Journal on Oncology

www.journalononcology.org

Research Article

Open Access, Volume 6

Weekly Mobile Health Engagement and Physical Activity in Cancer Survivors

Amin Zarmina; Riggenbach Jackson; Oginni John; Gao Zan*

Department of Kinesiology, Recreation, and Sport Studies, The University of Tennessee-Knoxville, Knoxville, USA.

Abstract

Introduction: Mobile health (mHealth) interventions have emerged as a promising strategy for promoting Physical Activity (PA) and psychological well-being among Cancer Survivors (CS). However, little is known about how week-to-week engagement with personalized mHealth interventions relates to behavioral and psychological outcomes. This study examined longitudinal changes in objectively measured PA and psychological well-being during an 8-week personalized mHealth intervention and evaluated whether weekly intervention engagement was associated with these outcomes.

Methods: Twenty-six CS enrolled in the intervention arm of an ongoing randomized controlled trial completed an 8-week personalized mHealth intervention using the sFitRx mobile application paired with a Fitbit Inspire 3 Health & Fitness Tracker. Weekly objectively measured average daily step counts, Moderate-To-Vigorous Physical Activity (MVPA), sedentary time, and light PA were collected using Fitbit, while psychological well-being was assessed weekly using the World Health Organization Five Well-Being Index (WHO-5). Intervention engagement was defined as completion of the weekly in-app check-in. Linear mixed-effects models were used to evaluate longitudinal changes in study outcomes and to examine within-person and between-person associations between engagement and outcomes.

Results: Average daily step counts increased significantly with participants accumulating significantly more steps during Week 3 compared with baseline (mean difference = 1,608 steps/day, 95% CI: 161 to 3,056; p= .020). Daily MVPA also increased significantly over time (β=1.32 min/day per week, 95% CI: 0.39 to 2.26; p=.006), while sedentary time and light PA remained unchanged. Psychological well-being improved significantly throughout the intervention (β=1.03 points/week, 95% CI: 0.05 to 2.00; p=.043). Weekly intervention engagement was not significantly associated with PA or well-being outcomes at either the within-person or between-person level.

Conclusion: PA and psychological well-being increased during the intervention, but weekly in-app check-in completion was not associated with these outcomes, highlighting the need for more comprehensive measures of engagement.

Keywords: Mobile health; Physical activity; Cancer survivors; Well-being; Intervention engagement; Wearable devices; Behavior change; Self-determination theory.

Manuscript Information: *Received: Aug 01, 2026; Accepted: Aug 15, 2026; Published: Aug 21, 2026*

Correspondence: *Zan Gao, Department of Kinesiology, Recreation, and Sport Studies. The University of Tennessee-Knoxville, 328 HPER Building, 1914 Andy Holt Avenue Knoxville. Tel: 865-974-7971; Email: zan@utk.edu*

Citation: *Amin Z, Riggenbach J, Oginni J, Gao Z. Weekly Mobile Health Engagement and Physical Activity in Cancer Survivors. J Oncology. 2026; 6(2): 1213.*

Introduction

Advances in cancer detection and treatment have resulted in a rapidly growing population of cancer survivors, shifting the focus of cancer care beyond survival toward optimizing long-term health, physical functioning, and psychological well-being. Although cancer mortality continues to decline, many cancer survivors continue to experience persistent fatigue, musculoskeletal impairment, reduced physical function, and diminished psychological well-being that negatively affect daily functioning and recovery [1-3]. Physical activity is one of the most effective nonpharmacological strategies for improving physical function, reducing treatment-related symptoms, and enhancing psychological well-being throughout survivorship [1]. However, despite its well-established benefits, only approximately 50% of cancer survivors achieve the recommended guideline of at least 150 minutes of moderate-intensity (or 75 minutes of vigorous-intensity) aerobic physical activity per week [4]. Persistent treatment-related side effects, fatigue, reduced motivation, diminished self-efficacy, and competing life demands represent common barriers that often interact to limit sustained participation in physical activity [5]. Consequently, identifying scalable and accessible interventions that promote long-term physical activity remains a major priority in cancer survivorship research.

Mobile health (mHealth) interventions, including smartphone apps, wearable activity trackers, and remote monitoring technologies, have emerged as promising approaches for promoting physical activity among cancer survivors. Across general adult populations, mHealth interventions reliably increase physical activity participation [6], with smartphone apps and wearable devices producing small-to-moderate improvements in daily step counts and physical activity levels [7]. These benefits have also been demonstrated among cancer survivors, with mHealth-supported interventions associated with increases in Moderate-to-Vigorous Physical Activity (MVPA), improvements in psychological well-being, and better sleep outcomes when combined with wearable activity monitoring and personalized coaching [8,9]. Although these findings demonstrate that mHealth interventions can improve physical activity and well-being, relatively little is known about which intervention components drive these improvements. Most studies report engagement descriptively as a measure of adherence rather than examining whether engagement itself is associated with physical activity and well-being outcomes.

Engagement itself remains an inconsistently defined construct in the mHealth literature. Prior work has distinguished behavioral engagement (e.g., frequency or duration of interaction with an intervention), cognitive engagement (attention to a processing of intervention content), affective engagement (emotional response to the intervention), and broader intervention exposure (opportunity to receive intervention components, regardless of interaction) [10]. In the present study, we operationalized engagement behaviorally, as completion of the weekly in-app checking, because it represented the most consistently measurable and clinically interpretable indicator of sustained participation across the 8-week intervention. We acknowledge, however, that this single behavioral indicator does not capture cognitive or affective dimensions of engagement, nor does it reflect engagement with intervention components delivered outside the check-in (e.g., passive Fitbit wear, receipt of AI-generated exercise prescriptions), and this narrower operationalization is revisited as a limitation in the discussion. Understanding this relationship could inform the design of more effective and sustainable mHealth interventions for cancer survivors.

An additional limitation of the existing literature is the lack of longitudinal analyses examining how physical activity, well-being, and intervention engagement change together over time. Previous studies among cancer survivors have primarily reported pre-post changes or overall intervention effectiveness rather than evaluating week-to-week trajectories of behavior and well-being [8,10]. A recent randomized trial of a personalized mHealth physical activity intervention for young adult cancer survivors assessed outcomes only at baseline, 6 months, and 12 months, leaving the short-term dynamics of behavioral change unresolved [11]. This represents an important gap because fatigue, symptom burden, mood, and physical activity fluctuate substantially throughout cancer survivorship, as demonstrated by ecological momentary assessment studies [12]. Furthermore, engagement with digital health interventions frequently declines over time, a pattern consistently reported among wearable device and activity tracker users [13], yet it remains unclear whether sustained engagement is associated with improvements in physical activity and well-being or simply reflects participants who were already more likely to succeed. Recent systematic reviews have similarly identified this relationship as a critical unanswered question in mHealth research [10,14].

Self-Determination Theory (SDT) provides a useful framework for understanding engagement within mHealth interventions. SDT proposes that sustained behavior change is more likely when interventions support individuals' basic psychological needs for autonomy, competence, and relatedness [15,16]. Within personalized mHealth interventions, individualized exercise recommendations, goal setting, self-monitoring, and tailored feedback may satisfy these needs by promoting perceived control, reinforcing progress, and encouraging continued interaction with the intervention [17]. From this perspective, repeated engagement with intervention components may represent an observable behavioral manifestation of motivation rather than simply reflecting intervention adherence [14]. However, to our knowledge, no study has examined whether week-to-week engagement with a personalized mHealth intervention is associated with concurrent changes in objectively measured physical activity and well-being among cancer survivors.

Therefore, the primary purpose of this study was to examine longitudinal changes in objectively measured physical activity and psychological well-being during an 8-week personalized mHealth intervention for cancer survivors. A secondary aim was to determine whether weekly intervention engagement was associated with physical activity and well-being outcomes by distinguishing within-person differences during weeks with versus without a completed weekly check-in from between-person differences in participants' overall engagement across the intervention. We hypothesized that weeks in which participants completed the weekly check-in would be associated with higher average daily steps, MVPA, light physical activity, and well-being, as well as lower sedentary time. We further hypothesized that participants with higher overall engagement across the intervention would demonstrate more favorable physical activity and well-being outcomes than participants with lower overall engagement.

Materials and Methods

Study design and setting: This study was a secondary longitudinal analysis of participants assigned to the intervention arm of an ongoing randomized controlled trial evaluating a personalized mHealth physical activity intervention for cancer survivors. Participants were recruited between June 2025 and February 2026 and completed an 8-week remotely delivered intervention using the Scitex mobile app with their respective smartphone in combination with a Fitbit Inspire 3 activity tracker (Google LLC, Mountain View, CA, USA). Weekly Fitbit-derived physical activity data, intervention engagement metrics, and well-being assessments were collected throughout the intervention.

Participants: Potential participants were screened for eligibility by trained research staff. Eligible participants were adults aged 18-85 years with a history of stage 0-III cancer who had completed active cancer treatment at least three months prior to enrollment, except for individuals receiving maintenance endocrine therapy or immunotherapy. Additional eligibility criteria included English proficiency, ownership of an Android or iOS smartphone (any version), willingness to participate in a remotely delivered mHealth physical activity intervention, and medical clearance for physical activity participation when indicated.

Individuals were excluded if they had metastatic disease, were currently receiving chemotherapy or radiation therapy, planned to undergo surgery during the study period, were already meeting recommended physical activity guidelines (>150 mins/3 days per week of MVPA), or had physical or mental health conditions that would preclude safe participation. Participants who screened positive on the Physical Activity Readiness Questionnaire (PAR-Q) were required to obtain physician clearance before enrollment.

Following eligibility confirmation, 26 cancer survivors were enrolled in the intervention. At baseline, participants completed questionnaires by self-reporting their demographic and clinical characteristics, including age, sex, race/ethnicity, cancer diagnosis, height, weight, and smartphone operating system. Body Mass Index (BMI; kg/m^2) was calculated using self-reported height and weight. These variables were administered, and data were collected remotely through a Qualtrics survey.

Intervention: The Scitex intervention was designed to promote physical activity through Artificial Intelligence (AI) personalized exercise recommendations delivered remotely via a smartphone app. Briefly, the AI algorithm is based on reinforcement learning methods, specifically a Partially Observable Markov Decision Process (POMDP) formulation with deep Q learning. Furthermore, the AI algorithm provides a personalized exercise program based on each participant's: (1) daily step goals, (2) previous week's PA, as collected by the Fitbit Inspire 3; and (3) current physical conditioning and well-being, as collected by Scitex. App. The AI algorithm is being updated at intervals with recent updates, including gamification features as a medal achievement when a participant unlocks an exercise stage.

The intervention incorporated established behavior change techniques, including self-monitoring, goal setting, personalized feedback, and adaptive exercise prescription. Participants wore a Fitbit Inspire 3 activity tracker continuously, except during charging or water-based activities. Fitbit data were synchronized with the Scitex platform to provide real-time monitoring of physical activity behaviors.

Each week, participants accessed the Scitex app to review their previous week's activity, complete a brief in-app check-in, and receive updated personalized physical activity recommendations. The Scitex app provided participants with a video demonstration of warm-up exercises and all prescribed exercise types, including aerobics, resistance, balance, and flexibility exercises. Recommendations were updated throughout the intervention to encourage gradual increases in physical activity while accounting for each participant's recent activity patterns.

Outcome measures

Physical activity: Participants wore a Fitbit Inspire 3 activity tracker continuously, except during charging or water-based activities. Fitbit wear-time compliance was monitored throughout the study via the Fitabase platform and reinforced through monthly check-in calls; however, a minimum daily wear-time threshold was not applied to exclude partial-wear days from physical activity estimates. Days with device synchronization failure were treated as missing rather than imputed, but low-wear days that successfully synchronized could still be included in the analysis, which may have introduced measurement error into the daily activity estimates. Fitbit data were synchronized with the Scitex platform to provide real-time monitoring of physical activity behaviors.

Objective physical activity outcomes were collected using the Fitbit Inspire 3 and synchronized through the Fitabase research platform (Small Steps Labs, San Diego, CA, USA). Weekly outcomes included total step count, MVPA (minutes), sedentary time (minutes), light physical activity (minutes), and estimated caloric expenditure (kilocalories).

Well-being. Psychological well-being was assessed weekly using the World Health Organization Five Well-Being Index (WHO-5). The WHO-5 consists of five positively worded items assessing psychological well-being during the previous week, with responses ranging from 0 ("At no time") to 5 ("All of the time"). For the present study, responses were averaged across the five items to generate a weekly mean score ranging from 0 to 5, with higher scores indicating better psychological well-being.

Intervention engagement: Intervention engagement was operationalized as completion of the weekly in-app check-in. During each check-in, participants accessed the apps to review their weekly physical activity progress and receive updated personalized exercise recommendations. Engagement was coded as a binary variable (completed vs. not completed) for each study week and served as the primary indicator of weekly intervention engagement. Participants received reminders to complete the weekly check-in during their monthly phone follow-up calls with research staff; reminder frequency (i.e., once per month) remained consistent throughout the intervention.

Data analysis: All statistical analyses were conducted in R version 4.5.3 (R Foundation for Statistical Computing, Vienna, Austria). Statistical significance was defined as a two-sided

$p<.05$. Longitudinal changes in average daily steps, moderate-to-vigorous physical activity (MVPA), sedentary time, light physical activity, and WHO-5 scores across the 8-week intervention were evaluated using linear mixed-effects models (LMMs). LMMs were selected because they account for the correlation of repeated observations within individuals and allow inclusion of participants with incomplete longitudinal data under the missing-at-random assumption.

For each outcome, alternative model specifications were compared to identify the most appropriate fixed- and random-effects structure. Time was initially modeled as both a continuous (linear) and categorical variable, and random-intercept models were compared with random intercept/random-slope models. Final model selection was based on likelihood ratio tests, Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and overall model parsimony.

Based on model comparisons, average daily steps were modeled using categorical study week because the outcome demonstrated a nonlinear trajectory over time. MVPA, sedentary time, light physical activity, and WHO-5 demonstrated approximately linear trajectories and were modeled with week as a continuous variable. Random-intercept models were retained for all outcomes except light physical activity, for which a random-intercept/random-slope model provided the best fit.

Following a significant overall effect of week for average daily steps, Holm-adjusted post hoc comparisons based on estimated marginal means were performed to compare each follow-up week with baseline (Week 1). Regression coefficients (β) with corresponding 95% Confidence Intervals (CIs) are reported for linear mixed-effects models, whereas estimated mean differences and 95% CIs are reported for post hoc comparisons.

To examine whether intervention engagement was associated with physical activity and well-being outcomes, person-mean-centered linear mixed-effects models were fitted for average daily steps, MVPA, sedentary time, light physical activity, and WHO-5. Person-mean centering was selected because it separates within-person (time-varying) associations from between-person (stable individual-difference) associations, which can otherwise be conflated into a single biased estimate when a time-varying predictor such as weekly engagement is entered into a mixed effects model without decomposition [23]. This approach allowed us to distinguish whether physical activity and well-being changed within a given participant during weeks when they completed a check-in, independent of whether that participant was, on average, more or less engaged than other participants across the intervention. Weekly engagement was decomposed into within-person (weekly check-in completion relative to an individual's average engagement) and between-person (participant-specific mean engagement across the intervention) components, allowing week-to-week associations to be distinguished from differences between participants. The between-person engagement variable was rescaled to represent 10-percentage-point differences in overall engagement to facilitate interpretation of regression coefficients.

A Generalized Linear Mixed-Effects Model (GLMM) with a logit link was additionally used to evaluate whether the probability of completing the weekly in-app check-in changed across the intervention. Fixed effects included study week, and participant-specific random intercepts accounted for repeated observations within individuals. Odds Ratios (ORs) and corresponding 95% confidence intervals are reported.

Model diagnostics: Model assumptions for linear mixed-effects models were evaluated using graphical residual diagnostics, including residual-versus-fitted plots, Quantile-Quantile (Q-Q) plots, homogeneity of variance, multicollinearity (variance inflation factors), and random-effects diagnostics using the performance package in R. Generalized linear mixed-effects models were additionally assessed for convergence, overdispersion, and singularity. No substantial violations of model assumptions were identified, and no data transformations were required.

Missing data: All analyses were conducted using all available observations. Fitbit-derived physical activity variables recorded as zero because of device synchronization failure were treated as missing rather than true zero values to minimize outcome misclassification. Linear mixed-effects models were estimated using Restricted Maximum Likelihood (REML), allowing all available repeated observations to contribute to parameter estimation without imputing missing data. The generalized linear mixed-effects model was estimated using maximum likelihood.

Ethical consideration: This study was approved by the Institutional Review Board at the University of Tennessee, Knoxville (IRB Approval No. IRB-24-07955-FB). All study procedures were conducted in accordance with the ethical principles outlined in the Declaration of Helsinki. Written informed consent was obtained from all participants prior to study enrollment.

Results

Participant characteristics: Participant demographic and clinical characteristics are presented in (Table 1). The study included 26 cancer survivors with a mean age of 62 years. Most participants were female, non-Hispanic White, and had a diagnosis of breast cancer. The majority had Stage I or Stage II disease.

Descriptive statistics: As shown in (Table 2), average daily steps, MVPA, and WHO-5 scores generally increased across the intervention, whereas sedentary time and light physical activity remained relatively stable. Weekly sample sizes ranged from 22 to 25 participants because of intermittent Fitbit synchronization and missing questionnaire responses.

Longitudinal changes: Linear mixed-effects models were used to evaluate longitudinal changes in physical activity and well-being outcomes across the intervention.

Average daily steps changed significantly over time (overall effect of week: $\chi^2(7)=14.16$, $p=.048$). Holm-adjusted post hoc comparisons indicated that participants accumulated significantly more average daily steps during Week 3 than at baseline (mean difference = 1,608 steps/day, 95% CI: 161 to 3,056; $p=.020$). No other weekly comparisons remained statistically significant after adjustment for multiple comparisons (Figure 1).

Daily MVPA increased significantly across the intervention ($\beta=1.32$ minutes/day per week, 95% CI: 0.39 to 2.26, $p=.006$).

No significant longitudinal changes were observed for sedentary time (β=0.23 minutes/day per week, 95% CI: -4.80 to 5.27, p=.928) or light physical activity (β=0.35 minutes/day per week, 95% CI: -2.63 to 3.33, p=.819).

WHO-5 scores increased significantly over time (β=1.03 points/week, 95% CI: 0.05 to 2.00, p=.043). This analysis included 80 observations from 19 participants because weekly WHO-5 assessments were unavailable for all study weeks.

Changes in weekly engagement: A total of 180 weekly observations from 25 participants were available for the engagement analysis. Weekly check-ins were completed during 81 (45.0%) of these observations. A generalized linear mixed-effects model demonstrated that the likelihood of completing a weekly check-in did not change significantly across the intervention (Odds Ratio [OR] = 1.06 per week, 95% CI: 0.87 to 1.30, p=.571).

Associations between engagement and study outcomes: Person-mean-centered linear mixed-effects models were used to distinguish within-person associations between weekly check-in completion and study outcomes from between-person associations related to participants' overall engagement across the intervention.

Within-person engagement was not significantly associated with average daily steps (β=704 steps/day, 95% CI: −186 to 1,595, p=.120), MVPA (β=1.77 minutes/day, 95% CI: -5.53 to 9.07, p=.633), sedentary time (β=9.60 minutes/day, 95% CI: -33.3 to 52.5, p=.659), light physical activity (β=-15.1 minutes/day, 95% CI: -34.2 to 3.98, p=.120), or WHO-5 scores (β=6.08 points, 95% CI: -2.72 to 14.9, p=.173).

Table 1: Participant demographic characteristics.

Characteristics	N (%) or Mean (SD)	N = 26
Age (years)	**Mean (SD)**	**Range**
Age	62.0 (8.4)	46–78
Body Mass Index (BMI, kg/m²)	**Mean (SD)**	**Range**
BMI	29.3 (7.0)	19.0–46.5
Sex	**n**	**%**
Female	25	96.2
Male	1	3.8
Ethnicity	**n**	**%**
Hispanic	2	7.7
Non-hispanic	24	92.3
Race	**n**	**%**
Caucasian or white	26	100.0
Cancer type	**n**	**%**
Breast cancer	21	80.8
Ovarian cancer	2	7.7
Prostate cancer	1	3.8
Uterine cancer	1	3.8
Squamous cell carcinoma	1	3.8
Cancer stage at diagnosis	**n**	**%**
Stage 0	2	7.7
Stage I	12	46.2
Stage II	9	34.6
Stage III	3	11.5

Table 2: Descriptive statistics for all outcomes across the 8-week Scitex intervention.

Week	n	Weekly Steps M (SD)	Avg Daily Steps M (SD)	MVPA Min M (SD)	Sedentary Min M (SD)	Light PA Min M (SD)	Well-being M (SD)
1	25	32,677 (26,761)	4,725 (3,828)	17.1 (14.9)	842.1 (130.6)	215.1 (71.5)	3.35 (1.02)
2	24	39,602 (31,901)	5,657 (4,557)	23.2 (20.2)	847.3 (168.6)	223.6 (75.4)	3.51 (0.78)
3	25	40,793 (33,030)	5,840 (4,709)	23.3 (19.2)	834.1 (173.4)	223.5 (83.9)	3.67 (0.83)
4	23	37,866 (30,871)	5,458 (4,432)	26.3 (25.3)	848.2 (173.2)	219.2 (59.3)	3.77 (0.91)
5	22	36,695 (28,419)	5,491 (3,983)	21.4 (14.7)	856.6 (157.2)	223.2 (71.2)	3.22 (1.40)
6	22	37,762 (30,209)	5,373 (4,325)	24.4 (23.1)	842.5 (125.4)	216.6 (58.6)	3.82 (0.84)
7	22	39,283 (29,275)	5,454 (3,841)	24.8 (17.7)	843.5 (141.6)	222.2 (59.9)	3.82 (0.96)
8	22	42,337 (34,371)	5,902 (4,693)	32.1 (29.5)	842.9 (169.2)	222.7 (69.0)	3.93 (0.95)

Note: M: Mean; SD: Standard Deviation; Min: Minutes. Steps and average daily steps reflect Fitbit-derived weekly totals/averages. MVPA: Moderate-to-Vigorous Physical Activity (Minutes). Sedentary and light PA are weekly averages in minutes. Well-being: (Mean of WHO-5 items, scale 1-5); n varies by week due to missing survey responses.

Table 3: Longitudinal change in physical activity and well-being during the 8-week intervention.

Outcome	Final Model	Effect Estimate (95% CI)	p-value
Average daily steps	Categorical time	Week 3 vs. Week 1: **+1,608 steps/day** (95% CI: 161 to 3,056)	.020
MVPA (min/day)	Linear time	β = 1.32 min/day per week (95% CI: 0.39 to 2.26)	.006
Sedentary time (min/day)	Linear time	β = 0.23 min/day per week (95% CI: -4.80 to 5.27)	.928
Light PA (min/day)	Linear time	β = 0.35 min/day per week (95% CI: -2.63 to 3.33)	.819
WHO-5 (well-being index)	Linear time	β = 1.03 points per week (95% CI: 0.05 to 2.00)	.043

Abbreviations: CI: Confidence interval; MVPA: Moderate-to-Vigorous Physical Activity; WHO-5: World Health Organization-Five Well-Being Index. †Average daily steps were modeled with week as a categorical variable because model comparisons indicated a nonlinear trajectory over time. The overall effect of week was statistically significant (χ^2 (7)=14.16, P=.048). Holm-adjusted pairwise comparisons demonstrated a significant increase in average daily steps during Week 3 compared with Week 1; no other pairwise comparisons were statistically significant.

Note: Linear mixed-effects models included participant-specific random intercepts for all outcomes except light physical activity, which included random intercepts and random slopes for time. Estimates for linear models represent the average weekly change across the intervention.

Results of Model Selection (Supplementary Material)			
Outcome	**Linear vs. Categorical**	**Random effects selected**	**Final model**
Average daily steps	Categorical retained (p = .041)	Random Intercept	Week (factor) + (1 | ID)
MVPA	Linear retained (p = .463)	Random Intercept	Week + (1 | ID)
Sedentary Time	Linear retained (p = .984)	Random Intercept	Week + (1 | ID)
Light PA	Linear retained (p = .974)	Random Intercept + Slope	Week + (Week | ID)
WHO-5	Linear retained (p = .740)	Random Intercept	Week + (1 | ID)

Table 4: Engagement and study outcomes.

Outcome	Within-person engagement effect, β (95% CI)	p	Between-person engagement effect per 10-percentage-point increase, β (95% CI)	p
Average daily steps	704 (-186 to 1,595)	.120	112 (-257 to 482)	.534
MVPA (min/day)	1.77 (-5.53 to 9.07)	.633	-0.07 (-1.81 to 1.67)	.935
Sedentary Time (min/day)	9.60 (-33.3 to 52.5)	.659	-0.14 (-14.5 to 14.2)	.984
Light PA (min/day)	-15.1 (-34.2 to 3.98)	.120	-0.35 (-6.42 to 5.72)	.907
WHO-5 (well-being)	6.08 (-2.72 to 14.9)	.173	0.94 (-1.79 to 3.66)	.478

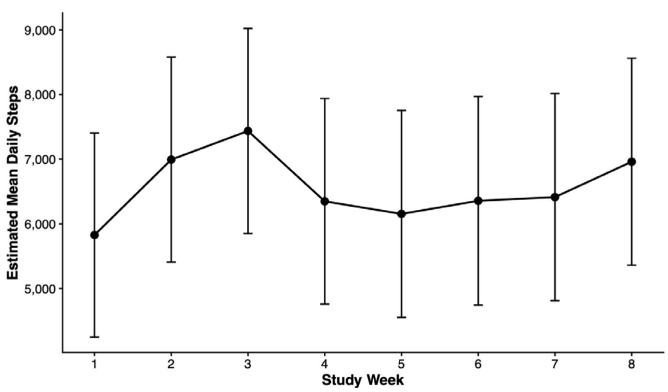

Figure 1: Estimated mean daily steps across the 8-week intervention. Points represent estimated marginal means from the linear mixed-effects model, and error bars represent 95% confidence intervals.

Similarly, participants with higher overall engagement across the intervention did not differ significantly from those with lower engagement on any study outcome. For every 10-percentage point increase in overall check-in completion, estimated differences were 112 steps/day (95% CI: -257 to 482, p=.534), -0.07 minutes/day of MVPA (95% CI: -1.81 to 1.67, p=.935), -0.14 minutes/day of sedentary time (95% CI: -14.5 to 14.2, p=.984), -0.35 minutes/day of light physical activity (95% CI: -6.42 to 5.72, p=.907), and 0.94 WHO-5 points (95% CI: -1.79 to 3.66, p=.478).

Discussion

The present study examined longitudinal changes in objectively measured physical activity and psychological well-being during an 8-week personalized mHealth intervention for cancer survivors and evaluated whether weekly intervention engagement was associated with these outcomes. Four principal findings emerged. First, average daily step counts increased significantly over the intervention, with the greatest improvement observed by Week 3. Second, daily MVPA increased significantly over the 8-week intervention, whereas sedentary time and light physical activity remained stable. Third, psychological well-being improved over time. Finally, contrary to our hypothesis, weekly intervention engagement was not associated with physical activity or well-being outcomes at either the within-person or between-person level, despite engagement remaining relatively stable throughout the intervention. Together, these findings suggest that the personalized mHealth intervention was associated with improvements in physical activity and well-being, but that completion of the weekly check-in alone was not the primary mechanism underlying these changes.

The observed improvements in physical activity are consistent with previous research demonstrating that remotely delivered mHealth interventions can increase physical activity among cancer survivors, particularly when wearable activity monitors are combined with personalized exercise recommendations [8,9]. Participants demonstrated increases in both average daily step counts and MVPA over the 8-week intervention, suggesting that meaningful behavioral changes can occur over a relatively short period. Personalized exercise prescriptions, continuous self-monitoring through Fitbit, and individualized feedback may have facilitated gradual increases in physical activity by supporting self-regulation and goal-directed behavior. Although only the Week 3 comparison for average daily step counts remained statistically significant after adjustment for multiple comparisons, the overall pattern of results suggested sustained improvement across the intervention.

Well-being also improved significantly during the intervention. Although the observed improvements were modest, they are consistent with systematic reviews and meta-analyses demonstrating that regular physical activity improves psychological health among cancer survivors by reducing cancer-related fatigue, alleviating symptoms of depression and anxiety, improving mood, and enhancing overall functioning [18-20]. Importantly, improvements in well-being occurred alongside increases in objectively measured physical activity, supporting the broader role of physical activity as a key component of comprehensive cancer survivorship care. Because well-being was assessed repeatedly throughout the intervention, these findings further suggest that relatively short-term changes in physical activity may be accompanied by measurable improvements in psychological well-being.

Contrary to our hypothesis, weekly intervention engagement was not significantly associated with physical activity or well-being outcomes. Neither completing a weekly check-in during a given week (within-person engagement) nor having higher overall engagement across the intervention (between-person engagement) predicted changes in any study outcome. Although these findings differed from our original hypothesis, they provide important insight into the complexity of engagement within digital health interventions. Most previous mHealth studies have characterized engagement descriptively using metrics such as adherence, application use, or retention while primarily evaluating overall intervention effectiveness rather than examining engagement as a predictor of behavioral outcomes [21]. Our findings suggest that completion of a weekly check-in alone may not adequately capture the dimensions of engagement that are most relevant for behavior change.

One possible explanation is that the weekly check-in represented only one component of a multifaceted intervention. Although participants were encouraged to complete the check-in because its responses informed the AI-driven personalized exercise recommendations, completion of the check-in was not required to access the prescribed exercises. Consequently, some participants may have perceived the check-in as optional while continuing to engage with other intervention components. Participants may have remained actively engaged with other intervention components-including wearing the Fitbit, reviewing activity feedback, and following personalized exercise prescriptions-even when they did not complete the weekly check-in. We consider this one of the most notable findings of the present study: physical activity increased, psychological well-being improved, and yet neither outcome was predicted by weekly check-in completion. A plausible interpretation is that the intervention remained functionally active for participants even during weeks without a completed check-in, sustained by components that operated independently of that single behavior. Specifically, participants continued to wear the Fitbit continuously, continued to receive AI-generated exercise prescriptions derived from their ongoing activity data, continued to self-monitor through the Fitbit-Scitex integration, and received reminders during monthly check-in calls regardless of whether a given week's check-in had been completed. Under this interpretation, the weekly check-in functioned as only one, and perhaps not the most consequential, touchpoint within a broader intervention infrastructure that continued to operate in the background, which would explain why physical activity and well-being improved even as engagement with this single behavioral indicator failed to predict either outcome.

These findings also have implications for understanding engagement within the context of Self-Determination Theory. SDT proposes that sustained behavior change is facilitated when interventions support individuals' needs for autonomy, competence, and relatedness [15,22]. Although weekly check-in completion was intended to reflect ongoing interaction with personalized intervention components, our findings suggest that this behavioral indicator alone may not adequately represent the motivational processes described by SDT. Psychological need satisfaction may instead have been supported through other aspects of the intervention, including individualized exercise recommendations, continuous self-monitoring through the Fitbit, or the experience of successfully achieving personalized activity goals. Because autonomy, competence, and relatedness were not measured directly, it remains unclear whether these psychological mechanisms contributed to the observed improvements in physical activity and well-being. Future studies should incorporate validated measures of SDT constructs alongside objective engagement metrics to better understand the mechanisms through which personalized mHealth interventions promote behavior change.

An important strength of this study was the use of objective Fitbit-derived physical activity measures collected repeatedly across the intervention, allowing week-to-week changes in physical activity to be evaluated rather than relying solely on pre-post comparisons. The longitudinal design also permitted examination of within-person and between-person engagement using person-mean-centered mixed-effects models, providing a more nuanced assessment of engagement than traditional adherence summaries. These methodological strengths contribute to the growing literature seeking to understand not only whether mHealth interventions are effective, but also how behavioral changes develop over time.

These findings also carry practical relevance for current cancer survivorship priorities.

Guidelines from major oncology and public health organizations emphasize maintaining physical activity after treatment completion, supporting long-term behavioral adherence, and promoting patient-driven symptom self-management as core components of comprehensive survivorship care [24]. The present findings, that physical activity and psychological well-being improved over the intervention independent of formal weekly engagement, suggest that scalable mHealth interventions may support these priorities even when a single engagement metric fails to capture the full mechanism of behavior change. Remote, technology-delivered interventions such as the one tested here are of particular relevance for reaching survivors for whom in-person survivorship care is difficult to access, including those in rural and medically underserved areas, where structured physical activity programming and survivorship care plans are often limited [25]. As mHealth interventions are increasingly integrated into survivorship care plans, identifying which components sustain physical activity and well-being over time, independent of any single adherence metric, will be critical for designing scalable, remotely delivered programs capable of serving these populations.

Several limitations should also be considered. This study was a secondary analysis of participants assigned to the intervention arm of an ongoing randomized controlled trial and included a relatively small sample that was predominantly White women with breast cancer, which may limit generalizability to more diverse survivor populations. Specifically, 80.8% (21 of 26) of participants had a breast cancer diagnosis. Exercise behaviors, fatigue, treatment related effects such as endocrine therapy, symptom burden, and psychosocial outcomes can differ substantially across cancer types, and these findings may therefore not generalize to survivors of other cancers. Relatedly, the small sample of only 26 participants limited statistical power throughout the study, which may have produced unstable mixed-model estimates and reduced our ability to detect modest engagement effects; the non-significant associations between engagement and physical activity or well-being outcomes should therefore be interpreted with caution, as they may reflect insufficient power rather than a true absence of association. Because engagement was not experimentally manipulated, causal relationships between engagement and study outcomes cannot be established. Additionally, engagement was operationalized solely as completion of the weekly in-app check-in and therefore may not fully capture the multidimensional nature of engagement with digital health interventions. Other aspects of engagement, such as application use, feature utilization, interaction frequency, or responsiveness to personalized recommendations, were not evaluated. Finally, psychological constructs central to SDT-including autonomy, competence, and relatedness-were not measured directly, limiting our ability to evaluate the theoretical mechanisms underlying intervention effects.

Future research should examine more comprehensive measures of engagement that extend beyond binary check-in completion. Application usage duration, feature utilization, response latency, interaction frequency, ecological momentary assessments, passive sensing technologies, and passive digital biomarkers may provide a more complete understanding of how participants interact with personalized mHealth interventions over time. Future studies should also incorporate repeated assessments of psychological constructs such as autonomy, competence, relatedness, self-efficacy, and motivation to determine whether these variables mediate improvements in physical activity and well-being. Identifying the specific intervention components responsible for promoting sustained behavior change will be essential for optimizing future mHealth interventions for cancer survivors. Our findings may also inform the development of more adaptive intervention designs. Modern mHealth interventions increasingly use Just-In-Time Adaptive Interventions (JITAIs), reinforcement learning, and other forms of dynamic tailoring that adjust content, timing, and intensity in response to a participant's real-time behavioral and contextual data [26]. Because physical activity and well-being improved in this study even when weekly check-in completion was inconsistent, relying on a fixed, calendar-based engagement structure may not be necessary, or even optimal, for supporting behavior change. Future mHealth interventions for cancer survivors may benefit from shifting away from static weekly check-ins toward adaptive designs that respond continuously to fluctuations in symptoms, motivation, and behavior throughout survivorship [27].

Conclusion

This study demonstrated significant improvements in objectively measured physical activity and psychological well-being during an 8-week personalized mHealth intervention for cancer survivors. The intervention used individualized Fitbit-derived physical activity data and weekly well-being responses to generate personalized exercise recommendations throughout the intervention [28]. Contrary to our hypothesis, weekly completion of the in-app check-in was not associated with changes in physical activity or well-being, suggesting that this single behavioral indicator did not fully capture participants' engagement with the intervention. Together, these findings indicate that meaningful improvements in health behaviors and psychological well-being can occur even when engagement is not reflected by one specific intervention feature. Future mHealth interventions should incorporate more comprehensive measures of engagement to better identify the behavioral and psychological mechanisms that promote sustained physical activity and well-being among cancer survivors [29,30].

Declarations

Conflicts of interest: The authors declare no conflicts of interest.

Funding sources: This work is based on data collected as part of an ongoing randomized controlled trial partially supported by The University of Tennessee Grand Challenge Grant under grant number [INT100015]. The secondary analysis presented in this manuscript received no additional funding.

Acknowledgement: The authors thank the cancer survivors who participated in this study for their time and commitment. The authors also acknowledge the research staff and students of the Physical Activity Epidemiology Laboratory at the University of Tennessee for their assistance with participant recruitment, data collection, and study coordination.

Abbreviations: MHealth: Mobile Health; APP: Application; MVPA: Moderate-to-Vigorous Physical Activity; IRB: Institutional Review Board; SDT: Self-Determination Theory; REML: Restricted Maximum Likelihood; CI: Confidence Interval; SE: Standard Error; SD: Standard Deviation.

References

1. Campbell KL, Winters-Stone KM, Wiskemann J, May AM, Schwartz AL, Courneya KS, et al. Exercise guidelines for cancer survivors: Consensus statement from International Multidisciplinary Roundtable. Med Sci Sports Exerc. 2019; 51: 2375-2390.

2. Siegel RL, Kratzer TB, Giaquinto AN, Sung H, Jemal A. Cancer statistics, 2025. CA Cancer J Clin. 2025; 75: 10-45.

3. Stein KD, Syrjala KL, Andrykowski MA. Physical and psychological long-term and late effects of cancer. Cancer. 2008; 112: 2577-2592.

4. Blanchard CM, Courneya KS, Stein K. Cancer survivors' adherence to lifestyle behavior recommendations and associations with health-related well-being: Results from the American Cancer Society's SCS-II. J Clin Oncol. 2008; 26: 2198-2204.

5. Clifford BK, Mizrahi D, Sandler CX, Barry BK, Simar D, Wakefield CE, et al. Barriers and facilitators of exercise experienced by cancer survivors: a mixed methods systematic review. Support Care Cancer. 2018; 26: 685-700.

6. Singh B, Ahmed M, Staiano AE, Gough C, Petersen J, Vandelanotte C, et al. A systematic umbrella review and meta-meta-analysis of eHealth and mHealth interventions for improving lifestyle behaviors. NPJ Digit Med. 2024; 7: 179.

7. Laranjo L, Ding D, Heleno B, Kocaballi B, Quiroz JC, et al. Do smartphone applications and activity trackers increase physical

activity in adults? Systematic review, meta-analysis and meta regression. Br J Sports Med. 2021; 55: 422-432.

8. Roberts AL, Fisher A, Smith L, Heinrich M, Potts HWW. Digital health behavior changes interventions targeting physical activity and diet in cancer survivors: A systematic review and meta-analysis. J Cancer Surviv. 2017; 11: 704-719.

9. Wang L, Langlais CS, Kenfield SA, Chan JM, Graff RE, et al. mHealth interventions to promote a healthy diet and physical activity among cancer survivors: A systematic review of randomized controlled trials. Cancers (Basel). 2022; 14: 3816.

10. Perski O, Blandford A, West R, Michie S. Conceptualizing engagement with digital behavior change interventions: A systematic review using principles from critical interpretive synthesis. Transl Behav Med. 2017; 7: 254-267.

11. Valle CG, Diamond MA, Heiling HM, Deal AM, Hales DP, et al. Physical activity maintenance among young adult cancer survivors in an mHealth intervention: Twelve-Month outcomes from the IMPACT randomized controlled trial. Cancer Med. 2023; 12: 16502-16516.

12. Whitaker M, Welch WA, Fanning J, Santa-Maria CA, Auster-Gussman LA, et al. Using ecological momentary assessment to understand associations between daily physical activity and symptoms in breast cancer patients undergoing chemotherapy. Support Care Cancer. 2022; 30: 6613-6622.

13. Attig C, Franke T. Abandonment of personal quantification: A review and empirical study investigating reasons for wearable activity tracking attrition. Comput Human Behav. 2020; 102: 223-237.

14. Milne-Ives M, Homer SR, Andrade J, Meinert E. Potential associations between behavior change techniques and engagement with mobile health apps: A systematic review. Front Psychol. 2023; 14: 1227443.

15. Ryan RM, Deci EL. Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. Am Psychol. 2000; 55: 68-78.

16. Sheeran P, Wright CE, Avishai A, Villegas ME, Lindemans JW, et al. Selfdetermination theory interventions for health behavior change: Meta-Analysis and metaanalytic structural equation modeling of randomized controlled trials. J Consult Clin Psychol. 2020; 88(8): 726-737. doi:10.1037/ccp0000501.

17. Gerstenberg R, Høeg ER, Van der Kaap-Deeder J, Hassenzahl M. Applying selfdetermination theory to behavior change technologies: Insights from two projects in the health domain. Front Psychol. 2025; 16: 1634267. doi:10.3389/fpsyg.2025.1634267.

18. Calder J, Kavanagh PS, Bacon R, Chau M, Sidhu D, et al. The effects of exercise dose on psychological health outcomes in people diagnosed with cancer: A systematic review and meta-analysis. Disabil Rehabil. 2025; 47(14): 3516-3527. doi:10.1080/09638288.2024.2432919.

19. Huizinga F, Westerink NL, Berendsen AJ, Walenkamp AME, de Greef MHG, et al. Home-based physical activity to alleviate fatigue in cancer survivors: A systematic review and meta-analysis. Med Sci Sports Exerc. 2021; 53(12): 2661-2674. doi:10.1249/MSS.0000000000002735.

20. Mishra SI, Scherer RW, Snyder C, Geigle P, Gotay C. Are exercise programs effective for improving health-related quality of life among cancer survivors? A systematic review and meta-analysis. Oncol Nurs Forum. 2014; 41(6): 326-342. doi: 10.1188/14.ONF.E326-E342.

21. Xiao K, Tang L, Chen Y, et al. The effectiveness of eHealth interventions promoting physical activity in cancer survivors: A systematic review and meta-analysis of randomized controlled trials. J Cancer Res Clin Oncol. 2024; 150: 72. doi:10.1007/s00432-023-05546-9.

22. Ntoumanis N, Ng JYY, Prestwich A, Quested E, Hancox JE, Thogersen-Ntoumani C, et al. A meta-analysis of self-determination theory-informed intervention studies in the health domain: Effects on motivation, health behavior, physical, and psychological health. Health Psychol Rev. 2021; 15: 214-244.

23. Curran PJ, Bauer DJ. The disaggregation of within-person and between-person effects in longitudinal models of change. Annu Rev Psychol. 2011; 62: 583-619.

24. Rock CL, Thomson CA, Sullivan KR, et al. American Cancer Society nutrition and physical activity guideline for cancer survivors. CA Cancer J Clin. 2022; 72: 230-262.

25. Dennett AM, Hirko KA, Porter KJ, et al. Embedding lifestyle interventions into cancer care: Has telehealth narrowed the equity gap? J Natl Cancer Inst Monogr. 2023; 2023: 133-139.

26. Nahum-Shani I, Smith SN, Spring BJ, Collins LM, Witkiewitz K, Tewari A, Murphy SA. Just-in-Time Adaptive Interventions (JITAIs) in mobile health: key components and design principles for ongoing health behavior support. Ann Behav Med. 2018; 52: 446-462.

27. Hu Y, Gu S, Bu Z, Liu Z, Dong J, Shi J, Xu Y. Effect of exercise for patients with advanced lung cancer and cancer-related fatigue: A systematic review and meta-analysis. J Sport Health Sci. 2025; 14: 101017. doi: 10.1016/j.jshs.2024.101017.

28. Hekler E, Tiro JA, Hunter CM, Nebeker C. Precision health: the role of the social and behavioral sciences in advancing the vision. Ann Behav Med. 2020; 54: 805-826.

29. Jones LW. Exercise and cancer outcomes: What do we know and where next? J Sport Health Sci. 2025; 14: 101068. doi: 10.1016/j.jshs.2025.101068.

30. Courneya KS. The emerging role of exercise as a cancer treatment. J Sport Health Sci. 2024; 13(4): 443-444. doi: 10.1016/j.jshs.2023.03.006.