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ABSTRACT

Understanding individual's exercise motives, participation patterns in a gym and reasons for dropout are essential for designing strategies to help gym-goers with long-term exercise adherence. In this work, we derive insights on various exercise-related behaviors of gym-goers, including evidence of a significant number of individuals exhibiting *early dropout* and also describing their attitudes towards digital technologies for sustained gym participation. By utilizing gym visitation data logs of 6513 individuals over a longitudinal period of 16 months in a campus gym, we show the retention and dropout rates of gym-goers. Our data indicates that 32% of the people quit their gym activity after initial 1 or 2 visits and about 65% of the users have less than 10 visits during the 16 months period. From this data, we also observed that people attending gym in a group and following a regular visiting time to the gym have a lower chance of ceasing gym activity. Further by surveying 615 individuals across varying demographics, we uncover the key reasons for dropout to be "lack of knowledge in using gym equipment" and "lack of access to a personal trainer", besides the prominent reason of "lack of time". Our survey also indicates the propensity of individuals towards using digital technologies (e.g., fitness apps) to track their gym activity. Somewhat surprisingly, our survey reveals a disinclination among individuals to use obtrusive wearable-based solutions in a gym, with 60% of them preferring a less-invasive and more convenient approach of machine-attached sensors for automated tracking of gym exercises.

CCS CONCEPTS

• **Applied computing** → **Health informatics**; *Consumer health*.

KEYWORDS

Physical Activity; Gym Exercises; Retention; Quantified Self; Personalized Coaching; Digital Intervention

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1 INTRODUCTION

Regular physical activity is essential to maintain good health, well-being and to stay fit. As individuals become more aware of the benefits of engaging in physical activity, the prevalence of people going to the gym or fitness centers is in the rise. Recent statistics [35] report that the number of fitness center memberships in the United States has steadily increased over the last decade (with the membership count reaching 60.87 million in 2017). However, *long-term adherence* to gym routines seems to be a major challenge among gym-goers. Prior studies in the behavioral literature [38, 41] have reported that participation in physical activity is influenced by a diverse range of personal, social, and environmental factors. However, little is known about the severity of the dropout problem, the temporal patterns exhibited by people who *dropout* (i.e., cease visiting the gym), and what other contextual factors seem to affect such individual-level dropout behavior.

Additionally, the rapid growth in the market for fitness devices and apps offers the possibility of providing quantified insights into an individual's exercise routine and enabling personalized interventions. Although there has been an explosion of such mobile applications for promoting healthful behaviors, relatively few have applied behavioral theory and lack aspects to get wider sustained adoption [18]. A review of such physical activity apps found that only 2% provided evidence-based guidelines for gym exercises training and report that these apps follow a one-size-fits-all approach and people find the recommendations or suggestions provided to be not helpful [19].

Given these facts, in this work, we focus on studying the gym visitation habits of people, their temporal consistency or chances of dropping out, as well as their reasons for quitting gym activity based on two kinds of data sources: (a) gym visitation data logs of people (captured through card transaction logs) for a longitudinal period and (b) survey of varying demographics of people who are gym-goers or have stopped going. We also obtain insights on the desired features and services that people would like to have in a gym–these insights help us identify possible digital monitoring and intervention capabilities (e.g., via wearable devices) that may prove more effective in ensuring sustained participation in gym activities. As such, we make the following **key contributions**:

- By utilizing two rich sources of data (the gym visitation logs and survey responses), we study individual's gym visit patterns and temporal behaviors and identify what forms of failure exists in gym participation. In particular, longitudinal visitation records (from 6513 individuals over a 16 month period) from our University gym in Singapore reveals the acuteness of dropout (32% dropout after 1 or 2 visits, while 65% of users have less than 10 gym visits). We also characterize features that seem to reduce dropout (e.g., group visits, regular time period of visiting the gym).
- Using survey responses gathered from 615 individuals, we identify the key reasons for gym usage dropout and the features that people desire from digital tools to help achieve sustained gym participation. While "lack of time" is the foremost and expected reason for dropout, individuals also report "lack of knowledge in using gym equipment" and "lack of access to a personal trainer" as two other key reasons behind their quitting of gym activities. The latter also hints at a possible economic divide: personal trainers are often expensive, and may not be affordable to poorer populations (whose diets and lifestyles are often unhealthier [29]) that might derive greater benefit from gym usage.
- From the survey data, we also identify that technologies that are "wearable-based" have adoption challenges and are not so preferred while exercising in a gym (*unless the wearable is a commonly used device, such as earphones*). Also, individuals who use existing fitness apps or have stopped using such apps report that these apps are intrusive and provide generalized (as opposed to useful personalized) recommendations. Our analysis reveals a capability gap in the existing pervasive digital technologies in providing (a) an unobtrusive and personalized monitoring of activities (especially via more-acceptable wearable devices), and (b) effective interventions & recommendations to gym-goers.

Overall, we believe insights presented in this work on gym user behavior draws attention to the need for improving the gym experience of people (in maintaining sustained participation) and helps to identify desired features for future digital intervention tools.

2 RELATED WORK

In this section, we present prior works that have studied the exercise adherence and dropout patterns of individuals and also provide a review of existing digital tools and technologies that are proposed by researchers to sustain motivation of exercisers as well as provide quantified insights into the exercise routine.

Studies on Exercise Adherence and Dropout: Trost et al. [38] present a review of the earlier literature that provide evidence relating to the personal, social, and environmental factors associated with physical activity. Similarly, Berger et al. [3] describe the aspects of psychological well-being that are influenced by physical activity and the factors that influence exercise participation. Existing works [15, 33, 41] have investigated the adherence behavior of people in specific exercise programs/physical activities and have reported that several factors (such as social support, guidance from staff, tangible health benefits) influence individual's motivation to continue in the program. Certain works have focused on understanding both the adherence and dropout behavior of specific user groups such as older adults (age above 50) [36], only women [13], low income groups [42], from various exercise programs. The works that specifically studied gym-goers [7, 16], have focused solely on understanding the motives of people for joining or continuing at the gym and not clearly identified the reasons to dropout. Pridgeon et al. [27] conducted a small scale study where they interviewed 14 gym-goers about their experiences in maintaining and dropping out of gym. They found loss of social support to be a key reason for dropout. Zarotis et al. [43] studies age-specific reasons for dropout from gym for different category of users. They report that personal and professional obligations and problems with maintaining a daily schedule were considered as key reasons for dropout among young and middle age groups. While the older respondents (above 55 years) report personal health conditions as the key reason affecting continuation of gym activity. Most of these studies are purely interview-based or survey-based and conducted on a smaller scale of users. In this work, we present a more systematic study and provide quantified insights based on the actual digitally captured traces of individual-level gym visits, identify the key reasons for dropout and characterize some features that seem to affect dropout propensity.

Techniques to Improve Exercise Behavior: Prior works in the behavioral and sports science literature have proposed several techniques such as providing entertainment at the gym [1, 2], giving incentives [37], interventions with information of peer's gym attendance [6, 31] to sustain motivation of individuals to continue exercising. Although, mechanisms such as incentives tended to improve behavior during the intervention, findings were mixed on whether the observed improvements were sustained after incentives were removed. Hence, further research is required to derive appropriate mechanisms that are more personalized and can keep individuals motivated to persist their gym activity.

Digital Tools to Support Gym Activity: In the recent years, several commercial mobile applications (e.g., Trackmyfitness [40], JEFIT [14]) and wearable devices (e.g., Apple Watch, Nike Fuelband) have spawned in the fitness space with the goal to digitally track and encourage physical activity among individuals. However, a review of such physical activity apps found that only 2% provided evidence-based guidelines for gym exercises training and people find it not helpful [19]. There are also other works in the literature [4, 10, 25] that have proposed technologies for motivating and digital training during physical activities. Some of these approaches are based on health behaviour-change theories exploring features for motivating people to exercise. Patel et al. [26] study the contextual influence of digital technologies' use and non-use while exercising in gym based on interviews and participant observation. They report that showing positive information in general while individuals are exercising helped them to monitor their performance and make necessary changes to their exercise behavior. However, the adoption of technologies varied according to people's individual differences, motivation and preferences. In our work, we find that the adoption of specific technologies while exercising in a gym is age-specific and also highly dependent on its ease of use and convenience. More recently, Rubin et al. [30] study the adoption factors of wearable technology in health and fitness space, specifically from a South African consumer perspective and identified that individuals did not enjoy using on-body devices during physical activity. This is similar to our finding from the survey conducted with gym-goers.

Pervasive Sensing Technologies for Gym Activity Monitoring: The key pervasive technologies for providing quantified insights into an individual's gym activity rely primarily on on-body wearable devices (e.g., [5, 23, 32]) and video-based sensing [12, 39]. However, each of these approaches have different drawbacks such as usability concerns with wearables and the reluctance to wear such devices while exercising in gym, the overly intrusive nature and privacy concerns associated with videos. The FEMO [9] system and the recently proposed JARVIS system [28] rely on the idea of attaching sensors to exercise equipment (dumbbell or weight machine) to track various aspects of specific class of gym exercises. Overall, there seems to be a gap existing in such technologies being unobtrusive, less invasive and still providing a complete fine-grained tracking of the exercises performed in a gym.

3 STUDY METHODOLOGY

In this work, our broader goal is to first obtain an overall understanding of gym usage behavior of individuals, identify the temporal variation in gym visiting patterns and investigate the retention and dropout rates of gym-goers. It has been hypothesized that temporal consistency helps maintain exercise habits [21]. So, we believe it is important to ascertain the severity and temporal properties of dropout behavior observed among gym visitors and quantify the reasons leading to such cessation of visits. The lessons learned can subsequently help identify the features desired in digital tools, technologies or services that can help ensure sustained gym participation by individuals. To investigate these factors, in this work, we focus on obtaining two kinds of data–(a) the gym visitation data of users and (b) survey responses gathered from gym-goers about their gym usage behavior. More specifically, we obtain the gym visit data logs from our University gym for a prolonged period and then conduct surveys on different demographics of people across our University campus and other community/neighborhood gyms. Below we describe in detail both the datasets obtained and the study methodology.

3.1 Gym Visitation Data

We obtained the gym visitation data of users of our University campus gym in Singapore for a continuous period of 16 months from September 2016 to December 2017 (including two fall terms, one spring term and one summer term). The campus gym can be accessed free of charge by all students and staff. After initial pre-processing and discarding of incomplete entries, the dataset we used included 94,188 data records from 6513 unique users who visited the gym during this period. The gym tap-in/tap-out data log contains details such as the user ID, time of entry and exit for each visit to the gym and other demographics information such as gender, school of study, user type (e.g., undergraduate, postgraduate, exchange student, admin staff, faculty, alumni), year of study and course code (for students). We utilize this dataset to study the following questions:

(1) How does the aggregated and individual visit patterns of users vary temporally (e.g., visit pattern across a day/week/academic term, frequency of visits of individuals)?
(2) Do people exhibit regular visit patterns to the gym and does the gym visitation logs help uncover any temporal patterns in how individuals discontinue their gym visits?
(3) Are there any key contextual factors that seem to affect the likelihood of continuing to visit the gym vs. dropping out?

In our definition, *"dropouts"* constitute individuals who cease to continue their gym activity after less than or equal to two visits within 40 days of their first entry to the gym. We also refer to another category of individuals, *"infrequent visitors"* who visit the gym only few number of times (e.g., less than 10 visits over a 16 month period in our data) and the difference in days between their successive visits is high (greater than 40 days).

3.2 Gym Survey Data

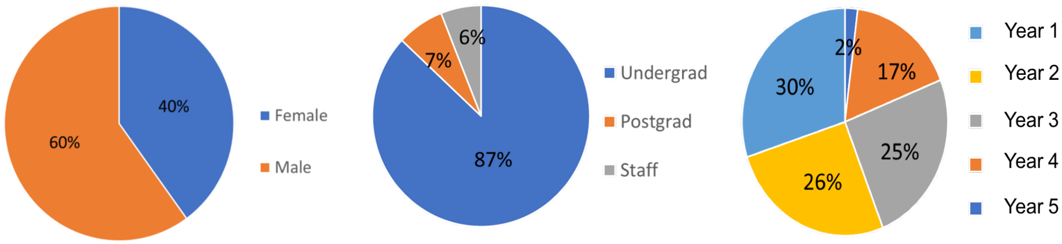
We next conducted a survey to understand the gym usage behavior of individuals (e.g., reasons for going to or dropping out from gym, self-rated usage of specific workout zones or equipment in the gym), preferences or services that would help improve the gym experience of individuals, usage of fitness apps, preferred mode of interventions and key features desired from such digital tools etc. The survey was hosted in Qualtrics and was approved by our Institutional Review Board. This survey was conducted in two phases:

- *Survey distributed at University gym:* Distributed to the students and staff who visited the campus gym at least once during the academic semester for which we obtained the gym visitation data.
- *Survey distributed to the Public:* Distributed to the members of the general public, via advertisements posted at a specific gym or solicitations at a trade show, and online via Amazon MTurk. This was to capture the differences in opinion (if any) from a varied demographics of users whose gym experience might be quite different.

Both the surveys consisted of 18 common questions (including 15 multiple choice and 3 open-ended ones). Based on the survey we mainly intend to answer the following questions:

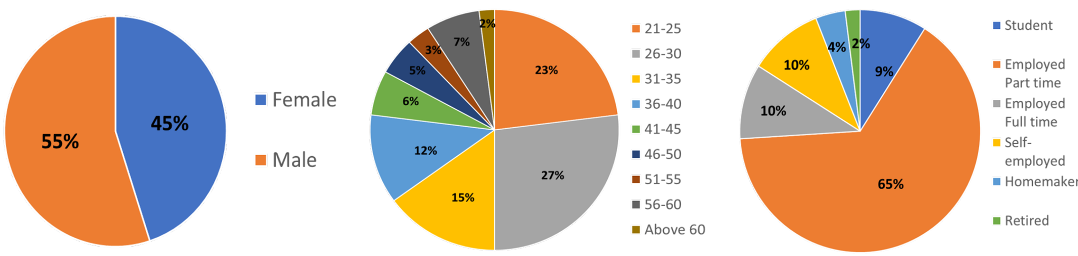
(1) What are the motives for people to go to a gym?
(2) What are the key reasons why people discontinue and quit activity in a gym?
(3) What are the desired features that people think would help in continuing their gym activity and improve their overall gym experience?
(4) How valuable would it be for the users to have access to a personal trainer at the gym and what are the various things that a personal trainer could help them with?
(5) What do individuals feel about the efficacy of existing fitness apps and wearable devices? Do they have any specific preferences in the technology they want to use while exercising in a gym?

In addition to the above, our survey also provide insights on the popular exercises done and the machines used in the gym. The survey distributed to the general public involved few additional questions (explained later in Section 3.2.2). The survey was designed such that the users rated the importance of specific statements under each question in a 5 point Likert scale ranging from *"Not at all important"* to *"Extremely important"*. The survey also gathered



(a) Gender (b) User Category (d) Year of Study

Figure 1: Demographics of University Gym Survey Participants



(a) Gender (b) Age Category (c) Employment Status

Figure 2: Demographics of Public Gym Survey Participants

other information from the respondents such as the frequency of their gym visits, the duration since the user started visiting a gym, self-rated usage of specific workout zones and exercise equipment, fitness apps used and reasons for liking or disliking those apps.

3.2.1 Survey at University Gym.

The survey was distributed to 1960 users who are either students or staff in our University campus via email. We utilized the gym visitation data for one academic term to identify and send the survey to only those users who visited the campus gym at least once during this term. We obtained responses from 402 users out of which 34 were partial responses. A monetary compensation of $5 was offered to the first 250 respondents.

In this survey, the respondents were categorized into three groups based on whether they (i) visited the gym at University campus, (ii) visited another gym or (iii) used to go to gym and have dropped out. We ensured validity of these responses (at least for group (i) and (iii)) by comparing against the gym tap-in/tap-out data. While most of the questions were common to all groups, certain questions designed were targeted at specific groups.

We only collected the user email id in this survey. Further demographics information of the respondents are obtained from the gym tap-in/tap-out data mapped based on the respondent's email ids. In Figure 1, we report the basic demographic details of these respondents. Out of the respondents, 220 were males and 148 were females. 87% of the survey takers were undergraduate students. The highest number of responses were from the *School of Business* followed by *School of Accountancy* and *School of Information Systems*, which also corresponds to the school size. More than half of the survey respondents were freshers and sophomores, who also comprise the highest percentage of regular visitors at the campus gym.

We present results only based on full responses from 368 respondents. Among these respondents, 280 of them are regular visitors at our campus gym, 52 of them used to go to gym and have stopped going now and remaining 36 users utilize public/external gyms. Admittedly, this data has a strong demographic bias, as 87% of users are undergrads and thus likely to be *millenials*.

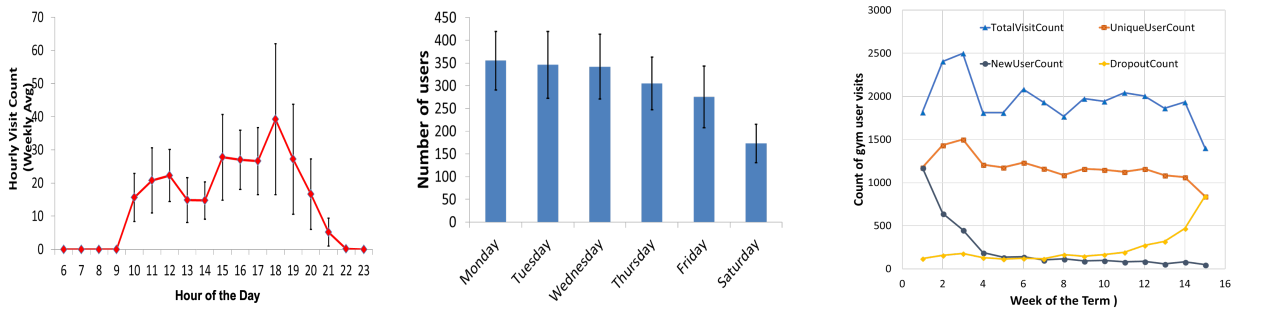
3.2.2 Survey distributed to General Public.

This survey was distributed online and was taken by the members of the general public. In total, we obtained 247 responses, out of which 147 responses were obtained by distributing the survey to users of a community gym and the remaining 100 responses were obtained by hosting the survey in Amazon Mechanical Turk (AMT). The questions in this survey were similar to that of the one distributed in the University campus. As we lacked records of any actual gym visits or electronically captured profiles for these respondents, we also asked basic demographics questions such as age, gender, employment status. In this survey, we also included additional questions on the possible futuristic digital technologies (that would help provide a better gym experience and quantified tracking of workout activities to the individuals) and individual preferences and desired features for such digital tools.

Out of these 247 respondents, 45 of them reported that they used to go to a gym and have stopped going now. The basic demographics details of these respondents are as reported in Figure 2.

4 BEHAVIORAL PATTERNS FROM GYM VISITATION DATA

We first seek to get a detailed understanding of the visit patterns and behavior of gym-goers using the *University* gym visitation data (explained earlier in Section 3.1). As briefly mentioned earlier, we



(a) Hourly visit pattern (b) Weekly visit pattern (c) Visit pattern during an entire academic term

Figure 3: Temporal variations in visit patterns aggregated across all users

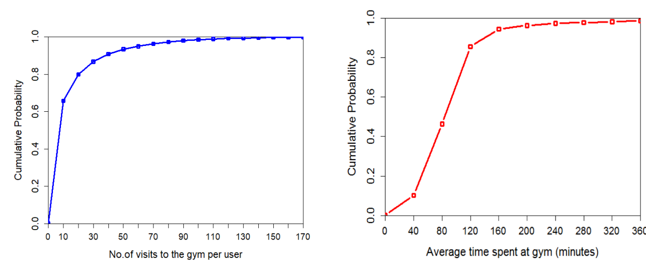
utilize this dataset to obtain aggregate usage statistics such as the temporal variation of gym usage pattern across a day/week/term and the dropout pattern of users, as well as infer factors that may help promote sustained gym participation.

4.1 Temporal Variation of Gym Visit Patterns

With the data from 6513 unique users over a period of 16 months, we first studied the *aggregated temporal patterns* in the data. Figure 3(a) plots the hourly variation in visit pattern during a day, averaged weekly across the entire study period. We observed that the visit count increases during the morning hours, then drops during the post lunch hours and peaks at evening 6 PM to 7 PM (the post-work hours) with an average count of 40 users and then starts dropping afterwards. We next looked at the weekly visit pattern of users (see Figure 3(b)). Intuitively, Monday was the most popular day with a total visit count of 350 users on an average. The number of gym goers tend to drop significantly after mid-week. We further studied the temporal variation in visit count of users over an academic term. In Figure 3(c), we plot the variation in total user count, unique user count, number of new incoming users and number of users not returning to the gym across the 15 weeks of the semester. As expected, the total user count over an academic semester tend to drop gradually as the term progresses (with a higher rates of reduction in no. of gym-goers especially during exam weeks). Although the total number of new users (i.e., ones with no past entry record in visit logs) joining the gym in the initial weeks is high, the count keeps decreasing significantly during the first four weeks. As the term progresses, we observe only about 50-100 new entrants every week. The data also suggests that people start dropping out from early weeks itself with the dropout count increasing steadily after mid-term.

We were further interested in studying the *per-person usage behavior* at the gym. We specifically studied the following:

- Total visit count to the gym per user and the rate of early dropout– i.e., people who come to the gym once or twice and then never return.
- For the regular users, the duration of each gym episode and the number of times a week people visit the gym, grouped by gender and user category.

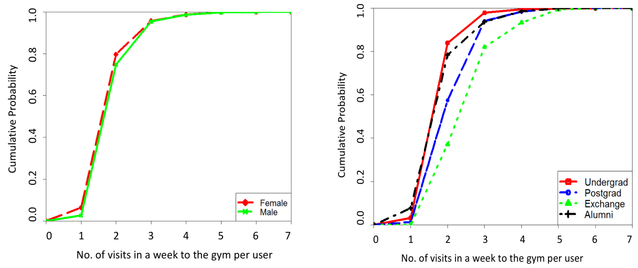


(a) CDF of total no. of visits to the gym per user **(b) CDF of duration of continuous gym episodes across users**

Figure 4: Cumulative distribution of the frequency of visit count and average time spend by users in gym

To understand the percentage of users who regularly visit the gym as well as those who dropout after one or two visits, we computed the total gym visit count per user for the period for which data was available. Figure 4a plots the cumulative probability distribution of the total visit count of the users. We found out that over 65% of the users (i.e., 4283 out of the 6513 users) have less than or equal to 10 visits to the gym during the 16 months. More importantly, the rate of dropout (i.e., users with only 1 or 2 visits) was found to be 32%. This demonstrates that even in a gym where most of the gym-goers correspond to the student population, there is a significant set of users who dropout. Later in Section 5, we describe some of the key reasons why people discontinue their gym activity.

For regular users, we also studied their average duration of a gym episode and also the number of visits to the gym in a week. For this, we only considered the users (2230 unique users) who had more than 10 visits to the gym in the study period. The average time spent by 50% of the users at the gym is found to be about 80 minutes (see Figure 4b). A significant 15% of the users also spent more than 2 hours in the gym. We also computed the weekly visit count per user. Figure 5(a) shows the CDF of the weekly visit count grouped by gender. 50% among all the users have an average weekly visit count of 1.8 and above 26% of the individuals visit the gym more than twice weekly. Out of the 2230 users, 66% of them are males and 34% are females. There is no significant difference in the visit count across males and females. 25% males and 20% females have



(a) CDF of weekly visit count per user grouped gender-wise

(b) CDF of weekly visit count per user grouped usertype-wise

Figure 5: Cumulative distribution of the frequency of visit count grouped (a) gender-wise and (b) user type-wise

an average weekly visit count greater than two. Figure 5(b) shows the CDF of the weekly visit count according to different user types.

4.2 Acuteness of Dropout & Factors Affecting it

As discussed earlier, we observed that a significant percentage of gym-goers had only 10 visits or less to the gym (out of which 2071 individuals visited the gym only once or twice) during 16 months. For those individuals, we wanted to further investigate their dropout behavior–i.e., does most of them exhibit an early dropout behavior or are there individuals who also exhibit infrequent visit patterns? To study this, we first compute the average difference in days between an individual's successive visits to the gym and plot the cumulative distribution of it in Figure 6. This helps to distinguish between individuals who dropout from the gym after initial 1 or 2 visits and those who are infrequent visitors to the gym and still have only a 10 visits or less over a prolonged period. We found that 80% of the users dropout within the first month of visiting the gym and never returns (i.e., their difference in number of days between successive gym visits were ≤ 40).

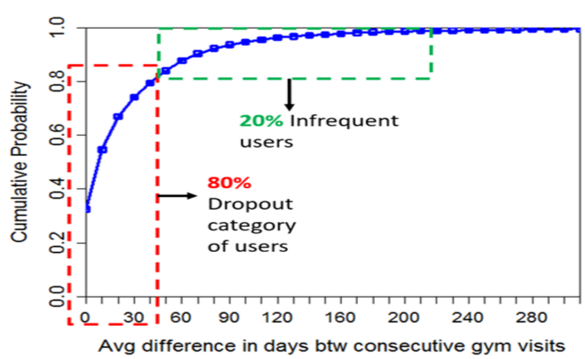


Figure 6: CDF of average difference in days between consecutive gym visits

Given that there is a high percentage of users that cease gym visits fairly early on, we were interested in understanding if there are any distinguishable behavioral patterns between regular gym-goers vs the dropout users. More specifically, we study two characteristics to see if there are any noticeable difference across regulars and dropouts: (i) visiting the gym alone vs as a group (e.g., with a friend or an exercise group), (ii) regularity in terms of time of visit to the gym.

	All males	All females	Mixed	Same School	Different School
% in groups	28.8%	45.9%	25.3%	63.2%	34.7%

Table 1: Breakdown of people visiting gym in groups characterized by gender and school of study

4.2.1 Difference in visit patterns–Groups vs Individuals: From the gym visitation data logs, we extracted the people who visited the gym as a group (i.e., with one or more individuals). For this, we first extracted all *user groups* whose gym entry time differences and exit time differences are both within *1 minute*–i.e., at an episode level, identify co-temporal gym visitors. We assume that people entering and exiting the gym within such short time gap visit the gym together and could be considered as in a group. Also, such joint visits should occur more than once to be declared as an actual group. As such, we extracted a total number of 1073 groups after discarding a count of 3416 singleton joint occurrences. Among these, 274 groups (25%) repeated five times or more. Also, 88% of these groups are 2 member groups and 10% are 3 member groups. This confirms that there is a trend of visiting gym as a group among users. Table 1 shows the breakdown of the repeated visit groups characterized by gender and school of study. We observe that 63% of the groups have members from the same school and 46% of them are *female-only* groups.

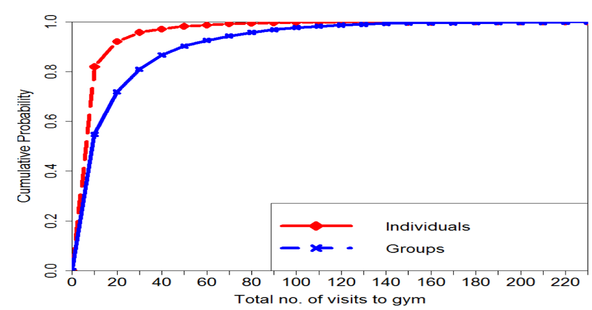
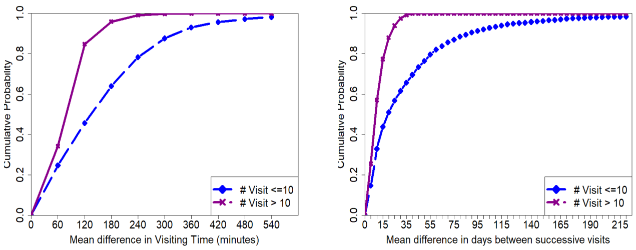


Figure 7: CDF of visit count for individuals vs groups

We next analyze the possible difference in visit patterns of individuals vs. those who come in groups. We obtained the cumulative distribution of the gym visit count for individuals vs groups (see Figure 7). The CDF plot shows that people going in groups visit the gym more number of times than people who go alone. Only 18% of the people who go alone have a visit count greater than 10 whereas for people visiting in groups it is greater than 45%. This indicates that visiting the gym with a friend or as a group may increase the motivation to continue, and thus minimize chances of dropout. This is also in accordance with prior work [22] in behavioral literature reporting peer support to be a key behavior change technique.

4.2.2 Regularity in visiting times–Regulars vs Dropout: We next examined the regularity in the visit pattern of individuals in terms of the time and days of visit and how it varied between those with a visit count greater than ten and less than or equal to 10 (i.e., regulars vs dropouts)–i.e., Do individuals continuing to visit the gym regularly also exhibit a regularity in their visit schedule and



(a) CDF of mean difference in visiting times between successive visits

(b) CDF of mean difference in number of days between successive visits

Figure 8: CDF of regularity in visiting time/days for those with *visit count* > 10 and *visit count* ≤10

are the time periods of visit more irregular for those dropping out? To investigate this, for each user we first computed the difference in their gym *entry time* and difference in the *number of days* between successive visits to the gym across all their records. This difference in visiting times is simply expressed as:

$$\Delta_t = EntryTime_{i+1} - EntryTime_i \qquad (1)$$

Figure 8a plots the CDF of the mean of such differences in time of visit (i.e., mean of all $\Delta_t' s$ in minutes) for the two user categories (≤ 10 visits and > 10 visits). For those individuals with *visit count* > 10, the difference in actual visiting times is within ±2hours for nearly 85% of them (with 34% having a 1hr difference). However, for those with *visit count* ≤ 10, the Δ_t values were much higher (nearly 55% had Δ_t > 2hrs), indicating greater irregularity in their actual time of visits to the gym.

We also computed the difference in number of days between successive visits and the exact days of visits for both category of users. We observed that people who visit the gym more number of times exhibit regularity in the days of visit to the gym (i.e., for example, an individual visiting the gym every two days or visiting only every Wednesdays). On the contrary, the individuals who had fewer visits barely exhibited any consistency in their visiting days or have longer gaps between successive visits. For example, from Figure 8b) we can see that more than 40% of users with *visit count* ≤ 10 have a gap of more than 30 days between their successive visits (i.e., visited gym only once a month). Whereas 78% of them with *visit count* > 10 visited the gym at least once every two weeks. This observation is also supported by the fact that environment/contextual cues play an important role in habit formation [24].

4.3 Key Takeaways:

- The aggregated temporal visit patterns of the campus gym shows 6 PM to 7 PM as the peak hour and Monday as the popular day of the week with most number of gym attendees. The data also reveals the initial surge in gym attendance at the beginning of a term and a higher percentage of people dropping out after mid term.
- About 32% of people drop out or quit gym activity after 1 or 2 visits. Among these 80% of them completely stopped visiting the gym within their first month of visit.
- Going to gym in a group and following a regular gym schedule might reduce dropout and improve chances for sustained participation.

5 INSIGHTS FROM SURVEY ON GYM USER BEHAVIOR

Having obtained an understanding of the underlying behavior and visit patterns of individuals in a gym (characterizing a high rate of dropout), we next seek to primarily study the key reasons why people quit gym activity. We also intend to understand individual preferences and desired features that they would like to see in gyms for a better experience. To study these we utilize the survey responses gathered from 615 individuals (across different demographics).

Although the surveys were conducted in multiple phases, when presenting the results we combine the responses from all surveys, and highlight any differences in responses among different demographics, when applicable. Note that several of the questions in the survey were matrix table questions (i.e., ones that allow to ask and rate about multiple items in one question) with a 5-point Likert scale rating. As such, when presenting the results, for each item in the multiple choice question, we combine the response count for the first two and last two scales (i.e.,*"Extremely important"* & *"Very important"* and *"Not at all important"* & *"Slightly important"*) and ignore the neutral response (e.g., "Moderately Important").

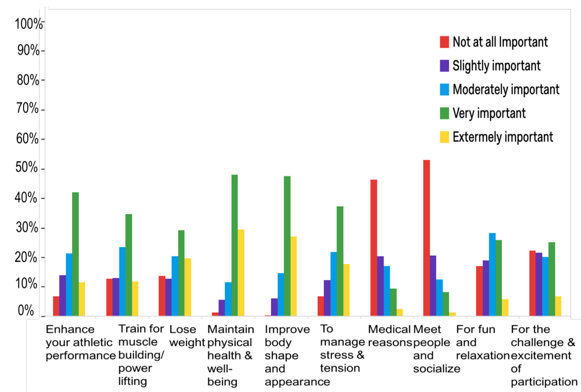
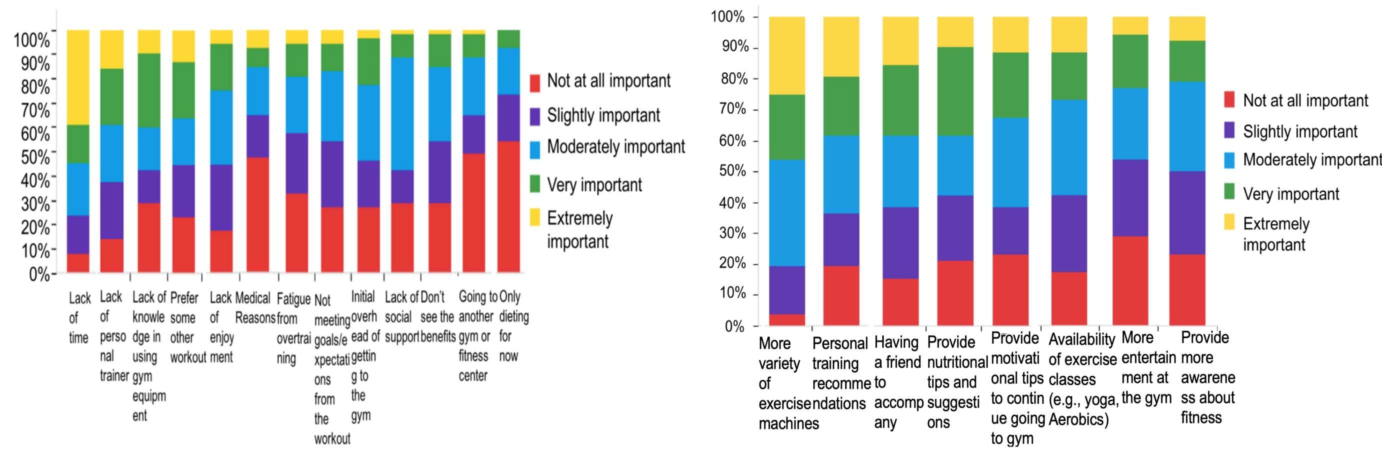


Figure 9: Survey response for motives for going to gym. Individuals bars in each label of X-axis is in order of "Not at all Important" to "Extremely Important" from left to right

5.1 Motives for Going to Gym

According to the survey responses, *maintaining physical health and well-being* was rated by about 81% of the respondents as their main motive for going to the gym (shown in Figure 9). The next two key reasons were *improving body shape and appearance* (78.1%) and *enhancing athletic performance* (56.2%). The percentages reported here are obtained by combining responses for *"Extremely important"* & *"Very important"* ratings (i.e., the green and yellow bars in Figure 9), which indicate the positive affinity of people towards specific motives. To understand if there was demographic diversity in these responses, we first re-grouped the responses into two category– students vs working adults, and obtained the percentage ratings. We



(a) Reasons for quitting activity in a gym (b) Desired features to continue going to a gym

Figure 10: Survey responses ratings for (a) reasons for quitting gym activity and (b) desired features/services to continue participation

found that, while the foremost reason remained the same across both the demographics, *managing stress and tension* (63.91%) and *losing weight* (57.1%) were rated as second and third most important reason by the working adults to go to a gym.

5.2 Dropout Reasons & Desired Features to Continue Gym Participation

Out of the 615 survey respondents, 104 of them (17%) indicated that they used to go to gym and have stopped going now (or dropped out). In the survey, we specifically asked them the reasons for dropping out as well as the services that could help them to continue going to the gym. The results of these two questions are as shown in Figure 10(a) and Figure 10(b) respectively. All the percentages reported are computed by combining the yellow and green blocks within each item in the x-axis of the plots.

As expected, *"lack of time"* is rated by 55% of the respondents as the main reason for quitting activity at the gym. More interestingly, *"lack of knowledge in using gym equipment"* (40.39%) and *"lack of personal trainer"* (38.43%) were among the top five reasons rated as important by the dropout users. This result holds across all the demographic groups (e.g., young, middle-aged, elderly) and suggests two facets that could be improved to help the gym-goers. When asked about the services that would be important to the dropout users when deciding to continue going to the gym, the top response (46%) indicated a preference for "more variety of exercise machines". However, interestingly, *"providing personalized training recommendations"* and *"having a friend to accompany"* were the next two common responses, rated as equally important by 39% of the users.

5.3 Need for a Personal Trainer

In the survey, we also included a question on the value of having access to a personal trainer in the gym and the key services that people would like to receive from a personal trainer. Having access to a personal trainer at the gym was rated as highly valuable by 44% of the respondents and another 22% of them rated it as moderately valuable. In Figure 11, we show the response ratings of the services that a personal trainer could provide. The survey responses also show that for 78% of the users across all demographics rate *"help with correcting body forms/postures"* as the most important service that a personal trainer may provide. Other top-rated services from a personal trainer were to help with setting a personalized exercise regimen (68%) and to teach how to perform specific exercises (67%).

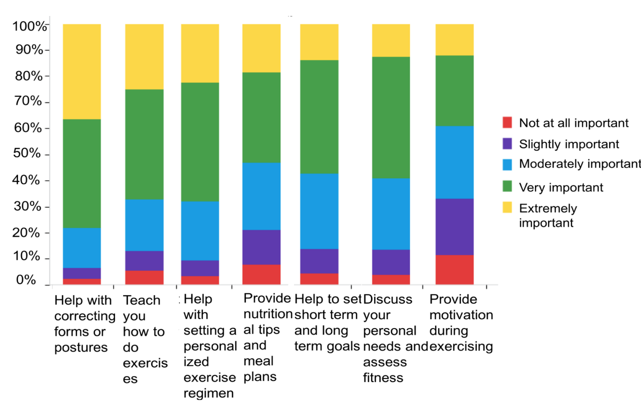


Figure 11: Services expected from a personal trainer

5.4 Usage of Fitness Apps

The next key question in the survey was to understand individual's affinity towards using a fitness application while exercising. To this question, 20% of the respondents stated that they are already using a fitness application, 63% expressed interest in using an app in the future and 17% responded that they stopped using fitness app(s). More importantly, over 70% of the people reported that they would be highly interested to use a fitness app that performs quantified exercise tracking and provides personalized feedback and corrective actions while exercising in a gym. People think that such recommendations would help make their exercise routine more effective and safer. The people (97 out of 615) who discontinued using fitness apps reported the top reason to be "apps not having met their expectations", as the provided recommendations were too generic and not useful. Some of them also commented that using apps while exercising was a distraction from the actual workout.

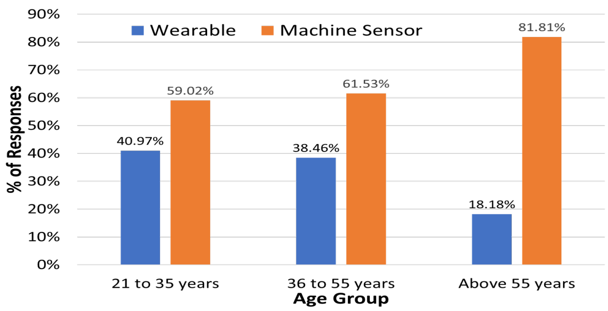


Figure 12: Preference of Wearable vs Machine Sensor-based technologies for people in different age groups

5.5 Adoption of Digital Technologies

The survey distributed to the public gym users also included a question on the preference of using a digital technology (which is either wearable OR a machine sensor-based technology) that can automatically track all the gym exercises performed and provide personalized quantified insights. From the 247 responses obtained, 59.9% (148 of those users) indicated an unwillingness to adopt wearable-based technology and preferred the machine sensor-based approach. Notably, 82% of the users in the 55+ age group were reluctant to adopt wearables, indicating a special adoption challenge among the elderly. This is also in accordance with the reported digital aversion and the lower likelihood of using technology among elderly [8]. Figure 12 plots the preference vs. different age groups. In general, the main reasons for the aversion towards wearable-based approach include: (i) the discomfort of wearing on-body devices and not wanting to use such devices while exercising, (ii) the inconvenience of requiring to wear multiple such devices for proper exercise tracking, (iii) forgetting to wear those devices and (iv) not wanting to spend money on wearables. Several of them who preferred the wearable approach over the machine sensor-based approach reported that they already own a wearable device and prefer it as it is more personalized and can also track outdoor physical activities.

In the survey, we also asked them about the usefulness of receiving real-time feedback through a fitness app (i.e., feedback while the individual is exercising) and also the preferred mode to receive feedback (among the five options: (i) audio-cues through smart earphones, (ii) haptic feedback through wearable bands, (iii) textual display on wearable, (iv) textual notification on smartphone, and (v) only summary reports at the end of session). According to the responses, 61% of the users indicated that obtaining real-time feedback on their exercising patterns to be "extremely useful" and would prefer to receive such feedback mainly while performing *free-weights* exercises. The specific interest for obtaining real-time feedback during free-weights exercising could be because other machines, say for cardio-exercises (e.g., treadmill, elliptical) are already instrumented and also performing exercises with weight machines are more straightforward and risk-free compared to free-weights exercises. Prior work [11] also reports that injuries sustained at gyms are mainly during free-weight activities, suggesting the need for more corrective feedback while performing these exercises.

Among the five different modes of real-time feedback, *audio-based feedback* provided through a smart earphone (e.g., "you're going too fast, please slow down", "please extend your arms fully") was chosen by individuals as the most preferred option (51% ranked this option as the top choice). This result also shows that people are more willing to use less obtrusive wearable devices like earphones (i.e., "earables") while exercising (as they are also commonly used by individuals to listen to music while exercising). The second most preferred option was providing *haptic feedback* (e.g., vibrate twice to indicate too fast pace) and the least preferred option was receiving textual notification on a smartphone while exercising.

5.6 Popular Exercises/Machines

To obtain a better understanding of the usage pattern of the various equipment and workout zones (such as cardio, free-weights, machine-weights, circuit training) in the gym, we asked them to self-rate their gym usage. The cardio-zone (69%) and free weights zone (56%) were the most popular zones. Among the various exercise machines, the most popular ones were the treadmill, free-weights machine, weight stack-based exercise machines, exercise bike and the squats/deadlift machine.

5.7 Key Takeaways from the Survey

The major takeaways from the survey are following:

- Key motives for going to the gym: to maintain physical health and well-being and improve body shape and appearance.
- Top 5 dropout reasons– lack of time, lack of knowledge in using gym equipment, preferring some other workout, lack of personal trainer and lack of enjoyment.
- Providing personal training recommendations and having a friend to accompany are rated among the top services that could help the dropout users in getting back to the gym.
- For 78% of the respondents, correcting form/posture is the most highly-valued service desired from a personal trainer.
- 63% of the respondents are interested in using a fitness app and 20% are already using one.
- Nearly 60% of the individuals indicated a reluctance to use wearable devices while exercising, mainly due to the discomfort and intrusive nature of it. However, people are willing to use dual-purpose devices like smart earphones while exercising and prefer to obtain audio-based corrective feedback.

6 DISCUSSION

We believe that the insights in this paper, based on real-world gym usage data and explicit surveys, have several implications for designing future monitoring services and intervention mechanisms.

Need for better mechanisms to sustain gym participation: As "lack of time" is mentioned by vast majority of individuals as the key reason for quitting gym activity, it will be important to design digital tools that provide reminders to visit gyms and also raise awareness of the importance of gym going. Additionally, providing personalized feedback based on digital tracking (using fitness apps and devices)

	Personalized Tracking	Privacy-preserving	Unobtrusive	Detection of Mistakes	Class of gym exercises tracked	Attributes tracked
RecoFit [23]	Yes	Yes	No	No	Free-weights & body-weights	Exercise type, rep count
FEMO [9]	Yes	Yes	Yes	No	Free-weights	Exercise type, rep count, quality
JARVIS [28]	Yes	Yes	No	No	Machine-weights	Exercise type, rep count
MiLift [34]	Yes	Yes	No	No	Cardio & free-weights	Exercise type, rep count
Velloso et al. [39]	Yes	No	No	Yes	Free-weights	Rep count, execution mistakes
GymCam [17]	No	No	Yes	No	Free-weights	Exercise type, rep count

Table 2: Proposed pervasive technologies for tracking gym exercises and its capabilities

of the workout activities could be a way to improve retention of gym-goers. However, both prior work [19] and our survey insights reveal that, gym-goers find majority of the existing fitness apps for tracking gym exercises to be ineffective. Therefore, further research is required to ensure that such apps incorporate elements that can make the experience more personalized and provide feedback or suggestions that are tuned to an individual's workout behavior. We believe that to be efficient, such apps should be developed in consultation with health care and behavior change professionals.

Pervasive sensing techniques for gym activity monitoring: Solutions for automated, quantified and fine-grained tracking of gym activities are of high value in the fitness domain. Such technologies should ideally be able to help gym-goers track all their exercises and provide feedback to maximize their workout effectiveness and reduce risk of injuries. In fact, the top capabilities desired of such pervasive solutions include: (a) being unobtrusive & privacy-preserving, (b) having the ability to track multiple aspects of the entire gym workout, (c) detecting mistakes in exercise execution and (d) providing personalized interventions & real-time feedback. In Table 2, we list down some such technologies proposed and their capabilities in tracking gym exercises. We observed that each of these technologies has its own limitations; moreover, most of the solutions that perform personalized tracking still do not integrate the subsequent, important step of providing appropriate *personalized* intervention and feedback. We believe there are several opportunities for designing better digital intervention technologies, especially ones that rely on *infrastructure-based sensing* or *less obtrusive wearables* (as opposed to customized wearable devices, which seems to have non-trivial adoption challenges). Infrastructure-based solutions, that utilize new technologies such as (a) short-range radar or less-invasive thermal cameras, and (b) unobtrusive wearable devices such as smart earphones (equipped with inertial and physiological sensors), thus represent an interesting direction for future research.

Integrating motivating elements & interventions at the right time: To retain long-term participation, fitness apps of the future should also include mechanisms to detect changing behavior of individuals (e.g., tendency to dropout) and incorporate motivational factors that are tuned to people at different stages of gym-going maturity (e.g., novice in the initial few days, weeks, expert after several months) in a gym. Our data suggests that 30+% of the gym users drop out fairly soon after joining–accordingly, applications need to incorporate motivational interventions aggressively in the initial few weeks of gym activity, with the frequency of intervention possibly dropping off after a while. Helping users connect with support groups of other people who are also initiating gym exercises, or simple tools for matchmaking gym-goers, could potentially foster useful interventions, as our data shows that people visiting the gym in groups experience lower dropout rates.

Incorporating Visual AI as motivational tools: Recent advances in generative machine learning (ML) techniques (e.g., [20]) have demonstrated that it might be possible to create realistic renditions of how people's appearance would change under anticipated transformations (e.g., weight gain or loss). As "improving body shape & appearance" is an important goal, incorporating such ML techniques might enable people to visually appreciate the possibly incremental, but noticeable, changes in appearance as a result of gym visits.

7 CONCLUSIONS

In this paper, we studied the exercise behavior of individuals going to a gym and obtained insights from people on the desired digital tools for quantified tracking of gym exercises. Using longitudinal data (over a 16 month period) of gym visitation logs across 6513 unique individuals visiting a campus gym, we provide insights on the aggregated and individual-level temporal visit patterns in gym. With the data showing that over 32% individuals (who are primarily students) quit their gym activity after initial 1 or 2 visits, we establish that "dropout" is a serious concern among gym-goers. Our data also characterize some features that seem to reduce dropout such as group visits, regular time period of visiting the gym. By surveying 615 people of varied demographics, we investigated their experiences of maintaining or dropping out of a gym and uncover the key reasons for ceasing gym activity to be lack of sufficient knowledge in using gym equipment and the lack of appropriate personalized feedback. This suggests that providing personalized recommendations and engaging with the gym users would be a way to keep them motivated to continue their gym participation. The survey responses also reveal that while people desire to use digital tools for automatically tracking their exercises, there is a strong adoption challenge, with about 60% indicating a reluctance in using wearable-based solutions for gym exercise tracking (with smart *earables* being a notable exception). We also provide our impressions about the current limitations, and opportunities for new digital technologies that can help promote more widespread and persistent usage of gyms.

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