BASELINE PREDICTORS OF PROGRAM ENGAGEMENT IN AN ONLINE PHYSICAL ACTIVITY INTERVENTION

by

Reagan E. Moffit

B.S. Exercise Science, Saginaw Valley State University, 2019

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This essay is submitted

by

Reagan E. Moffit

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and approved by

Essay Advisor: Bonny Rockette-Wagner, PhD, Assistant Professor, Department of Epidemiology, Graduate School of Public Health, University of Pittsburgh

Essay Reader: Kathleen McTigue, MD MPH MS, Associate Professor, Department(s) of Epidemiology and Medicine, Graduate School of Public Health, School of Medicine, University of Pittsburgh

Essay Reader: Andrea Kriska, PhD MS, Professor, Department of Epidemiology, Graduate School of Public Health, University of Pittsburgh

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Reagan E. Moffit, MPH

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Abstract

INTRODUCTION: Physical inactivity is a significant problem worldwide. Digital health interventions coordinated with clinical care may be a feasible way to improve physical activity (PA) levels of US adults. It has been shown that high program engagement is associated with positive changes in PA, yet little is known about baseline factors which influence program engagement. The purpose of this study was to 1) describe program engagement in an online digital health intervention for PA improvement and 2) to identify baseline factors related to program engagement. **METHODS:** ActiveGOALS was a three-month one-on-one online intervention designed to increase PA levels and decrease sedentary time in adults. All participants were randomized to receive the intervention (15 total online lessons, 2 technical, 13 instructional) immediately or after a three-month wait period. Variables across seven domains (confidence, environment, health, healthcare, demographic, lifestyle, and quality of life) were self-reported at baseline. Six engagement outcome variables were identified at the conclusion of the study. A step-wise model building strategy was used to identify statistically significant baseline predictors for each of the six outcome engagement variables. General linear and nonlinear mixed models were used to model the relationship between baseline factors and engagement outcomes. **RESULTS:** The majority of participants were female (77.2%), white non-Hispanic (74.7%) and self-reported an average of 27 min of PA per week. Overall, program engagement was high. A small number of baseline factors belonging to five of the seven domains were identified as significantly relating to program engagement. **DISCUSSION:** These results suggest that program engagement was high across all engagement outcomes. This effort is one of only a few to assess the relationship between many baseline factors across multiple domains and program engagement. These findings can help future public health efforts to provide extra supports to those who may struggle to engage with online PA interventions.

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Preface

I would like to first thank my research mentor and essay advisor, Dr. Bonny Rockette-Wagner, for her mentorship over the past year and a half and her willingness to allow me to take the lead on this manuscript. Her insight and expertise have been invaluable. I also would like to thank my other essay readers Drs. Andrea Kriska and Kathleen McTigue for their valuable comments and guidance. I have learned so much during this process and am very grateful for the thought and time they put into this essay. Finally, I would like to thank my family for supporting me on my journey. I especially would like to thank my parents who taught by example the importance of a good work ethic and who, as teachers, always emphasized the importance of education.

1.0 Introduction

1.1 Physical Activity is a Public Health Problem

Physical inactivity is a significant public health problem, attributing to 9%, or ~5.3 million, premature deaths worldwide each year.[1] Physical inactivity is also associated with higher risk of morbidity, including increased risk for cardiovascular disease, type 2 diabetes, osteoporosis, arthritis, neurodegenerative diseases, and some cancers.[2,3] The 2018 US Physical Activity (PA) Guidelines recommend that adults should aim to achieve a minimum of 150 minutes of moderate-intensity aerobic activity or 75 minutes of vigorous-intensity aerobic activity or a combination of the two each week.[2] However, only about half of US adults currently meet these guidelines.[4,5] Additionally, adherence to PA Guidelines in US adults have not significantly improved from 2008 to 2018.[6] Increased efforts including ones focused on earlier prevention are needed to raise PA levels across the U.S. adult population.

1.2 Integrating PA Interventions in Clinical Care

Primary care providers may be uniquely positioned to help support efforts for improving PA, given their long-term relationships with patients and their mission which includes prevention. In 2007, to engage primary care providers in addressing the widespread prevalence of low PA, the American College of Sports Medicine (ACSM) launched its Exercise is Medicine (EIM) global initiative.[7] EIM is an initiative designed to integrate PA assessment, promotion, and referral in clinical care settings in support of US Preventive Services Task Force (USPSTF) clinical guidelines that endorse PA in the prevention and treatment of common cardiometabolic health conditions. This approach offers a unique opportunity for promoting PA in a large proportion of US adults who attend primary care visits. However, only about a third of patients receive PA counseling or referral from their healthcare provider, with disparities in counseling seen by gender, education, and race/ethnicity.[8,9] This may reflect the barriers faced by healthcare providers, which includes lack of time, knowledge, confidence in ability to prescribe and/or counsel patients on PA, and lack of trust that their patients will change their behaviors.[10-12] Additionally, primary care providers may not have the resources available to refer patients to existing programs or professionals to improve PA levels.

Establishing referral programs for PA promotion is one option for better integration of PA into routine primary care without placing additional burden on healthcare providers. This includes proven intervention programs that can be coordinated with clinical care and provide patients with support for activity improvement outside of the clinical care setting while reporting results back to clinical care teams and addressing any emergent safety or health issues as part of routine health management.

1.3 Use of Digital Health PA Interventions Coordinated with Clinical Care

Digital health interventions coordinated with clinical care may be a more feasible way to facilitate lifestyle interventions for clinical care patients because they require less contact from physicians and clinical team members, shifting the burden of contact to a remote lifestyle coach and/or automated messaging. Such programs can be advantageous due to reduced cost for both participant and healthcare services, reduced burden on physicians and participants, more flexibility for completion, and ability to reach a wider population.[13,14] Additionally, online-based interventions may be better integrated into electronic health systems and provide better coordination with clinical care. Over the past few years, the use of telemedicine and digital health interventions (includes any intervention that uses or is mediated by digital technology) has greatly increased in clinical care settings.[15] This trend is likely to continue into the future.

Existing intervention programs with increasing PA as one of the primary goals have included wearable or assistive devices, app-based program platforms, social media, and/or online-based programming. Despite the potential benefits of digital PA interventions, existing evidence suggests there is a large degree of heterogeneity in results across interventions with fewer programs succeeding in making clinically significant changes to participant PA levels.[16-18] The variation in success across studies may be related to the variation in the interventions themselves, which may differ in content, theoretical approach (including non-theory driven), support features (such as coaching and trackers), and delivery platform (e.g. app-based, online-based, social media-based).[18] Additionally, lack of clinically relevant improvements in PA for some programs could result from low program engagement in one or more components.[19]

It is worth noting that few digital PA interventions are theory-driven and are often short in duration (only 1-3 sessions/contacts). The short duration of low contact programs leads to reduced costs but can be problematic as changing lifestyle behaviors typically takes weeks or months to achieve.[20] Program contact, including lesson attendance and coach interaction, has been previously shown to be important toward participant success in non-digital in-person interventions.[21,22] Online programs may supplement (or replace) the more traditional participant-coach contact with other types of support. Many online platforms collect data related to both participant-coach and participant-platform contact (often collected as platform usage) and are therefore in the unique position to increase our understanding of the importance of different aspects of contact in these programs.

1.4 Engagement in Digital Health Interventions

To be able to accurately assess the success of digital health lifestyle interventions, engagement must be examined. However, program engagement in digital lifestyle intervention, including measures of participant-coach and participant-platform contact, are not often reported. Program engagement varies widely across PA interventions that do report these measures, ranging from high to low, [23-37] and tends to decrease over time. [23,29,33-35,37] Previous studies have shown a direct relationship between program engagement and PA levels.[38] Unfortunately, existing studies are not consistent in how they report engagement, especially in digital interventions where there are many modes of engagement, including but not limited to platform usage, lesson completion, tracking or self-monitoring PA or sedentary behaviors, and participant-initiated contact with a coach (real or automated) or other participants through messaging boards or direct emails and digital messaging. Of these, platform usage and lesson completion are most commonly used as a measure of program engagement in digital interventions. Recent literature shows mixed relationships between usage-related engagement and PA outcomes.[38] In general, meeting PA goals in previous weeks has been shown to increase adherence to tracking PA in subsequent weeks[29] and the use of wearable trackers in interventions is associated with higher PA levels.[39] To our knowledge, no research has examined the relationship between participant-initiated contact engagement (e.g. online social groups or discussion boards) and PA outcomes in a digital health intervention. The many modes of program engagement in digital health interventions allows participants to engage with the intervention in a variety of ways. Each mode of engagement may influence program success differently. Because of this, it is important to accurately capture and understand the effects of each mode of engagement to be able to provide better support to participants and maximize overall engagement with the intervention.

1.5 Factors Related to Program Engagement in Digital Health Interventions

There is currently only a small amount of existing research examining factors related to program engagement in digital health PA interventions and the results of such studies are mixed. Multiple studies have been unable to identify any significant demographic predictors of engagement.[27,40,41] This may be due to small sample sizes for some of the studies, low participant engagement causing a floor effect, or conversely high participation due to the convenience of online interventions, causing a ceiling effect and diminishing differences in barriers across groups of people.[27,41] Among the studies that did identify baseline characteristics significantly related to engagement, demographic factors were the most commonly studied. Multiple studies found older age to be related to better engagement. [25,42] Other demographic factors significantly related to engagement include sex and employment status, with male sex related to higher engagement and unemployment (pre-retirement) related to lower engagement.[42] Health status is another factor previously studied in literature, with lower baseline BMI identified as relating to higher engagement among overweight and obese populations.[42] Psychological health, including depression, anxiety, stress, and initial motivation, have also been identified as factors important to engagement. This relationship is inverse, with lower levels of depression, anxiety, and stress leading to higher engagement.[42] Attitudes towards internet usage also may be important to engagement in digital interventions, with anxiety about internet usage shown to be significantly related to lower engagement levels.[43]

1.6 Gaps in the Literature/ Public Health Significance

Despite efforts to better understand factors relating to program engagement in digital PA interventions, to our knowledge, no existing study has examined factors relating engagement to lifestyle, healthcare, or quality of life measures. This is relevant because current lifestyle behaviors, access to healthcare, and attitudes towards life are important when determining program success and may impact program engagement. It is important to understand how these characteristics may impact engagement to improve overall engagement across a target population as well as provide individualized assistance to individuals who may need extra support. Additionally, while differences in residencies (urban vs. rural) have been studied, environment characteristics such as access to parks and neighborhood safety have not been studied in previous research. Participants rely on their environment to get and stay active in digital health PA interventions. Therefore, understanding environmental barriers to engagement and PA is important to better address individuals' needs. Additionally, a more comprehensive examination of the relationship between health and program engagement is needed, especially in digital online-based interventions offered in a clinical setting. More research is needed to identify health factors that may necessitate extra support.

Understanding program engagement is crucial to increase program effectiveness in improving PA across populations, to identify groups who may need extra supports to be successful, and to identify areas where the intervention should be improved. Few studies have examined the relationship between baseline factors and engagement as the primary aim, instead exploring this relationship as a secondary aim. Because of this, it is possible that studies are not powered to identify any relationships between baseline factors and engagement which could result in an erroneous lack of association. To our knowledge, only one study examined a list of baseline factors across multiple domains to program engagement. They found no significant relationship between any baseline factor and engagement.[41] However, this study likely was not powered to examine the association between baseline factors and program engagement. Due to the small number of comprehensive studies and the lack of consistency across previous research, more research is needed to understand the relationship between baseline demographic and personal factors and engagement to ensure the accessibility and effectiveness of digital PA interventions across a diverse population.

2.0 Objectives

Understanding factors which influence digital health intervention engagement is crucial for identifying participants who are more likely to succeed and those who may need additional supports. The primary aims of this manuscript are 1) to describe participant engagement in an online PA digital health intervention for physical activity improvement and 2) to identify baseline factors related to program engagement.

3.0 Methods

The ActiveGOALS study was a three-month, one-on-one digital online-based intervention study designed to increase physical activity levels and decrease sedentary time in adults. We used a randomized controlled trial (RCT) design with a wait-listed control group. All enrolled participants were randomized to receive the intervention immediately or after a three-month waiting period. A stratified recruitment strategy by age (21-54 vs 55-70 years) was employed to ensure equal distribution of younger and older adults across assignment groups. An a priori secondary hypothesis is to determine primary outcomes (of change in activity and sedentary behavior) across age groups . Assessments were completed at baseline and after three months when the immediate participants completed the ActiveGOALS program and before the wait-listed participants began the program. All participants were followed for six months after the start of their intervention. The study was approved by the Human Research Protection Office at the University of Pittsburgh (STUDY19080212).

3.1 Participants and Recruitment

Participants were eligible to participate if they were between the ages of 21-70 years, had at least a sixth-grade literacy level, access to a computer and internet, and were able to complete PA for bouts of 10 minutes at a moderate intensity. Participants were also excluded if they were pregnant or planning to become pregnant in less than 6 months and/or were non-ambulatory or planning a procedure that would cause them to become non-ambulatory in less than 6 months.

Recruitment took place between October 2018 and May 2019 through a local primary care office (University of Pittsburgh Physicians- General Internal Medicine- Oakland, Pittsburgh, Pennsylvania [UPP-GIMO]) and through an online recruitment tool "Pitt+Me." The Pitt+Me system is a registry of over 200,000 volunteers interested in participating in research studies.[44] Flyers and brochures were distributed in the waiting room at UPP-GIMO and patients were able to ask their physicians for a referral or directly contact the study to complete screening. Physicians were also able to identify and refer eligible patients to the study. A targeted email was sent to approximately 3,500 adults aged 21 to 70 years who expressed interest in lifestyle programs through Pitt+Me. Interested individuals were referred to ActiveGOALS study staff for screening. All participants were required to have their primary care physician complete a referral form that indicated that the intervention would be safe and appropriate for their patient.

3.2 Intervention

The intervention has been described elsewhere.[45] Briefly, the ActiveGOALS study was a three-month, one-on-one online intervention study based on the social-cognitive theory designed to increase physical activity levels and decrease sedentary time in adults. Participants had access to all ActiveGOALS program materials (13 weekly lessons, 2 technical lessons, tracking tools, and workbook pages) through the online platform. Trained health coaches tracked participant progress and communicated weekly with participants through a secure messaging system. They also provided feedback on participant workbook pages, worked with participants to set and achieve goals, and were available if a participant had questions or needed further support.

Participants were given a body-worn step counter as an intervention tool. Participants randomized to immediate intervention were given an Omron Alvita monitor and wait-listed participants were given a Fitbit Alta monitor to examine whether a monitor with additional features may add to the success of the program.

Additional contact was used to promote adherence to the intervention and ensure high rates of follow-up. Participants who did not log-in to the platform for over 14 days received an extra message from their health coach. If there was no response, additional contacts were used. After lessons were completed, participants retained access to the ActiveGOALS platform, including lesson materials, tracking software, and supplementary materials. Coaching support was no longer provided after the completion of the weekly lesson materials.

3.3 Wait-Listed Control Group

Participants randomized to the wait-listed control group received the full intervention after a three-month waiting period. During the waiting period, they received monthly health fliers on health topics unrelated to the ActiveGOALS intervention. Wait-listed participants had one additional preintervention assessment.

3.4 Baseline Measures

Participants were asked to complete assessments at baseline, three months, and six months. All study assessments were completed online using REDcap to reduce participant burden.

Participants were asked to answer study-specific questions that covered the following domains: confidence in performing PA, demographic, environment, health, healthcare, lifestyle, and quality of life. All variables were self-reported.

At baseline, participants were given a series of two questions to determine sex and gender identity. The first question asked participants to identify sex at birth and the second question asked individuals to identify their pronoun preferences, with choices of "he/him", "she/her", "they/them", "ze/zer", "I prefer not to answer", or the option to report another pronoun not listed. All participants reported only one set of pronouns which matched with their reported sex at birth. Therefore, sex (referring to sex at birth) was used in all analyses. Participants were also asked to report race and ethnicity as two questions that were later collapsed to one variable including both race and ethnicity. A complete list of variables used in the analyses can be found in Appendix A.

Financial score was calculated from the abbreviated 5-item version of the self-report questionnaire developed by the Consumer Financial Protection Bureau.[46] The consumer-driven questionnaire was developed from input by consumers on how they define financial well-being to provide practitioners and researchers with a standard, reliable, and broadly available way to measure individual financial well-being. The original questionnaire and the abbreviated version have been shown to be both valid and reliable. Scores are calculated using a standard scoring sheet and converted to produce a score between 0 and 100 that accounts for age group (18-61 and 62+ years), with higher scores indicating higher perceived financial well-being.

The visual analog scale (EQ VAS) from the EuroQoL (EQ-5D-5L) Health Questionnaire was used at baseline to assess participants' quality of life (QoL). The EQ VAS asks participants to rate their current health state on a visual analog scale from 0 "worst imaginable health state" to

100 “best imaginable health state.” The EQ-5D-5L has been validated across many populations and is comparable to other quality of life measures.[47,48]

The Patient-Reported Outcomes Measurement Information System (PROMIS-29) was also used to assess quality of life across multiple domains. PROMIS-29 has been shown to be reliable and valid.[49] It is a publicly available tool that asks participants to self-report their health across multiple domains, including physical function, pain, sleep, and psychological health.

3.5 Engagement Outcomes

Engagement was defined in terms of breadth, depth, and frequency and aimed to describe all modes of participant-initiated contact with the intervention. Lesson completion was measured as the total number of lessons completed (categorical, 0-4 lessons=Low Completion, 5-14 lessons=Moderate Completion, 15 lessons=Perfect Completion) and average time (days) to complete lesson. Perfect lesson completion was of particular interest because it indicates program completion and therefore was given its own category. Participant-initiated coach contact was defined as the number of weeks (out of a total of 15) that the participant contacted the coach through secure messaging. Tracking was defined by three variables: 1) the number of weeks that the participant tracked PA on at least three days (out of total of 14), 2) the number of weeks that the participant tracked sedentary behavior on at least three days (out of a total of nine), and 3) the average lag time in days from date tracked to date entered into the ActiveGOALS platform [of physical activity and sedentary behaviors] (categorical, <5 days, >=5 days).

3.6 Data Analysis

Descriptive statistics (means, standard deviations, median, interquartile range [IQR] frequencies) were calculated for all variables. Normality was assessed using histogram plots and normality tests. Predictor and outcome variables were examined by age (21-54 years and 55-70 years). Two sample t-test, chi-squared test, and fishers exact test were used to examine differences in predictor and outcome variables by age. To provide robust estimates, Generalized Linear and Nonlinear Mixed Models (PROC MIXED and PROC GLIMMIX) were used to examine the relationship between predictor and outcome variables. A step-wise model building procedure was used in which predictor variables were classified into seven domains: confidence, environment, health, healthcare, demographic, lifestyle, and quality of life. Individual models were developed within each classification group. For these models, each predictor variable within a domain was individually added to a univariate model to examine the relationship between predictor and outcome variable. A univariate p-value <0.25 was required for initial inclusion into domain-specific models. Variables were removed one by one until only variables with p-values <0.10 were included in the model, resulting in domain-specific models for each outcome variable. Variables retained in each domain-specific model were then included in the final model building procedure. Variables with $p>0.10$ in the full model were removed sequentially starting with the highest p-value until only those variables from across all categories with $p<0.05$ were retained in the parsimonious model for a given outcome variable. This method was used to enable the investigation of a larger number of potential predictor variables, despite the small size of the pilot study population. All data analyses were conducted in SAS v 9.4 (SAS Institute, Inc., Cary, NC).

4.0 Results

A total of 79 participants were included in the sample. On average, participants were 50.8± 15.8 years. The majority of participants were female (77.2%), white non-Hispanic (74.7%), and self-reported an average of 27 minutes per week of PA at baseline (Table 1).

Table 1. Descriptive Data of Participants (N=79)

	M±SD or N (%)
Age	50.8±15.8
Sex	
Female	61 (77.2)
Male	18 (22.8)
Race/Ethnicity	
White, non-Hispanic	59 (74.7)
Black and/or African American	12 (15.2)
Other	8 (10.1)
Education Level	
Some High School or Less Than High School	1 (1.3)
High School or GED	2 (2.5)
Post-High School Technical Training	2 (2.5)
Some College	16 (20.3)
College Degree	29 (36.7)
Post-College Degree	29 (36.7)
Finance score (0-100)	59.4±15.5
Work Status	
Fully Retired	22.0 (27.9)
Partially Retired	4.0 (5.1)
Unemployed-Preretirement	9.0 (11.4)
Employed 40+	31.0 (39.2)

Employed <40 preretirement	13.0 (16.5)
Self-Reported PA (min/wk)	27.0±31.4
Self-Report Urgent Care Visit in last 3 months	
No	70 (88.6)
Yes	9 (11.4)
BMI >25	
No	23 (29.1)
Yes	56 (70.9)
Receiving Depression Treatment	
No	58 (73.4)
Yes	21 (26.6)
High Triglycerides	
No	62 (78.5)
Yes	17 (21.5)
Ever Diagnosed with Diabetes or Pre-Diabetes	
No	74 (93.7)
Yes	5 (6.3)
Metabolic Conditions (3+)	
No	66 (83.5)
Yes	13 (16.5)
PROMIS-29 Anxiety (T Score) (N=78)	48.7±8.7
PROMIS-29 Depression (T Score) (N=78)	47.4±8.3
PROMIS-29 Fatigue (T Score) (N=78)	50.6±9.9
PROMIS-29 Function (T Score) (N=78)	53.3±6.1
PROMIS-29 Pain (T Score) (N=78)	47.6±7.2
PROMIS-29 Sleep (T Score) (N=78)	50.4±5.1
PROMIS-29 Social Rules (T Score) (N=78)	50.5±9.1
Self-Report ER or Overnight Hospital Stay in Past 3 Months	
No	74 (93.7)
Yes	5 (6.3)
When Seen Any Doctor Last	
<6 months	65 (82.3)
6 months- 1 year	10 (12.7)
1-3 years	3 (3.8)

	>3 years	1 (1.27)
Living with Children < 18 years		
	No	69 (87.3)
	Yes	10 (12.7)

4.1 Description of Engagement Variables

Program engagement was described using six outcome variables, lesson completion, time to complete lessons, participant-initiated coach contact, tracking both PA and sedentary behaviors on at least three days, and lag time between tracking and logging PA and sedentary behaviors. Overall, lesson completion was high, with 58.2% of participants completing all 15 intervention lessons. Participants completed each lesson on average 6.6± 4.6 days after the lesson was released. Participant-initiated coach contact was also assessed. On average, participants messaged their health coach 5.6±3.3 weeks out of a possible 15 weeks. Self-monitoring also occurred frequently. On average, participants tracked PA for at least 3 days out of the week on 11.3±4.0 weeks out of a possible 14 weeks. Participants tracked sedentary breaks for at least 3 days out of the week for an average of 6.1±3.8 weeks out of a possible 9 weeks. The majority of participants took longer than five days to log activity for a given day (61.4%). See Table 2 for complete description of all engagement outcomes.

4.2 Engagement by Age Group (21 to 54 and 55 to 70 years)

The primary engagement outcomes were also examined by age group to identify whether there were significant differences in engagement for younger versus older adults (21-54 vs 55-70 years). Lesson completion was similar across age groups with adults aged 55 to 70 having a slightly longer mean lesson completion time than younger adults (7.4 $\pm$5.1 versus 5.5 $\pm$3.6) (n.s. p=0.07). Adults aged 55 to 70 years old were also more likely to initiate contact with their health coach compared to younger adults (6.7±3.4 vs. 4.4±2.7, p=0.001). However, there were no significant differences by age in the number of weeks where PA was tracked on at least three days or the number of weeks where sedentary breaks were tracked on at least three days. The time between tracking PA and sedentary breaks and logging it on the ActiveGOALS platform was also not significantly different by age.

Table 2 Engagement Outcome Variables, Stratified by Age (21-54 vs 55-70 years)

	Age, years			
	Total	**21-54 years**	**55-70 years**	
	M±SD or N(%)	**M±SD or N(%)**	**M±SD or N(%)**	**P-value**
Number of Lessons Completed (N=79)				0.307
Low Completion	12 (15.2)	7 (18.9)	5 (11.9)	
Medium Completion	21 (26.6)	7 (18.9)	14 (33.3)	
Perfect Completion	46 (58.2)	23 (62.2)	23 (54.8)	
Average Lesson Completion Time, days (N=74)	6.6±4.6	5.5±3.6	7.4±5.1	0.073
Participant-initiated coach contact (N=77)	5.6±3.3	4.4±2.7	6.7±3.4	0.001

Number of Weeks PA tracked ≥3 days (0-14) (N=74)	11.3±4.0	11.5±3.8	11.1±4.1	0.636
Number of Weeks Sedentary Breaks tracked ≥3 days (0-14) (N=74)	6.1±3.8	6.6±3.6	5.8±3.9	0.336
Tracking lag time to reporting days				0.248
< 5 days	27 (38.6)	10 (31.3)	17 (44.7)	
>5 days	43 (61.4)	22 (68.8)	21 (55.3)	

4.3 Baseline Predictors of Total Number of Lessons Completed

Table 3 depicts the final model for total number of lessons completed. Perfect lesson completion was of particular interest to this study. The final model included current treatment for depression and sex. Current treatment for depression was associated with 0.68 lower odds of achieving perfect lesson completion compared to those not receiving treatment for depression (OR=0.32, CI= 0.11, 0.89), while being female was associated with 3.84 higher odds of achieving perfect lesson completion compared to being male (OR=3.84, CI= 1.31, 11.28).

Table 3 Total Number of Lessons Completed, Final Model [a,b]

[a]adjusted for assignment group [b]Modelling perfect lesson completion compared to less than perfect lesson completion

	Estimate (SE)	P Value	Odds Ratio	CI
Intercept 3	-0.19 (0.49)	0.700	-	-
Intercept 2	1.33 (0.52)	0.012	-	-
Self-Reported Depression Treatment	-1.13 (0.51)	0.029	0.32	0.11, 0.89

Female (vs. Male) Sex	1.35 (0.54)	0.015	3.84	1.31, 11.28

4.4 Baseline Predictor of Average Lesson Completion Time, Days

The final parsimonious model included having an urgent care visit in the 3 months prior to baseline, being overweight or obese (BMI>25), and current treatment for depression (see Table 4). Reporting an urgent care visit in the three months prior to baseline was associated with an estimated 4.58 day decrease in time to complete lesson compared to those who did not report an urgent care visit in the three months prior to baseline (p=0.008). Furthermore, a BMI > 25 was associated with a 2.74 day increase in time to complete lesson compared to BMIs < 25 (p=0.015). Finally, reporting current depression treatment was associated with an estimated 2.6 day increase in time to complete each lesson (p=0.022).

Table 4 Average Lesson Completion Time, days: Final Model [a]

[a]adjusted for assignment group

	Estimate (SE)	P-value
Intercept	3.49 (1.20)	0.004
Self-Report Urgent Care Visit in Last 3 Months	-4.58 (1.69)	0.008
BMI>25	2.74 (1.10)	0.015
Self-reported Depression Treatment	2.61 (1.12)	0.022

4.5 Baseline Predictors of Number of Weeks of Participant-Initiated Coach Contact

The final model included high triglycerides and PROMIS t-scores for function and for sleep (see Table 5). Reporting high triglyceride levels was associated with an estimated 2.20 increase in number of weeks a participant initiated contact with their health coach compared to lower triglyceride levels (p=0.009). Every one-unit increase in PROMIS function t-score was associated with a 0.13 decrease in number of participant-initiated coach contact in weeks (p=0.019) and every one-unit increase in PROMIS sleep t-score was associated with an estimated 0.21 decrease in number of participant-initiated coach contact in weeks (p=0.002).

Table 5 Number of Weeks Participant-Initiated Coach Contact: Final Model[a]

[a]adjusted for assignment group

	Estimate (SE)	P-value
Intercept	22.52 (4.81)	<0.0001
High Triglycerides	2.19 (0.82)	0.009
PROMIS-29 Function (T Score)	-0.13 (0.055)	0.019
PROMIS-29 Sleep (T Score)	-0.21 (0.07)	0.002

4.6 Baseline Predictors of Number of Weeks Participant Tracked PA on at Least Three Days

No baseline factor significantly predicted tracking physical activity. See Appendix B for non-significant factors influencing PA tracking.

4.7 Baseline Predictors of Number of Weeks Participant Tracked Sedentary Breaks on at Least Three Days

The final model included self-reported ER or overnight hospital stay in the 3 months prior to baseline, time since last doctor's visit, and sex (Table 6). Reporting an ER or overnight hospital stay in the three months prior to baseline was associated with an estimated 3.32 increase in the number of weeks sedentary breaks were tracked on at least three days (p=0.037). Additionally, compared to last seeing a doctor > 3 years ago, seeing a doctor within six months of baseline was associated with an estimated 7.32 increase in the number of weeks sedentary breaks were tracked on 3+ days (p=0.035). Finally, being male was associated with tracking sedentary breaks an estimated 2.29 less weeks on average (p=0.018).

Table 6 Number of Weeks Participant Tracked Sedentary on at Least 3 Days, Final Model[a]

[a]adjusted for assignment group

	Estimate (SE)	P-value
Intercept	-1.19 (3.44)	0.730
Self-report ER or Overnight Hospital Stay in Past 3 Months	3.32 (1.56)	0.037
When Last Seen Doctor (ref=>3 years)		0.037
<6 months	7.32 (1.56)	0.035
6 months-1 year	8.38 (3.58)	0.022
1-3 years	0.73 (3.87)	0.851
Male (vs. Female) Sex	-2.29 (0.95)	0.018

4.8 Baseline Predictors of Average Lag Time Between Tracking PA or Sedentary and Logging it on ActiveGOALS Platform

The final model included living with children < 18 years old (Table 7). Living with children < 18 years old was associated with 1.27 higher odds of an average lag time greater than five days (OR=1.27, CI=0.45, 3.61).

Table 7 Average Time Between Tracking PA or Sedentary and Logging it on ActiveGOALS Platform, Final Model[a]

[a]adjusted for assignment group

	Estimate (SE)	P-value	OR	CI
Intercept	0.58 (0.36)	0.117		
Living with children < 18 years	-2.48 (1.11)	0.029	1.27	0.45, 3.61

5.0 Discussion

This study, involving an online intervention for physical activity improvement, assessed several components of engagement, including lesson completion, tracking, and messaging. These results suggest that program engagement was high across all engagement outcomes. Furthermore, this effort is one of only a few to assess the relationship between a large number of baseline factors across multiple domains (confidence, environment, health, healthcare, demographic, lifestyle, and quality of life) and program engagement. The results suggested that a smaller number of factors across five of the seven domains were related to program engagement, after adjusted for all other relevant factors.

Previous research studies report a wide range of participant engagement (from low to high) in physical activity digital interventions, which may be a result of the wide variation in program formats, materials, and delivery strategies.[23-37] Programs with high levels of engagement tended to include individualized programming and support from a health coach or other exercise/health professional,[24,29,30] whereas programs with low engagement tended to have low external accountability to complete lessons or to interact with the digital platform.[23,26-28] One study by Glasgow et al. found that those who received support in addition to online intervention access had better engagement than those who had access to the online intervention alone.[41] The ActiveGOALS program resulted in relatively high levels of engagement. Compared to other programs, this program could be considered as having a moderately high level of participant support for a digital intervention due to the inclusion of a low-touch remote health coach that provided support, encouragement, and accountability to each participant toward completing the intervention and improving PA levels. The coach's time investment was expected to be 10-15 minutes/ week per participant. The program also included optional automated push messaging reminders to complete the weekly program lessons and log activity. On average, lesson completion was high, and participants completed each lesson within a week after the lesson was released. A lag time of 5 days between completion of a lesson and release of the next lesson was already built into the program to allow participants time to implement lesson materials and achieve new weekly goals. When added to the time participants took to complete a lesson after it was released, this suggests that the average time between lesson completion is closer to 10 days, instead of the 7 days we would have expected. This may have been the result of participants waiting for a push message reminder to login or a coach-initiated login reminder included in their weekly feedback. It could also be the result of some individuals taking a hiatus from the program. In all, 22% of participants (n=18) paused their participation for 28 days or more from the program. Individuals reporting a race/ethnicity other than non-Hispanic white were more likely (45% versus 15%) to take a hiatus ≥28 days; differences across age and sex groups were not apparent (data not shown). To encourage participants to return after a hiatus protocol was in place for health coaches to contact participants after a 14-day period of inactivity on the ActiveGOALS platform and after 21 days a postcard was sent to encourage participants to return to the program. It is possible that the combination of regular reminders and the flexible design that allowed participants to "pick back up" where they left off after a hiatus were important contributing factors to the high program engagement.

Behavior tracking has been shown to be one of the most important components of social-cognitive theory based interventions, like ActiveGOALS, and is a central component in PA intervention programs.[50] These results suggest that tracking physical activity and sedentary behaviors was relatively high. This could be expected as tracking was emphasized in lesson materials (including a technical lesson specific to tracking) and by the health coach on a weekly basis. While participants appeared to log at least three days of tracking information on most weeks, the majority of participants had an average lag time of greater than five days between the day the activity took place and logging the behavior on the ActiveGOALS platform. This suggests that participants were relying on their memory, the activity monitor memory or hand tracking with paper logs and were not engaging with the ActiveGOALS platform on a daily basis as intended. Based on the lag time, it is possible that they were only logging their records into ActiveGOALS when logging in for another reason (e.g. completing a lesson or messaging their coach).

The effect of age on program engagement is of interest, especially in digital health interventions where those who are older may have more difficulties navigating digital platforms. Due to concerns regarding whether older adults would have more difficulties engaging with a digital intervention, the recruitment and randomization for this study was stratified to ensure that an equal number of older (aged 55-70) adults were in each randomized group as younger adults (aged 21-54 years). When program engagement metrics were stratified by these groups, we found significant differences in engagement by age for participant-initiated messaging with adults aged 55 to 70 years initiated messaging to their health coach more often (6.7±3.4 vs. 4.4±2.7 weeks; p=0.0014). Although not significant, adults aged 55 to 70 years also took slightly longer on average to complete lessons (7.4 ±5.1 versus 5.5 ±3.6; p=0.07). While older adults took a slightly longer time to complete lessons, the distributions within each age groups are similar. Additionally, there were outliers in the older adults group who took much longer (28 days or more) to complete lessons. This is an important finding as older adults may need more time and higher flexibility to complete lessons and appear to benefit from the ability to request extra coaching support that would not be available in "automated touch" programs that push out messages and reminders to participants, but do not provide live coaching support. There were no significant differences by age for number of lessons completed, tracking PA, tracking sedentary behaviors, or average lag time between tracking and logging health behaviors, suggesting that older adults were able to access the online platform and utilized the electronic tracking tools provided by the study as well as younger adults. It is also worth noting that while age was considered along with other baseline variables as a predictor of program engagement, it was not significant in any of the fully adjusted models. This suggests that, unlike previous programs,[25,42] there were not important differences in engagement across age groups for this program.

Because participants are initiating contact with digital PA interventions, a detailed picture of program engagement is needed to understand the effectiveness of these programs, which is why we sought to examine the association between baseline factors and several aspects of program engagement. Perski et al. suggested measuring program engagement by capturing the breadth, depth, and frequency of interaction with the intervention that is specific to the mode of program delivery (e.g. social media, online-based, app-based).[51] The results of this current effort suggest that baseline factors from five of the seven domains examined had significant relationships with five of the six engagement outcome variables examined.

Multiple previous studies examining the relationship between baseline factors and program engagement did not find any associations.[27,40,41] However, most digital health interventions measure engagement by platform usage (e.g. website log-ins) alone,[38,51] while this study captured a more comprehensive description of engagement by seeking to quantify all aspects of participant-initiated interactions with the intervention platform, materials, and other components.

To our knowledge, only one prior study has examined the relationships between many baseline factors across multiple domains and program engagement. Like ActiveGOALS, this was a social-cognitive theory based intervention coordinated with clinical care that included a PA goal.

[41] Unfortunately, it is difficult to compare the two studies because their intervention was developed to improve type II diabetes management and though it included an activity goal, PA was not the primary goal. Their program also required a different level of engagement and only measured engagement as the number of website log-ins and number of website pages visited, whereas our study examined all aspects of participant-initiated interactions with the intervention platform, materials, and other components. They also did not examine any factors that relate to environment, lifestyle, or quality of life. Our study is the first PA focused study we are aware of to examine relationships between baseline factors across this many domains and program engagement. It is worth noting that, in our review of the literature, we found that the few studies reporting on engagement and the wide variation between study methods makes it difficult to compare results across studies. More research is needed toward developing an understanding of systemic issues that may be barriers to program engagement.

The results of this current effort did identify several baseline factors related to program engagement. Being male was associated with completing fewer total lessons and less tracking of sedentary behaviors, but not less tracking of PA, appearing to contradict previous studies in which males had higher program engagement in digital health interventions.[42] This difference between previous research and our results may be in part due to differences in the way engagement was defined and measured as well as the inclusion of sedentary behaviors in our intervention program materials. More information toward male perspective on reducing sedentary behavior as well as a better understanding of time spent in specific leisure physical activities would be helpful toward understanding approaches to better support uptake of sedentary tracking.

In this study, self-reported depression treatment was significantly inversely related to total number of lessons completed and average days to complete lesson. This agrees with previous literature which found an inverse relationship between depression and program engagement.[42] Other health factors related to program engagement include BMI > 25 and high triglycerides. In this present study, BMI >25 was associated with an almost three day increase in time to complete lessons. A systematic review by Burgess et al. showed that lower BMI was related to higher engagement measured by adherence.[42] Other healthcare factors were related to program engagement, including self-reported urgent care visit in the past 3 months, self-reported ER or overnight hospital stay, and the amount of time since they had last seen any doctor. Self-reported urgent care visit was associated with an average of a nearly 5-day decrease in average time to complete lessons. Both self-reported ER or overnight hospital stay and seeing a doctor within the past year was positively associated with tracking sedentary behaviors. Those with recent contact with a healthcare provider may be more aware of their health status, have a better understanding of the importance of tracking behaviors, or be more motivated to engage in provider-referred online health intervention. To our knowledge, this was the first study to examine the relationship between healthcare baseline factors and program engagement. Further research should examine this relationship in a larger sample size.

Quality of life PROMIS-29 function and sleep t-scores were significantly negatively related to participant-initiated messaging to the health coach. However, the beta estimates are small, meaning that though it is significant, the impact is not great. This was the first study to examine the relationship between any quality-of life measure and engagement. Living with children <18 years was significantly related to lag time between tracking behaviors and logging it on the ActiveGOALS platform. This may be indicative of the difficulty with time management related to the additional responsibility of caring for children. Future research should examine this relationship in a larger sample size.

Finally, it is worth noting that we did not identify any baseline factors that were significantly associated with tracking PA behaviors. Participants were highly engaged in tracking PA behaviors with a median (IQR) of 13 (11, 14) weeks out of a possible 14 weeks with at least three days of recorded PA tracking. PA tracking was an important part of this digital online-based lifestyle intervention and participants received regular reminders to complete their weekly tracking with the intervention lessons stressing the importance of tracking their PA behaviors.

Ofili et al found a significant association between anxiety about internet use and engagement with a digital online lifestyle intervention. However, self-rated ability to use a computer was not associated with engagement.[43] We did not measure anxiety towards internet use or ability to use a computer and therefore were not able to examine the relationship between those factors and program engagement with our digital online-based intervention. To ensure equitable access and support for digital online-based lifestyle interventions, future research should examine this relationship.

5.1 Strengths and Limitations

The present study had several limitations. First, though this study was able to successfully examine the relationship between a large number of baseline factors and program engagement, this was a secondary analyses and was not included in the original power calculations. In relation to this, although this was large for a pilot study, we had a relatively small sample size (N=79) to examine such a large number of predictor variables. Even with using our domain specific approach, if many of the variables had been significant in the univariate analyses, we may have been underpowered to see any relationships in our final model building procedures. Finally, our sample was more educated than the general population and it is possible that these clinical care patients had higher technology literacy compared to the general population of patients. Because we did not capture technology literacy, we cannot verify this.

A major strength of our study is measuring program engagement in terms of depth, breadth, and frequency. By capturing engagement across all components of our digital online-based PA intervention, we were able to provide an accurate description of how participants interacted with this intervention. We also were able to identify baseline factors related to five out of the six engagement outcome variables measured. In relation to this, we were able to examine the relationship between baseline factors across seven domains and program engagement. This allowed us to gain a deeper understanding of our participant sample as well as understand what influences program engagement. This information can be used to improve program support for engagement and begin to develop phenotypes of individuals who may need different types of additional support toward engagement in specific components of these programs.

5.2 Public Health Significance

Overall, engagement was high in this digital online-based PA intervention. Significant baseline factors relating to engagement include variables across multiple domains, including demographic, health, healthcare, and quality of life. More research should focus on understanding program engagement in males, those with depression and other psychosocial conditions, and those who do not have regular contact with a healthcare provider. For digital online-based PA interventions to be successful, it is important to engage participants across all components of the intervention. These findings can help future public health efforts to provide extra supports to those who may struggle to engage with digital PA interventions.

Appendix A List of Predictor Variables Used to Examine Relationship Between Baseline Factors and Engagement Outcomes

Table 8 List of Predictor Variables Used to Examine Relationship Between Baseline Factors and Engagement Outcomes

All variables were self-reported by participant at baseline. Baseline factors were divided into seven domains: Confidence, Environment, Health, Healthcare, Demographics, Lifestyle, and Quality of Life.

CONFIDENCE	
Confidence in PA on 3 days when anxious	Scale 0-10
Confidence in PA on 3 days when depressed	Scale 0-10
Confidence in PA on 3 days when discomfort	Scale 0-10
Confidence in PA on 3 days when health low	Scale 0-10
Confidence in PA on 3 days when pressure	Scale 0-10
Confidence in PA on 3 days when other priorities	Scale 0-10
Confidence in PA on 3 days when problems	Scale 0-10
Confidence in PA on 3 days when no support	Scale 0-10
Confidence in PA on 3 days when no time	Scale 0-10
Confidence in PA on 3 days when tired	Scale 0-10
Confidence in PA on 3 days when have visitors	Scale 0-10
Confidence in PA on 3 days when bad weather	Scale 0-10
Confidence in PA on 3 days when working	Scale 0-10
Total confidence score for exercise 3 days/week	Scale 0-130
ENVIRONMENT	
Neighborhood type	Categorical
Neighborhood has sidewalks	Yes/no
Neighborhood has safe roads	Yes/no
Neighborhood has walking/biking trails	Yes/no
Neighborhood has public park	Yes/no
Neighborhood has public walking/running track	Yes/no
Neighborhood has sports courts/fields	Yes/no
Neighborhood has community and/or senior center	Yes/no
Neighborhood has fitness center	Yes/no
Neighborhood has indoor shopping mall	Yes/no
Neighborhood has golf course	Yes/no
Total number of neighborhood activity features	Categorical, 0-10
HEALTH	
Body Mass Index as baseline	Continuous

Injury related to PA in last 3 months	Yes/no
Urgicare visit in last 3 months	Yes/no
ER or overnight hospital stay in last 3 months	Yes/no
Overweight or Obese based on BMI	Yes/no
Anxiety or depression diagnosis	Yes/no
Any diagnosis of arthritis, all types	Yes/no
Any cancer diagnosis	Yes/no
Any cardiovascular diagnosis, stroke, MI, atherosclerosis, myopathy	Yes/no
High cholesterol	Yes/No
Current depression treatment	Yes/no
Mother, father, brother, or sister with diabetes	Yes/no
Any diagnoses of diabetes or prediabetes	Yes/no
High blood pressure	Yes/No
Diagnosis of any lung illnesses, COPD, asthma, emphysema	Yes/no
Number of MET conditions, self-report	Continuous
3 or more METS components diagnoses or treated	Yes/no
Prediabetes	Yes/No
Self-report any hypothyroid diagnosis	Yes/no
High Triglycerides	Yes/no
Weight in kilograms	Continuous
Weight in pounds	Continuous
HEALTHCARE	
When seen any doctor	1=<6 months 2=6 months – 1 year 3= 1 – 3 year 4=>3 year 5-Never
When doctor asked about physical activity behaviors	1=<6 months 2=6 months – 1 year 3= 1 – 3 year 4=>3 year 5-Never
When doctor asked about any other lifestyle behaviors	1=<6 months 2=6 months – 1 year 3= 1 – 3 year 4=>3 year 5-Never
When doctor asked about weight	1=<6 months 2=6 months – 1 year 3= 1 – 3 year 4=>3 year 5-Never
Has health insurance	Yes/no

When last seen a primary care doctor	1=<6 months 2=6 months – 1 year 3= 1 – 3 year 4=>3 year 5-Never
LIFESTYLE	
Diet quality	Scale 1 (very bad) – 4 (very good)
8oz water servings per day past month	Continuous
8oz sugary beverage servings per day past month	Continuous
Has exercised in last month	Yes/no
How many days exercised in last month	Continuous (1+)
Has tracked physical activity in last month	Yes/no
How many days tracked physical activity in last month	Continuous (1+)
Actual sleep in hours per night past month	Continuous
Sleep quality	Scale 1 (very bad) – 4 (very good)
0.5 cup servings of vegetables per day past month	Continuous
Has weighed self in last month	Yes/no
How many days weighed self in last month	Continuous (1+)
Currently attempting to lose weight	Yes/no
Currently smoking (at baseline)	Yes/no
Past smoking	Yes/no
Smoking	0=neither 1=past 2=now
Physical activity in minutes per week	Continuous
PERSONAL/DEMOGRAPHIC	
Age, years	Continuous
Age, categorical	Categorized (21-54, 55-70)
Number of adults cohabitating	Continuous
Number of youth cohabitating	Continuous
Living with any adults 18+ years old	Yes/no
Living with any children/youth <18 years old	Yes/no
Total number of individuals cohabitating	Continuous
Current relationship status	1=single 2=married 3=partnered 4=in relationship, not married or partnered
Sex assigned at birth	Male/ Female
Education level achieved	
Work Status	1=fully retired 2=partially retired

	3=unemployed, pre-retirement 4=employed 40+ 5=employed <40, preretirement
Finance Score (0-100)	Continuous
Number of jobs worked	1=1 2=2 3=3+
Race/Ethnicity	1=White, non-Hispanic 2=Black and/or African American 3=All remaining
QUALITY OF LIFE	
EQVAS Visual Analog Scale	Continuous, scale 0-100
PROMIS-29 Anxiety t-score	Continuous
PROMIS-29 Depression t-score	Continuous
PROMIS-29 Fatigue t-score	Continuous
PROMIS-29 Function t-score	Continuous
PROMIS-29 Pain t-score	Continuous
PROMIS-29 Sleep t-score	Continuous
PROMIS-29 Social Rules t-score	Continuous

Appendix B Univariate Models Used in Model-Building Process

Table 9 Univariate Model Building Baseline Predictor Variables vs Engagement Outcome Variables

The table illustrates p-values for each univariate model between predictor variable and engagement outcome. Univariate models were used in the first round of model building to examine the relationship between baseline factors and engagement outcomes. An * denotes variables with p-values <0.25 that were included in the second round of model-building.

	Engagement Outcome Variables					
	Average Time to Complete Lesson, days	Total Number of Lessons Completed, Perfect vs Medium vs Low	Participant-Initiated Coach Contact, weeks	Number of Weeks Participant Tracked PA 3+ Days	Numbers of Weeks Participant Tracked Sedentary 3+ Days	Tracking Lag Time to Reporting, < 5 days or >5 days
Predictor Variables						
Assignment group	0.6298	0.6444	0.2781	0.3466	0.2186*	0.4461
Confidence Domain						
Total confidence score for exercise 3 days/week	0.5509	0.7963	0.6922	0.9495	0.7952	0.8769
Confidence in PA on 3 days when anxious	1	0.5032	0.5302	0.1142*	0.249*	0.8605

Confidence in PA on 3 days when depressed	0.4124	0.6391	0.7951	0.4067	0.4568	0.6128
Confidence in PA on 3 days when discomfort	0.9648	0.8897	0.8896	0.4267	0.8595	0.6931
Confidence in PA on 3 days when health low	0.4965	0.5219	0.7888	0.8848	0.7976	0.7897
Confidence in PA on 3 days when pressure	0.7789	0.9766	0.2389*	0.3713	0.9409	0.6978
Confidence in PA on 3 days when other priorities	0.3461	0.9091	0.7441	0.7878	0.9893	0.2957
Confidence in PA on 3 days when problems	0.2828	0.5515	0.9436	0.2532	0.1608*	0.9901
Confidence in PA on 3 days when no support	0.7649	0.4581	0.7074	0.8031	0.9248	0.9133
Confidence in PA on 3 days when no time	0.3302	0.7947	0.8335	0.3749	0.8715	0.804
Confidence in PA on 3 days when tired	0.4495	0.7742	0.7313	0.8771	0.7056	0.526
Confidence in PA on 3 days when have visitors	0.1219*	0.6875	0.7391	0.97	0.7336	0.9147
Confidence in PA on 3 days when bad weather	0.8472	0.7004	0.4753	0.7313	0.6514	0.6139

Confidence in PA on 3 days when working	0.4255	0.8027	0.3319	0.605	0.5587	0.7503
Environment Domain						
Self-reported neighborhood type	0.2274*	0.9828	0.8733	0.4861	0.8813	0.4352
Neighborhood has sidewalks	0.932	0.9864	0.4392	0.0861*	0.9164	0.9937
Neighborhood has safe roads	0.8107	0.1695*	0.6379	0.3914	0.3535	0.5603
Neighborhood has walking/biking trails	0.4614	0.2523	0.3074	0.0951*	0.9317	0.0985*
Neighborhood has public park	0.4034	0.6738	0.0673*	0.6194	0.7682	0.2192*
Neighborhood has public walking/running track	0.6409	0.5523	0.8688	0.8115	0.8988	0.6826
Neighborhood has sports courts/fields	0.9414	0.9909	0.2216*	0.6562	0.8006	0.6286
Neighborhood has community and/or senior center	0.5506	0.9385	0.5333	0.1896*	0.3217	0.4198
Neighborhood has fitness center	0.2156*	0.1653*	0.3701	0.7955	0.8323	0.3029
Neighborhood has indoor shopping mall	0.9566	0.4239	0.5471	0.735	0.8848	0.4753
Neighborhood has golf course	0.9575	0.8323	0.6824	0.9684	0.4404	0.1727*
Total number of neighborhood	0.8453	0.7019	0.7084	0.6872	0.5971	0.5142

activity features 0-10						
Self-report neighborhood safety	0.036*	0.6394	0.104*	0.9846	0.9187	0.9031
Health Domain						
Body Mass Index as baseline	0.586	0.9746	0.4578	0.6633	0.8132	0.6272
Self-report injury related to PA in last 3 months	0.7989	0.453	0.6945	0.9116	0.5524	0.5352
Self-report urgicare visit in last 3 months	0.0107*	0.8449	0.9432	0.148*	0.1728*	0.297
Self-report ER or overnight hospital stay in last 3 months	0.2538	Unable to get p-value	0.0394*	0.3549	0.0687*	0.746
Overweight or Obese based on BMI	0.0277*	0.6253	0.3406	0.4668	0.5498	0.6982
Self-report anxiety or depression diagnosis	0.165*	0.1549*	0.3813	0.3301	0.7645	0.6894
Self-report any diagnosis of arthritis, all types	0.6181	0.5731	0.0307*	0.5247	0.4598	0.8081
Self-report any cancer diagnosis	0.4531	0.4994	0.0875*	0.7844	0.4913	0.1905
Self-report any cardiovascular diagnosis, stroke, MI, atherosclerosis, myopathy	0.6814	0.4689	0.4404	0.4921	0.6966	0.1531*
High Cholesterol	0.3311	0.3357	0.94	0.8802	0.9939	0.8641
Depression treatment	0.0747*	0.0672*	0.3705	0.327	0.511	0.6944

Mother, father, brother, or sister with diabetes	0.6671	0.5843	0.4496	0.667	0.352	0.9976
Self-report any diagnoses of diabetes or prediabetes	0.4116	0.7351	0.3035	0.291	0.5664	0.87
High blood pressure	0.5235	0.5125	0.7799	0.7314	0.7062	0.6785
Self-report diagnosis of any lung illnesses, COPD, asthma, emphysema	0.4615	0.772	0.7083	0.8855	0.6276	0.7016
Number of MET conditions, self-report	0.1622*	0.6087	0.4988	0.6263	0.893	0.9315
3 or more METS components diagnoses or treated	0.1251*	0.1462*	0.7678	0.7978	0.6847	0.99
Ever diagnosed with prediabetes	0.1825*	0.6002	0.6921	0.78	0.8493	0.9906
Self-report any hypothyroid diagnosis	0.6262	0.9957	0.4034	0.1547*	0.1968*	0.6045
High Triglycerides	0.6938	0.7053	0.0051*	0.309	0.2774	0.327
Weight in kilograms	0.6723	0.5958	0.7129	0.3536	0.9944	0.5878
Weight in pounds	0.6723	0.5958	0.7129	0.3536	0.9944	0.5878
Healthcare Domain						
When seen any doctor	0.4166	0.1584	0.4235	0.1222*	0.0097*	0.6071
When doctor asked about any other lifestyle behaviors	0.6706	0.3731	0.2052*	0.1789*	0.2949	0.6072

When doctor asked about physical activity behaviors	0.9715	0.6804	0.7699	0.2011*	0.0946*	0.8902
When doctor asked about weight	0.6496	0.5799	0.6154	0.293	0.388	0.4653
Has health insurance	.	.	.	.	.	.
When last seen a primary care doctor	0.6899	0.7066	0.1412*	0.9448	0.9576	0.0921*
Lifestyle Domain						
Self-reported diet quality	0.1424	0.888	0.2878	0.4466	0.9658	0.6684
8oz water servings per day past month	0.1124	0.196	0.4364	0.7931	0.48	0.2299*
8oz sugary beverage servings per day past month	0.6826	0.2482	0.3501	0.371	0.3891	0.8403
Has exercised in last month	0.3726	0.5975	0.9032	0.7671	0.7228	0.4826
How many days exercised in last month	0.2863	0.9691	0.5836	0.7324	0.8029	0.7273
Has tracked physical activity in last month	0.7702	0.7704	0.9241	0.8766	0.3436	0.3852
How many days tracked physical activity in last month	0.9063	0.1486	0.7944	0.1482*	0.0926*	0.4367
Self-reported actual sleep in hours per night past month	0.5382	0.6527	0.2503*	0.1948*	0.4269	0.3629
Self-reported sleep quality	0.9984	0.8019	0.3963	0.8655	0.9718	0.6326

0.5 cup servings of vegetables per day past month	0.3524	0.951	0.7764	0.5439	0.6827	0.0676*
Has weighed self in last month	0.305	0.755	0.4023	0.471	0.6955	0.7947
How many days weighed self in last month	0.2062	0.8265	0.8829	0.5527	0.524	0.651
Currently attempting to lose weight	0.274	0.3614	0.3318	0.0918*	0.2013*	0.7158
Currently smoking (at baseline)	0.2884	0.9674	0.6879	0.5642	0.652	0.8168
Past smoking	0.0517	0.5737	0.5871	0.5059	0.7793	0.9183
Smoking	0.1139	0.8517	0.7686	0.7145	0.8833	0.9711
Self-reported physical activity in minutes per week	0.4751	0.7057	0.0907*	0.2195*	0.449	0.1376*
Demographic Domain						
Age, years	0.087	0.6073	0.0097*	0.7436	0.3786	0.1031*
Age, categorical	0.0477	0.7601	0.0016*	0.6374	0.3371	0.2015*
Number of adults cohabitating	0.1061	0.2039	0.8159	0.9876	0.3707	0.9445
Number of youth cohabitating	0.1595	0.5774	0.3644	0.2742	0.1347*	0.0677*
Living with any adults 18+ years old	0.0896	0.2285	0.9566	0.5225	0.4844	0.2098*
Living with any children/youth <18 years old	0.2048	0.7287	0.4534	0.1821*	0.103*	0.0288*

Total number of individuals cohabitating	0.0281	0.4434	0.4541	0.5532	0.1117*	0.2343*
Current relationship status	0.1513	0.0909	0.1714*	0.4541	0.2025*	0.6154
Sex assigned at birth	0.9539	0.0333	0.8212	0.053*	0.1066*	0.55
Education level achieved	0.1871	0.0896	0.0984*	0.4779	0.0612*	0.9774
Work Status	0.4442	0.1947	0.0331*	0.2526	0.0716*	0.2426*
Finance Score (0-100)	0.4184	0.6306	0.0549*	0.8781	0.6529	0.7477
Number of jobs worked	0.4897	0.9618	0.1408*	0.789	0.9746	0.0999*
Race/Ethnicity	0.1631	0.133	0.6289	0.3851	0.3416	0.6411
Quality of Life Domain						
EQVAS Visual Analog Scale	0.5006	0.6189	0.2602	0.4143	0.2951	0.5891
PROMIS-29 Anxiety t-score	0.3051	0.9774	0.669	0.7458	0.6305	0.2506*
PROMIS-29 Depression t-score	0.1455	0.2303	0.3589	0.5711	0.3272	0.4728
PROMIS-29 Fatigue t-score	0.7167	0.7261	0.471	0.5224	0.8723	0.168*
PROMIS-29 Function t-score	0.7292	0.7042	0.047*	0.9204	0.9632	0.7531
PROMIS-29 Pain t-score	0.6881	0.7751	0.2167*	0.9219	0.9965	0.0656*
PROMIS-29 Sleep t-score	0.702	0.154	0.0071*	0.7476	0.7955	0.9859
PROMIS-29 Social Rules t-score	0.9248	0.6058	0.5385	0.5159	0.7257	0.3291

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