Odom *et al. BMC Cancer* (2025) 25:614
https://doi.org/10.1186/s12885-025-14009-y

BMC Cancer

RESEARCH

Open Access

Associations between smartphone GPS data and changes in psychological health and burden outcomes among family caregivers and patients with advanced cancer: an exploratory longitudinal cohort study

J. Nicholas Odom[1,2,3*], Kyungmi Lee[4], Erin R. Harrell[5], Kristen Allen Watts[6], Avery C. Bechthold[1], Sally Engler[1], Frank Puga[1], Natashia Bibriescas[1], Arif H. Kamal[7,8], Christine S. Ritchie[9], George Demiris[10], Alexi A. Wright[11], Marie A. Bakitas[1,2,3] and Andres Azuero[1]

Abstract

Background Managing advanced cancer can be psychologically distressing and burdensome for family caregivers and their care recipients. Innovations in the collection and modelling of passive data from personally-owned smartphones (e.g., GPS), called digital phenotyping, may afford the possibility of remotely monitoring and detecting distress and burden. We explored the potential of using passively-collected GPS data from smartphones to assess and predict caregiver and patient distress and burden.

Methods This exploratory longitudinal cohort study enrolled smartphone-owning family caregiver and patient participants with advanced cancer (August 2021-July 2023) recruited via an oncology clinic or self-referral through Facebook. Participants downloaded a digital phenotyping research app, called Beiwe, that passively collected GPS data for 24 weeks. Participants completed self-report measures (PROs) of anxiety and depressive symptoms (Hospital Anxiety and Depression Scale [HADS]), mental health (PROMIS Mental Health), and caregiver burden (Montgomery-Borgatta Caregiver Burden scale) at baseline and every 6 weeks for 24 weeks. After pre-processing raw GPS data into daily GPS features (e.g., time spent at home, distance traveled/day), computing biweekly moving averages and standard deviations, and conducting a principal components analysis (PCA) of the resulting variables, within-person regression models were used to assess associations between changes in PRO measures and changes in PCA scores, with adjusted-R^2 as the measure of effect size (small = 0.02, medium = 0.13, large = 0.26).

Results Evaluable data were collected from 48 participants (family caregivers = 32; patients = 16). Caregiver smartphone data explained small-to-medium variance in caregiver anxiety (0.06), depression (0.15), and mental health (0.07). Patient smartphone data predicted small to medium variance in caregiver depressive symptoms (0.12) and

*Correspondence:
J. Nicholas Odom
dionneod@uab.edu

Full list of author information is available at the end of the article

© The Author(s) 2025. **Open Access** This article is licensed under a Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License, which permits any non-commercial use, sharing, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if you modified the licensed material. You do not have permission under this licence to share adapted material derived from this article or parts of it. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit http://creativecommons.org/licenses/by-nc-nd/4.0/.

burden (0.05). Combined caregiver and patient smartphone data explained small variance in caregiver depressive (0.02) and anxiety symptoms (0.10) and large variance for PROMIS-mental health (0.36) and burden (0.50). For patient outcomes, caregiver smartphone data accounted for small variance in anxiety symptoms (0.07); patient smartphone data predicted large variance in anxiety symptoms (0.24). Combined data explained medium variance in patient depressive symptoms (0.18).

Conclusions The exploratory study demonstrates the potential predictive utility of using passive smartphone data to detect changes in caregiver and patient psychological distress and burden. A larger study is needed to validate these findings and further explore the clinical application of digital phenotyping in cancer.

Keywords Family caregivers, Advanced cancer, Remote monitoring, Digital phenotyping

Background

Managing advanced cancer can be psychologically distressing and burdensome for family caregivers and their care recipients. Among the 3.3 million U.S. family caregivers of individuals with cancer [1], up to 50% may experience distress, including anxiety and depressive symptoms, burden, and reduced quality of life [2, 3, 4]. Their care recipients with cancer have been found to have similar high rates of distress [5, 6]. Assessing and intervening upon this distress can be challenging given the fundamental difficulty of acquiring and the participant burden of completing self-report data using questionnaires.[7,8] To address this challenge, a burgeoning field is emerging that uses sensor data collected via personally-owned smartphones to predict health outcomes and other adverse events. Modeling this type of passively collected smartphone sensor data, such as accelerometer, global positioning system (GPS), and gyroscope data, is called digital phenotyping.[9–11].

The overall vision of current research in digital phenotyping is a clinical model of care that can unobtrusively monitor and detect signs of anxiety, depression, and other mental health outcomes.[12] The underlying premise of digital phenotyping and this potential care model is that a person's mental and health state affects the way they interact with their smartphone. Those interactions can leave digital traces, or digital biomarkers, that can reflect biopsychosocial states and behaviors, including emotions, moods, relationships, and mental and physical health.[13,14] For example, depressive symptoms may manifest as a decrease in locations visited and reduced call and text activity.[15,16] Digital phenotyping is being explored and tested in diverse domains of health, including basic psychological science (e.g., attention, speed of processing), [13] addiction, [15] mental disorders (e.g., schizophrenia), [17] obesity, [18] social isolation, [19] and pharmaceutical development.[20].

Work in digital phenotyping has also begun with patients in oncology.[21–25] For example, Jenciūtė and colleagues are conducting an ongoing study to observe smartphone-based system for tracking mobility, sociability, and psychological well-being in patients to predict cancer trajectories.[21] Panda et al. used smartphone accelerometer data to assess postoperative recovery, finding that lower physical activity correlated with worse recovery trajectories.[23] However, to our knowledge there and other studies have yet to collect and explore data from both patients *and* their family caregivers.

Hence, in this study, we explored longitudinal correlations over 24 weeks between variations in passively collected smartphone GPS data and mental health and burden outcomes among a modest sample of family caregivers and patients with advanced cancer. The goals were to assess whether changes in biweekly smartphone GPS summary features (e.g., number of locations visited per day, average distance traveled per day) were associated with changes in anxiety and depressive symptoms, mental health, and caregiver burden, within individuals.

Methods

This was an exploratory longitudinal cohort study that enrolled smartphone-owning family caregiver and patient participants from August 2021 to July 2023 recruited via outpatient oncology clinics at the University of Alabama at Birmingham or through self-referral through Facebook advertisements. Participants downloaded a digital phenotyping research app, called Beiwe, to their personal smartphones that passively collected GPS data for 24 weeks. Participants also completed measures at baseline and every 6 weeks for 24 weeks by mail or online that assessed anxiety and depressive symptoms, mental health, and caregiver burden (Fig. 1). Eligible caregivers were 18 years of age or older, owners of a personal smartphone (either Android or iOS), and self-identified as "an unpaid relative or friend who knows the patient well and who provides regular support due to their cancer." Eligible patients were 18 years of age or older and diagnosed with metastatic stage III or IV cancer, including hematologic malignancies. Patients were not required to participate in the study (as some patients were unable or unwilling to participate). Participants were paid $25 at baseline for successfully downloading the Beiwe app and $25 every 6 weeks that smartphone data was transmitted to the study team. In addition, participants were paid $25 for each

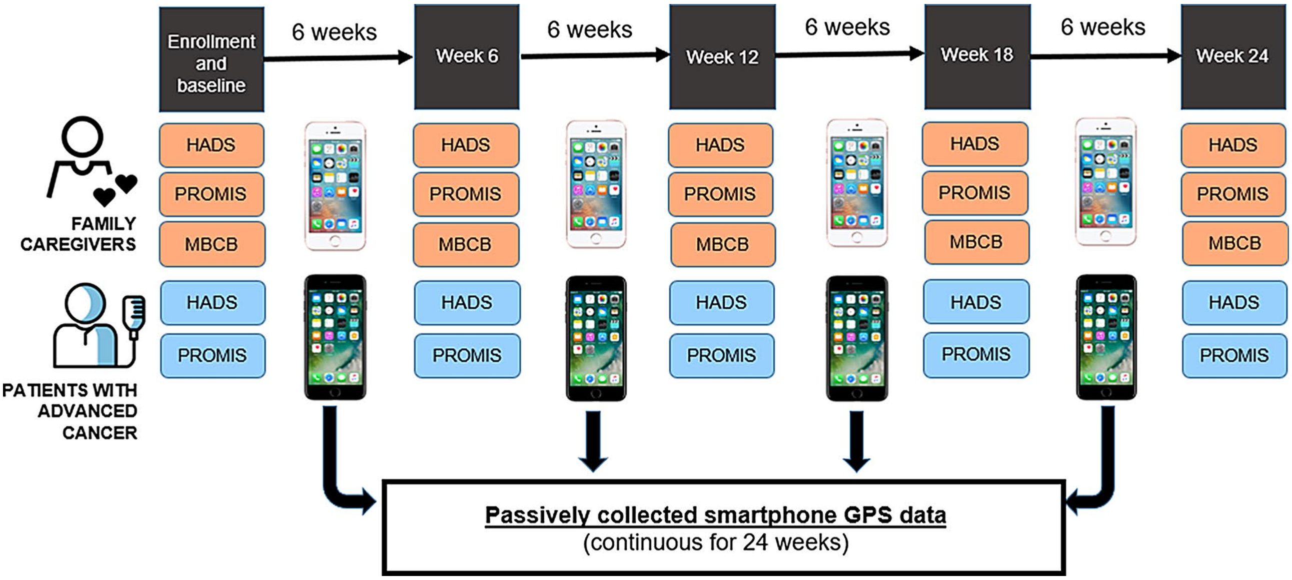

Fig. 1 Schema of exploratory longitudinal cohort study

completed set of surveys. The study was approved by the UAB Institutional Review Board (IRB-300006575). Of 58 participants ($n=40$ caregivers and $n=18$ patients) who both consented to participate in the study and initially downloaded the app, only 46 ($n=32$ caregivers and $n=14$ patients) provided data that was usable for analysis (i.e., if there was at least one instance of health outcome report that could be date-matched with sensor data). Feasibility and acceptability of recruitment and data collection procedures were discussed in a prior report.[26].

Ethics approval and consent to participate

This study was conducted in accordance with the ethical principles outlined in the Declaration of Helsinki. The study was approved by the Institutional Review Board at the University of Alabama at Birmingham (IRB-300006575). All caregiver and patient participants provided informed consent prior to their inclusion in the study.

The Beiwe digital phenotyping smartphone app

For this study, the Beiwe Research Platform at Harvard University was contracted to allow usage and study-specific customization of their Beiwe app, which collects research quality digital phenotyping data from personally owned smartphones.[9,11] The Beiwe platform is comprised of a study portal, smartphone applications for Android and iOS operating systems, data storage using Amazon Web Services cloud, and data preprocessing software. The platform ensures the security and privacy of collected data through encryption and compliance with research ethics and data protection regulations. Data is de-identified and anonymized.

Measures

Participant-reported outcome (PRO) measures

Anxiety and depressive symptoms were measured using the Hospital Anxiety and Depression Scale (HADS).[27,28] The 14-item scale is equally divided into two subscales: one measuring depressive symptoms and the other measuring anxiety symptoms over the past week. Each subscale has a score range of 0 to 21, with higher scores indicating higher levels of anxiety or depression. To measure mental health, we used the global mental health subscale (5 items) of the Patient-Reported Outcomes Measurement Information System (PROMIS) Global Health 10.[29,30] Each item is rated on a five-point Likert scale, with responses reflecting the individuals experiences and perceptions over the past week. The overall scale score is transformed to a T-score with Mean = 50 and SD = 10, using the reference population of U.S. adults. Caregiver burden was measured using the validated and widely used 22-item Montgomery-Borgatta Caregiver Burden Scale (MBCB).[31] The MBCB includes three domains of objective, subjective, and stress burden with a total score range of 22 to 110, with higher scores representing higher burden.

Smartphone data

For this study, the Beiwe app was set up to collect GPS data (i.e., latitude, longitude, and altitude coordinates), when available (i.e., when the phone is “on” and not in a “inactive” or “idle” mode). To minimize the impact on battery life, the app was set to collect GPS data for intervals of 90 s with 810 s “off” in between, or 6 min per hour.

Analysis

GPS data processing

Raw GPS data were pre-processed with R scripts provided by the Beiwe platform. For days when data were collected, this step generated daily summaries of 14 mobility-derived features, [32] including: number of significant locations visited, proportion of day spent paused, significant location entropy, circadian routine metric, weekday/weekend routine metric, time spent at home in hours, total distance traveled in kilometers (km), maximum diameter in km, maximum distance from home in km, average flight length in km, standard deviation of flight length in km, average flight duration in minutes, standard deviation of flight duration in minutes, and radius of gyration in km. Some extreme values were observed in the daily summaries which were then confirmed in the raw data to be caused by either long-distance travel or GPS malfunction. Therefore, for all derived variables, extreme outliers, if any, were identified using Tukey's extreme fence criterion (i.e., values > 75th percentile + 3*IQR), then set to missing and substituted by imputed estimates via Random Forest, [33] including a categorical vector of individual IDs as a covariate to address nesting of days within person. Across the derived daily features, the percentage of substituted extreme outliers ranged from 0 to 10%, with a median of 3.9%. Due to the exploratory, rather than confirmatory nature of the analyses, a single imputation was used. Next, moving biweekly (i.e., retrospectively over 14 days) averages and standard deviations of each derived daily feature were computed for each day that had at least 8 preceding days of data (i.e., half of the target days plus 1, assumed to provide sufficient information on 2 weeks if not all days were collected), resulting in 28 biweekly summary features: 14 biweekly means and 14 biweekly standard deviations. Consistent with previous research, [34] we chose biweekly summaries because shorter summaries (e.g., weekly) could have excessive variability, while longer summaries (e.g., monthly) may mask short-term changes. To reduce the dimensionality of the processed GPS features prior to association analysis, a principal components analysis (PCA) was conducted on the 28 biweekly summary features. Principal components with eigenvalues > 1 were retained and principal component scores were extracted for downstream analyses. To assess stability of the resulting PCA solution, a 95% confidence interval (CI) on the number of components was estimated using resampling methods (i.e., cluster Jackknife). [35].

Association analyses

When available, a caregiver's PRO measurements were date-matched with their smartphone sensor biweekly principal component scores as well as principal component scores of their patient. Likewise, a patient's PRO measurements were date-matched with their GPS biweekly principal component scores and the principal component scores of their caregiver. To conduct within-person analyses, change from subsequent PROs was estimated (Fig. 2) and used as the outcome in regression models with predictors being their corresponding time-matched changes in GPS biweekly PC scores. This approach to within-person analysis was used (as opposed to subtracting a within-person mean) because this approach would be more applicable to potential use in a clinical setting. Models were fitted separately for caregivers and patients, using the individual's and dyad's principal component scores as predictors. Intra-class correlations of the repeated within-person change scores were estimated at 0, indicating that linear regression

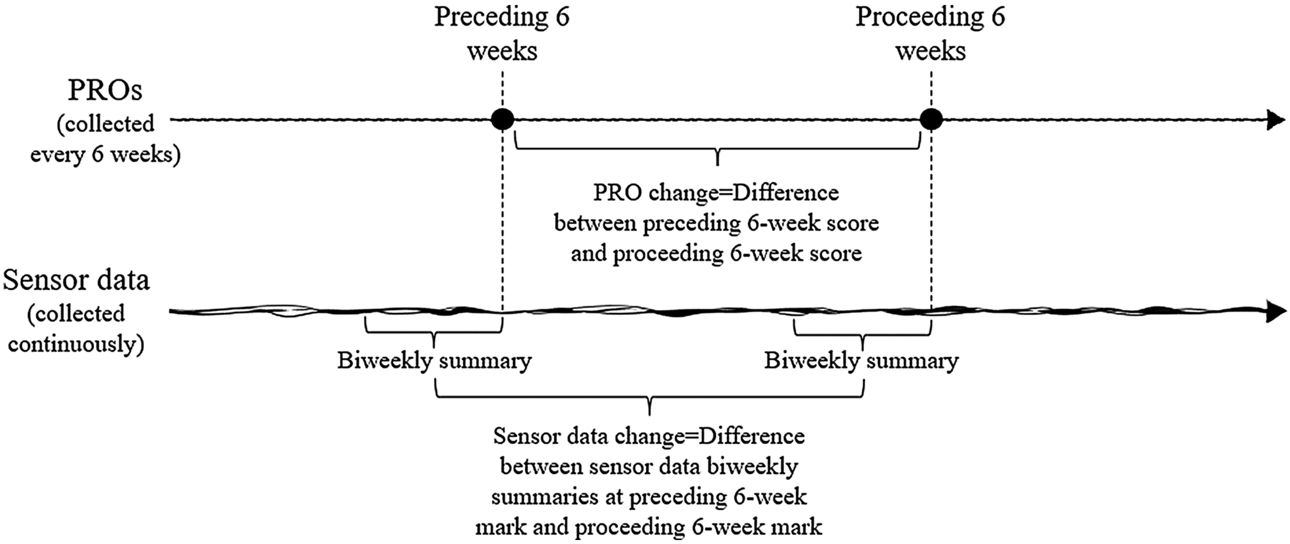

Fig. 2 Correlations are calculated between PRO change and sensor data change at preceding and proceeding 6-week timepoints

analysis was an appropriate methodological approach. For the regression models, the overall measure of effect size was adjusted-R^2. A 95% confidence interval for adjusted-R^2 was computed using resampling (i.e., cluster Jackknife) to provide a measure of uncertainty of the estimate. For individual predictors (i.e., principal component scores), the measure of effect size was Omega^2 (interpreted as small = 0.01, medium = 0.06, large = 0.14).

Results

Participant characteristics

Demographic characteristics of caregivers (N = 32) and patients (N = 14) whose data were usable for this report are shown in Table 1. Family caregivers were a mean of 49.4 years old, mostly female (84.4%), White (78.1%) or Black/African American (21.9%), employed full or part time (72.5%), and the spouse (43.8%) or adult child (31.2%) of the patient. Most caregivers provided care 7 days a week (50%) for 1–4 h/day (40.6%). Patients were a mean of 59.1 years old, mostly White (92.9%), and with a wide range of advanced cancer types.

Bivariate correlation analyses

Details of the smartphone GPS sensor data processing, including descriptive statistics of biweekly features and PCA results are shown in Supplemental Table (1) Correlation estimates between change in PROs and change in principal component scores are shown in Supplemental Table (2) These correlations were estimated with sample sizes ranging from 29 to 57 instances, although they also should be interpreted as exploratory. Of note, for all PROs there was at least one principal component score for which there was a bivariate correlation of moderate magnitude.

Regression analyses

Results from the analyses are shown in Table 2. For caregiver smartphone data predicting caregiver outcomes (n = 27), adjusted-R^{2}s were of small to medium magnitude for the HADS anxiety (0.06) and depressive symptom (0.15) and PROMIS-mental health subscales (0.07), however the estimate was at zero for the MBCB. For patient smartphone data predicting caregiver outcomes (n = 12), adjusted-R^{2}s were of small to medium magnitude for the HADS depressive symptom (0.12) and MBCB (0.05) scales but of small or negligible magnitude for the HADS anxiety (0) and PROMIS-mental health subscales (0.02). Regarding both caregiver and patient smartphone data predicting caregiver outcomes (n = 11), adjusted-R^2 for HADS depression (0.02) and anxiety (0.10) was small and for PROMIS-mental health (0.36) and MBCB was large (0.50).

In terms of caregiver smartphone data predicting patient outcomes (n = 14), adjusted-R^2 for HADS anxiety (0.07) was small and was estimated at zero for HADS depressive symptom and PROMIS-mental health subscales. For patient smartphone data predicting patient outcomes (n = 13), adjusted-R^2 for HADS anxiety (0.24) was of large magnitude, but was estimated at zero for HADS depressive symptom and PROMIS-mental health subscales. Regarding both caregiver and patient smartphone data predicting patient outcomes (n = 11), adjusted R^2 for HADS depression (0.18) was of medium magnitude.

Discussion

The aim of this exploratory study was to investigate the potential of using smartphone sensor data and digital phenotyping to detect changes in the psychological health of family caregivers and their care recipients with advanced cancer over 24 weeks. Despite the preliminary nature of our findings, largely due to a small sample size, our results demonstrated small to large correlations between changes in caregivers' and patients' GPS smartphone data and changes in anxiety and depression symptoms, mental health, and caregiver burden. We believe this shows the potential clinical utility of using passive smartphone data to signal changes in caregiver and patient psychological health, warranting larger studies with this innovative dyadic approach to remote monitoring.

To our knowledge, this is one of the first studies to explore whether passively collected smartphone GPS data from one member of a caregiver-patient dyad can be used to indicate changes in the other's self-reported psychological health. Caregivers and patients with advanced cancer are often tightly linked individuals in their day-to-day routines, and numerous actor-partner studies have documented these linked interrelationships between caregivers' and patients' mental and physical health, their coping strategies, self-efficacy, and many other relationship factors.[36–38] This study expands this dyadic interdependence work[39] to include caregivers' and patients' engagement and interaction patterns with technology, namely their smartphones, as potential digital behavioral markers of their own and others' psychological wellbeing. While our findings are exploratory, we observed that caregiver's smartphone GPS data were associated with changes in their care recipient's anxiety symptoms and that a patient's GPS data indicated changes in their caregiver's depressive symptoms and burden. Future studies with larger sample sizes and with longer follow-up periods are needed to verify and more conclusively substantiate these relationships.

To our knowledge, this is also one of the first studies that has used smartphone-based digital phenotyping to combine passive data from a dyad to predict each individual member's outcomes. Most smartphone-based

Table 1 Caregiver and patient demographics

Characteristic	Family Caregivers ($N=32$)	Patients ($N=14$)
	Number (%) or Mean (standard deviation)	
Age	49.4 (12.8)	59.1 (8.7)
Gender		
Female	27 (84.4)	8 (57.1)
Male	5 (15.6)	6 (42.9)
Race		
White	25 (78.1)	13 (92.9)
Black/African American	7 (21.9)	1 (7.1)
Hispanic/Latino/a/x		
No	30 (93.5)	14 (100.0)
Yes	2 (6.5)	0 (0.0)
Employment		
Full/part-time	20 (72.5)	3 (21.4)
Retired	2 (6.2)	4 (28.6)
Homemaker	5 (15.6)	3 (21.4)
Disability / Other	5 (15.6)	4 (28.6)
Education		
8th grade or less	1 (3.1)	0 (0.0)
High school grad or GED	8 (25.0)	3 (21.4)
Some college or technical school	10 (31.2)	4 (28.6)
College graduate	8 (25.0)	4 (28.6)
Graduate degree	5 (15.6)	3 (21.4)
[a]Caregiver-patient relationship (The patient is the caregiver's…)		
Spouse	14 (43.8)	n/a
Parent	10 (31.2)	n/a
Other	7 (21.9)	n/a
Missing	1 (3.1)	n/a
[a]Days/week providing care		
1 day a week or less	5 (15.6)	n/a
2–3 days/week	6 (18.8)	n/a
4–5 days/week	3 (9.4)	n/a
6 days/week	1 (3.1)	n/a
7 days/week	16 (50.0)	n/a
[a]Hours/day providing care		
< 1 h/day	5 (15.6)	n/a
1–4 h/day	13 (40.6)	n/a
5–8 h/day	6 (18.7)	n/a
> 8 h/day	7 (21.9)	n/a
Missing	1 (3.1)	n/a
[a]Cancer type		
Colon/Rectal	5 (15.6)	3 (21.4)
Head/Neck	5 (15.6)	3 (21.4)
Lung	4 (12.5)	1 (7.1)
Prostate	4 (12.5)	2 (14.3)
Breast	3 (9.4)	1 (7.1)
Bladder/Kidney	3 (9.4)	2 (14.3)
Other	8 (25.0)	2 (14.3)
[b]HADS-Anxiety subscale (baseline)	9.1 (5.1)	5.8 (4.6)
[b]HADS-Depression subscale (baseline)	6.0 (5.2)	4.5 (3.7)
PROMIS-Mental Health subscale (baseline)	46.6 (11.0)	49.7 (10.0)
[c]MBCB-Caregiver Burden (baseline)	45.4 (8.0)	n/a

[a] Caregiver only

[b] Hospital Anxiety and Depression Scale

[c] Montgomery Borgatta Caregiver Burden scale (total score)

Table 2 Measures of effect (Omega^2) in linear regressions of within-person changes in outcomes predicted by changes smartphone biweekly feature principal components

Outcomes	Omega^2 for 6 Principal Components - Caregivers						Omega^2 for 6 Principal Components - Patients						Adjusted R^2	95% CI		Multiple R
	1	2	3	4	5	6	1	2	3	4	5	6		Lower	Upper	
Caregiver smartphone data predicting CAREGIVER OUTCOMES (57 instances of change from $n=27$ caregivers)																
HADS-Anxiety	0	0	0	0	0.1	0	-	-	-	-	-	-	0.06	0	0.56	0.24
HADS-Depression	0.1	0	0	0.1	0	0	-	-	-	-	-	-	0.15	0.02	0.34	0.39
PROMIS-Mental health	0	0	0	0	0.1	0	-	-	-	-	-	-	0.07	0	0.45	0.26
MBCB Total Score (CG burden)	0	0	0	0	0	0	-	-	-	-	-	-	0	0	0.27	0
Patient smartphone data predicting CAREGIVER OUTCOMES (27 instances of change from $n=12$ dyads)																
HADS-Anxiety	-	-	-	-	-	-	0	0	0	0	0	0	0	0	0.37	0
HADS-Depression	-	-	-	-	-	-	0	0	0	0.2	0	0	0.12	0	0.73	0.35
PROMIS-Mental health	-	-	-	-	-	-	0	0.1	0	0	0	0	0.02	0	0.69	0.14
MBCB Total Score (CG burden)	-	-	-	-	-	-	0	0	0	0.1	0	0	0.05	0	0.66	0.22
Caregiver and Patient smartphone data predicting CAREGIVER OUTCOMES (23 instances of change from $n=11$ dyads)																
HADS-Anxiety	0	0	0.1	0	0.3	0	0	0	0	0	0	0	0.10	0	0.99	0.32
HADS-Depression	0	0	0	0	0	0	0	0	0	0.2	0	0	0.02	0	0.89	0.14
PROMIS-Mental health	0.2	0	0	0	0	0	0	0.1	0	0	0	0	0.36	0	0.99	0.6
MBCB Total Score (CG burden)	0	0.1	0	0.1	0	0	0.1	0	0	0.1	0	0.2	0.50	0.05	0.83	0.71
Caregiver smartphone data predicting PATIENT OUTCOMES (32 instances of change from $n=14$ dyads)																
HADS-Anxiety	0.1	0	0	0.1	0	0	-	-	-	-	-	-	0.07	0	0.64	0.26
HADS-Depression	0	0	0	0	0	0	-	-	-	-	-	-	0	0	0.26	0
PROMIS-Mental health	0	0	0	0	0	0	-	-	-	-	-	-	0	0	0.32	0
Patient smartphone data predicting PATIENT OUTCOMES (31 instances of change from $n=13$ patients)																
HADS-Anxiety	-	-	-	-	-	-	0.1	0	0	0	0.1	0	0.24	0	0.71	0.49
HADS-Depression	-	-	-	-	-	-	0.1	0	0	0	0	0	0	0	0.39	0
PROMIS-Mental health	-	-	-	-	-	-	0	0	0	0	0	0.1	0	0	0.52	0
Caregiver and Patient smartphone data predicting PATIENT OUTCOMES (26 instances of change from $n=11$ dyads)																
HADS-Anxiety	0.1	0	0	0.1	0	0	0.1	0	0	0	0	0	0.06	0	0.84	0.24
HADS-Depression	0.1	0	0	0	0.1	0	0	0	0	0.1	0	0	0.18	0	0.92	0.42
PROMIS-Mental health	0.1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Notes: Adjusted R^2 as effect size: small = 0.02; medium = 0.13; large = 0.26

Omega2 as effect size: small = 0.01; medium = 0.06; large = 0.26

digital phenotyping to date has only looked at using single individual's smartphone data to predict their own (within person) outcomes.[40,41] The primary advantage in principle of using a dyad's combined data to predict outcomes is the increased number of variables and hence, predictive power. In our findings for example, one can note the higher adjusted-R^2 values for caregivers' outcomes when combined data are modeled. Large adjusted-R^2 values were particularly salient for mental health and caregiver burden. Caution is warranted, however, given the small sample sizes and the risk of overfitting the data.[42] As a case in point, we found it counterintuitive that there would be such a large adjusted-R^2 value for caregiver PROMIS-mental health (0.36) compared to their HADS depressive (0.02) and anxiety symptom (0.10) scores, given the close relationship of these psychological domains. Hence, we believe these exploratory findings warrant further investigation in larger studies to more robustly assess the added value of dyadic-based remote monitoring.

Our study is part of a larger ongoing effort to assess the potential of smartphone-based digital phenotyping clinical models to provide continuous, real-time assessment of the health of both caregivers and patients, thereby offering a non-invasive tool for early detection and support (e.g., predicting acute psychological distress). As noted by others, [43,44] this approach to remote monitoring may be superior in its ecological validity to other forms of activity monitoring (e.g., actigraphy monitors, fitness trackers like Fitbit or Garmin trackers) because it leverages technologies (like smartphones) that individuals already own and are accustomed to using on a daily basis. Based on our experiences and others' work to date, we believe it is unlikely that even the most optimized smartphone sensing tools alone will be sufficient to monitor changes in the psychological health of patients and families. The upper bounds of our findings' confidence intervals suggest that even in the most optimistic case, estimates of the presence or severity of distress are only suggestive but not large enough to be confirmatory. Hence, digital phenotyping tools would most likely need to be used in conjunction with other more diagnostic assessment strategies to avoid "false" alarms, as we have learned in our prior qualitative work.[26].

This study has a number of important limitations. As we have highlighted throughout this discussion, the sample size for this study was small and our analyses were exploratory. Hence, robust interpretations and conclusions cannot be made on these results concerning the definitive ability of smartphone data to predict caregiver and patient psychological outcomes. Future larger studies are needed to maximize interpretability and more robustly assess potential clinical utility. Second, our approach to GPS data feature extraction and principal components analysis of those features precluded assessment of the relationship between individual features (e.g., time spent at home, total distance traveled per day) and caregiver and patient outcomes. While many studies take this approach, [43] our overall goal in our team's line of research is to develop approaches that maximize prediction (i.e., total variance explained) in changes in clinical relevant psychological outcomes so as to potentially develop new just-in-time clinical models of remote monitoring. Third, this report does not directly address other challenges of smartphone-based digital phenotyping, such as privacy and confidentiality concerns, challenges of integrating this into real-world cancer care delivery, and clinical capacity to address caregiver distress and burden.[45,46] We have reported and discussed a number of these topics in a separate qualitative analysis.[47].

Conclusion

We investigated the potential of smartphone-based digital phenotyping to remotely monitor psychological health changes in caregivers and patients with advanced cancer. While our findings are exploratory, we observed promising associations between passively collected GPS data and changes in anxiety, depression, and caregiver burden. This study extends dyadic interdependence research by highlighting how smartphone data from one member of a caregiver-patient dyad may be able to signal psychological changes in the other. Furthermore, our findings demonstrate the potential clinical utility of this dyadic-based remote monitoring approach and underscore the need for larger studies to validate and refine predictive models. This work is a step toward leveraging everyday, personally-owned technologies for real-time, ecologically valid monitoring that supports family caregivers and patients with cancer.

Abbreviations

GPS	Global positioning system
PROs	Participant-reported outcomes
HADS	Hospital Anxiety and Depression Scale
MBCB	Montgomery Borgatta Caregiver Burden scale
PROMIS	Patient-reported outcomes measurement information system
PCA	Principal components analysis
CI	Confidence interval
IQR	Interquartile Range
Km	Kilometers

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12885-025-14009-y.

Supplementary Material 1

Acknowledgements

We thank all partnering oncologists, clinicians, and staff at the O'Neal Comprehensive Cancer Center at the University of Alabama at Birmingham for supporting this study. We also acknowledge the tremendous efforts of our research staff, including Kayleigh Curry, MPH; Stephanie Ford, MPH; Charis Smith; James Mapson; Julie Schach; Diane Williams; and Brianna N. Odom.

Author contributions

JNO: conceptualization, methodology, investigation, resources, data curation, writing– original draft, writing– review and editing, supervision, project administration, funding acquisition. KL: data curation, writing– review and editing, project administration. ERH: writing– review and editing. KAW: writing– review and editing. ACB: writing review and editing, project administration. SE: data curation, writing– review and editing, supervision, project administration. FP: writing– review and editing. NB: writing– review and editing. AHK: conceptualization, writing– review and editing. CSR: conceptualization, writing– review and editing. GD: conceptualization, writing– review and editing. AW: conceptualization, writing– review and editing. MAB: conceptualization, writing– review and editing. AA: conceptualization, methodology, software, data curation, writing– original draft, writing– review and editing. All authors read and approved the final manuscript.

Funding

This work was supported by a grant from the Cambia Health Foundation (no grant number). The funder had no role in the study's design; data collection, analysis, and interpretation; writing of the report; and decision to submit the study for publication.

Data availability

The datasets used and analyzed for the current study are available from the corresponding author upon reasonable request.

Declarations

Ethics approval and consent to participate

This study was approved by the University of Alabama at Birmingham Institutional Review Board (IRB-300006575). All caregiver and patient participants completed informed consent.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

Author details

[1]School of Nursing, University of Alabama at Birmingham, 1720 2nd Avenue South, NB 485J, Birmingham, AL 35294-1210, USA
[2]Division of Gerontology, Geriatrics, and Palliative Care, School of Medicine, University of Alabama at Birmingham, Birmingham, AL, USA
[3]Center for Palliative and Supportive Care, University of Alabama at Birmingham, Birmingham, AL, USA
[4]Frances Payne Bolton School of Nursing, Case Western Reserve University, Cleveland, OH, USA
[5]National Institute on Aging, National Institutes of Health, Bethesda, MD, USA
[6]Division of General Internal Medicine and Population Science, School of Medicine, University of Alabama at Birmingham, Birmingham, AL, USA
[7]Department of Medicine, Duke University School of Medicine, Durham, NC, USA
[8]American Cancer Society, Kennesaw, GA, USA
[9]Division of Palliative Care and Geriatric Medicine, Mongan Institute Center for Aging and Serious Illness, Massachusetts General Hospital, Harvard Medical School, Boston, MA, USA
[10]Department of Biobehavioral Health Sciences, School of Nursing & Department of Biostatistics, Epidemiology and Informatics, Perelman School of Medicine, University of Pennsylvania, Philadelphia, PA, USA
[11]Division of Population Sciences, Department of Medical Oncology, Dana-Farber Cancer Institute, Harvard Medicine School, Boston, MA, USA

Received: 18 December 2024 / Accepted: 24 March 2025
Published online: 04 April 2025

References

1. National Alliance for Caregiving. Cancer Caregiving in the U.S.: An Intense, Episodic, and Challenging Care Experience. 2016.
2. Dionne-Odom JN, Demark-Wahnefried W, Taylor RA, et al. The self-care practices of family caregivers of persons with poor prognosis cancer: differences by varying levels of caregiver well-being and preparedness. Support Care Cancer Mar. 2017. https://doi.org/10.1007/s00520-017-3650-7.
3. Geng HM, Chuang DM, Yang F, et al. Prevalence and determinants of depression in caregivers of cancer patients: A systematic review and meta-analysis. Med (Baltimore) Sep. 2018;97(39):e11863. https://doi.org/10.1097/MD.0000000000011863.
4. Nielsen MK, Neergaard MA, Jensen AB, Bro F, Guldin MB. Psychological distress, health, and socio-economic factors in caregivers of terminally ill patients: a nationwide population-based cohort study. Support Care Cancer Jul. 2016;24(7):3057–67. https://doi.org/10.1007/s00520-016-3120-7.
5. Zeilinger EL, Oppenauer C, Knefel M, et al. Prevalence of anxiety and depression in people with different types of cancer or haematologic malignancies: a cross-sectional study. Epidemiol Psychiatr Sci Oct. 2022;17:31:e74. https://doi.org/10.1017/S2045796022000592.
6. Vehling S, Tian Y, Malfitano C, et al. Attachment security and existential distress among patients with advanced cancer. J Psychosom Res Jan. 2019;116:93–9. https://doi.org/10.1016/j.jpsychores.2018.11.018.
7. Anhang Price R, Elliott MN. Measuring Patient-Centeredness of Care for Seriously Ill Individuals: Challenges and Opportunities for Accountability Initiatives. J Palliat Med. 03 2018;21(S2):S28-S35. doi:https://doi.org/10.1089/jpm.2017.0452
8. Schneider KL, Clark MA, Rakowski W, Lapane KL. Evaluating the impact of non-response bias in the Behavioral Risk Factor Surveillance System (BRFSS). J Epidemiol Community Health. Apr 2012;66(4):290-5. doi:https://doi.org/10.1136/jech.2009.103861
9. Torous J, Kiang MV, Lorme J, Onnela JP. New Tools for New Research in Psychiatry: A Scalable and Customizable Platform to Empower Data Driven Smartphone Research. JMIR Ment Health. May 2016;3(2):e16. doi:https://doi.org/10.2196/mental.5165
10. Torous J, Onnela JP, Keshavan M. New dimensions and new tools to realize the potential of RDoC: digital phenotyping via smartphones and connected devices. Transl Psychiatry. 03 2017;7(3):e1053. doi:https://doi.org/10.1038/tp.2017.25
11. Onnela JP, Rauch SL. Harnessing Smartphone-Based Digital Phenotyping to Enhance Behavioral and Mental Health. Neuropsychopharmacology. 06 2016;41(7):1691-6. doi:https://doi.org/10.1038/npp.2016.7
12. Insel TR. Digital Phenotyping: Technology for a New Science of Behavior. JAMA. Oct 2017;318(13):1215–1216. doi:https://doi.org/10.1001/jama.2017.11295
13. Dagum P. Digital biomarkers of cognitive function. NPJ Digit Med. 2018;1:10. doi:https://doi.org/10.1038/s41746-018-0018-4
14. Coravos A, Khozin S, Mandl KD. Developing and adopting safe and effective digital biomarkers to improve patient outcomes. NPJ Digit Med. 2019;2(1)doi:https://doi.org/10.1038/s41746-019-0090-4
15. Markowetz A, Błaszkiewicz K, Montag C, Switala C, Schlaepfer TE. Psycho-informatics: Big Data shaping modern psychometrics. Med Hypotheses. Apr 2014;82(4):405 – 11. doi:https://doi.org/10.1016/j.mehy.2013.11.030
16. Saeb S, Zhang M, Karr CJ, et al. Mobile Phone Sensor Correlates of Depressive Symptom Severity in Daily-Life Behavior: An Exploratory Study. J Med Internet Res. Jul 2015;17(7):e175. doi:https://doi.org/10.2196/jmir.4273
17. Barnett I, Torous J, Staples P, Sandoval L, Keshavan M, Onnela JP. Relapse prediction in schizophrenia through digital phenotyping: a pilot study. Neuropsychopharmacology. Jul 2018;43(8):1660–1666. doi:https://doi.org/10.1038/s41386-018-0030-z
18. Williams LM, Pines A, Goldstein-Piekarski AN, et al. The ENGAGE study: Integrating neuroimaging, virtual reality and smartphone sensing to understand self-regulation for managing depression and obesity in a precision medicine model. Behav Res Ther. 02 2018;101:58–70. doi:https://doi.org/10.1016/j.brat.2017.09.012
19. Doryab A, Villalba DK, Chikersal P, et al. Identifying Behavioral Phenotypes of Loneliness and Social Isolation with Passive Sensing: Statistical Analysis, Data Mining and Machine Learning of Smartphone and Fitbit Data. JMIR Mhealth Uhealth. Jul 2019;7(7):e13209. doi:https://doi.org/10.2196/13209
20. Rodarte C. Pharmaceutical Perspective: How Digital Biomarkers and Contextual Data Will Enable Therapeutic Environments. Digit Biomark. 2017 Sep-Dec 2017;1(1):73–81. doi:https://doi.org/10.1159/000479951

21. Jenciūtė G, Kasputytė G, Bunevičienė I, et al. Digital Phenotyping for Monitoring and Disease Trajectory Prediction of Patients With Cancer: Protocol for a Prospective Observational Cohort Study. JMIR Res Protoc. Oct 10 2023;12:e49096. doi:https://doi.org/10.2196/49096
22. Wright AA, Raman N, Staples P, et al. The HOPE Pilot Study: Harnessing Patient-Reported Outcomes and Biometric Data to Enhance Cancer Care. JCO Clin Cancer Inform. Dec 2018;2:1–12. doi:https://doi.org/10.1200/CCI.17.00149
23. Panda N, Solsky I, Huang EJ, et al. Using Smartphones to Capture Novel Recovery Metrics After Cancer Surgery. JAMA Surg. Feb 01 2020;155(2):123–129. doi:https://doi.org/10.1001/jamasurg.2019.4702
24. Low CA. Harnessing consumer smartphone and wearable sensors for clinical cancer research. NPJ Digit Med. 2020;3:140. doi:https://doi.org/10.1038/s41746-020-00351-x
25. Straczkiewicz M, Keating NL, Thompson E, et al. Open-Source, Step-Counting Algorithm for Smartphone Data Collected in Clinical and Nonclinical Settings: Algorithm Development and Validation Study. JMIR Cancer. Nov 15 2023;9:e47646. doi:https://doi.org/10.2196/47646
26. Odom JN, Lee K, Currie ER, et al. Feasibility and Acceptability of Collecting Passive Smartphone Data for Potential Use in Digital Phenotyping Among Family Caregivers and Patients With Advanced Cancer. JCO Clin Cancer Inform. Jan 2025;9:e2400201. doi:https://doi.org/10.1200/CCI-24-00201
27. Snaith RP. The Hospital Anxiety And Depression Scale. Health Qual Life Outcomes. Aug 2003;1:29. doi:https://doi.org/10.1186/1477-7525-1-29
28. Bjelland I, Dahl AA, Haug TT, Neckelmann D. The validity of the Hospital Anxiety and Depression Scale: An updated literature review. Journal of Psychosomatic Research. 2002;52(2):69–77. doi:https://doi.org/10.1016/s0022-3999(01)00296-3
29. Cella D, Riley W, Stone A, et al. The Patient-Reported Outcomes Measurement Information System (PROMIS) developed and tested its first wave of adult self-reported health outcome item banks: 2005–2008. J Clin Epidemiol. Nov 2010;63(11):1179-94. doi:https://doi.org/10.1016/j.jclinepi.2010.04.011
30. Thompson NR, Lapin BR, Katzan IL. Mapping PROMIS Global Health Items to EuroQol (EQ-5D) Utility Scores Using Linear and Equipercentile Equating. Pharmacoeconomics. Nov 2017;35(11):1167–1176. doi:https://doi.org/10.1007/s40273-017-0541-1
31. Montgomery R, Gonyea J, Hooyman N. Caregiving and the Experience of Subjective and Objective Burden. Family Relations. 1985;34:19–26
32. Barnett I, Onnela JP. Inferring mobility measures from GPS traces with missing data. Biostatistics. Apr 01 2020;21(2):e98-e112. doi:https://doi.org/10.1093/biostatistics/kxy059
33. Stekhoven DJ, Bühlmann P. MissForest–non-parametric missing value imputation for mixed-type data. Bioinformatics. Jan 2012;28(1):112-8. doi:https://doi.org/10.1093/bioinformatics/btr597
34. Meyerhoff J, Liu T, Kording KP, et al. Evaluation of Changes in Depression, Anxiety, and Social Anxiety Using Smartphone Sensor Features: Longitudinal Cohort Study. J Med Internet Res. Sep 03 2021;23(9):e22844. doi:https://doi.org/10.2196/22844
35. Ramachandran K, Tsokos C. Mathematical Statistics with Applications in R, 2nd Edition. Elsevier, Inc.; 2015.
36. Sannes TS, Simoneau TL, Mikulich-Gilbertson SK, et al. Distress and quality of life in patient and caregiver dyads facing stem cell transplant: identifying overlap and unique contributions. Support Care Cancer. Jun 2019;27(6):2329–2337. doi:https://doi.org/10.1007/s00520-018-4496-3
37. Kershaw T, Ellis KR, Yoon H, Schafenacker A, Katapodi M, Northouse L. The Interdependence of Advanced Cancer Patients' and Their Family Caregivers' Mental Health, Physical Health, and Self-Efficacy over Time. Ann Behav Med. Dec 2015;49(6):901 – 11. doi:https://doi.org/10.1007/s12160-015-9743-y
38. Jacobs JM, Shaffer KM, Nipp RD, et al. Distress is Interdependent in Patients and Caregivers with Newly Diagnosed Incurable Cancers. Ann Behav Med. Aug 2017;51(4):519–531. doi:https://doi.org/10.1007/s12160-017-9875-3
39. Thompson T, Ketcher D, Gray TF, Kent EE. The Dyadic Cancer Outcomes Framework: A general framework of the effects of cancer on patients and informal caregivers. Soc Sci Med. Oct 2021;287:114357. doi:https://doi.org/10.1016/j.socscimed.2021.114357
40. Choi A, Ooi A, Lottridge D. Digital Phenotyping for Stress, Anxiety, and Mild Depression: Systematic Literature Review. JMIR Mhealth Uhealth. May 23 2024;12:e40689. doi:https://doi.org/10.2196/40689
41. Terhorst Y, Knauer J, Philippi P, Baumeister H. The Relation Between Passively Collected GPS Mobility Metrics and Depressive Symptoms: Systematic Review and Meta-Analysis. J Med Internet Res. Nov 01 2024;26:e51875. doi:https://doi.org/10.2196/51875
42. Harrell F. Regression Modeling Strategies with Applications to Linear Models, Logistic and Ordinal Regression, and Survival Analysis, 2nd Edition. Springer; 2015.
43. Leaning IE, Ikani N, Savage HS, et al. From smartphone data to clinically relevant predictions: A systematic review of digital phenotyping methods in depression. Neurosci Biobehav Rev. Mar 2024;158:105541. doi:https://doi.org/10.1016/j.neubiorev.2024.105541
44. Trifan A, Oliveira M, Oliveira JL. Passive Sensing of Health Outcomes Through Smartphones: Systematic Review of Current Solutions and Possible Limitations. JMIR Mhealth Uhealth. Aug 23 2019;7(8):e12649. doi:https://doi.org/10.2196/12649
45. Kamdar M, Jethwani K, Centi AJ, et al. A Digital Therapeutic Application (ePAL) to Manage Pain in Patients With Advanced Cancer: A Randomized Controlled Trial. J Pain Symptom Manage. Jun 10 2024;doi:https://doi.org/10.1016/j.jpainsymman.2024.05.033
46. Aapro M, Bossi P, Dasari A, et al. Digital health for optimal supportive care in oncology: benefits, limits, and future perspectives. Support Care Cancer. Oct 2020;28(10):4589–4612. doi:https://doi.org/10.1007/s00520-020-05539-1
47. Odom J, Lee K, Currie E, et al. Feasibility and acceptability of collecting passive smartphone data for potential use in digital phenotyping among family caregivers and patients with advanced cancer. JCO Clinical Cancer Informatics. In press.

Publisher's note

Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.