

College Community-Based Physical Activity Support at a Northeast USA Public University During COVID-19: Retrospective Longitudinal Analysis of Intra- Versus Inter-Personal Components for Uptake and Outcome Association

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Abstract

Background: Evidence suggests low physical activity (PA) levels among college students could be addressable by both intrapersonal fitness tracking (e.g., step-counting) and interpersonal support tailored to the campus environment. However, no studies have examined the appeal and influence of intra- and interpersonal components in campus-based PA interventions.

Objective: Retrospectively observe a campus-based PA promotion program to compare usage of intervention components between students and faculty/staff, then test whether such usage was associated with successful retention and goal-achievement in the program.

Methods: A public university used a commercial platform for a 30-day PA promotion program with intrapersonal (step-tracker syncing, education, self-monitoring, motivational messaging) and interpersonal (friend interactions, team games) components.

All students and faculty were invited to participate. App usage was operationalized as intrapersonal (frequency of opening app, use of educational and self-monitoring features) and interpersonal components (friends made in-app, team affiliation and size). These metrics were compared between students and faculty using bivariate tests. They were tested as predictors of retention (i.e., duration of usage before abandonment) and step-goal achievement by a Cox frailty proportional hazard model and a generalized estimating equation respectively.

Results: Campuswide email elicited signup by 156 undergraduate students, 57 graduate students, and 126 faculty/staff members. Most participants (92%) were retained for the first 7 days but by 30 days there was lower retention which differed by academic status: undergraduates 53%, graduates 68%, faculty/staff 74% ($H=13.3$, $P<.001$). Undergraduates used the app less frequently (median [IQR] 0.8 [0.4,1.7] per day) than other groups (grad 1.4 [0.7,2.7], faculty 1.3 [0.7,2.7]) ($H=14.5$, $p=.001$). However, there were no differences in number of friends (undergrad 2 [0,3], grad 1 [0,4], faculty 2 [0,3]) ($H=0.5$, $P=.77$) or teammates made (undergrad 9 [6,10], grad 9 [5,10], faculty 8 [6,10]) ($H=0.1$, $P=.93$). Retention was predicted by app engagement frequency (frailty model hazard 0.56 (95% CI=[0.43, 0.72], $P<.001$)) and affiliation with a team having high median app engagement frequency and/or large size (intra-cluster correlation coefficient 0.064). Meeting daily step goal was predicted by app engagement frequency ($\beta=0.36-0.72$), number of friends ($\beta=0.33-0.40$), and initial motive of maintaining or increasing (rather than starting) PA ($\beta=0.63-0.99$). The latter was also predictive of adherence with wearing or carrying a step-tracker ($\beta=1.69-1.70$).

Conclusions: College students, compared with faculty/staff, 1) used the app less frequently; 2) used the app for shorter duration before abandonment; and 3) met step goal on fewer days. Engagement with the program suggests longer retention and better PA outcomes, that were critically modified by the interpersonal aspects of this engagement. These findings suggest college students could benefit from more tailored implementation strategies such as timed prompts and team reassignments.

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Original Manuscript

Original Paper

College Community-Based Physical Activity Support at a Northeast USA Public University During COVID-19: Retrospective Longitudinal Analysis of Intra- Versus Inter-Personal Components for Uptake and Outcome Association

Abstract

Background:

College students are vulnerable to setting long-term trajectories of low physical activity (PA) but reachable by mobile health fitness tracking (e.g., mHealth step-counting) and interpersonal support tailored to the college community. Yet, no studies have statistically isolated the appeal and influence of these intra- and interpersonal components in college-based PA interventions.

Objective:

Retrospectively observe a college-based PA promotion program at a northeast USA public university during COVID-19: (1) to test the impact of student status on the usage of intervention components and (2) to test whether such usage was associated with successful retention and goal-achievement in the program.

Methods:

The university used a commercial platform for a 30-day PA promotion program during April 2021 with intrapersonal (step-tracker syncing, education, self-monitoring, and motivational messaging) and interpersonal (friend interactions, team games) components. All students and faculty were invited to participate. App usage was operationalized as intrapersonal (frequency of opening app, education, and self-monitoring) and interpersonal features (friends made in-app and team affiliation and size). For objective 1, these metrics were compared between students and faculty using bivariate tests. For objective 2, they were tested for association with retention (i.e., duration of usage before abandonment) and step-goal achievement by, respectively, a Cox proportional hazard model and a generalized estimating equation.

Results:

Campuswide email elicited signup by 156 undergraduate students, 57 graduate students, and 126 faculty/staff members. Objective 1: Undergraduates used the app around half as frequently (median [IQR] 0.8 [0.4,1.7] per day) than other groups (grad 1.4 [0.7,2.7], faculty 1.3 [0.7,2.7]; $H_2=14.5$, P 's=.006-.01) but made the same number of friends (medians 1-2) and teammates (medians 8-9; P 's =.77/.93). Objective 2: Most participants (313/335, 92%, 95% CI=[89%, 95%]) were retained for the first 7 days but by 30 days retention dropped, most so for undergraduates (82/154, 53% [45%, 61%]), followed by graduates (39/56, 68% [55%, 80%]) and faculty/staff (93/125, 74% [66%, 82%]; $\chi^2_2 = 12.6$, $P<.001$). Retention was associated with app engagement frequency (model hazard ratio 0.56 [0.43, 0.72], $P<.001$) and affiliation with a team having high median app engagement and/or large size (intra-cluster correlation coefficient 0.064 [0.001, 0.164], $P=.05$). Meeting a daily step goal was associated with app engagement frequency ($\beta=0.72$ [SE ± 0.21], $P=.001$) number of friends ($\beta=0.40\pm 0.20$, $P=.04$), and an initial motive of maintaining or increasing (rather than starting) PA ($\beta=0.99\pm 0.21$, $P<.001$).

Conclusions:

College students, compared with faculty/staff, used the app less frequently, used the app for shorter duration before abandonment, and met the step goal on fewer days. Engagement with the program suggests longer retention and better PA outcomes, that were critically modified by the interpersonal

engagement. These findings suggest college students with virtual PA support during times of physical isolation could benefit from more tailored implementation strategies (e.g., timed prompts and team reassignments).

Keywords: Universities; Students; Faculty; Mobile Applications; Goals; Social Networks; Education



Introduction

Physical Activity (PA) levels are important determinants of long-term health outcomes. For instance, 6,000-8,000 steps/day is associated with lower risk of health problems such as all-cause mortality, diabetes, and mental health concerns [1, 2]. One critical life stage for PA support is college student years for those who attend. For some people, college is a transition when great positive or negative change from adolescence is possible, and the lifestyle at the end of this transition is a predictor of long-term health trajectory [3]. Studies have found that around half of college students have low PA levels [4] which declined further by 32%-366% during the COVID-19 pandemic [5]. Thus, college is a critical window for interventions that maintain and/or increase PA to have powerful and sustained impact on an individual's life.

College students are a prime population to reach by mobile health (mHealth; medicine involving mobile devices) since most consider the Internet a source of health information [6, 7], almost all own a smartphone and around half use a fitness tracker or other wearable device [8]. mHealth could be a viable strategy to help college students increase their PA since their use of wearable fitness trackers and mobile apps has been associated with higher PA levels .

This association in these studies was mediated by the social aspects of using this technology (e.g., real-time sharing of step counts) making it critical to understand the social context in which students are functioning. Starting college presents students with a new set of social circumstances [9]. When they leave the outside world and enter the college community, often one with cultural and geographic differences from where they grew up, there is a desire to belong and feel accepted in this new community [9]. Such innate want for interpersonal connections is a fundamental determinant of human cognition and health outcomes including PA [10-12]. Fortunately, this new community presents unique opportunities to make social connections. First, students are assigned class instructors with high education levels and experience mentoring young adults, a cross-demographic connection less likely to occur in the outside world [9, 11]. Second, students share experiences and concerns with other students such as accessing unique or licensed educational content, feeling eustress or distress about academic performance, and worrying about loneliness due to the restricted size of the college community [9, 11]. On the other hand, students often struggle to initially adapt to these aspects of college [9, 12]. The COVID-19 pandemic further heightened students' unmet needs and desire for social connection [13, 14]. However, when students are able to utilize the college environment opportunities to join peers in pursuing activities and exploring interests, these connections correlate with increased PA participation and engagement [11]. In fact, social support from friends effectively motivates PA among college students, more so than family support [15]. Yet, despite these rewards of connecting to peers of like age and education level in college, it can also be overwhelming. For instance, while social support in college correlates with situational interest in PA, one study found that the college students' environment was a barrier to PA due to feeling overwhelmed by change in their first year of attendance [16]. For these reasons, college PA support must consider and tailor to the college environment.

There are several frameworks for understanding determinants of humans setting and accomplishing goals such as increasing PA. Goal-setting theory and the theory of planned behavior focus on intrapersonal determinants such as specificity of the goal and beliefs about results from the goal. Self-determination theory also includes such intra-personal competence but then extends to the inclusion of interpersonal relationships (autonomy, relatedness) [17]. Social Cognitive Theory (SCT) extends beyond one-to-one and small group interpersonal relationships to the broader socio-cultural environment [18]. SCT's intrapersonal determinants include self-efficacy (belief in oneself to perform a behavior) and outcome expectations (expectation that a desired outcome will result from the behavior). SCT's interpersonal determinants include socio-cultural factors (the influences from an individual's social and physical environment). Importantly there is a reciprocal determinism (i.e., feedback loops) between the intra- and inter-personal determinants. For example, social persuasion and support from peers can boost a person's self-efficacy to become a successful athlete. But likewise, when peers see that heightened self-efficacy and athleticism, they are even more inclined to support

that person. Therefore, it is critical to study both the intra- and inter-personal aspects of PA support programs.

Wearables can support the above SCT constructs. They can support self-efficacy by conveyance of personal accomplishment (e.g., tracking step counts in relation to previous days or a preset goal) and verbal persuasion (e.g., encouragement messages to reach goal), as well as the opportunity to leverage this self-efficacy for goal-setting. Self-efficacy has been shown to impact both engagement with wearable technology [19] and behavioral outcomes from using wearable technology [20]. Wearables can also support outcome expectations since the metrics they collect and display such as step counts are associated with health benefits [1, 2]. Finally, wearables can support socio-cultural influences by methods such as group step challenges and social media postings of achievements [21, 22]. Overall this robust applicability to SCT shows that wearables should be explored to deliver both inter- and intrapersonal intervention components among college students.

Health-related interventions often have low uptake among college students [23-25]. Some reasons related to intrapersonal aspects like students prioritizing more pressing needs and lack of belief the information was valid and applicable to them. But others related to interpersonal aspects like lack of peer involvement with designing the intervention, and the interpersonal interactions occurring over a social media platform they were not accustomed to using. Students also noted the criticality of being able to conveniently select which intervention components to use. Thus, both the intra- and interpersonal components clearly represent areas for improvement. Some preliminary evidence suggests that social support could be incorporated into mHealth PA interventions for the college student population to promote PA adherence. Findings from a systematic review of 19 papers suggest a positive association between PA and social support for PA among college students [26]. Fourteen primary studies leveraged social interactions in college community populations to promote PA through mobile apps including social components [21-23, 27-38]. Some of these mobile apps provided an “open forum” feature (e.g., Facebook-style news feed, WeChat group chat) where participants could share PA performance, interact, and provide social (i.e., interpersonal) support [21, 23, 27-32, 35, 36]. Some discussed an additional feature in the mobile app which allowed participants to form ongoing “team” relationships. These relationships included ongoing comparison of step counts with other team members (i.e., a social norm) [22, 27-30, 38], discussions fostering mutual support (e.g., complimenting success and empathizing with barriers) [21, 22, 33-37] and discussing educational materials on PA [22]. These activities were rewarded with team success scores thus leveraging the established gamification strategies of cooperation [39] and socially-oriented persuasion [40]. These studies incorporated a mobile app with these interpersonal components, activity trackers, and standard solitarily (i.e., intrapersonally) used behavior change techniques such as, text message reminders to be active, health education, goal-setting, self-monitoring, and extrinsic incentives (e.g., prizes). The utility for tracking devices without support from a multimodal application tailored for college students has yielded mixed results (reviewed in [41]), thus the multimodality of communication is considered a best practice recommendation for mHealth interventions [42].

One challenge with current research is determining the use and effectiveness of each of the multiple intervention components, for this information is crucial to the refinement and success of the intervention [43]. Edney et al [30] found self-monitoring and ongoing team relationships were rated highly by 50%-70% of participants compared to individual incentives and open forum social interactions which were only rated highly by 20%-30% of participants. Tong et al [29] found use of self-monitoring and ongoing team relationships were used an average of ~2x/week, while open forum usage was less than weekly. When the app was subsequently refined to include more personalization of the individual self-monitoring, by tailoring to the participants' weekly progress and barriers, this approach was reported to be well-received [32]. Zhang et al [37] found participants randomized to participate in an interpersonal team did not increase PA differently than those randomized to receive intrapersonal text messages. There is a need to build upon these mixed findings from clinical trials by statistically isolating which of the intrapersonal (i.e., education, self-monitoring, personalized advice) and interpersonal components (i.e., open forum, team feature) are associated with successful engagement and PA promotion among college students in real-world settings.

The motive for the present study was to build upon prior findings from clinical trials by retrospective observation of an mHealth PA promotion program incorporating both intrapersonal and interpersonal

components, which was delivered with community-wide outreach to students and faculty/staff. The first research question was how intervention components were used and whether this usage was different between students and faculty/staff, and the second question was whether such usage was associated with successful retention and goal-achievement in the program. We hypothesized that undergraduate students would have lower usage of intervention components than graduate students and faculty/staff, and such usage would be associated with successful retention and goal-achievement in the program. This statistical isolation of specific components builds upon prior studies by providing insight to specific facilitators and barriers of the program, which could inform future refinement of interventions aimed at increasing PA in situations of physical isolation from peers and PA spaces.

Methods

Intervention Design

The American College of Sports Medicine Exercise is Medicine® On Campus initiative recognizes ~150 higher educational institutions per year with campus PA initiatives. One of their gold-level programs, the Southern Connecticut State University (SCSU) MoveSpring™ Steps Challenge was suited to our study purpose due to use of mHealth delivery with backend data capture. The university initiated the challenge in response to COVID-19 pandemic policies that restricted use of their fitness and recreational facilities. It operated April 1-30 of 2021, directed by the campus fitness center, incorporating input from the campus exercise physiology club and health center, and digitally supported by the MoveSpring™ mobile application platform (Chicago, IL). The latter provides fitness tracking and interactions for users that are customizable for individual companies and organizations. SCSU and MoveSpring collaborated to program the targeted intervention with both intra- and inter-personal components (Table 1). For the passive monitoring component, users could sync their own device such as a fitness watch or smartphone pedometer.

Table 1. Program components and content.

Type	Component	Content	
Intra-Personal			
	Educational content on-demand ¹	● Videos ● Articles ● Actionable health tips ● Motivational Quotes	
	Motivational content as push notifications	Content	Frequency
		● Topic and mini challenge of the week (e.g., benefits of nature walking, post a picture of your nature walk)	2-3 times per week
		● Campus events (e.g., group walk)	Once per month
		● Prize reminders	3 times per week

		● Achievement acknowledgment	Once per week
	Active monitoring (self-reported yes/no response) ²	● Ate ≥ 3-4 servings of veggies ● Slept ≥ 7 hours ● Drank ≥ 8 glasses water	
	Passive Monitoring (device)	● Steps (15,000 limit) in relation to both personal goal³ and tiered cutoffs for prize raffles⁴ ● Minutes of moderate-to-vigorous physical activity⁵ ● Distance	
Inter-Personal			
	Community engagement & Peer support	● Peer leaders and fitness center director ● Chat box⁶ ● Friend activity (average daily steps of friends) ● Team-specific challenges⁷ ● Team Leaderboard (top 4 teams' avatar, name, average daily steps per member)	
	¹ Content from MoveSpring proprietary collection and SCSU student leaders related to physical activity, diet, sleep, hydration, mindfulness. ² Completing $\geq 67\%$ (20 of 30) days gave entry into \$50 gift card raffle. ³ Personal goal options were 6500, 10000, or 12500 per day. ⁴ Average values of 7000, 10000, or 12500 per day gave entry into raffle for \$50 / \$75 / \$100 respectively. 1 entry for days 1-15 and 2 for days 16-30. ⁵ Meeting ≥ 20 min on 67% (20 of 30) days gave entry into \$50 gift card raffle ⁶ Chat topics were wide-ranging and sometimes unrelated to physical activity. This feature was only used by a few individuals, whereas the features in the subsequent 3 bullets were used by a majority of the 335 participants (see Table 3). ⁷ Top-3 teams by average step count per member received t-shirts. Grouped by academic status of user who founded the team. Participants could actively form their own teams. Those not doing so were randomly assigned to a team in the first half of the first week of the challenge.		

Recruitment and Enrollment

Nine days before the challenge start (March 22, 2021), the campus fitness center coordinator sent a single advertisement email to all SCSU students and employees with instructions guiding those interested to download the MoveSpring/SCSU customized app to their personal smartphone, create an account, and sync a watch or pedometer for passive monitoring. Upon registration, all participants were required to complete an intake survey of academic status, campus visit frequency, reason for enrolling, daily step goal, and device used for activity tracking (Appendix 1). To minimize onboarding burden there was no query of sex or other demographics.

Data Capture

The SCSU Fitness Center and MoveSpring deleted identities and donated the dataset to the Dataverse repository [49] and a research team based at Yale University (GA, SM, MA, BB, JL, SL, XX, SJ, LMF, SJ, MSK, MG), who performed data cleaning, analysis, interpretation, and writeup. They liaised with several co-designers of the Steps Challenge program content (AH, PB, RA) to summarize intervention methodology for this manuscript.

Ethical Considerations

No researchers had contact with participants or access to identifiers, so the Yale University Institutional Review Board determined that the project did not constitute human subjects research (determination #2000033852).

This manuscript follows STROBE guidelines for cohort studies (Appendix 2). Participant identities were deleted prior to transfer of the data to Dataverse and Yale.

Data Analysis

Overview

This study was a retrospective analysis of longitudinal observations on campus community members over the 30 days they were exposed to a steps challenge intervention app. Analyses utilized SPSS v26 (Aim 1) and SAS v9.4 (Aim 2). Significance was .05. Study size was based upon the available dataset.

Outcomes

The first objective was to determine how the app was used, and whether app usage differed by academic status. The outcomes for this first objective were app usage metrics, operationalized as intrapersonal (average frequency of opening app, education, and self-monitoring, as continuous variables) and interpersonal features (friends made in-app, team affiliation, and team size, as discrete variables). The second objective was to determine whether app usage was associated with successful retention and goal achievement in the program. The outcomes for this second objective were: 1) days of retention quantified as a time-to-event discrete variable censored at the end of the 30-day exposure [i.e., the event being discontinuation of app syncing], and 2) each day's success at meeting step goal quantified as a ternary categorical variable [tracking device not worn, tracking device worn but not reaching goal, tracking device worn and reaching goal]. The first objective analyzed outcomes at the person-level (i.e., daily averages), while the second objective analyzed outcomes at the day-level adjusted for within-person correlations. These units were chosen based on the available granularity of the data from the app that both delivered the intervention and tracked its outcomes.

Research Question 1: How was the app used, and did App Usage Differ by Academic Status?

Participant characteristics (Table 2) were tabulated as frequencies and compared by academic status using Chi-Square (χ^2). The duration of app use before abandonment (Table 3) was compared by academic status using the Kaplan-Meier estimate of survival probability, since it was right-censored at the 30-day length of the program. Most metrics of app usage before abandonment (Table 3) were compared by academic status using Kruskal-Wallis (H) tests since they were interval scale variables with distributions that were bimodal (number of teammates) or right-skewed (frequency of opening app before abandonment, friends made in-app, use of self-monitoring and education features) and visually similar between the academic statuses. Two metrics of app usage before abandonment were even more heavily right-skewed - use of self-monitoring and education features - so they were recoded as binary ($<1x/weekly$ or $\geq 1x/weekly$) and compared by academic status using Chi-Square (χ^2). All variables with a significant main effect across the three academic groups were further tested by post hoc pairwise comparisons with P-value multiplied by three to Bonferroni-adjust for multiple comparisons.

Research Question 2: Was App Usage Associated with Successful Retention and Goal Achievement in the Program?

Independent variables were app usage metrics (engagement frequency, number of friends made, number of teammates made) and all available participant characteristics (academic status, campus visit frequency, motive for joining program, step count goal). Each of the below analyses tested each independent variable's bivariate association with the retention or goal achievement outcome, those meeting a $P < .10$ cutoff were tested in a multiple variable model, and those appearing to influence that model ($P < .20$) were retained in the final parsimonious model.

Retention (i.e., duration until last time app was opened before abandonment) was estimated using the Kaplan-Meier estimate and effects of independent variables were examined using a Cox frailty proportional hazard model incorporating correlation within teams. Besides accounting for the right-censorship of the data

these methods can adjust for possible correlations within the dataset, in this case the correlation between teammates. The lone influential independent variable was visualized by survival curve (Figure 1), and correlation within teammates was visualized as a bubble plot (Figure 2).

Goal achievement was labeled for each person-day as device non-wear (zero steps), wear-below-goal (steps non-zero but below goal), or goal (steps at or above goal). We tested independent variables associated with non-wear vs goal and wear-below-goal versus goal, using a generalized estimating equation that incorporated correlation within-participants by a working correlation structure, a random intercept, and team affiliation as a random effect (Table 4). We also ran a supplemental analysis where the outcome variable was total steps per day among participants meeting the standard minimum representative PA sampling of 4 days [44] (Appendix 3).

Results

Enrollment

For school year 2020-2021, there were 11,055 individuals affiliated with SCSU (7,047 or 63.7% female, 6,287 or 56.9% non-Hispanic white) as either an undergraduate student (n=7,440), graduate student (n=1,891), or faculty/staff member (n=1,724) (Appendix 4) [60]. Among these individuals, who each received a recruitment invitation email, 339 respondents (4%) registered for the steps challenge. A total of 156 undergraduate students, 57 graduate students, and 126 faculty/staff members enrolled in the program, which represented 2%, 3%, and 7%, respectively, of the total SCSU population. All 339 enrolled individuals were included in the sample description (Table 2), although 4 of them were excluded from the subsequent analysis due to missing data on the MoveSpring backend.

Participant Characteristics from Intake Survey

Table 2. Participant Descriptive Characteristics

	Overall	Undergraduates	Graduates	Faculty/ staff	$\chi^2_{df=4}$	P
Participants, n	339	156	57	126	N/A	N/A
Campus Visit Frequency, n (%)						
Remote	82 (24)	34 (22)	32 (56)	16 (13)	71.9	<.001
Regularly visit	102 (30)	61 (39)	18 (32)	23 (18)		
Live or work	155 (46)	61 (39)	7 (12)	87 (69)		
Step count mechanism, n (%)						
Apple	207 (61)	110 (71)	41 (72)	56 (44)	N/A ¹	N/A ¹
Fitbit	63 (19)	22 (14)	12 (21)	29 (23)		
Garmin	14 (4)	4 (3)	1 (2)	9 (7)		
Withings	1 (0.3)	0 (0)	0 (0)	14 (11)		
Google	25 (7)	11 (7)	0 (0)	1 (1)		
Manual entry	21 (6)	5 (3)	2 (4)	14 (11)		
Dropped out before syncing	8 (2)	4 (3)	1 (2)	3 (2)		
Motive for joining program, n (%)						
Start physical activity	68 (20)	31 (20)	10 (18)	27 (21)	2.5	.65
Increase physical	102 (30)	44 (28)	22 (39)	36 (29)		

	activity						
	Maintain physical activity	169 (50)	81 (52)	25 (44)	63 (50)		
Step Goal, n (%)							
	6,500	176 (52)	82 (53)	30 (53)	64 (51)	0.8	.94
	10,000	132 (39)	62 (40)	21 (37)	49 (39)		
	12,500	31 (9)	12 (8)	6 (11)	13 (10)		
¹ Not compared across groups due to small cell sizes							

Campus Visit Frequency

Most undergraduate students (78%) frequently visited campus, of whom about half reported also residing on campus. Conversely, only 44% of graduate students frequently visited campus, of whom the majority reported residing off campus. Nearly all faculty/staff (87%) worked on campus but lived off campus as the university did not have faculty/staff housing.

Mechanism to Sync Step Count

The majority of participants (84%) synced a device brand for which the majority of studies in a quantitative systematic review found to meet Consumer Technology Association validity standards (<10% mean absolute percent error) (i.e., Apple, Fitbit, Garmin) [45]. Some (7.5%) used a Google product to collect step count data (e.g., Android phone step counter), with faculty/staff members utilizing this feature more than undergraduate and graduate students. Six percent of participants manually entered step count, but it was unclear how the data were collected; 2% of participants did not sync a device after sign-up and thus did not report any step count data.

Motives and Goals

Among possible motives for program enrollment, 20% enrolled to initiate PA, 30% to increase PA, and about half for PA maintenance. These 169 “maintainers” had step goals (n=75 [44%] 6,500 steps, n=76 [45%] 10,000 steps, n=18 [11%] 12,500 steps) that were similar to the 102 “increasers” (n=55 [54%] 6,500 steps, n=39 [38%] 10,000 steps, n=8 [8%] 12,500 steps; $\chi^2=2.4$, df=2, $P=.30$) but higher than the 68 “starters” (n=46 [68%] 6,500 steps, n=17 [25%] 10,000 steps, n=5 [7%] 12,500 steps; $\chi^2=10.6$, df=2, $P=.005$).

Research Question 1: Use of App Overall and by Academic Status

Duration before Abandonment

Most (92%) participants stayed in the program for the first 7 days and 63% stayed in the program for the full 30 days. At all timepoints beyond the first week, retention among undergraduate students tended to be lower than graduate students and was lower than faculty/staff (Table 3).

Table 3. Use of app by academic status. Median [25 th %'ile, 75 th %'ile]						
	Overall	Undergraduate s	Graduates	Faculty/staff	Test Statistic	P
Participants, n	335	154	56	125		
Overall Usage						
					$\chi^2_{df=2}$ of Kaplan- Meier Log Rank¹	
Days of App Use					12.6	.002

Before Abandonment						
>7 days	313 (92%)	145 (93%)	51 (90%)	117 (93%)		
>14 days	291 (86%)	126 (81%)	49 (86%)	116 (92%)		
> 21 days	260 (77%)	110 (71%)	46 (81%)	104 (83%)		
> 28 days	226 (67%)	88 (56%)	42 (74%)	96 (76%)		
30 days	214 (63%)	82 (53%)	39 (68%)	93 (74%)		
					H_{df=2} of Kruskal-Wallace Test	
App Openings Per Day Before Abandonment	1.1 [0.5, 2.3]	0.8 [0.4, 1.7] ²	1.4 [0.7, 2.7]	1.3 [0.7, 2.7]	14.5	<.001
≥1x weekly	304 (91%)	138 (90%)	54 (96%)	112 (90%)		
≥1x daily	190 (57%)	71 (46%)	39 (70%)	80 (64%)		
≥2x daily	95 (28%)	32 (21%)	21 (38%)	42 (34%)		
Friends made	2 [0, 3]	2 [0, 3]	1 [0, 4]	2 [0, 3]	0.5	.77
≥1	211 (63%)	96 (62%)	35 (63%)	80 (64%)		
≥2	168 (50%)	77 (50%)	27 (48%)	64 (51%)		
≥3	116 (35%)	49 (32%)	18 (32%)	49 (39%)		
≥6	36 (11%)	14 (9%)	5 (9%)	17 (14%)		
Teammates made	9 [6, 10]	9 [6, 10]	9 [5, 10]	8 [6, 10]	0.1	.93
1	1 (1%)	0 (0%)	1 (1%)	0 (0%)		
3-5	70 (21%)	31 (20%)	15 (27%)	24 (19%)		
6-9	132 (39%)	62 (40%)	15 (27%)	55 (44%)		
10+	132 (39%)	61 (40%)	25 (45%)	46 (37%)		
					χ²_{df=2} of binary comparison	P
Sleep logged ³	54 (16%)	23 (15%)	15 (27%)	16 (13%)	5.9	.053
Diet logged ³	40 (12%)	18 (12%)	9 (16%)	13 (10%)	1.2	.55
Hydration logged ³	62 (19%)	28 (18%)	15 (27%)	19 (15%)	3.5	.18
Education viewed ³	9 (3%)	4 (3%)	3 (5%)	2 (2%)	2.1	.35
¹ Pairwise results: undergraduate tended to be lower than graduate ($\chi^2_{df=1} = 3.4$, adjusted $P=.19$) and was lower than faculty ($\chi^2_{df=1} = 11.7$, adjusted $P<.001$). Graduate and faculty were not different ($\chi^2_{df=1} = 0.5$, adjusted $P>.99$) ² Pairwise results: undergraduate was lower than graduate ($H_{df=1} = 43.6$, adjusted $P=.01$) and faculty ($H_{df=1} = 35.9$, adjusted $P=.006$). Graduate and faculty were not different ($H_{df=1} = 0.5$, adjusted $P>.99$) ³ Recoded as binary (<1x/weekly or ≥1x/weekly) due to substantial right-skew.						
Bolded indicates $P < .05$						

Frequency before Abandonment

Most participants opened the app with some regular frequency - at least 0.5 times per day – but undergraduates did so less frequently than both faculty/staff and graduate students. Lower values of this metric were associated with both sooner abandonment and fewer step counts logged before abandonment.

Self-Monitoring and Education Features

In addition to regularly opening the app as described above, almost all participants ($n=331/335$, 99%) used at least one of the educational or self-monitoring features at least once to collect data about sleep, diet, and/or hydration. At the same time, the proportions using them at least weekly were much smaller: accessing education content 9/335 (3%), recording sleep data 54/335 (16%), recording diet 40/335 (12%), recording hydration 62/335 (19%). Usage of these features did not differ by academic status although sleep logging had a non-significant tendency to be more common among graduate students than undergraduates or faculty/staff.

Social Friends and Teams

Most participants made at least one friend on the app, and half the participants made multiple friends. All participants were part of a team, which ranged in size from 2 to 62. The majority of teams comprised six or more individuals. Faculty/staff members were most often part of a team of six to nine participants, and graduate students were most often part of a team of ten or more participants. The majority of undergraduate participants were split between being in a team of six to nine and a team of ten or more participants. We did not detect statistically significant differences between the number of friends made or number of teammates by academic status.

Research Question 2: Association of App Usage With Successful Retention and Goal-Achievement in the Program

Variables Associated with Retention

The final model of variables associated with retention (i.e., duration of usage before abandonment) included app engagement frequency (Figure 1) with adjustment for correlation within teams. Overall frailty model hazard ratios for abandonment were 0.56 (95% CI=[0.43, 0.72], $P<.001$) for those in the first and second quartile of engagement frequency (≥ 1.0 per day), and 0.69 (95% CI=[0.50, 0.96], $P=0.03$) for those in the third quartile of engagement frequency (0.5-1.0 per day), in comparison to those in the fourth quartile of engagement frequency (<0.5 per day). At 10 days, abandonment was highest among those in the fourth quartile compared to the three other quartiles (30% vs 5%). At 30 days, abandonment was again highest among those in the fourth quartile (62%), followed by those in the third quartile (44%), and those in the first and second quartiles (24%).

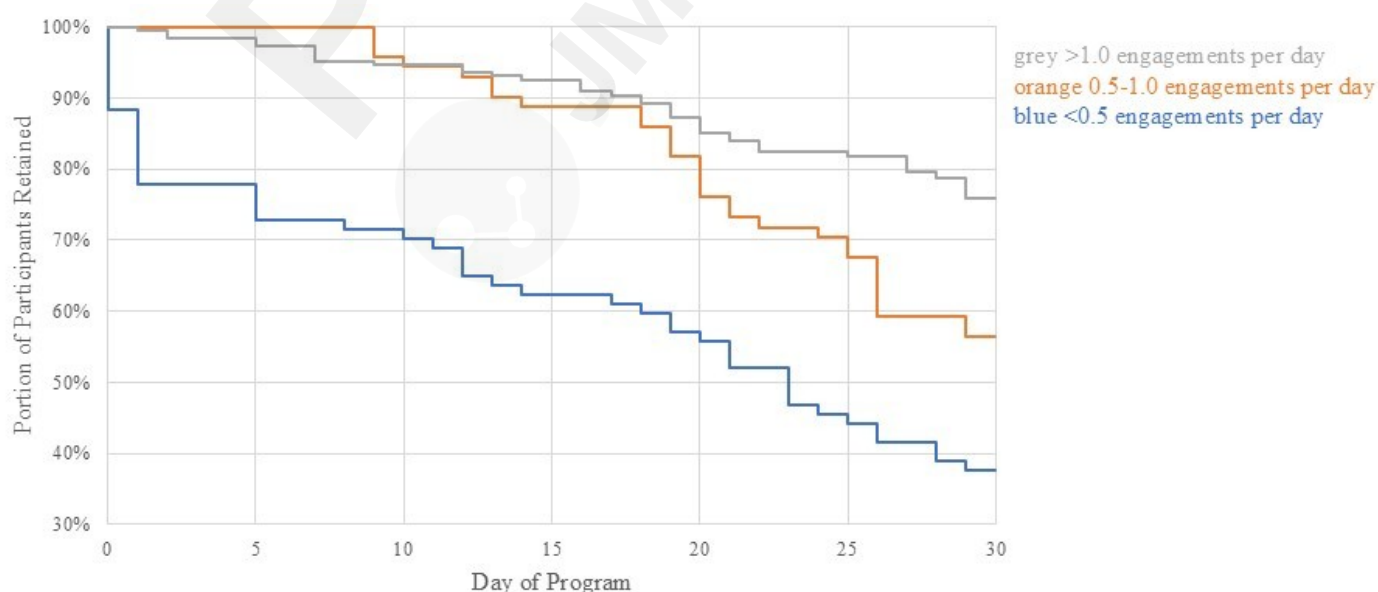


Figure 1. Retention survival curve according to engagements per day, which was the only predictor of retention retained in the parsimonious final model.

The intra-class correlation coefficient by teams was .064 [.001, .164] ($P=.05$). Specifically, the longer retained individuals were those on the teams with larger size and/or higher median rate of app engagement (Figure 2).

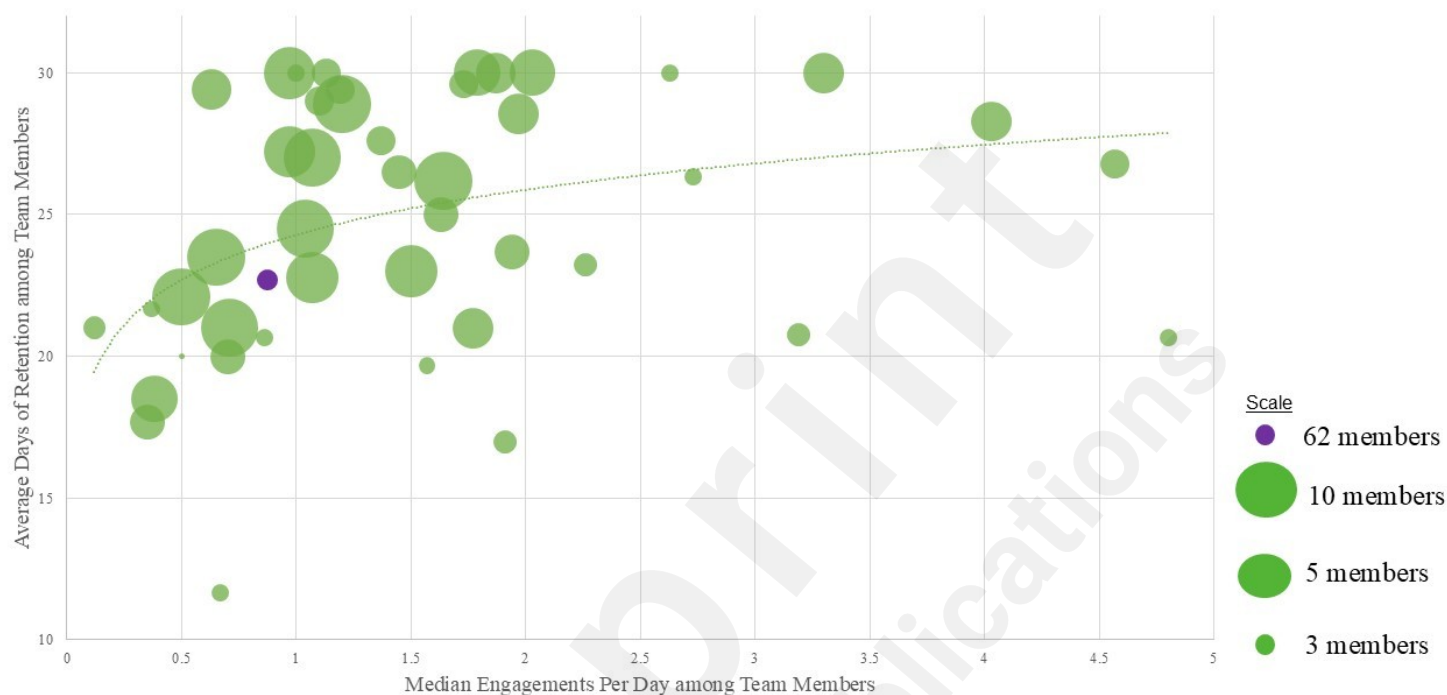


Figure 2. Retention (i.e., duration of app usage before abandonment) was clustered by team affiliation (intra-cluster correlation coefficient 0.064 [.001, .164] ($P=.05$)). Therefore, we plotted average retention among team members in relation to team characteristics including team size (bubble size) and median app engagements per day among team members (x-axis). It is visually apparent that the longer retained individuals were those on the teams with larger size and/or higher median rate of app engagement. Dotted curve is for visual purposes and approximates retention days as $2.29 \cdot \ln(\text{median engagement of team}) + 24.29$.

Variables Associated with Step Goal Achievements

Among the 10,050 participant-days, 1,763 occurred after app abandonment. From the remaining 8,287 participant-days, there were 3,550 where steps meeting or exceeding goal amount were recorded, 4,670 where steps exceeding a reasonable daily value (>250) but not meeting goal amount were recorded, and 80 days (among 28 participants) where no steps were recorded indicating non-wear of the device. On days the device was worn, median step count was 6756 (IQR 4649, 9793).

Both failing to meet step goal and failing to wear the watch were less likely for individuals whose initial motive was maintaining or increasing physical activity, compared to those whose initial motive was to start physical activity (Table 4). Failing to meet step goal was also less likely for individuals who engaged most frequently with the app and made a high number of friends. Finally, failing to meet step goal was less likely for faculty/staff compared with students. When this analysis of meeting step goal was repeated on average step counts, the associated independent variables were the same (Appendix 2).

Table 4. Generalized estimating equation of day-level step goal achievement among 8,287 daily observations occurring before app abandonment. Adjusted $\beta \pm$ standard error (P -value).

	Below Goal (k=4,659) vs. At Goal (k=3,548)	Non-Wear (k=80) vs. At Goal (k=3,548)
Baseline Characteristics		
Academic Status		
Undergraduate student	0.35$\pm$0.16 (.03)	0.82 $\pm$ 0.53 (.12)
Graduate Student	0.50$\pm$0.22 (.02)	-0.21 $\pm$ 0.76 (.78)
Faculty/staff (reference group)		
Motive for joining		
Maintain physical activity	-0.99$\pm$0.21 (<.001)	-1.69$\pm$0.70 (.02)
Increase physical activity	-0.63$\pm$0.22 (.01)	-1.70$\pm$0.70 (.02)
Start physical activity (reference group)		
Goal		
12,500	0.38 $\pm$ 0.27 (.15)	0.35 $\pm$ 1.05 (.74)
10,000	0.35$\pm$0.16 (.03)	0.80 $\pm$ 0.48 (.09)
6,500 (reference group)		
Use of App Features		
App engagements per day before abandonment		
> 1.00	-0.72$\pm$0.21 (.001)	-0.81 $\pm$ 0.61 (.19)
0.50 ~ 1.00	-0.36 $\pm$ 0.23 (.12)	-0.60 $\pm$ 0.60 (.31)
<0.50 (reference group)		
Teammates Made		
9+	-0.41 $\pm$ 0.27 (.13)	-1.08 $\pm$ 0.76 (.16)
5-8	-0.37 $\pm$ 0.27 (.17)	-1.40 $\pm$ 0.81 (.09)
0-4 (reference group)		
Friends Made		
4+	-0.40$\pm$0.20 (.04)	-0.69 $\pm$ 0.88 (.44)
1-3	-0.33 $\pm$ 0.18 (.07)	-0.24 $\pm$ 0.46 (.60)
0 (reference group)		

Positive coefficient indicates greater likelihood of “below goal” or “not-wear”.

Bolded highlights $P < .05$.

Within-subject correlations were incorporated using a working correlation structure.

The “team affiliation” random effect was ignorable, because its estimated variance was very small compared to the variance of the random intercept.

Exploratory Analysis: Role of Gift Card Incentives as Possible Confounder

The escalation of incentive for extrinsic goals in the second compared to first half (i.e., 2 raffle entries instead of 1) was not associated with a positive change in attaining these goals: among the 182 not meeting 7,000 steps in first half, just 11 (6%) met it in the second half, whereas among the 157 meeting 7,000 steps in the first half there were 36 (23%) who did not meet it in the second half. A similar 4x-10x smaller preponderance of upward compared to downward transitioners was apparent for the step cutoffs of 10,000 (17 / 247 [6%] vs 20 / 75 [27%]) and 12,500 (8 / 304 [3%] vs 8 / 27 [30%]). In addition, visually there was no indication that participants made a “sprint finish” as they approached day 15 or day 30 to qualify for the entries of that period (Figure 3).

The incentive of a drawing for completing self-reports on $\geq 67\%$ (20 of 30) days also appeared

uninfluential as 0 participants met this goal. The incentive of a drawing for achieving 20 minutes of moderate-to-vigorous activity on $\geq 67\%$ (20 of 30) days could not be evaluated for influence since the database did not contain this metric on a day-level. The incentive of achieving a t-shirt for being a top-3 team was not separable from the intrinsic motivation of being on a successful team.

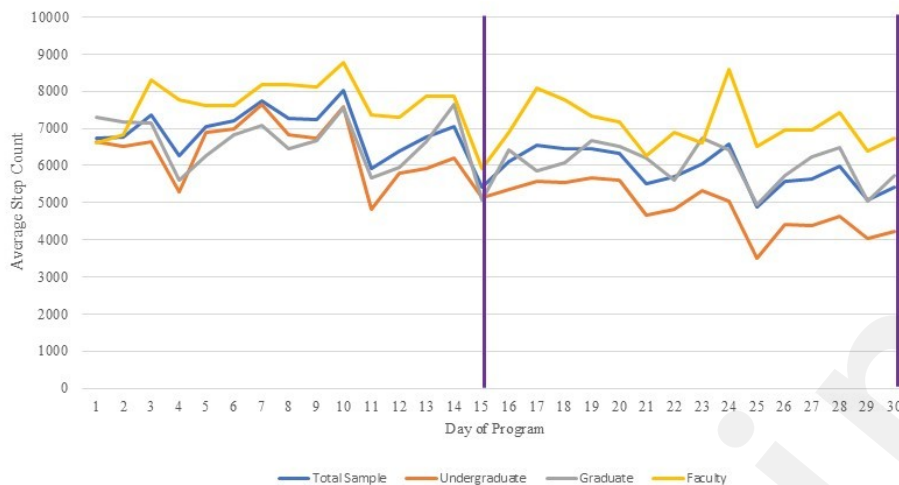


Figure 3. Temporal trends in steps per day relative to the cutoffs for the prize drawings (purple).

Discussion

Principal Results

We assessed intrapersonal and interpersonal factors to better understand facilitators and barriers to college community-based PA support at a northeast public university during COVID-19. For intrapersonal factors, most participants engaged solitarily with the app at least several times per week and this frequency was positively associated with both retention and step goal achievement while retained. College students, when compared with faculty/staff, 1) used the app less frequently; 2) used the app for a shorter duration before abandonment; and 3) were less successful in step count goal achievement. For interpersonal factors, students and faculty/staff equally used the open friends forum and the ongoing teams feature, which were positively associated with step goal achievement and retention before abandonment respectively. In fact, retention before abandonment clustered among teammates (Figure 2) with a similar intra-cluster correlation coefficient as various PA metrics cluster among high school classmates [50]. Overall, it is important to note this interaction between intrapersonal (i.e., use of app) and interpersonal characteristics (i.e., social support).

College students are vulnerable to establishing a lifelong trajectory of low PA levels. Findings from our study suggest that expanding interventions beyond self-monitoring to a multimodal intervention including interpersonal components may help address engagement and retention. The multi-component mHealth PA promotion program provided insight to enrollment, usage of specific app features, retention, device wear, and achievement of step goals in a real-world setting of a public university during pandemic circumstances which had presented barriers to PA. As well, the sample was reflective of USA 4-year public university averages with respect to the proportion of students living on campus (2.1M / 5.8M, 37%) [46], studying remotely (2.1M / 9.1M, 23%) [47], and choosing Apple tracking devices (567 / 768, 74%) [48]. This situation presented an opportunity to retrospectively observe the intervention in the naturalistic college community environment with individuals having varying degrees and types of participation.

Comparison with Prior Work

Teams were included in this program because small-group team challenges within a fitness program improve individual challenge completion and improve degree of participation [51]. Tong et al [29] and Edney et al [30] found that ongoing team relationships were a relatively popular aspect of such an intervention among college

students, more so than open forum usage. Similarly, we found that most of the social interaction on our app occurred in the “teams” rather than the “friends” feature. Our additional multiple variable and multilevel (person, team) analyses revealed that differential usage of both intra- and interpersonal components critically modified outcomes in step-counting and retention. This finding builds upon two previous studies that revealed correlations of intrapersonal component usage (goal-setting, content completion) with increased PA [52, 53]. There is a need for further research with additional methodologies to provide further insight to how we could better deploy engagement strategies such as “teams” or “open forum friends” features to promote PA.

The MoveSpring/SCSU program was highly accessible to the college population because participants were able to participate from anywhere. Accessibility during this time was crucial due to COVID-19 pandemic restrictions creating a very inaccessible environment for PA. The steps challenge enabled participants to stay engaged within a social network, despite being physically isolated from their friends, family, and/or prior PA partners during the COVID-19 pandemic. Individuals were able to join teams with other individuals they may not have known previously. This virtual connection allowed individuals to immediately have at least one other individual on their campus also participating in the same activity.

However, because employing an intensive recruitment and retention strategy would have been challenging during the pandemic, the program adopted a more pragmatic approach to implementation, which revealed a more true-to-life scenario. Naturalistic studies provide an opportunity to observe patterns in college students' physical activity patterns. In addition to examining participant results from an individual point of view, including teams in the intervention provided additional information about the potential of virtual teams in facilitating program engagement and retention, even in situations where participants are separated from each other and common PA spaces (e.g., rural areas, satellite campuses, online degree programs). As college students can be a hard-to-engage population, having this knowledge as well as understanding their PA habits can better inform future implementation and intervention efforts.

First, intervention planners should consider the added value of virtual interaction within an educational community, and its ability to withstand barriers of geography and cost. The Movespring/SCSU program was accessible to those not physically on campus, incurred zero cost of devices (everyone used their own device), and had peer uptake and interactions that were mostly automatically facilitated by the app's team features. The minimal human facilitation required was achievable by student leaders and the fitness center director without extra staffing required in a minimal resource environment.

Second, these findings suggest that college students could benefit from a more tailored implementation strategy. For example, retention prompts could be targeted at those with the lowest overall engagement early in the program, and at those with medium engagement after 3 weeks of the program, in accord with when these respective groups fell below the highest engaged group in retention (Figure 2). Such anticipation of vulnerability to abandonment has been done elsewhere [54]. In addition, these prompts could include team reassignment to teams with high engagement to leverage the clustering of engagement by team affiliation. This strategy aligns with recent recommendations that interventions should be examined not only for their overall effects but also the contribution of individual components to determine the active versus unnecessary ingredients, and achieve tailoring to individuals and contexts [43]. Further tailoring could be attained by a machine-learning prediction algorithm to trigger just-in-time adaptive intervention prompts.

Limitations and Strengths

This study had several limitations. First, although the program was offered campus-wide to recruit a representative sample, just 3.1% of the campus participated which could lead to biased results. However, this representation is higher than typical clinical trial enrollment of a population where often <3% even click the advertisement and <1% can commit to the logistical burdens of participation [55]. Nonetheless future programs could make more extensive recruitment efforts to increase representation. Second, because it was a retrospective evaluation of a real-world program rather than a human subjects research study, we did not have survey assessments to test theoretical mechanisms (e.g., self-efficacy and outcome expectations to test social cognitive

theory) nor participant demographics other than identification as undergraduate, graduate, or faculty/staff. Collecting more demographical and theoretical construct data would help target key program factors and their relationship with PA outcomes accounting for theoretical mechanisms and diversity of participants. Although, in young adulthood, stage of independence or education is a more meaningful metric than biological age [56]. Third, also to reduce burden of signup, participants used their own step-counting device. Almost all were previously validated up to consumer standards, but they nonetheless varied in brand and likely in model. However, the study outcome was behavioral goal achievement rather than a surrogate of ground truth step [2]. Fourth, the program had a relatively short duration. Although, in our study and others [14, 57] the first month of app usage was critical in terms of emergent differences between individuals in retention and degree of participation, so it was an appropriate timeframe for our research question. Finally, we isolated the inter- versus intra-personal component comparison by controlling for within-person correlations statistically and within-environment correlations by using a single site, which held a gold-level designation. Nonetheless, it could also be useful to run a between-site design in which an alternate “control” site offered fewer of the components. It might also be useful to set up a design isolating intrinsic from extrinsic (i.e., prize incentives) motivation, but our brief analysis of the latter indicated a lack of influence.

While prior clinical trials evaluated interpersonal college community-based PA support [27-30, 32], a unique strength of our study was addressing its real-world potential for retention, engagement, and association with step-goal achievement. Moreover, we ran this evaluation at the level of individual intervention components across the spectrum from intra- to interpersonal. Doing so required detailed statistical analysis including survival curves and models including multiple variables and levels (person, team). This analysis was a critical advancement from prior studies that tested such associations only univariately and only for intrapersonal not interpersonal components [52, 53]. Finally, the study was strengthened by its timing: it occurred during the COVID-19 pandemic before vaccine rollout to young adults, which was a time of extensive barriers to both PA and social interactions. As well, it was the month prior to the university’s final exams, when college mHealth interventions are vulnerable to abandonment [24]. Thus, the results will inform guidance for coping with difficult times for PA and social interactions.

Future Directions

Clinical trials cannot address the real-world potential for retention and engagement by these applications. App disengagement and abandonment is prevalent in real-world settings according to survey data [58]. In direct assessments of interventions, while these metrics are challenging to standardize across studies, a recent systematic review found just 9% of 62 published studies considered their retention and engagement to be successful [59]. Retention was 10 times less likely if participants were not financially compensated, and 4 times less likely if the app was for general lifestyle maintenance rather than for an existing clinical condition [59]. Although none of the included studies had an average age under 30 years, other researchers have reported that college students are challenging to retain [23]. As such, despite the availability of pre-post outcomes on retained participants, there is a dearth of information regarding how to achieve retention and engagement, especially for preventive interventions for college students in real-world settings without financial compensation for participation. These retention issues also speak to concerns about representativeness of the select group that is successfully recruited and retained. While concerns about representativeness apply to any research, the topic of social support approaches is particularly affected because it depends on the environment of these interactions; there is a need for open forums that represent the full university sociocultural environment, rather than the subsample who met the criteria and commitment for research procedures.

We also considered that lack of goal achievement can result not only from lower-than-desired step counts but also from non-wear of the tracking device. In our analysis, these two occurrences were both associated with motive for joining program being the start rather than increase or maintenance of physical activity. These findings suggest that the act of wearing and monitoring a fitness wearable has motivational

etiology, rather than simply being a methodological concern as it is usually treated in research contexts. Stricter study procedures with more controlled observation can sometimes cause participants to act differently than they would usually (i.e., Hawthorne Bias), potentially leading to different outcomes when implemented in a real-world setting. On the other hand, successful step goal achievement on days the watch was worn was associated with variables that were not relevant to successful watch wear, including high engagement and high number of friends. Thus, although having similar etiology these two behaviors may require different interventions.

Finally, the intervention and analyses reported herein among several hundred participants from a single campus should be repeated at other campuses to test generalizability. Efforts should be made to engage campuses from the American College of Sports Medicine Exercise is Medicine® On Campus initiative lists and others for means that interventions can collect data and transfer it to research teams. The MoveSpring platform would be one excellent mechanism; many institutions offer it to faculty and staff but should consider offering it to students as in the present study.

Conclusions

Engagement with the program suggests longer retention and better PA outcomes, that were critically modified by the interpersonal aspects of this engagement. Adopting a pragmatic approach to implementation highlights opportunities for future trials and the need for specific strategies tailored to different groups to account for differences in demographics and baseline motives and goals.

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Conflicts of Interest

The authors declare no potential conflict of interest.

Abbreviations

PA: physical activity

SCSU: Southern Connecticut State University

Data Availability

All data analyzed in this study are publicly available on Dataverse [49].

Author Contributions

Garrett I. Ash: Conceptualization (equal), data curation (lead), formal analysis (support), funding acquisition (equal), investigation methodology (equal), validation (lead), visualization (support), writing – original draft (equal), writing – review & editing (equal). **Selene S Mak,** Conceptualization (equal), investigation

methodology (equal), writing – original draft (equal), writing – review & editing (equal). **Adrian D Haughton**, project administration (equal), resources (equal), writing – original draft (support), writing – review & editing (support). **Madilyn Augustine**, conceptualization (support), writing – original draft (support), writing – review & editing (support), writing – review & editing (support). **Philip Bodurtha**, project administration (equal), resources (equal), writing – review & editing (support). **Robert S. Axtell**, project administration (equal), resources (equal), writing – review & editing (support). **Beatrice Borsari**, investigation methodology (support), writing – review & editing (support). **Jason Liu**, investigation methodology (support), writing – review & editing (support). **Shaoke Lou**, investigation methodology (support), writing – review & editing (support). **Xin Xin**, investigation methodology (support), writing – review & editing (support). **Lisa M. Fucito**, conceptualization (support), investigation methodology (support), writing – review & editing (support). **Sangchoon Jeon**, formal analysis (equal), visualization (lead), writing – original draft (support), writing – review & editing (equal). **Matthew Stults-Kolehmainen**, conceptualization (equal), formal analysis (support), investigation methodology (equal), writing – original draft (support), writing – review & editing (equal). **Mark B. Gerstein**, conceptualization (equal), formal analysis (support), funding acquisition (equal), investigation methodology (equal), supervision (lead), visualization (support), writing – review & editing (lead).

Generative Artificial Intelligence

No generative artificial intelligence was used in any aspect of this work.

References

1. Paluch AE, Bajpai S, Bassett DR, Carnethon MR, Ekelund U, Evenson KR, et al. Daily steps and all-cause mortality: a meta-analysis of 15 international cohorts. *Lancet Public Health*. 2022 Mar;7(3):e219-e28. PMID: 35247352. doi: 10.1016/S2468-2667(21)00302-9.
2. Master H, Annis J, Huang S, Beckman JA, Ratsimbazafy F, Marginean K, et al. Association of step counts over time with the risk of chronic disease in the All of Us Research Program. *Nat Med*. 2022 Nov;28(11):2301-8. PMID: 36216933. doi: 10.1038/s41591-022-02012-w.
3. Association ACH. The healthy campus framework. Silver Spring, MD: American College Health Association; 2020.
4. Coakley KE, Lardier DT, Holladay KR, Amorim FT, Zuhl MN. Physical Activity Behavior and Mental Health Among University Students During COVID-19 Lockdown. *Front Sports Act Living*. 2021;3:682175. PMID: 34308346. doi: 10.3389/fspor.2021.682175.
5. Lopez-Valenciano A, Suarez-Iglesias D, Sanchez-Lastra MA, Ayan C. Impact of COVID-19 Pandemic on University Students' Physical Activity Levels: An Early Systematic Review. *Front Psychol*. 2020;11:624567. PMID: 33519653. doi: 10.3389/fpsyg.2020.624567.
6. Rouvinen H, Turunen H, Lindfors P, Kinnunen JM, Rimpelä A, Koivusilta L, et al. Online health information-seeking behaviour and mental well-being among Finnish higher education students during COVID-19. *Health Promotion International*. 2023;38(6). doi: 10.1093/heapro/daad143.
7. Schäfer M, Stark B, Werner AM, Tibubos AN, Reichel JL, Pfirrmann D, et al. Health information seeking among university students before and during the corona crisis—findings from Germany. *Frontiers in public health*. 2021;8:616603.
8. U.S. Y. Wearables Devices - Ownership - Biannual Tracker. 2024; Available from: <https://today.yougov.com/topics/technology/trackers/wearable-devices-ownership?crossBreak=1829>.
9. Gravett KW, N. Making connections: authenticity and alienation within students' relationships in higher education. *Higher Education Research & Development*. 2022;41(2):360-74. doi: <https://doi.org/10.1080/07294360.2020.1842335>.
10. Baumeister RF, Leary MR. The need to belong: desire for interpersonal attachments as a fundamental human motivation. *Psychol Bull*. 1995 May;117(3):497-529. PMID: 7777651.

11. Otundo JOM, S. O. Effect of Situational Interest and Social Support on College Students' Physical Activity Motivation: A Mixed Methods Analysis *The Physical Educator*. 2019;76(2):502-23. doi: 10.18666/TPE-2019-V76-I2-8502.
12. Alshehri MA, Kruse-Diehr AJ, McDaniel J, Partridge JA, Null D. Impact of Social Support on the Physical Activity Behaviors of International College Students in the United States. *Int J Exerc Sci*. 2021;14(5):1305-19. PMID: 35096246.
13. Marler EK, Bruce MJ, Abaoud A, Henrichsen C, Suksatan W, Homvisetvongsa S, et al. The impact of COVID-19 on university students' academic motivation, social connection, and psychological well-being. *Scholarship of Teaching and Learning in Psychology*. 2024;10(3):320.
14. Lattie EG, Cohen KA, Hersch E, Williams KDA, Kruzan KP, MacIver C, et al. Uptake and effectiveness of a self-guided mobile app platform for college student mental health. *Internet Interv*. 2022 Mar;27:100493. PMID: 35036331. doi: 10.1016/j.invent.2021.100493.
15. Kim GS, Lee CY, Kim IS, Lee TH, Cho E, Lee H, et al. Dyadic Effects of Individual and Friend on Physical Activity in College Students. *Public Health Nurs*. 2015 Sep-Oct;32(5):430-9. PMID: 25565084. doi: 10.1111/phn.12176.
16. Lieffers JRL, Quintanilha M, Trottier CF, Johnson ST, Mota JF, Prado CM. Experiences with and Perception of a Web-Based Mindfulness, Nutrition, and Fitness Platform Reported by First-Year University Students: A Qualitative Study. *J Acad Nutr Diet*. 2021 Dec;121(12):2409-18 e3. PMID: 34119458. doi: 10.1016/j.jand.2021.04.019.
17. Ryan RM, Deci EL. Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *Am Psychol*. 2000 Jan;55(1):68-78. PMID: 11392867. doi: 10.1037//0003-066x.55.1.68.
18. Conner M, Norman P. Predicting health behaviour: Research and practice with social cognition models. Maidenhead, BRK, England: Open University Press; 2005. ix, 230 p. ISBN: 0-335-19321-8.
19. Bao H, Lee EWJ. Examining Theoretical Frameworks and Antecedents of Health Apps and Wearables Use: A Scoping Review. *Health Commun*. 2023 Nov 15:1-11. PMID: 37968803. doi: 10.1080/10410236.2023.2283655.
20. Kang HS, Exworthy M. Wearing the Future—Wearables to Empower Users to Take Greater Responsibility for Their Health and Care: Scoping Review. *JMIR Mhealth Uhealth*. 2022 2022/7/13;10(7):e35684. doi: 10.2196/35684.
21. Hartson KR, Della LJ, King KM, Liu S, Chatman JM, Rhodes RE. A Web-Based Intervention for Insufficiently Active College Students: Feasibility and Preliminary Efficacy. *Western Journal of Nursing Research*. 2024;01939459241253218.
22. Mo D, Xiang M, Luo M, Dong Y, Fang Y, Zhang S, et al. Using gamification and social incentives to increase physical activity and related social cognition among undergraduate students in Shanghai, China. *International Journal of Environmental Research and Public Health*. 2019;16(5):858.
23. Fackler CA, Baugh N, Lovegren AA, Nemeroff C, Whatley Blum J. Technology-Enhanced Health Promotion for College Students: A Seed Development Project. *Nurs Rep*. 2021 Mar 1;11(1):143-51. PMID: 34968319. doi: 10.3390/nursrep11010014.
24. Krzyzanowski MC, Kizakevich PN, Duren-Winfield V, Eckhoff R, Hampton J, Blackman Carr LT, et al. Rams Have Heart, a Mobile App Tracking Activity and Fruit and Vegetable Consumption to Support the Cardiovascular Health of College Students: Development and Usability Study. *JMIR Mhealth Uhealth*. 2020 Aug 5;8(8):e15156. PMID: 32755883. doi: 10.2196/15156.
25. Melcher J, Camacho E, Lagan S, Torous J. College student engagement with mental health apps: analysis of barriers to sustained use. *J Am Coll Health*. 2022 Aug-Sep;70(6):1819-25. PMID: 33048626. doi: 10.1080/07448481.2020.1825225.
26. Wang X, Yang X, Juzaily bin Mohd Nasiruddin N, Wei S, Dong D, bin Samsudin S. Social Support and Physical Activity in College and University Students: A Meta-Analysis. *Health Education & Behavior*. 2024;10901981231216735.
27. Cavallo DN, Tate DF, Ries AV, Brown JD, DeVellis RF, Ammerman AS. A social media-based physical

- activity intervention: a randomized controlled trial. *Am J Prev Med.* 2012 Nov;43(5):527-32. PMID: 23079176. doi: 10.1016/j.amepre.2012.07.019.
28. Rote AE. Physical activity intervention using Fitbits in an introductory college health course. *Health Educ J.* 2017 Apr;76(3):337-48. PMID: WOS:000408776700008. doi: 10.1177/0017896916674505.
29. Tong HL, Coiera E, Tong W, Wang Y, Quiroz JC, Martin P, et al. Efficacy of a Mobile Social Networking Intervention in Promoting Physical Activity: Quasi-Experimental Study. *JMIR Mhealth Uhealth.* 2019 Mar 28;7(3):e12181. PMID: 30920379. doi: 10.2196/12181.
30. Edney SM, Olds TS, Ryan JC, Vandelanotte C, Plotnikoff RC, Curtis RG, et al. A Social Networking and Gamified App to Increase Physical Activity: Cluster RCT. *Am J Prev Med.* 2020 Feb;58(2):e51-e62. PMID: 31959326. doi: 10.1016/j.amepre.2019.09.009.
31. Wang M, Guo Y, Zhang Y, Xie S, Yu Z, Luo J, et al. Promoting healthy lifestyle in Chinese college students: evaluation of a social media-based intervention applying the RE-AIM framework. *Eur J Clin Nutr.* 2021 Feb;75(2):335-44. PMID: 32366994. doi: 10.1038/s41430-020-0643-2.
32. Tong HL, Quiroz JC, Kocaballi AB, Ijaz K, Coiera E, Chow CK, et al. A personalized mobile app for physical activity: An experimental mixed-methods study. *Digit Health.* 2022 Jan-Dec;8:20552076221115017. PMID: 35898287. doi: 10.1177/20552076221115017.
33. Nam SJ, Cha C. Effects of a social-media-based support on premenstrual syndrome and physical activity among female university students in South Korea. *Journal of Psychosomatic Obstetrics & Gynecology.* 2020;41(1):47-53.
34. Rote AE, Klos LA, Brondino MJ, Harley AE, Swartz AM. The efficacy of a walking intervention using social media to increase physical activity: a randomized trial. *Journal of Physical Activity and Health.* 2015;12(s1):S18-S25.
35. Mandic D, Bjegovic-Mikanovic V, Vukovic D, Djikanovic B, Stamenkovic Z, Lalic NM. Successful promotion of physical activity among students of medicine through motivational interview and Web-based intervention. *PeerJ.* 2020;8:e9495.
36. Todorovic J, Terzic-Supic Z, Djikanovic B, Nesic D, Piperac P, Stamenkovic Z. Can social media intervention improve physical activity of medical students? *Public Health.* 2019;174:69-73.
37. Zhang J, Brackbill D, Yang S, Centola D. Efficacy and causal mechanism of an online social media intervention to increase physical activity: Results of a randomized controlled trial. *Preventive medicine reports.* 2015;2:651-7.
38. Sofro ZM, Wibowo RA, Wasityastuti W, Kusumadewi AF, Utomo PS, Ekawati FM, et al. Physical activity virtual intervention for improving mental health among university students during the COVID-19 pandemic: A Co-creation process and evaluation using the Behavior Change Wheel. *Heliyon.* 2023;9(8).
39. Marker AM, Staiano AE. Better together: outcomes of cooperation versus competition in social exergaming. *Games for health journal.* 2015;4(1):25-30.
40. Orji R, editor. Why are persuasive strategies effective? Exploring the strengths and weaknesses of socially-oriented persuasive strategies. *Persuasive Technology: Development and Implementation of Personalized Technologies to Change Attitudes and Behaviors: 12th International Conference, PERSUASIVE 2017, Amsterdam, The Netherlands, April 4–6, 2017, Proceedings 12; 2017: Springer.*
41. Sultoni K, Peralta LR, Cotton W. Using a design-based research approach to develop a technology-supported physical education course to increase the physical activity levels of university students: Study protocol paper. *PLoS One.* 2022;17(12):e0269759. PMID: 36454897. doi: 10.1371/journal.pone.0269759.
42. Afshin A, Babalola D, McLean M, Yu Z, Ma W, Chen CY, et al. Information Technology and Lifestyle: A Systematic Evaluation of Internet and Mobile Interventions for Improving Diet, Physical Activity, Obesity, Tobacco, and Alcohol Use. *J Am Heart Assoc.* 2016 Aug 31;5(9). PMID: 27581172. doi: 10.1161/JAHA.115.003058.
43. Collins LM. Optimization of Behavioral, Biobehavioral, and Biomedical Interventions : The Multiphase Optimization Strategy (MOST). Cham: Springer International Publishing : Imprint: Springer; 2018.
44. Troiano RP, Berrigan D, Dodd KW, Masse LC, Tilert T, McDowell M. Physical activity in the United States measured by accelerometer. *Medicine and science in sports and exercise.* 2008;40(1):181-8. doi: 10.1249/

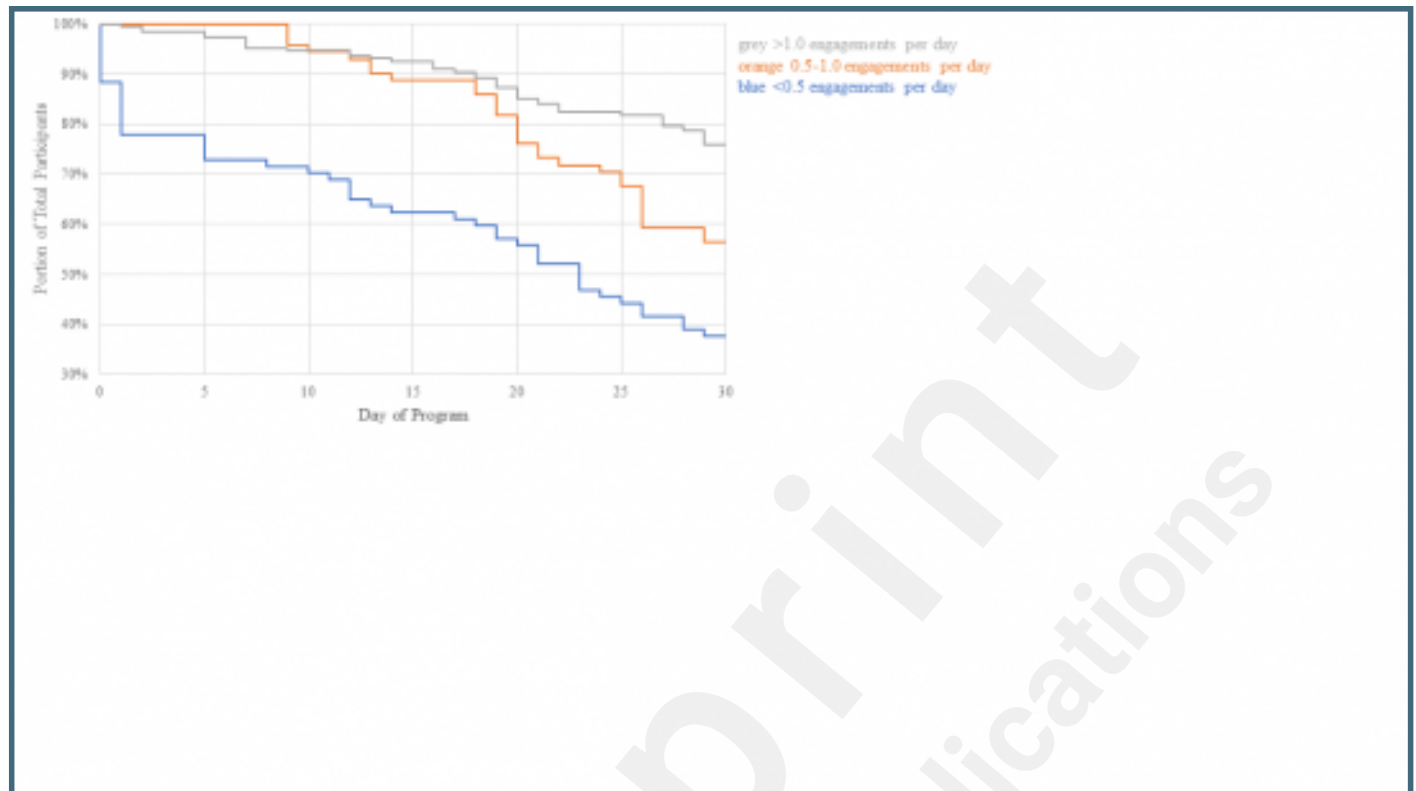
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45. Fuller D, Colwell E, Low J, Orychock K, Tobin MA, Simango B, et al. Reliability and Validity of Commercially Available Wearable Devices for Measuring Steps, Energy Expenditure, and Heart Rate: Systematic Review. *JMIR mHealth and uHealth*. 2020;8(9):e18694. doi: 10.2196/18694 [doi].
46. National Postsecondary Student Aid Study: 2020 Undergraduate Students. National Center for Education Statistics. Accessed September 15, 2024. <https://nces.ed.gov/datalab/powerstats/157-national-postsecondary-student-aid-study-2020-undergraduate-students/percentage-distribution>
47. National Center for Education Statistics. Number and percentage of students enrolled in degree-granting postsecondary institutions, by distance education participation, location of student, level of enrollment, and control and level of institution: Fall 2021 and fall 2022. 2023. Available at: https://nces.ed.gov/programs/digest/d22/tables/dt22_311.15.asp
48. [Consumer](#) Insights by Statista. Wearables: Apple users in the United States. October 2024. Available at: <https://www.statista.com/study/74021/wearables-apple-users-in-the-united-states/>
49. Haughton, Adrian; Ash, Garrett, 2024, "Southern Connecticut State University MoveSpring (TM) Steps Challenge", <https://doi.org/10.7910/DVN/IJNAVQ>, Harvard Dataverse, V1
50. Steenholt CB, Pisinger VSC, Danquah IH, Tolstrup JS. School and class-level variations and patterns of physical activity: a multilevel analysis of Danish high school students. *BMC public health*. 2018;18(1):255-018-5155-9. doi: 10.1186/s12889-018-5155-9 [doi].
51. Tullar JM, Walker TJ, Page TF, Taylor WC, Roman R, Amick BC, 3rd. Evaluation of a Worksite-Based Small Group Team Challenge to Increase Physical Activity. *Am J Health Promot*. 2019 Feb;33(2):259-66. PMID: 29996662. doi: 10.1177/0890117118784229.
52. Valle CG, Tate DF, Mayer DK, Allicock M, Cai J. A randomized trial of a Facebook-based physical activity intervention for young adult cancer survivors. *J Cancer Surviv*. 2013 Sep;7(3):355-68. PMID: 23532799. doi: 10.1007/s11764-013-0279-5.
53. Looyestyn J, Kernot J, Boshoff K, Maher C. A Web-Based, Social Networking Beginners' Running Intervention for Adults Aged 18 to 50 Years Delivered via a Facebook Group: Randomized Controlled Trial. *J Med Internet Res*. 2018 Feb 26;20(2):e67. PMID: 29483065. doi: 10.2196/jmir.7862.
54. Bricker J, Miao Z, Mull K, Santiago-Torres M, Vock DM. Can a Single Variable Predict Early Dropout From Digital Health Interventions? Comparison of Predictive Models From Two Large Randomized Trials. *J Med Internet Res*. 2023 Jan 20;25:e43629. PMID: 36662550. doi: 10.2196/43629.
55. Ellington M, Connelly J, Clayton P, Lorenzo CY, Collazo-Velazquez C, Trak-Fellermeier MA, et al. Use of Facebook, Instagram, and Twitter for recruiting healthy participants in nutrition-, physical activity-, or obesity-related studies: a systematic review. *Am J Clin Nutr*. 2022 Feb 9;115(2):514-33. PMID: 34669955. doi: 10.1093/ajcn/nqab352.
56. Settersten RA, Ottusch T. M., and Schneider, B. In: edited by Scott R. KS, editor. *Emerging Trends in the Social and Behavioral Sciences*. New York, NY: Wiley Online Library.; 2015. p. 1-16.
57. Adu MD, Malabu UH, Malau-Aduli AE, Drovandi A, Malau-Aduli BS. User Retention and Engagement With a Mobile App Intervention to Support Self-Management in Australians With Type 1 or Type 2 Diabetes (My Care Hub): Mixed Methods Study. *JMIR Mhealth Uhealth*. 2020 Jun 11;8(6):e17802. PMID: 32525491. doi: 10.2196/17802.
58. Mustafa AS, Ali N, Dhillon JS, Alkawsy G, Baashar Y. User Engagement and Abandonment of mHealth: A Cross-Sectional Survey. *Healthcare (Basel)*. 2022 Jan 24;10(2). PMID: 35206837. doi: 10.3390/healthcare10020221.
59. Amagai S, Pila S, Kaat AJ, Nowinski CJ, Gershon RC. Challenges in Participant Engagement and Retention Using Mobile Health Apps: Literature Review. *J Med Internet Res*. 2022 Apr 26;24(4):e35120. PMID: 35471414. doi: 10.2196/35120.
60. Integrated Postsecondary Education Data System, Southern Connecticut State University Page, Year 2020. National Center for Education Statistics. Available online at: <https://nces.ed.gov/ipeds/reported-data/130493?year=2020&surveyNumber=9>

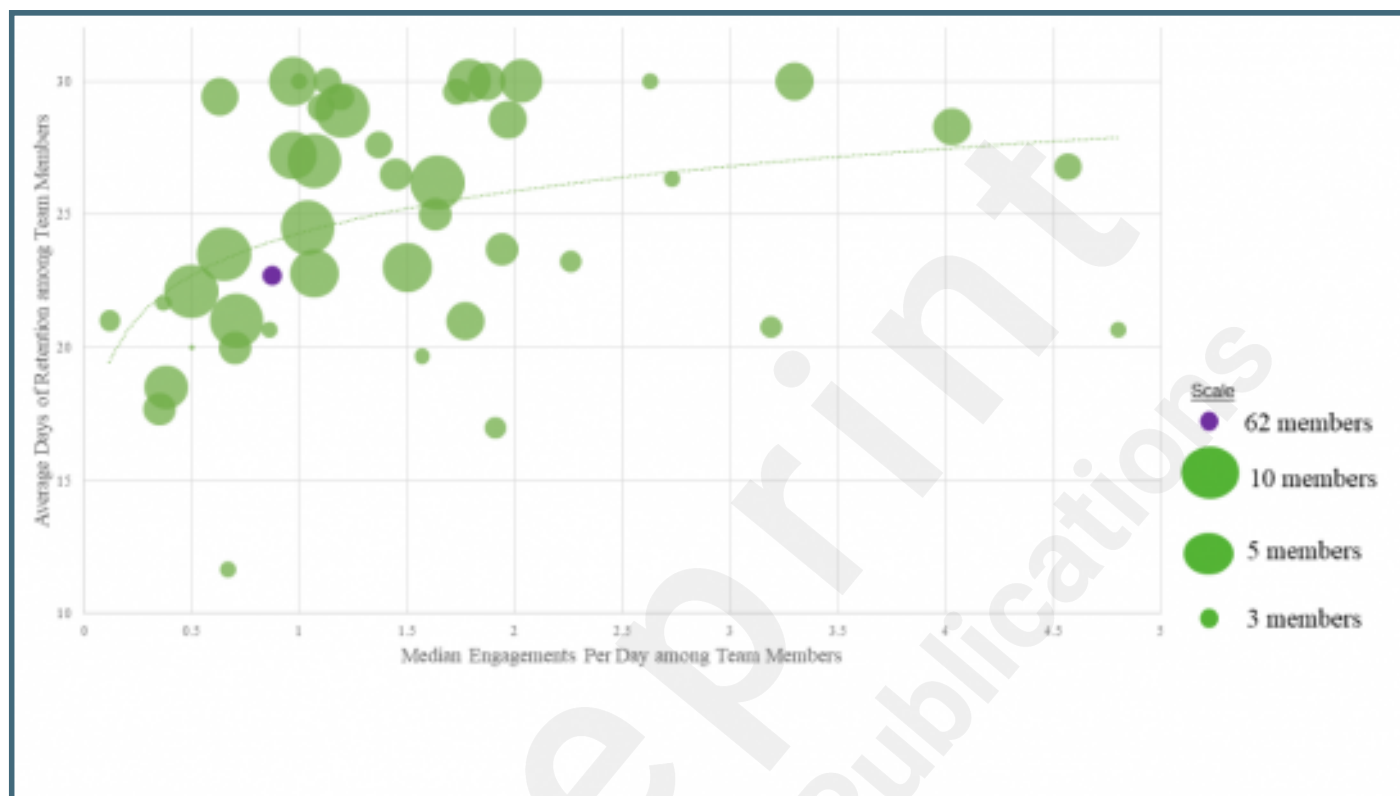
Supplementary Files

Figures

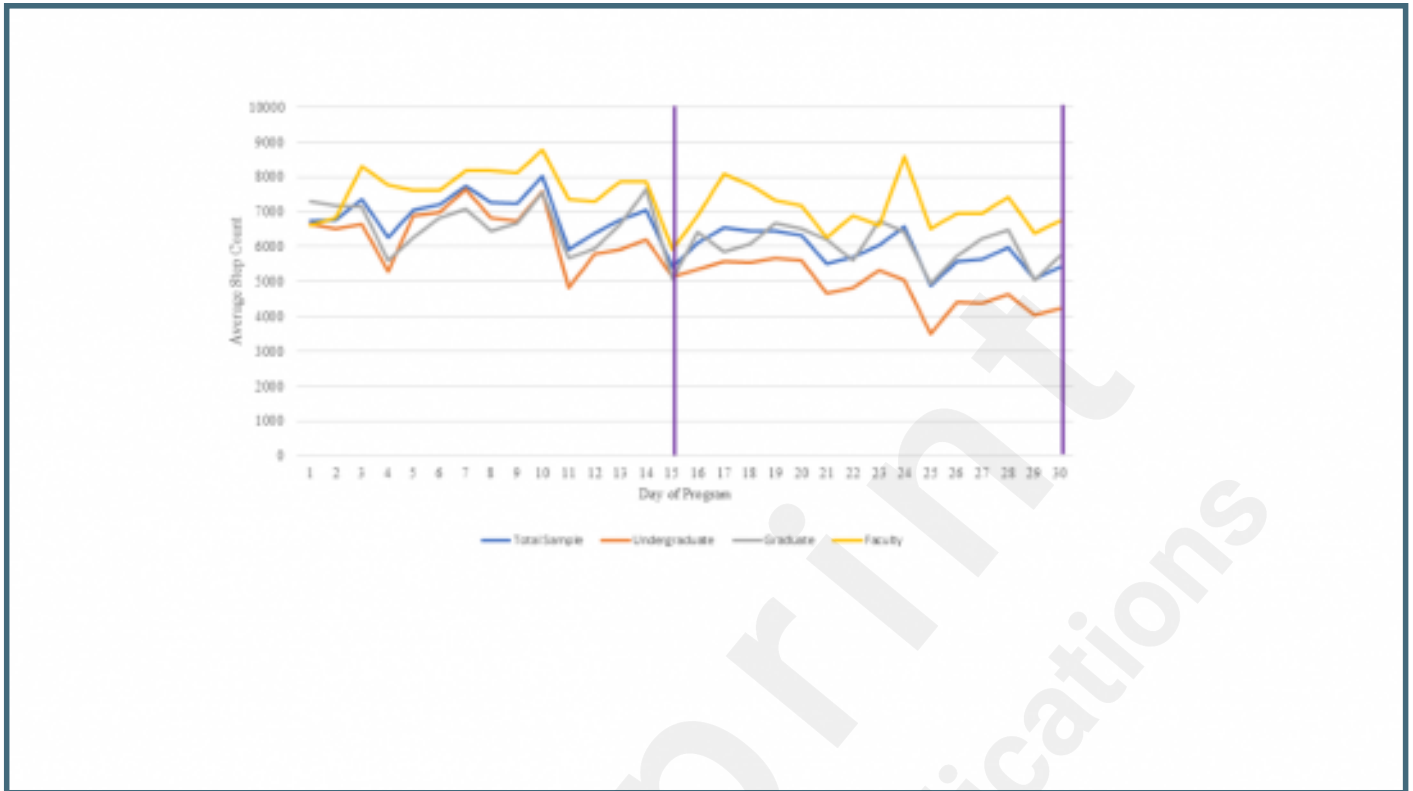
Retention survival curve according to engagements per day, which was the only predictor of retention retained in the parsimonious final model.



Retention (i.e., duration of app usage before abandonment) clustered by team affiliation (intra-cluster correlation coefficient 0.064). Therefore, we plotted average retention among team members in relation to team characteristics including team size (bubble size) and median app engagements per day among team members (x-axis). It is visually apparent that the longer retained individuals were those on the teams with larger size and/or higher median rate of app engagement. Dotted curve is for visual purposes and approximates retention days as $2.29 * \ln(\text{median engagement of team}) + 24.29$.



Temporal trends in steps per day relative to the cutoffs for the prize drawings (purple).



Multimedia Appendixes

Intake Survey.

URL: <http://asset.jmir.pub/assets/47530bd49332b20e95156a0fa243b3c6.docx>

Supplemental Analysis.

URL: <http://asset.jmir.pub/assets/ab046109ed1221fcfe47fbccc9909fc6.docx>

Campus demographics.

URL: <http://asset.jmir.pub/assets/0466125535bc77c14fb5226f68ff133f.docx>



CONSORT (or other) checklists

STROBE Checklist.

URL: <http://asset.jmir.pub/assets/488e736a2457c6f8d0892896a145d5a9.pdf>