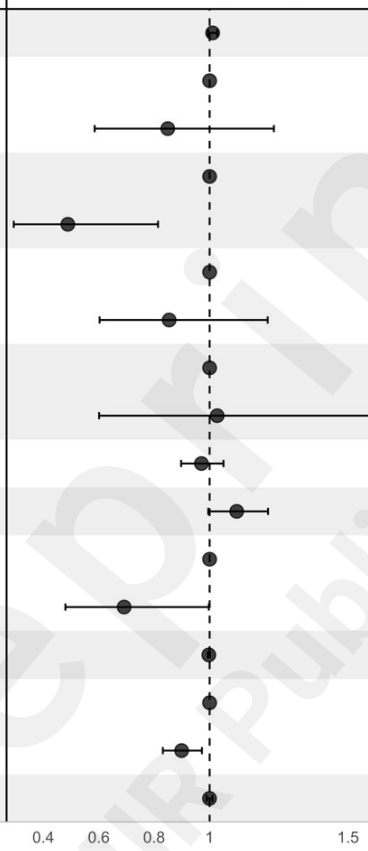

Figure 1. Results of the multivariable model for the daily survey adherence outcome. Each row corresponds to a covariate or covariate category, with separate covariates delineated by alternating grey and white bands. The center panel displays the adjusted odds ratio point estimate and 95% confidence interval. Adjusting for other covariates in the model, odds of adherence to daily survey completion were significantly lower among non-White/Caucasian participants, participants with stage 4 cancer, and on weekend days. N: number of observations; CI: confidence interval; PROMIS: Patient-Reported Outcomes Measurement Information System.

For the smartphone adherence outcome (Figure 2), we again found that there were significant effects of phone type, baseline depression, and time since last chemotherapy treatment. Relative to participants with iPhone devices, participants with Android devices were less likely to be adherent to smartphone data collection, defined as at least 8 valid hours of data collected from any AWARE sensor, due to differences in sampling rates across device platforms (OR 0.10, 95% CI 0.05-0.19, *P*<.001). In the adjusted model, each 10 percentage-point increase (i.e., an increase of 0.1) in baseline PROMIS preference depression subscale score, reflecting less depression, was again associated with higher odds of adherence (OR 1.18, 95% CI 1.03-1.36, *P*=.021), while each additional day since the participant's last chemotherapy treatment was associated with lower odds of

adherence to smartphone data collection (OR 0.98, 95% CI 0.97-0.99, *P*=.001).

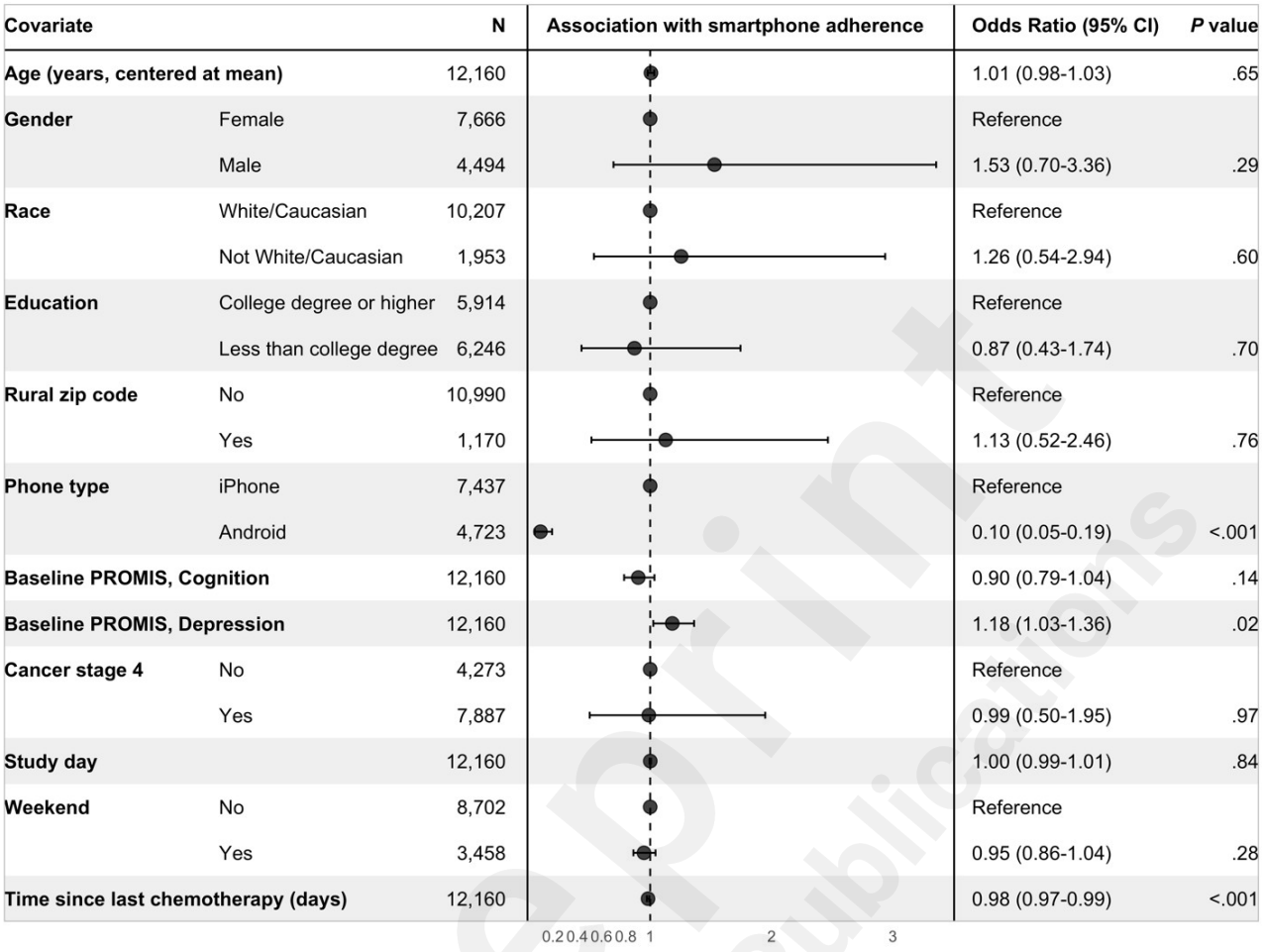

Figure 2. Results of the multivariable model for the smartphone adherence outcome. Each row corresponds to a covariate or covariate category, with separate covariates delineated by alternating grey and white bands. The center panel displays the adjusted odds ratio point estimate and 95% confidence interval. Adjusting for other covariates in the model, odds of adherence to smartphone data collection were significantly lower among participants with Android devices and with each additional day since the participant's last known chemotherapy treatment; odds of adherence were higher among participants with higher PROMIS depression subscale scores (reflecting less depression). N: number of observations; CI: confidence interval; PROMIS: Patient-Reported Outcomes Measurement Information System.

For the Fitbit adherence outcome (Figure 3), we again found that there were significant effects of age, race, and time since last chemotherapy treatment. Odds of adherence to Fitbit data collection increased with each additional year of age relative to the mean age of the sample (OR 1.03, 95% CI 1.01-1.06, *P*=.011). Odds of adherence to Fitbit data collection were significantly lower for non-White/Caucasian participants relative to White/Caucasian participants (OR 0.35, 95% CI 0.17-0.73, *P*=.005) and with each additional day since the participant's last chemotherapy treatment (OR 0.98, 95% CI 0.96-0.99, *P*=.002). Additionally, adjusting for other covariates in the model, there was a significant effect of baseline cognition, with each 10 percentage-point increase in baseline PROMIS preference cognition subscale score (i.e., an increase of 0.1), reflecting better cognitive abilities, associated with 18% higher odds of adherence to Fitbit data collection (OR 1.18, 95% CI 1.03-1.34, *P*=.017). Controlling for other covariates, the effects of time in the study and weekends were no

longer statistically significant.

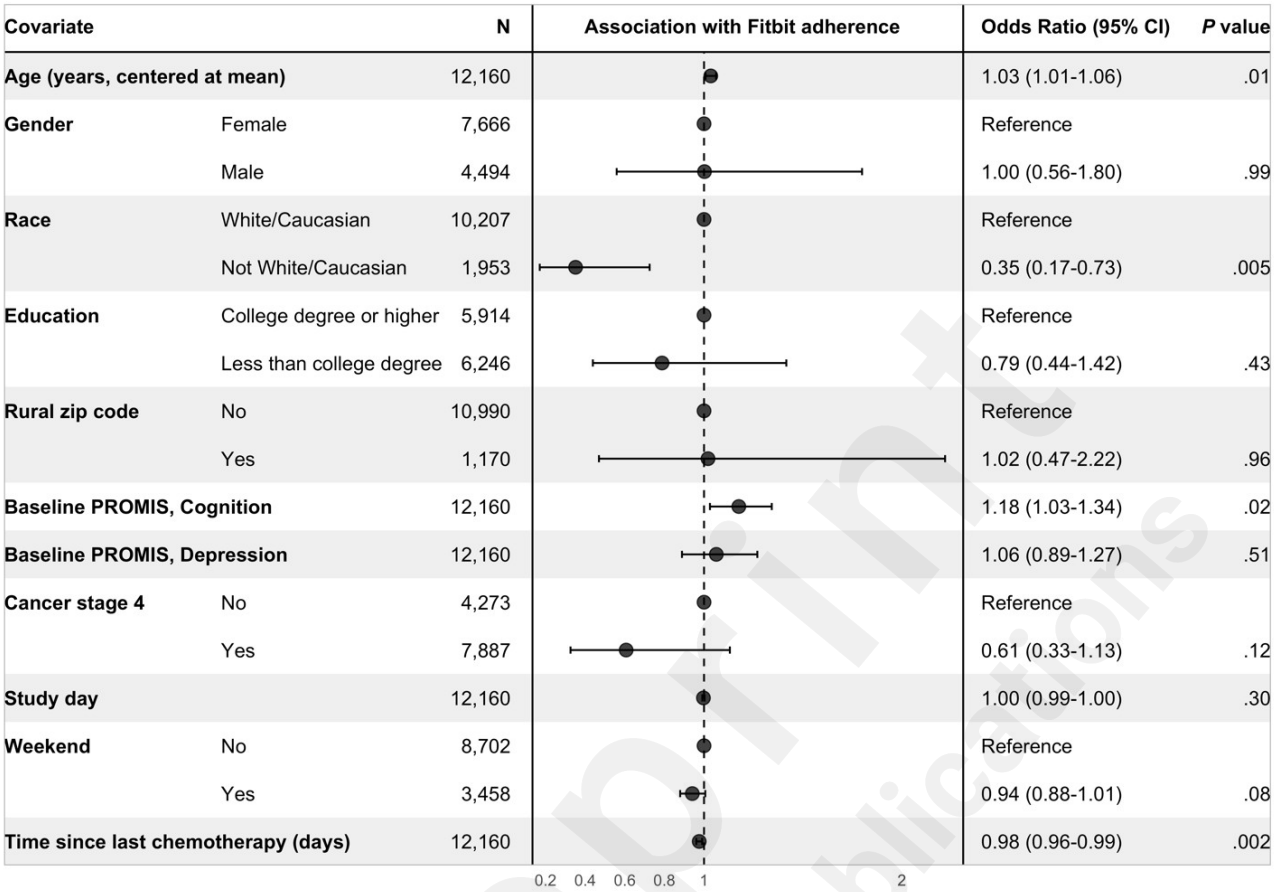

Figure 3. Results of the multivariable model for the Fitbit adherence outcome. Each row corresponds to a covariate or covariate category, with separate covariates delineated by alternating grey and white bands. The center panel displays the adjusted odds ratio point estimate and 95% confidence interval. Adjusting for other covariates in the model, odds of adherence to Fitbit data collection were significantly lower among non-White/Caucasian participants and with each additional day since the participant's last known chemotherapy treatment; odds of adherence were higher among older participants and those with higher PROMIS cognitive subscale scores (reflecting better cognitive abilities). N: number of observations; CI: confidence interval; PROMIS: Patient-Reported Outcomes Measurement Information System.

Discussion

Principal Findings

The goal of this study was to characterize engagement with daily symptom reporting via smartphone, passive smartphone sensing, and wearable device data collection over a 90-day observational study of patients undergoing chemotherapy for any solid tumor. Other studies have measured patient engagement levels with symptom tracking systems; however, we believe this is the first study to evaluate patient engagement with multiple methods of data collection (daily symptom reporting, passive smartphone sensing, and wearable device) in the same study. By measuring patient engagement from three different data streams, we are better able to understand which method of data collection is most reliable for future studies. Additionally, our study examined the effects that different socio-demographic, quality of life, clinical, and time-related factors had on patient

engagement with each of the three different data streams.

Overall adherence rates support the feasibility of mobile technology-based data collection during chemotherapy, with higher rates of adherence to both smartphone sensing and wearable data collection relative to daily symptom surveys. This is likely because the daily symptom surveys required active engagement from the participant compared to the passive smartphone and wearable data collection. Upon enrollment, a member of our team worked with each participant individually to set up their Fitbit and ensure that it was working properly, which likely contributed to this difference. Overall, our results are consistent with other studies that have shown high levels of patient engagement with symptom reporting systems and wearable devices [8-15].

Our results suggest that adherence varied based on demographic factors (age and race), clinical factors (cancer stage and patient-reported depression and cognition), and timing (including days since last chemotherapy treatment, time in study, and weekend vs weekday). Relative to White participants, non-White patients demonstrated lower levels of engagement with both the daily symptom surveys and wearable data collection, suggesting that we need new methods of engaging cancer patients from racial and ethnic minority groups in technology-based monitoring. Patients with Stage 4 cancer exhibited lower rates of engagement with daily symptom reporting than those with earlier stage disease, likely due to greater disease burden and associated life disruption. Additionally, time since last chemotherapy treatment was associated with both smartphone and wearable device engagement, with participants more likely to engage with both data streams the less time that had elapsed since their last chemotherapy treatment. This association was likely due to several factors, including coordinators being able to meet with participants and troubleshoot technology difficulties during treatments. The treatments also likely served as reminders for participants to engage with the study. Participants were also less likely to complete symptom surveys on weekend days relative to weekdays. This pattern has not been observed in the literature to our knowledge, and several factors could contribute to this finding. Patients likely have more “routine” schedules during the week, and thus are more easily able to remember to fill out the surveys. Additionally, many participants had work responsibilities during the week, and thus interference related to symptoms such as fatigue may have been more salient and served as a reminder to report their symptoms.

One surprising finding was that older age was associated with better adherence to wearable device data collection, which contradicts beliefs that older adults are less likely to adopt or engage with health technology. There remains a false belief within the scientific community that older patients are unable or unwilling to engage with health technology [28]. Unfortunately, because of this stigma, there is a relative lack of research in this patient population with regards to their engagement with health technology. We also found that better self-reported cognitive abilities at study entry predicted greater engagement with wearable Fitbit data collection, suggesting that while older adults may be more adherent, additional reminders or strategies may need to be implemented to support patients with any cognitive impairments in collecting wearable data.

Limitations

This study is not without limitations. First, participants needed to own a smartphone that was compatible with study apps to enroll in the study. This likely skewed our sample population to be more “tech literate” than the general population of chemotherapy patients. Second, there was likely a selection bias present in our sample, as participants who were less likely to engage in our study would be more likely to decline enrollment. Third, we assessed engagement in the context of a research study where we were monitoring incoming data closely and reaching out to participants to troubleshoot technical or compliance issues frequently; it is likely that we would have lower rates of

engagement without these interactions with research staff. Fourth, a participants's day-to-day symptom burden likely affected their survey response rate. Participants may have been more or less likely to fill out the surveys on days where they had particularly high (or low) symptom burden, which could skew our results. Finally, it is important to note that the remote assessments collected as part of the current study were not shared with providers or used to inform clinical care, and participants were advised upon consent that data would not be shared or accessed by their providers. This is different from other symptom monitoring studies that incorporated provider alerts or other communication with the care team [7]. Participants may be more motivated to engage with remote technology-based assessments when they know this information is being used to guide their cancer care. Future studies should also explore the feasibility of similar data collection methods in broader populations, including adolescents and young adults with cancer, patients receiving other forms of cancer treatment (radiation, immunotherapy, etc.), and patients with non-solid tumor cancers.

Conclusion

Despite these limitations, our study showed relatively high levels of engagement with all three of our data streams over 90 days. These results demonstrate that collecting patient-reported symptom ratings via smartphone, passive smartphone sensor data, and wearable device data over long periods of time is feasible in cancer trials, even among older and advanced cancer patients receiving active treatment. Findings provide some support for the idea that the digital divide may widen existing health disparities, with non-White participants demonstrating lower levels of engagement, but also challenge the idea that older adults will be less likely to adopt or engage with technology, as least with regard to wearable devices. Future work should experiment with different ways of optimizing engagement for all groups, including different delivery formats and schedules of reminders, onboarding and training procedures, and levels of integration with the clinical care team. More pragmatic studies should also explore levels of engagement with symptom reporting and other patient-generated health data collection in the context of routine clinical care, without research staff monitoring or intervening with participants. To our knowledge, this is the first study to examine patterns and predictors of participant engagement with daily symptom reporting, smartphone sensing, and wearable devices data collection during outpatient chemotherapy, and results provide encouragement and guidance for additional work in this area.

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Authors' Contributions

SM, JF, and CAL conceptualized the analyses reported in this manuscript. CAL planned the study and obtained funding. JF performed the data analyses. CB, LC, and KCD coordinated and managed

the study. SM, JF, and CAL wrote the first draft of the manuscript, and CB, LC, and KCD reviewed and edited the manuscript.

Conflicts of Interest

None declared.

References

1. Reilly CM, Bruner DW, Mitchell SA, et al. A literature synthesis of symptom prevalence and severity in persons receiving active cancer treatment. Support Care Cancer. 2013;21(6):1525-1550. doi:10.1007/s00520-012-1688-0
2. Chen J, Ou L, Hollis SJ. A systematic review of the impact of routine collection of patient reported outcome measures on patients, providers and health organisations in an oncologic setting. BMC Health Serv Res. 2013;13:211. doi:10.1186/1472-6963-13-211
3. Basch E, Deal AM, Kris MG, et al. Symptom monitoring with patient-reported outcomes during routine cancer treatment: a randomized controlled trial. J Clin Oncol. 2016;34(6):557-565. doi:10.1200/JCO.2015.63.0830
4. Basch E, Deal AM, Dueck AC, et al. Overall survival results of a trial assessing patient-reported outcomes for symptom monitoring during routine cancer treatment. JAMA. 2017;318(2):197-198. doi:10.1001/jama.2017.7156
5. Cho Y, Zhang H, Harris MR, Gong Y, Smith EL, Jiang Y. Acceptance and use of home-based electronic symptom self-reporting systems in patients with cancer: systematic review. J Med Internet Res. 2021;23(3):e24638. doi:10.2196/24638
6. Solk P, Gavin K, Fanning J, et al. Feasibility and acceptability of intensive longitudinal data collection of activity and patient-reported outcomes during chemotherapy for breast cancer. Qual Life Res. 2019;28(12):3333-3346. doi:10.1007/s11136-019-02278-7
7. Patt D, Wilfong L, Hudson KE, et al. Implementation of electronic patient-reported outcomes for symptom monitoring in a large multisite community oncology practice: dancing the Texas two-step through a pandemic. JCO Clinical Cancer Informatics. Published online June 4, 2021. doi:10.1200/CCI.21.00063
8. Teckie S, Solomon J, Kadapa K, et al. A mobile patient-facing app for tracking patient-reported outcomes in head and neck cancer survivors: single-arm feasibility study. JMIR Form Res. 2021;5(3):e24667. doi:10.2196/24667
9. Crafoord MT, Fjell M, Sundberg K, Nilsson M, Langius-Eklöf A. Engagement in an interactive app for symptom self-management during treatment in patients with breast or prostate cancer: mixed methods study. J Med Internet Res. 2020;22(8):e17058. doi:10.2196/17058
10. Low CA. Harnessing consumer smartphone and wearable sensors for clinical cancer research. npj Digit Med. 2020;3(1):1-7. doi:10.1038/s41746-020-00351-x
11. Kos M, Pijnappel EN, Buffart LM, et al. The association between wearable activity monitor metrics and performance status in oncology: a systematic review. Support Care Cancer. 2021;29(11):7085-7099. doi:10.1007/s00520-021-06234-5
12. Kos M, Brouwer CG, van Laarhoven HWM, Hopman MTE, van Oijen MGH, Buffart LM. The association between wearable device metrics and clinical outcomes in oncology: A systematic review with evidence synthesis and meta-analysis. Critical Reviews in Oncology/ Hematology. 2023;185:103979. doi:10.1016/j.critrevonc.2023.103979
13. Miyaji T, Kawaguchi T, Azuma K, et al. Patient-generated health data collection using a

wearable activity tracker in cancer patients-a feasibility study. Support Care Cancer. 2020;28(12):5953-5961. doi:10.1007/s00520-020-05395-z
14. Huang Y, Upadhyay U, Dhar E, Kuo LJ, Syed-Abdul S. A scoping review to assess adherence to and clinical outcomes of wearable devices in the cancer population. Cancers. 2022;14(18):4437. doi:10.3390/cancers14184437
15. Dreher N, Hadeler EK, Hartman SJ, et al. Fitbit usage in patients with breast cancer undergoing chemotherapy. Clin Breast Cancer. 2019;19(6):443-449.e1. doi:10.1016/j.clbc.2019.05.005
16. Basch E, Reeve BB, Mitchell SA, et al. Development of the National Cancer Institute's patient-reported outcomes version of the common terminology criteria for adverse events (PRO-CTCAE). J Natl Cancer Inst. 2014;106(9):dju244. doi:10.1093/jnci/dju244
17. Ferreira D, Kostakos V, Dey AK. AWARE: Mobile Context Instrumentation Framework. Frontiers in ICT. 2015;2. Accessed October 13, 2023. https://www.frontiersin.org/articles/10.3389/fict.2015.00006
18. Federal Office of Rural Health Policy (FORHP) Data Files | HRSA. Accessed October 13, 2023. https://www.hrsa.gov/rural-health/about-us/what-is-rural/data-files
19. Cella D, Choi SW, Condon DM, et al. PROMIS® Adult Health Profiles: efficient short-form measures of seven health domains. Value in Health. 2019;22(5):537-544. doi:10.1016/j.jval.2019.02.004
20. HealthMeasures Scoring Service. Accessed October 13, 2023. https://www.assessmentcenter.net/ac_scoringservice
21. Dewitt B, Feeny D, Fischhoff B, et al. Estimation of a preference-based summary score for the Patient-Reported Outcomes Measurement Information System: The PROMIS®-Preference (PROPr) Scoring System. Med Decis Making. 2018;38(6):683-698. doi:10.1177/0272989X18776637
22. Vega J, Li M, Aguillera K, et al. Reproducible Analysis Pipeline for Data Streams: open-source software to process data collected with mobile devices. Front Digit Health. 2021;3:769823. doi:10.3389/fdgth.2021.769823
23. Liang KY, Zeger SL. Longitudinal data analysis using generalized linear models. Biometrika. 1986;73(1):13-22. doi:10.1093/biomet/73.1.13
24. Højsgaard S, Halekoh U, Yan J. The R Package geepack for Generalized Estimating Equations. Journal of Statistical Software. 2006;15:1-11. doi:10.18637/jss.v015.i02
25. Benjamini Y, Hochberg Y. Controlling the false discovery rate: a practical and powerful approach to multiple testing. Journal of the Royal Statistical Society: Series B (Methodological). 1995;57(1):289-300. doi:10.1111/j.2517-6161.1995.tb02031.x
26. R Core Team. R: A language and environment for statistical computing. Published online 2023. https://www.R-project.org/
27. MoSHI. carissalow/rosa-adherence. Published online February 2, 2024. Accessed February 12, 2024. https://github.com/carissalow/rosa-adherence
28. Mace RA, Mattos MK, Vranceanu AM. Older adults can use technology: why healthcare professionals must overcome ageism in digital health. Transl Behav Med. 2022;12(12):1102-1105. doi:10.1093/tbm/ibac070

Abbreviations

ar1: first-order autoregressive
CI: confidence intervals
EMR: electronic medical record
FDR: false discovery rate

GEE: generalized estimating equations
GI: gastrointestinal
OR: odds ratios
PROMIS: Patient-Reported Outcomes Measurement Information System
PROPr: PROMIS-Preference scoring system
PROs: patient-reported outcomes
QIC: Quasi Information Criterion
RAPIDS: Reproducible Analysis Pipeline for Data Streams