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ORIGINAL RESEARCH

Applying Sequence Analysis to Explore Real-World Usage Patterns in the 10,000 Steps Digital Physical Activity Program

Yanshu Huang,[1] Danielle Taylor,[1] Matthias Kubler,[1] Sarah-Ann Burger,[1] Anetta Van Itallie,[2] Corneel Vandelanotte,[2] and Mark Robinson[1]

[1]Institute for Social Science Research, The University of Queensland, St Lucia, QLD, Australia; [2]Appleton Institute, School of Health, Medical and Applied Sciences, Central Queensland University, Rockhampton, QLD, Australia

Background: Digital health programs can enhance physical activity, but engagement duration influences behavioral impact. We examined general medium/long-term engagement and disengagement patterns of the 10,000 Steps program. ***Methods:*** Sequence analysis identified patterns of program use over 7 years (2018–2024) of adults from Queensland, Australia. Subgroup patterns of program engagement were identified. Logistic regression identified demographic and program correlates of subgroup membership. ***Results:*** Most users showed short-term program engagement. Two user groups engaged over a longer period compared with most users. One group (7.1%) showed a pattern of program use between periods of inactivity. These users were more likely to have heard about the program through health professionals/programs (odds ratio [OR] = 4.59; 95% CI, 3.49–6.06) or family/friends (OR = 3.88; 95% CI, 2.94–5.12), and participated in Tournaments (OR = 1.37; 95% CI, 1.30–1.45), or used Fitbit devices (OR = 1.73; 95% CI, 1.42–2.11) or the website (OR = 2.25; 95% CI, 1.82–2.78). A small group consistently used the program with little inactivity (4.5%), characterized by participating in more individual Challenges (OR = 1.32; 95% CI, 1.26–1.38) and Tournaments (OR = 1.76; 95% CI, 1.59–1.94), and using Garmin devices (OR = 319.37; 95% CI, 219.20–465.31) and the Google app (OR = 6.37; 95% CI, 2.50–16.21). ***Conclusions:*** These findings reveal that medium/long-term engagement with the 10,000 Steps program is characterized by varying levels of engagement over time, depending on program feature engagement and device use.

Keywords: behavioral science, pedometry, health behavior

Key Points

- Longitudinal real-world program data of a digital physical health program aimed at increasing physical activity were used to understand program engagement patterns and demographic factors associated with medium/long-term engagement.
- Using sequence analysis on 7 years (2018–2024) of program engagement data, results showed that although a majority of users engage in short-term 'bursts,' 2 subsets of users remained consistently active.
- Consistently active users either reengaged with the program at regular intervals between inactivity periods or were consistently active, revealing novel medium/long-term engagement patterns with digital health programs.

Digital health interventions, such as those using websites or smartphone apps, are a widely accessible resource for improving health outcomes[1] and offer an opportunity to decrease the cost of noncommunicable disease.[2] User engagement with these programs through the active use of their features presents an important proxy to assess program effectiveness in improving physical activity levels. While engagement with digital physical activity interventions can increase levels of physical activity,[3] the primary challenge of digital health programs is of nonusage attrition.[4] Specifically, nonusage attrition in these digital health applications manifests as a loss of interest or infrequent use of the program, resulting in a loss of participation. Participants of such programs typically engage in the short term, ranging from a few days to about a month,[5] but program success is contingent on longer term adherence.[6] Re-engagement—a return to the active use of a program following a period of cessation—with health programs provides an opportunity for behavioral change in the future, particularly if engagement has seemingly ceased.

Determinants of attrition from and adherence to digital health programs have been thoroughly researched.[5,7,8] Users typically discontinue around 2 to 26 days after commencement.[5] Factors associated with longer adherence to digital physical activity programs include demographic factors such as being older age[5] and male,[6] personal health improvement motivations,[5,7] and program features such as platform user-friendliness and "gamified" or social features (eg, challenges or competitions against other users or peers).[6,8,9] However, studies examining longer term program adherence or re-engagement of users of digital health programs remain nascent. Furthermore, a systematic review of mobile health interventions revealed that user engagement as a research outcome comprised only 19.2% of the reviewed studies.[10] In a similar vein, a systematic review of real-world digital health program evidence found that long-term maintenance was assessed in 42% of reviewed studies.[11] Thus, understanding longer-term engagement and re-engagement patterns is important for understanding how digital health programs can operate in longer timescales, which is important for improving chronic health outcomes which require longer-term behavioral changes.

Van Itallie https://orcid.org/0000-0001-6506-1996
Vandelanotte https://orcid.org/0000-0002-4445-8094
Robinson https://orcid.org/0000-0003-4911-7106
Huang (yanshu.huang@uq.edu.au) is corresponding author, https://orcid.org/0000-0003-2120-6609

The aim of this study is to examine medium- to long-term use and engagement patterns of a digital physical activity program targeted toward inactive adults. Prior research has focused on shorter periods of engagement, typically when program engagement first ceases (eg, up to 26 d).[5] We define medium- to long-term use as periods longer than typical periods of engagement, with enough time elapsed to capture re-engagement patterns following cessation. In our study, we consider medium- to long-term use patterns over a period of between 2 months and 7 years (depending on when participants joined the program) that facilitates tracking program engagement beyond an initial burst as observed in prior studies. Additionally, our paper has exploratory character and focuses on general usage patterns of a digital physical activity program targeted at inactive adults to increase their awareness of their levels of physical activity and supporting them to become more active. These insights will improve understanding of how people use digital programs to support improving physical activity and what features would benefit implementation and improvement to support these goals.

We use a novel method of understanding longitudinal patterns of program engagement through sequence analysis. Sequence analysis has been more commonly used in the social sciences to understand phenomena such as labor market trajectories.[12] Examples of this method in medical and health research include studies on care pathways of multiple sclerosis patients,[13] utilization patterns of different rehabilitation service types,[14] or how education trajectories are associated with physical health outcomes.[15] Prior studies examining longer term engagement have used quasi-experimental methods which target a predetermined period of time following participant engagement,[16] limiting the timescale for potential re-engagement. For real-world engagement patterns, previous studies have utilized longitudinal methods such as survival analysis to understand the time it takes to cease program engagement.[17] As nonusage attrition is often operationalized as not engaging with the program for 14 or 28 days, these analytical methods are unable to account for re-engagement with a program, following the first instance of nonusage or program engagement outside the study conditions. Applying sequence analysis to program usage data provides an opportunity to examine the types of engagement that occur within digital physical activity programs, namely, the *10,000 Steps* program (the focus of the present study). These insights can help identify features within the *10,000 Steps* program that might be better leveraged to enhance engagement and build physical activity in everyday life.

Although our study is largely exploratory, we anticipate a few broad patterns of program engagement to emerge. First, we expect program attrition or cessation of engagement with the program following an initial burst of engagement, aligning with past research on program engagement cessation.[5] In addition, a meta-analysis found that behavior changes from some physical activity interventions can be sustained if the mechanism underlying the program emphasized comparative processes (eg, social comparison) or self-belief motivations (eg, recalling past successes).[18] Correspondingly, we expect that some patterns of program use might be reflective of being drawn to "gamified" *10,000 Steps* program features that emphasize competition (eg, team-based competition challenges) or self-reflection (eg, monthly steps challenges aimed at reaching a monthly physical activity goal). These patterns might therefore show more periods of activity beyond an initial short period of engagement.

We analyzed 7 years of program data of the *10,000 Steps* program to understand engagement of users. To understand similar patterns of engagement, cluster analysis was used to identify common trends of program engagement. Finally, demographic and program-use correlates of distinct medium-/long-term engagement patterns were identified.

Method

About the *10,000 Steps* Program

The *10,000 Steps* program is a free digital physical activity program, targeted at inactive adults and intended to increase individual physical activity levels, through tracking steps, setting goals, and participating in group activities.[19] Users track their physical activity through an interactive website and mobile applications. Although the program is based in Queensland, Australia, users worldwide are able to participate. On the website and mobile application, users are able to set and update daily goals, record their daily steps or minutes of moderate or vigorous physical activity, and add "friends" among other users.

The program supports users either through individual features or through group-based activities. Specifically, users can participate in individual monthly Challenges or team Tournaments. In Challenges, individual users can track their physical activity to meet a program-set Challenge goal (eg, achieving a goal distance in the equivalent number of steps within a set amount of time, such as a month). In Tournaments, participants can form teams within organizations to compete against each other through physical activity and step-tracking. Organizations might choose to reimplement Tournaments within their workplaces, with frequencies depending on the organization's interests. Individuals who coordinate Tournaments are volunteers within their organization and recruit participants from the organization's employees or members, with participation being voluntary. Finally, the program also conducts annual Health Challenges which are large-scale Tournaments for cross-organizational competition within an industry such as higher education (eg, the Australasian University Health Challenge) or regional health service providers within Queensland (eg, the Queensland Health Steps Challenge or Campaign).

While the roots of the program go back to 2001, a majority of *10,000 Steps* participants (93.8%) joined the program from 2018 onward. An earlier study found that most participants joined because of their workplace (82.4%), most often because their employer had adopted the *10,000 Steps* program as a health and well-being initiative, particularly through the implementation of Tournaments or team-based challenges.[20]

Sample Participants

The population in scope of this study are participants of the *10,000 Steps* program. When signing up for the program, users provided informed consent for the usage of their data for research purposes. While the program targets adults, a small percentage of users were under age 18 when joining the program.

Due to limits in computing power of the statistical package and the nature of the computational processes of sequence analysis, we were not able to include all participants in scope in our analyses.[21] After identifying acceptable sample size limits, we randomly selected a 16.9% sample that was stratified by the year of entry into the program and the referral source. This resulted in a sample of n = 13,689 participants.

There were notable variations in the number of people who entered the *10,000 Steps* program over the period 2018–2024, which partly correspond to the timeframe of the COVID-19 pandemic. Consistent with previous research,[20] the majority of the in-scope population entered the program after referral from workplaces including through workplace/organizational Tournaments.

The stratification was applied to ensure that the sample reflected the representation of the in-scope *10,000 Steps* participant population in relation to the year in which participants joined the program and in relation to how they found the program (ie, referral source) to account for the variation in factors that potentially influence medium- to long-term participation patterns.

Finally, it is important to note that as our analyses focused on general engagement patterns of medium- to long-term active users in recent years, the participants only include users who were ever-active (ie, logged any step counts) within the timeframe. Users who registered during this time period but were never-active are not reflected in the engagement patterns, neither are users who registered and only engaged prior to the analyzed time period.

Measures

Program Engagement/Stepping

The outcome variable, program engagement or logging steps, was measured using a categorical variable, with 3 elements indicating different statuses of program use: (1) "Not a member": calendar month(s) prior to the participant registering on the *10,000 Steps* platform; (2) "Nonactive member": calendar month(s) in which the participant did not log any steps on the platform; and (3) "Active member": calendar month(s) in which the participant logged at least one step entry on the platform. The outcome variable was measured across the 84 calendar months between January 2018 and December 2024, with each sequence or participant having one of each of the 3 statuses for the whole time series, depending on when they became a *10,000 Steps* member and whether they entered any steps into the platform for each month after becoming a member.

Explanatory Variables

Demographic factors are collected from participants when they register for the program. These included age (in categories), gender, referral source (where the participant heard about the program from), and deciles of a socio-economic index for areas index of relative socio-economic disadvantage (SEIFA IRSD; higher values indicating lower disadvantage), derived from postcodes provided by participants.

Additional program engagement measures assessed the number of Tournaments and Challenges that the participants have engaged in during the time series, as well as the number of friend requests they have sent or received. These collectively indicate additional platform engagement beyond entering steps.

The modes of how steps were entered into the program were also included as explanatory variables. Binary variables indicating if participants *ever* entered steps into the platform using (1) the program mobile app, (2) their Fitbit device, (3) their Garmin device, (4) the Google Health app, or (5) the program website. Responses for these variables were not mutually exclusive.

Analytical Approach

Stata version 18.0 was used to perform all analyses. The *SQ*[21]and *SADI*[22] packages were used to conduct all sequence analyses. Sequence analyses were used to identify common patterns of program engagement and re-engagement, while accounting for timing-related engagement patterns associated with the climate and seasons of Queensland, Australia.

To construct the sequences, step logging data were transformed to form discrete units of engagement. Step logging data (ie, users entering nonzero step entries to the *10,000 Steps* platform) are recorded by days, associated with unique calendar dates. To transform these data into an appropriate analytic format, daily steps were first summed into calendar month units for every participant. Each value was then transformed into one of the 3 program engagement categories for 84 calendar month units (January 2018–December 2024).

There are computational limits for the SQ package and Stata that limits the number of sequences (or cases) that can be analyzed for sequence analysis.[21] Specifically, with longer sequences and a higher number of sequences, the running-time complexity of the *Needleman–Wunsch* algorithm underlying the package increases. The SQ package is able to reliably run sequence analyses with 2000 sequences and 100 positions. After that, each of the 13,689 participants in the sample had an individual sequence of program engagement statuses over the period 2018–2024. Of these 13,689 participant status sequences, 3446 were unique sequences.

The dissimilarity matrix was then constructed using the dynamic Hamming distance, due to its responsiveness to seasonality.[23] The algorithm computes the distance between each unique sequence through status substitutions to identify how different each sequence is from each other, and these distances are stored in a matrix. Substitution costs were specified to respond to plausibility of the status transition between the "Not a member" status to either an "Active member" or "Nonactive" member status. Because it is impossible to transform from a "Nonactive" member status or "Active member" to a "Not a member" status, a higher penalty applied for substitutions with the "Not a member" status.

Hierarchical cluster analysis, using Ward's clustering algorithm, was applied to dissimilarity matrix to identify groups of similar sequences. A combination of methods was used to decide on the final number of clusters. These methods included a visual inspection of a dendrogram (a figure displaying groups of similar observations, hierarchically clustered in a tree pattern), inspections of sequence visualizations across different cluster solutions, and inspection of the Calinski–Harabasz pseudo-F and Duda–Hart pseudo T^2 statistic. Due to discrepancies between each of the methods for cluster analysis, the final cluster solution was decided using the visual inspection of cluster solutions.

Finally, to identify demographic and program-related factors associated with cluster membership of distinct clusters, logistic regression models were conducted. Three sets of models were run, the first modeling demographic factors, the second modeling program engagement indicators along with demographic factors, and the third collectively modeling modes of step entries, demographic factors, and program engagement.

Results

Sequence Analysis of Program Engagement Patterns

Figure 1 presents a sequence index plot of overall patterns of engagement across all 13,689 sequences included in the analyses. A visual inspection of these patterns suggests seasonal patterns of engagement with the program overall, around August, coinciding with the start of Spring in Queensland, Australia.

Cluster Analysis

The visual inspection of the dendrogram suggested a 5 or 8 cluster solution. The Duda–Hart stopping rules suggested a 9- or 13-cluster solution (as identified by the smallest pseudo T^2 values; see Table 1). Calinski–Harabasz criteria suggested a 2-, 3-, or 4-cluster

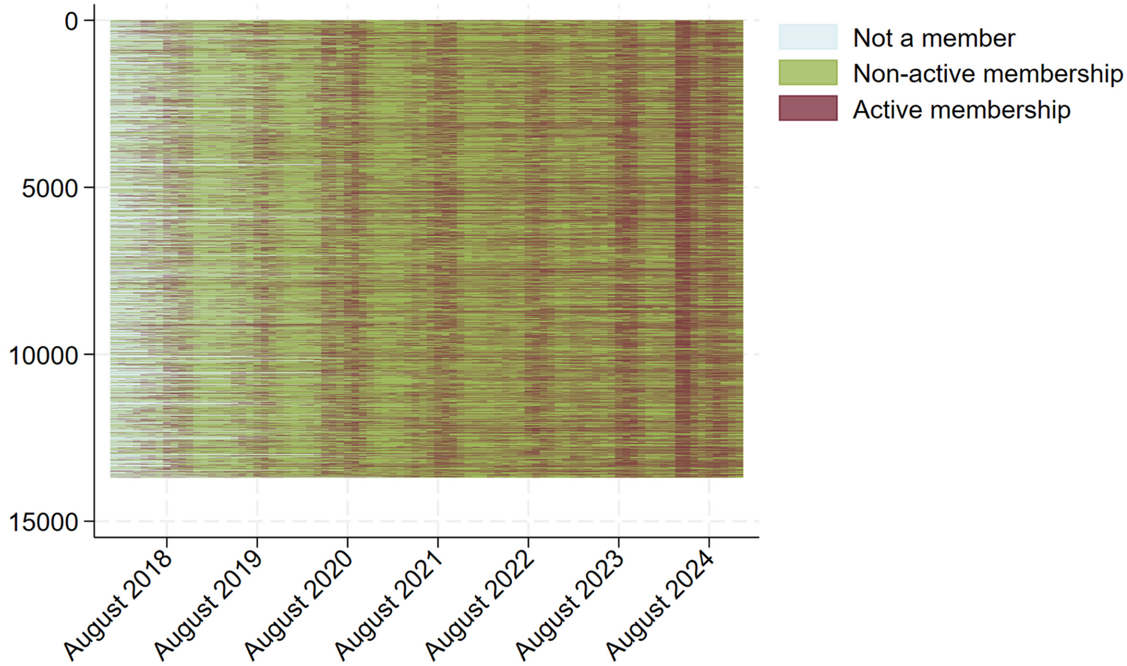

Figure 1 — Sequence index plot visualizing step statuses for 10,000 Steps participants from January 2018 to December 2024. The number of sequences analyzed are displayed on the *y*-axis. Note that these sequences represent a subsample of the full active user base within this time series.

Table 1 Summary of Duda–Hart and Calinski–Harabasz Indices From 2 to 15 Cluster Solutions

Number of clusters	Duda–Hart		Calinski–Harabasz
	Je(2)/Je(1)	Pseudo-T^2	Pseudo-*F*
2	0.4194	10,872.51	37,647.18
3	0.4596	6853.89	36,772.06
4	0.6723	2708.81	35,093.02
5	0.7081	904.51	34,231.85
6	0.2914	8173.70	30,503.20
7	0.3946	4786.47	31,473.29
8	0.2774	5978.10	31,519.28
9	0.9605	111.49	29,646.36
10	0.2324	4412.87	26,770.02
11	0.4068	2707.77	30,808.39
12	0.3444	3669.40	30,070.97
13	0.9193	156.75	29,453.42
14	0.3323	2533.89	27,910.89
15	0.4838	433.12	26,548.64

solution (as identified by the higher pseudo-*F* values). The visual inspection of the clustered sequences across different cluster solutions was guided by knowledge of the *10,000 Steps* program, particularly of trends in participation with relation to larger-scale participation drives such as Tournaments or Health Challenges. This approach suggested that a 11-cluster solution would be the most appropriate. Given the lack of a unanimous solution across methods and a reflection of how engagement patterns would likely occur in the program, the 11-cluster solution was chosen to reflect the most meaningful subsets of patterns for the *10,000 Steps* program.

Summary statistics of demographic characteristics and other program features for each of the 11 clusters are presented in Table 2. Figure 2 presents the sequence index plots of each of the 11 derived clusters showing patterns of program engagement from the sequence analysis. Visual inspection of the clusters informed the naming of each cluster. The timing of registration (ie, calendar months and years) and duration of and frequency of "Active member" states were considered alongside knowledge of typical user engagement, and large-scale events (eg, Health Challenges) that might influence overall activity patterns were used to determine the defining features of each cluster and their corresponding names.

Describing Engagement Clusters.

The first cluster *Long-term intermittent* (7.1%) represents users who have a longer history of using the *10,000 Steps* program (ie, participants who joined prior to 2018). These users are characterized by bursts of "Nonactive member" statuses and "Active member" statuses across the time series.

The next 7 clusters represent new registrants each year from 2018 to 2024, joining around August each year (*2018 newcomers*, 9.7%; *2019 newcomers* 10.5%; *2020 newcomers*, 14.1%; *2021 newcomers*, 13.1%; *2022 newcomers*, 9.2%; *2023 newcomers*, 13.6%; *2024 newcomers*, 8.1%). As shown in the plots, a portion of participants re-engage annually with the program at a regular schedule but the majority of these users are "one-time" program users.

The ninth cluster represents users who likely joined the 2024 Queensland Health Steps Challenge (*2024 QH campaign*; 10.0%), a large campaign facilitated by the program in Hospital and Health Services across the state and held in April to May 2024. This was indicated by a large pattern of registrations in 2024 prior to August.

Finally, the 10th (*2022 enthusiasts*, 1.6%) and 11th clusters (*2020 enthusiasts*, 2.9%) represent users who joined the program in

Table 2 Summary Statistics of Demographic Factors, Platform Engagement, and Modes of Step Entry Across Sequence Clusters

	All participants	Long-term intermittent	2018 newcomers	2019 newcomers	2020 newcomers	2021 newcomers	2022 newcomers	2023 newcomers	2024 newcomers	2024 QH challenge	2022 enthusiasts	2020 enthusiasts
	13,689	974	1323	1434	1930	1788	1263	1859	1113	1372	225	408
N	% or mean (SD)	% or mean (SD)	% or mean (SD)	% or mean (SD)	% or mean (SD)	% or mean (SD)	% or mean (SD)	% or mean (SD)	% or mean (SD)	% or mean (SD)	% or mean (SD)	% or mean (SD)
Age categories, y												
<18	1.3	1.0	1.1	1.0	4.3	1.5	0.7	0.5	0.5	0.2	0.0	0.3
18–34	34.7	31.7	32.7	34.2	33.6	36.9	36.0	36.0	33.3	36.1	36.4	33.3
35–44	27.3	29.9	27.7	29.0	25.4	27.2	27.2	25.2	28.6	26.1	32.0	31.4
45–54	22.4	25.7	24.0	21.7	22.2	21.6	21.9	20.9	20.7	23.2	24.9	23.5
55–64	10.7	10.3	11.3	10.3	12.5	10.6	10.2	10.7	11.7	9.4	4.9	10.1
65+	3.7	1.4	3.2	3.8	2.1	2.2	3.9	6.7	5.2	5.0	1.8	1.5
Gender												
Men	27.1	24.4	26.1	28.4	25.9	27.4	28.5	27.3	31.1	21.4	36.2	36.2
Women	72.9	75.6	73.9	71.6	74.1	72.6	71.5	72.7	68.9	78.6	63.8	63.8
SEIFA IRSD[a]	6.63 (2.60)	6.15 (2.50)	6.65 (2.55)	6.52 (2.56)	6.41 (2.71)	6.78 (2.63)	6.74 (2.00)	6.81 (2.59)	6.83 (2.59)	6.52 (2.63)	7.10 (2.45)	6.71 (2.63)
Referral source												
Workplace	82.4	67.3	81.2	80.8	74.8	81.1	87.7	89.8	90.3	89.9	90.7	69.6
Health professionals or programs	3.1	8.0	1.4	1.9	1.9	2.3	3.5	2.7	3.0	5.0	2.2	4.4
Online	3.1	4.7	3.0	3.9	5.6	2.8	1.9	1.9	1.2	1.0	1.3	7.4
Family or friends	3.0	7.7	3.9	3.1	4.8	3.5	0.1	0.0	2.5	2.7	0.0	5.9
Other or unknown	8.4	12.3	10.5	10.4	13.0	10.4	6.8	5.6	3.1	1.5	5.8	12.8

(continued)

Table 2 *(continued)*

	All participants	Long-term intermittent	2018 newcomers	2019 newcomers	2020 newcomers	2021 newcomers	2022 newcomers	2023 newcomers	2024 newcomers	2024 QH challenge	2022 enthusiasts	2020 enthusiasts
	13,689	974	1323	1434	1930	1788	1263	1859	1113	1372	225	408
N	% or mean (SD)	% or mean (SD)	% or mean (SD)	% or mean (SD)	% or mean (SD)	% or mean (SD)	% or mean (SD)	% or mean (SD)	% or mean (SD)	% or mean (SD)	% or mean (SD)	% or mean (SD)
Platform engagement												
Challenge count	0.20 (2.10)	0.16 (1.04)	0.08 (0.48)	0.26 (2.2)	0.10 (0.52)	0.13 (0.93)	0.06 (0.00)	0.08 (0.44)	0.13 (0.82)	0.04 (0.28)	0.64 (3.23)	2.79 (10.29)
Tournament count	1.29 (1.01)	1.67 (1.37)	1.34 (1.01)	1.41 (1.09)	1.30 (1.06)	1.32 (0.92)	1.35 (1.00)	1.27 (0.77)	0.91 (0.49)	0.87 (0.43)	1.68 (1.18)	1.94 (1.96)
Friend requests sent	0.18 (0.97)	0.14 (0.73)	0.24 (1.17)	0.25 (1.15)	0.18 (0.92)	0.15 (0.92)	0.14 (1.00)	0.17 (0.96)	0.10 (0.74)	0.13 (0.87)	0.38 (1.43)	0.39 (1.52)
Friend requests received	0.17 (0.60)	0.19 (0.55)	0.21 (0.68)	0.21 (0.62)	0.22 (0.73)	0.14 (0.54)	0.17 (0.56)	0.15 (0.64)	0.09 (0.42)	0.11 (0.44)	0.16 (0.44)	0.25 (0.72)
Modes of step entry												
Used the app	51.3	33.5	25.6	35.6	45.4	49.5	56.4	66.7	68.6	75.2	64.4	48.8
Used a Fitbit	9.0	16.0	12.8	15.0	10.5	8.1	6.5	6.9	3.2	4.4	1.8	8.3
Used a Garmin	8.5	1.9	0.2	5.0	1.6	6.2	2.1	5.1	19.1	1.9	90.7	89.0
Used Google app	1.4	0.3	0.2	0.1	0.1	0.7	2.5	3.2	2.9	1.8	3.1	2.0
Used the website	66.5	84.0	88.2	83.6	73.5	69.1	56.3	46.1	52.2	37.3	92.4	97.6

Abbreviation: SEIFA IRSD, socio-economic index for areas index of relative socio-economic disadvantage.
Note: Although participants aged <18 years are included in the analysis, they are a small group that is not the target population (adults) of the program.
[a]Higher values indicate lower area-level socioeconomic disadvantage.

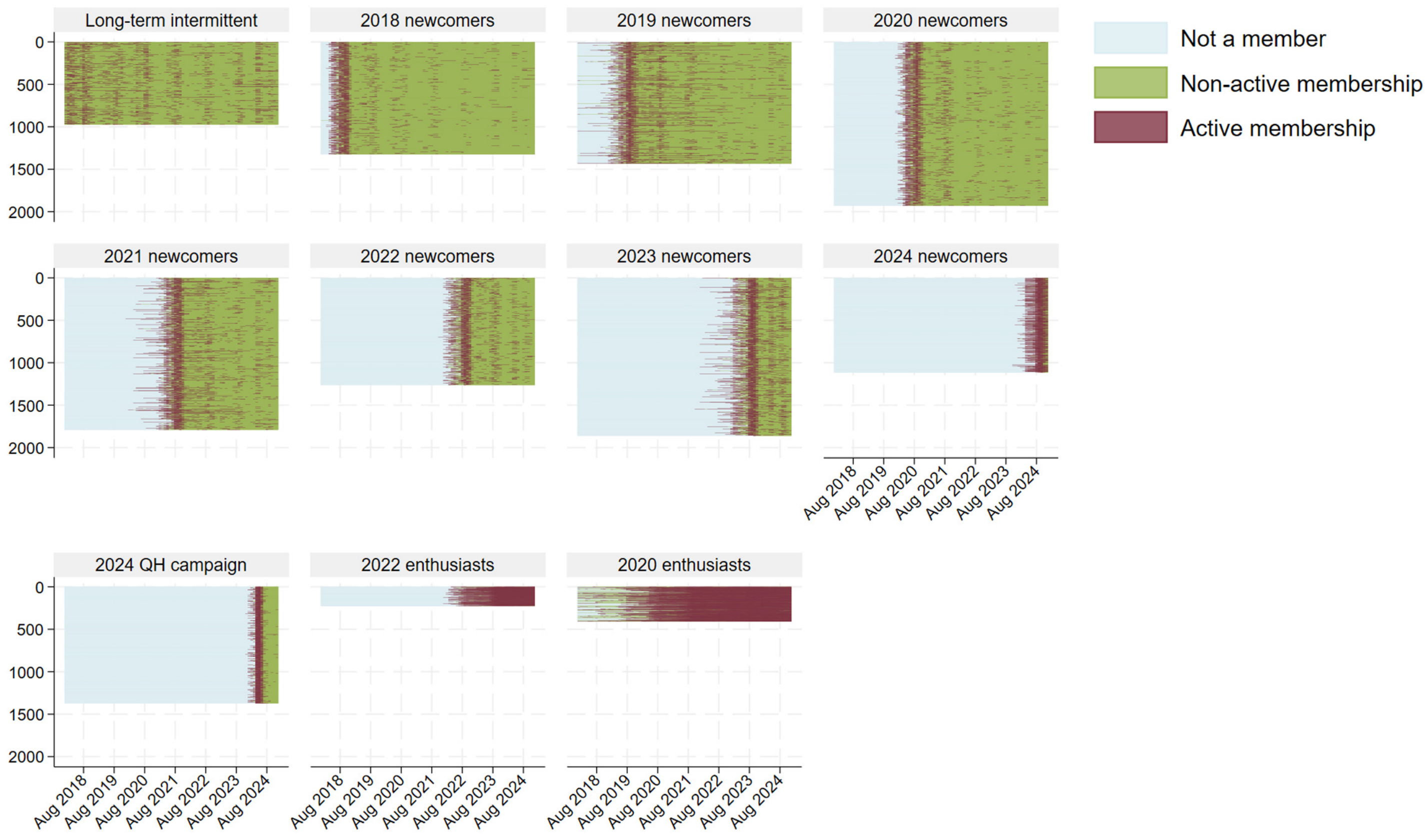

Figure 2 — Sequence index plot of overall patterns of engagement, disengagement, and reengagement across 11 clusters from January 2018 to December 2024. The *y*-axis displays the number of sequences within each cluster. The *x*-axis displays the calendar months across the time series, with labels for August of each year to identify the month with the most engagement (ie, stepping) across sequences within clusters.

2022 and 2020, respectively, and are characterized by consistent "Active member" statuses following registration (ie, after transitioning out of the "Not a member" status).

Figure 3 presents the distribution of statuses (ie, "Not a member," "Non–active member," "Active member") across each month from January 2018 to December 2024, across each of the 11 clusters of program engagement. This figure displays the percentage of each status within each month, across all participants within each cluster.

Interpreting Engagement Clusters.

The *Long-term intermittent* cluster is characterized by a high percentage of "Non-active member" statuses across the months, with peaks of "Active member" statuses occurring seasonally, around August. The *2018* to *2024 newcomers* as well as the *2024 QH campaign* clusters are characterized by a high percentage of "Not a member" statuses preceding a peak of "Active member" statuses immediately after a drop in "Not a member" statuses, indicating the first instance of participation in the program by these users. Each of these clusters then displays higher percentages of "Non-active member" with the occasional seasonal peaks of "Active member" statuses after the initial large peak of participation. The *2024 newcomers* and *2024 QH campaign* clusters joining late in the time series have only one peak in participation, suggesting that not enough time has passed since registration to observe follow-up engagement with the program. Additionally, the *2024 QH campaign* cluster might represent participation in an event rather than an engagement with the program itself.

Finally, the 2 *Enthusiasts* clusters (ie, *2020 enthusiasts* and *2022 enthusiasts*) are characterized by participants who joined the program either earlier in the time series (around 2019) or later, after the COVID-19 pandemic (around 2022). These participants have a consistently high percentage of "Active member" statuses across the time series after starting with the program and low levels of "Non-active member" periods. They distinctively lack the seasonal peaks of "Active member" periods, in between nonactive periods, as characteristic of other clusters of participants. Although registering with the program appears to be based on timing (ie, calendar year), the defining feature of these clusters is their consistent use of the program following the first initial burst of participation or multiple bursts as characterized by the previous clusters.

Logistic Regression

In order to understand the characteristics associated with cluster membership, particularly for participants who consistently engage with the program, logistic regression models were conducted for specific clusters. These sets of models assessed the 2 main groups of consistent participation: (1) consistently engaged clusters (*Enthusiast* clusters, namely *2020 enthusiasts* and *2022 enthusiasts*) and (2) longer term re-engagement cluster (*Long-term intermittent* cluster).

Consistently Engaged Clusters.

The 2 consistently engaged clusters (*Enthusiasts*) membership was tested against membership in the remaining clusters which

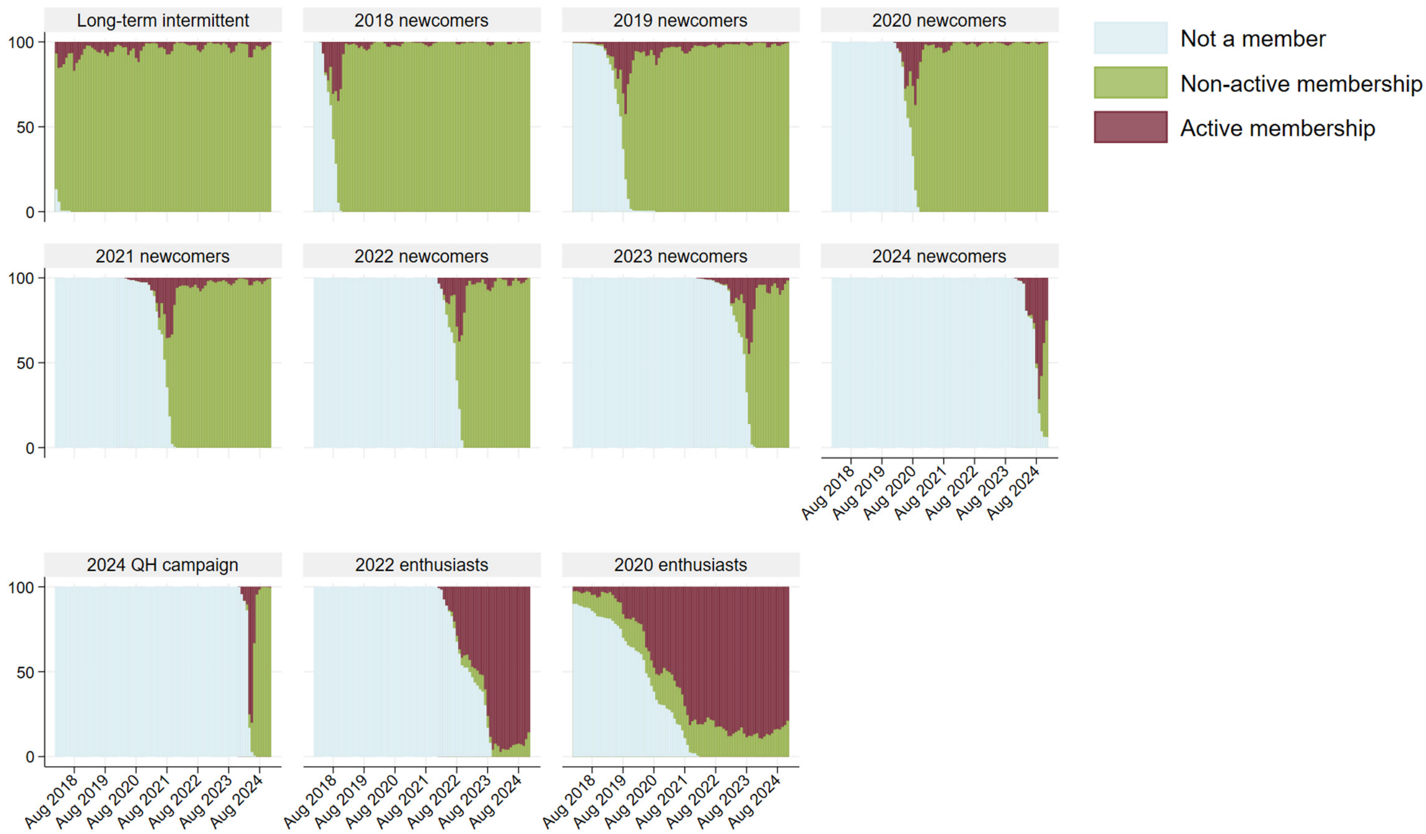

Figure 3 — Status distribution percentage plots of engagement patterns across 11 clusters of from January 2018 to December 2024. The x-axis displays the calendar months within the time series. The y-axis displays the percentage within each cluster that each status holds, per unit (ie, calendar month) across the time series.

indicated more inconsistent program engagement. The results of the logistic regression models examining demographic factors, program engagement measures, and modes of step entry are presented in Table 3.

In the first model, when only accounting for demographic factors and how the participant found the program, relative to the young adult age group (18–34 y), participants age 65 years and older were less likely to belong to a consistently engaged cluster. Additionally, men (relative to women), people who joined after hearing about the program from an online source or another source (either offline, an "unable to be categorized" source, or an unknown source), were more likely to belong to a consistently engaged cluster, relative to those who joined because of their workplace.

A similar pattern of results for demographic factors was seen in model 2 when also accounting for program engagement variables, with the addition of the age category 55–64 years now also significantly less likely to belong to a consistently engaged cluster. Those who joined from an online or other/unknown source remained significant factors of increased likelihood of being consistently engaged. In terms of platform engagement factors, participants who engaged in more Challenges, Tournaments, and sent more friend requests were significantly more likely to belong to a consistently engaged cluster.

In the final model, accounting for modes of step entry, the only demographic factor associated with belonging to a consistently engaged cluster was gender with men remaining more likely to be an *Enthusiast.* The same referral sources (online and other/unknown relative to those joined through a workplace) remained significant predictors of a higher probability of belonging to an engaged cluster. Participating in more Challenges and Tournaments remained significant predictors of a higher likelihood of belonging to a consistently engaged group. Finally, when accounting for all other factors, participants who used the mobile app were less likely to belong to a consistently engaged cluster. Descriptive statistics show that a majority of these users entered steps on the website at least once, but using the website was not significantly related to being an *Enthusiast* in our multivariate model. Alternatively, participants who entered steps into the program through a Garmin device or a Google app were more likely to belong to a consistently engaged cluster.

Long-Term Intermittent.

Membership to the *Long-term intermittent* cluster was tested against all other clusters; the results of these models are presented in Table 4.

In the first model examining demographic and referral factors, when compared with those aged 18–34 years, participants aged 35 to 54 were more likely to belong to the *Long-term intermittent* cluster. These participants were also more likely to have heard about the program from sources other than a workplace, such as through a health professional or program or their family or friends.

A similar pattern for demographics and referral source was found when accounting for platform feature variables. Engaging in more Tournaments was related to belonging to this consistently re-engaging cluster which confirms the seasonal pattern of engagement seen in their sequences.

Table 3 Logistic Regression Coefficients Modeling Associations Between Demographic Factors, Platform Engagement, Modes of Step Entry, and Membership in a Consistently Engaged (Enthusiast) Cluster ($N_{Total} = 13,603$, $n_{Enthusiasts} = 633$)

	Model 1 (demographic factors)				Model 2 (platform engagement)				Model 3 (modes of step entry)			
	B	OR	OR 95% CI	*P*	*B*	OR	OR 95% CI	*P*	*B*	OR	OR 95% CI	*P*
Age (Ref: 18–34 y)												
<18 y	−2.36*	0.09	0.01–0.68	.019	−2.11*	0.12	0.02–0.88	.037	−1.54	0.21	0.02–1.96	.173
35–44 y	0.16	1.18	0.97–1.44	.106	0.13	1.14	0.93–1.39	.210	−0.04	0.96	0.73–1.27	.784
45–54 y	0.09	1.09	0.88–1.36	.409	−0.00	1.00	0.80–1.25	.992	0.15	1.17	0.86–1.59	.330
55–64 y	−0.29	0.75	0.55–1.02	.069	−0.38*	0.68	0.49–0.95	.024	−0.36	0.70	0.44–1.11	.130
65+ y	−1.16**	0.31	0.15–0.64	.001	−1.12**	0.33	0.15–0.70	.004	−0.80	0.45	0.19–1.09	.076
Women (Ref: men)	−0.45***	0.64	0.54–0.76	<.001	−0.49***	0.61	0.51–0.73	<.001	−0.30*	0.74	0.58–0.94	.014
SEIFA IRSD	0.02	1.03	0.99–1.06	.124	0.03	1.03	1.00–1.07	.064	0.01	1.01	0.97–1.06	.571
Referral source (Ref: workplace)												
Health professionals or programs	0.37	1.44	0.94–2.22	.096	0.38	1.46	0.93–2.28	.098	0.25	1.28	0.69–2.39	.429
Online	0.78***	2.18	1.51–3.16	<.001	0.64**	1.89	1.23–2.89	.003	0.91**	2.48	1.33–4.63	.004
Family or friends	0.35	1.41	0.92–2.16	.110	0.25	1.28	0.82–2.01	.282	0.59	1.81	0.93–3.51	.078
Other or unknown	0.45**	1.58	1.20–2.07	.001	0.41**	1.51	1.13–2.01	.005	0.72***	2.05	1.34–3.13	.001
Challenge count					0.19***	1.46	1.16–1.25	<.001	0.28***	1.32	1.26–1.38	<.001
Tournament count					0.38***	1.89	1.38–1.56	<.001	0.56***	1.76	1.59–1.94	<.001
Friend requests sent					0.11***	1.28	1.06–1.19	<.001	0.08	1.08	0.99–1.19	.096
Friend requests received					−0.05	1.51	0.83–1.09	.482	−0.04	0.96	0.79–1.16	.662
Used the app									−0.28*	0.75	0.60–0.95	.018
Used a Fitbit									−0.13	0.88	0.49–1.57	.661
Used a Garmin									5.77***	319.37	219.20–465.31	<.001
Used Google app									1.85***	6.37	2.50–16.21	<.001
Used the website	0.37	1.44	0.94–2.22		0.38	1.46	0.93–2.28		0.26	1.30	0.78–2.17	.317
Constant	−2.99***	0.05	0.04–0.07	<.001	−3.63***	0.03	0.02–0.04	<.001	−6.78***	0.00	0.00–0.00	<.001

Abbreviations: OR, odds ratio; SEIFA IRSD, socio-economic index for areas index of relative socio-economic disadvantage. Note: Inconsistency in sample size between logistic models and total number of sequences is due to missing data across variables. Although participants aged <18 years are included in the analysis, they are a small group that is not the target population (adults) of the program.
$^*P < .05$. $^{**}P < .01$. $^{***}P < .001$.

Table 4 Logistic Regression Coefficients Modeling Associations Between Demographic Factors, Platform Engagement, Modes of Step Entry, and Membership in the Long-Term Intermittent Cluster (N_{Total} = 13,608, $n_{Long\text{-}term\ intermittent}$ = 974)

	Model 1 (demographic factors)				Model 2 (platform engagement)				Model 3 (modes of step entry)			
	B	OR	OR 95% CI	P	B	OR	OR 95% CI	P	B	OR	OR 95% CI	P
Age (Ref: 18–34 y)												
<18 y	–0.73*	0.48	0.25–0.93	.031	–0.62	0.54	0.28–1.05	.068	–0.87*	0.42	0.22–0.82	.011
35–44 y	0.21*	1.23	1.04–1.45	.016	0.20*	1.22	1.03–1.45	.020	0.16	1.17	0.98–1.39	.076
45–54 y	0.26**	1.30	1.09–1.55	.003	0.26**	1.29	1.08–1.54	.005	0.14	1.15	0.96–1.38	.119
55–64 y	0.00	1.00	0.79–1.27	.971	0.07	1.08	0.85–1.37	.547	–0.06	0.94	0.74–1.20	.645
65+ y	–1.19***	0.30	0.17–0.54	<.001	–1.09***	0.34	0.19–0.59	<.001	–1.28***	0.28	0.16–0.49	<.001
Women (Ref: men)	0.10	1.11	0.95–1.29	.191	0.12	1.13	0.97–1.32	.128	0.09	1.10	0.94–1.28	.257
SEIFA IRSD[a]	–0.07***	0.93	0.91–0.96	<.001	–0.07***	0.93	0.91–0.96	<.001	–0.08***	0.93	0.90–0.95	<.001
Referral source (Ref: workplace)												
Health professionals or programs	1.33***	3.77	2.90–4.89	<.001	1.40***	4.06	3.12–5.29	<.001	1.52***	4.59	3.49–6.06	<.001
Online	0.68***	1.97	1.43–2.71	<.001	0.93***	2.52	1.82–3.49	<.001	0.92***	2.50	1.79–3.48	<.001
Family or friends	1.32***	3.75	2.88–4.88	<.001	1.36***	3.89	2.97–5.10	<.001	1.36***	3.88	2.94–5.12	<.001
Other or unknown	0.74***	2.10	1.70–2.59	<.001	0.81***	2.24	1.81–2.77	<.001	0.70***	2.02	1.63–2.51	<.001
Challenge count					–0.08**	0.92	0.87–0.98	.006	–0.06*	0.95	0.90–1.00	.037
Tournament count					0.32***	1.38	1.31–1.45	<.001	0.32***	1.37	1.30–1.45	<.001
Friend requests sent					–0.09*	0.92	0.84–1.00	.050	–0.09*	0.91	0.83–1.00	.043
Friend requests received					0.03	1.03	0.92–1.15	.642	0.01	1.01	0.90–1.13	.907
Used the app									–0.47***	0.62	0.53–0.74	<.001
Used a Fitbit									0.55***	1.73	1.42–2.11	<.001
Used a Garmin									–1.93***	0.15	0.09–0.24	<.001
Used Google app									–1.27*	0.28	0.09–0.89	.031
Used the website									0.81***	2.25	1.82–2.78	<.001
Constant	–2.50***	.08	0.06–0.10		–3.00***	0.05	0.04–0.06		–3.23***	0.04	0.03–0.05	<.001

Abbreviations: OR, odds ratio; SEIFA IRSD, socio-economic index for areas index of relative socio-economic disadvantage. Note: Inconsistency in sample size between logistic models and total number of sequences is due to missing data across variables. Although participants aged <18 years are included in the analysis, they are a small group that is not the target population (adults) of the program.
[a]Higher values indicate lower area-level socioeconomic disadvantage.
*$P < .05$. **$P < .01$. ***$P < .001$.

In the final model, examining modes of step entry, participants who used a Fitbit and the website to enter steps were more likely to belong to the *Long-term intermittent* cluster. In contrast, those who used the app, a Garmin device, or a Google app to enter steps were less likely to belong to this cluster.

Discussion

Principal Findings

This study examined engagement patterns of a subsample of users of the *10,000 Steps* platforms using longitudinal real-world program use data from 2018 to 2024, encompassing a period before, during, and after the COVID-19 pandemic. The paper also presents a novel use of sequence analysis and cluster analysis to understand heterogenous digital program usage patterns. The findings suggest that a majority of these users (95.5%) have similar engagement patterns, characterized by short-term use before becoming inactive. It appears that most clusters correspond to recruitments into Tournaments and Health Challenges, which has potential to bring groups of new users to the program, reflected by each annual *Newcomer* cluster and the *2024 QH campaign* cluster. These findings extend on past research on the *10,000 Steps* program on platform traffic patterns. Previous research on *10,000 Steps* usage found that despite an initial drop off in step entries in the early days of the COVID-19 lockdown period (around April 2020), program engagement returned to normal.[24] Indeed, our results suggest that program use was largely unaffected by the COVID-19 pandemic.

Previous research on the *10,000 Steps* program has also found that 50% of users drop off after 30 days, consistent with the typical length of a Tournament or Challenge.[25] However, this was not the case for our *Long-term intermittent* group of users (around 7.1% of participants) who are more likely to re-engage with the program in bursts, following periods of inactivity, suggesting that users have not dropped out entirely. This group of users reveals a new subset of program usage within *10,000 Steps* where users return to the program, over a multiyear time span. The typical pattern of this subgroup of users, who appear to drop out, are actually re-engaging, often in a regular pattern. The regularity suggests that they may be engaging in program-specific features such as Tournaments or Challenges. A visible peak of engagement at the start of Spring (around August in Queensland) was identified, a season in which the population of interest would experience ideal weather conditions for outdoor activity. This time of year appears to be aligned with increased Tournament implementation by organizations, contributing to the re-engagement of users. This is suggested by the finding that participating in more Tournaments (but not monthly individual Challenges) was associated with a higher probability of being a member of this group. They were also more likely to have joined prior to the time series, suggesting this group of users might have a longer-term relationship with using the program. These findings suggest that participant retention is more complicated than initial program attrition and reveals opportunities to evaluate medium- to long-term participation patterns with longer timescales. Furthermore, these findings emphasize the value of understanding engagement patterns of digital health program users,[10] particularly those who are more motivated by social and "gamified" aspects of programs (like Tournaments and Challenges) and have potential to direct program improvements for re-engaging users.

There was a small but distinct group of participants (*Enthusiasts*; around 4.7%) who—after registering—showed a consistent pattern of active engagement. *Enthusiasts* were more likely to be men. It also appeared that users with this engagement pattern rapidly increased in number from 2020 (although a general subset of users with consistent and long-term program use has been previously identified by the program[26]). This is in contrast to most users who typically drop off (seen in many of the *Newcomer* clusters) or suspend platform use at the end of a Tournament (as seen in the *Long-term intermittent* group) as it appears these users continue program use. One program feature that might help explain this is receptiveness to how the program follows up with users upon Tournament completion. Specifically, the *10,000 Steps* program staff began an initiative of follow-up emails to these users to encourage further use of the platform, beyond Tournament participation. Although it is unclear whether all of these participants initially joined *10,000 Steps* to participate in a Tournament (ie, these participants may have joined the platform due to personal motivations that were unaccounted for by the study), one possible explanation is that the *Enthusiasts* cluster may have been influenced by re-engagement initiatives.

Although we were unable to directly measure reasons for consistent usage, users in the *Enthusiasts* subgroup may have been more attracted to "gamified" aspects of the program such as joining monthly individual Challenges or Tournaments. These users were also more likely to have linked their Garmin activity tracking device to the *10,000 Steps* platform. These findings extend on a previous paper on nonusage attrition in the *10,000 Steps* program (prior to the integration of Garmin devices), which found that users who used a combination of a Fitbit device and the website to log steps had the longest engagement periods compared with other methods of step entry.[27] However, in our case, the *Long-term intermittent* group were the most similar to previously identified profile of users in that they were more likely to use a Fitbit and the Web platform. Given the distinct activity profile of the *Enthusiast* group, another explanation for their consistent active platform use could be that they are subset of users who are more interested in physical activity. Indeed, past research has suggested that Garmin devices are more popular with people with a strong interest in sports and exercise.[28,29] In addition, given the financial cost of purchasing an activity tracker like a Garmin device, these individuals may have already demonstrated a commitment to monitoring physical activity levels.[30] As such, they might also be inherently interested in other physical activity goals, such as participating in Tournaments and Challenges.

A study on a digital mental health program using a wearable device also found that participants remained longer in the program relative to those relying on phone-based engagement.[31] Passive modes of data input—compared with more active modes such as entering steps or minutes of physical activity into the *10,000 Steps* app—may reduce user burden and extend participant retention while enabling more consistent program use.[32] However, previous research has suggested that Web use of the platform (whether alongside another mode of entry or not) was associated with lower attrition risk from the program.[25] Additionally, a combination of Web and another mode of step entry was associated with longer engagement periods relative to sole Web or app users.[27] Together these results suggest that a combination of engagement modes, particularly with the website, is related to longer and more consistent use of the *10,000 Steps* program.

Strengths, Limitations, and Future Directions

A key strength of this study is the use of 7 years of real-world longitudinal use data of a freely available digital health intervention program. In addition, we demonstrated a novel use of sequence analysis in understanding physical activity behavior and digital health program engagement. Using cluster analyses to analyze sequences revealed subsets of medium- to long-term usage patterns, particularly uncovering cyclical engagement patterns. Although users differed by how long they have been registered with the program, the analyses revealed heterogenous patterns of engagement, disengagement, and re-engagement.

A number of limitations need to be considered. First, patterns of program usage may not necessarily reflect changes in physical activity, either before becoming a member or after becoming an inactive user. A popular use of the program is to participate in Tournaments, something reflected by the majority of usage patterns. Consequently, the findings might reflect patterns associated with usage patterns of organizations implementing Tournaments (eg, as an annual well-being initiative) and their participants' engagement rather than changes in physical activity.

Second, our categorization of program engagement statuses reflected an interest in general engagement patterns over a longer timeframe that was limited to observing whether a user was active or not per calendar month. This pragmatic categorization, also influenced by computing considerations, did not allow identifying and capturing variations in physical activity behavior in more detail. For example, the level of physical activity intensity was not included in these analyses. Although users of the platform have the option to input minutes of moderate or vigorous activity as well as input numbers of steps, our categorization of program use as a binary between active versus inactive within calendar months obscures potential differences in physical activity. As a result, user engagement with the program might be overestimated (eg, if users only entered a handful of step entries). Future studies could extend on our findings, for example, studies with shorter time spans to enable greater granularity that may also investigate whether participants met their physical activity goals within a month (using the goal setting feature of the program).

Next, the interpretation of findings related to the mode of step entry requires careful consideration. Users who used a Garmin device to enter steps were more likely to be an *Enthusiast*. Although most *Enthusiasts* also used the *10,000 Steps* website, a pattern of consistent activity (ie, recording steps or activity minutes) may be more reflective of automatic synchronization of activities from the Garmin application to the *10,000 Steps* platform. After the Garmin application is connected to the *10,000 Steps* platform by the user, step entries are automatically synchronized onto the program application. As a result, for some of these users, program engagement patterns by *Enthusiasts* may not necessarily be associated with active engagement with *10,000 Steps* program, but rather a general interest in physical activity as recorded by their wearable device that automatically logs step entries. However, they are also more likely to participate in gamified activities in the program such as Tournaments and Challenges. Additional research on these users could reveal extra insights into motivations for continued use of the platform as well as joining Challenges and Tournaments.

Finally, the usage pattern clusters derived from the analysis may be largely influenced by *10,000 Steps* design features that are not prevalent in many other programs concerned with impacting physical activity behaviors. A majority of clusters are differentiated by year, likely reflecting a response to event drives (ie, Tournaments and Challenges) rather than meaningful subgroups, in terms of behavioral motivations. Although participation is voluntary, periods of activity, whether one-time or repeated, appears highly correlated with the commencement of work Tournaments, emphasizing it as a key feature of the program's design.

Nonetheless, the prominence of these features, particularly for longer-term engaged users, suggests these findings can help understand how to increase engagement with digital health promotion programs more generally. These users include those who have consistently used the platform as well as those who return to the platform at intermittent intervals. Qualitative studies probing how participants use different aspects of the program from usage habits to behavioral motivations and theories of change[33] can reveal ways in which digital health programs can enhance longevity in program engagement. Past research on "super engaged users" of the *10,000 Steps* program—similar to the *Enthusiast* cluster of users—suggests that the platform provides motivation to keep up with meeting physical activity goals.[26] Furthermore, many of these users first registered for the program because of a workplace Tournament, suggesting that these features are an important avenue of reaching subgroups of users who could become consistently active. Although it remains unclear if the *Long-term intermittent* group are returning solely to respond to program features (ie, Tournaments), these findings emphasize the importance of understanding the motivational role of these features and how they can inform program improvements of digital health programs to support longer-term re-engagement.

Future research could also investigate the influence of other program features designed to increase re-engagement, such as follow-up email strategies implemented by the program to support onboarding, understand reasons for disengaging, and improve continued program engagement. There may be distinctions between the two 2020 and 2022 *Enthusiast* clusters that could not be directly assessed with the current study. However, given the timing of the implementation of some follow-up email strategies which occurred in 2022, there is opportunity in future research to probe the influence of these methods further in how they interact with program usage patterns. Specifically, some email types (onboarding welcome series) were only implemented from 2022 in Queensland (the state in which participants of this study reside) and not other states and territories within Australia (except South Australia). Thus, there is opportunity to compare user registration and longevity of engagement in Queensland against states and territories in which the re-engagement email strategies were not implemented. Then, the effectiveness of these strategies can be directly assessed. This could provide opportunities to understand the impact of email communication strategies on *10,000 Steps* usage patterns.

Implications

Our sequence analysis of program usage enabled us to track and visualize periods of activity and inactivity for different clusters of users. Visualizing these sequences revealed the timing and duration of episodes of activity, including when participants were likely to join the program and for how long. Most clusters of engagement patterns reflected the strength of Tournaments (run by workplaces and other organizations) and individual monthly Challenges (run by the program) to draw new users into the program as well as actively participate. Participants in these patterns exhibit a short-term period of consistent engagement. Some participants appeared to return intermittently in order to re-participate in these events. This understanding of the timing of inactivity in the *10,000 Steps* program can provide opportunities for timely intervention to re-engage users. Given the interest in the challenge aspects of the program (ie, Tournaments, Challenges, and QH campaign), these "gamified" components of the program appear to be associated with program re-engagement. Indeed, the most consistent users also engage with Tournaments and Challenges.

Conclusions

This study revealed engagement patterns of users of a digital physical activity program using the novel approach of sequence analysis. Although a majority of users had patterns of short-term bursts of engagement, likely associated with participation in program events such as Tournaments and Challenges, a small subset of individuals were found to be more consistently active or had periods of activity over a longer period of time. These findings reveal that medium- to long-term engagement with digital health programs are more complex than previously reported by revealing that participants may have inconsistent engagement patterns rather than outright discontinuation. These findings have important implications for digital health programs for attracting, engaging, and retaining users enabling new avenues for public health promotion strategies focused on both individual- and group-based strategies.

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