Effects of Simple Personalized Goals on the Usage of a Physical Activity App

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Abstract
Walking is the most ubiquitous physical activity. Natural walking and other physical activity opportunities, however, have been declining in developed societies. This decline has been linked to the rise of obesity. Smartphone health and fitness apps aim to reverse this trend by motivating people to be more physically active. The core philosophy in many of these applications is to either promote user competition or set universal goals and overwhelm the user with information. We present a physical activity app design that is closer to a goal oriented approach but with a twist. This new design is based on minimalism, where simple targets are set in a personalized manner and social comparison takes a secondary role. Specifically, the app gives to the user a daily caloric goal to consume by walking or biking. The formula that computes this goal is based on the user's food intake, Basal Metabolic Rate (BMR), and Body Mass Index (BMI). Our hypothesis is that methods emphasizing simple and precise personalized directions have better chance than pure competition methods to keep users engaged. Results from a pilot comparative study render initial support to this hypothesis.

Author Keywords
Walking app; physical activity monitoring; energy expenditure; obesity; weight loss; social competition; personalized goal.

(a) Nike+

(b) Old iBurnCalorie

Figure 1: Social competition apps.

ACM Classification Keywords

H.5.m. [Information Interfaces and Presentation]: User Interfaces, Design, Measurement.

Introduction

The sedentary lifestyle has assumed pandemic proportions in modern societies. According to the U.S. Department of Health and Human Services (DHHS), only 33% of adults engage in physical activity on a regular basis in the United States [15]. Long-term inactivity is associated with the emergence of the obesity epidemic and significant morbidity [4]. Several mobile applications aim to address this problem by motivating people to be more active. One approach is to leverage social competition; examples include the Nike+ app (Fig. 1a) and our old iBurnCalorie app (Fig. 1b). Here, social competition sets the physical activity goal. The user has to compete with another virtual or real user of her/his choice. The goal of the user is to expend more calories than her/his competitor on a daily basis. This approach situates the user to gauge her/his physical activeness in reference to others. Such healthy competition can be motivational. However, if the competitor were expending fewer calories than the ones required for the user to maintain a healthy metabolic balance, then the goal would be non-optimal and perhaps unsuitable to act as a behavioral orthotic. On the other hand, if the competitor were highly active, the goal would become overambitious and could demotivate the user. Finding an optimal goal is a challenge in competition based designs.

Another approach is based on heuristically derived universal goals. Examples of this approach are the Pacer app and the Fitbit device. They give every user a fixed goal of 10,000 steps. Multiple studies suggest that 10,000 steps/day is a reasonable goal for healthy individuals but may not be suitable for some groups, including older adults, and it is probably non-optimal for obese people [8, 16, 17, 18]. An improvement over the universal goal approach would be to have the goal customized per individual.

The importance of goal oriented approaches has been discussed in [9]. Indeed, goal oriented approaches appear to hold promise for instilling health behaviors to people [2, 14]. Many of these approaches, however, tend to overwhelm the user with a torrent of information (e.g., steps, calories, distance, speed, and other measures) - the Runkeeper and FitStar apps are two examples.

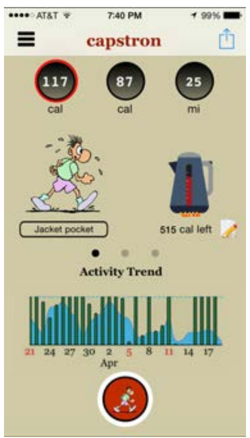
Overall, physical activity apps often lack either optimized goal setting or simplicity. In this paper, we propose a simple personalized goal design, featuring awareness of social trends as a secondary motivator [7]. We compare the performance of this goal variant design with a pure social competition design, represented by our old iBurnCalorie app. The results offer intriguing insights to the behavioral effects of these two apps and may generalize to some degree to the broader design families they represent.

App Design

Intuitive User Interface

The interface of our personalized goal app (new iBurnCalorie) ascribes to Maeda's design principle of "SHE", which stands for "shrink, hide, and embody" [10]. The app's home screen is left clean to support the main and secondary orthotic mechanisms. Specifically, the top half of the screen communicates the status of the personalized health goal (i.e., calories left to expend for the day), while the bottom half of the screen communicates the user's status with respect to the social trend (Fig. 2a).

Although both our old and new iBurnCalorie apps are mainly walking apps, they can also record biking activity and car mileage. Switching among these modes is automatic, based



(a) Walking mode

(b) Biking mode

Figure 2: New iBurnCalorie app.

on sensed speed via GPS; thus, the home screen shifts to the mode that is currently active, with an animation depicting the corresponding activity. In bike mode (Fig. 2b), the home screen remains largely the same as in walk mode, because calories expended in biking are part of the user's total caloric expenditure. Based on the apps' recordings, biking sessions have been negligible with respect to walking sessions and did not play any significant role in data analysis.

Car activity is considered a behavioral detractor - the more driving the less chance for physical activity [1, 6]. Ideally, the user should not drive at all and walk or bike instead. For many people this is not practical and thus, no daily driving quota is suggested by the personalized goal app. Consequently, in drive mode there is no prescriptive indicator at the top of the screen (Fig. 3), as is the case in the physical activity modes. At the bottom of the driving screen, the personalized goal app communicates the user's driving trend using a red graph that carries a negative connotation. This is in contradistinction to the green trend graphs in the physical activity modes (Figs. 2a & 2b), which carry a positive connotation. For the moment, driving data carries clear value for the study investigators only, as it gives them the opportunity to check if there is any association with physical activity patterns. In the future, as this research matures, a distinct benefit may be identified for the app users, too.

Personalized Prescription

The ultimate goal of a physical activity regime is the maintenance of a healthy metabolic balance. The key measure to follow in this respect is the number of calories expended. All other physical activity indicators (e.g., steps taken) are less informative as they don't give feedback in metabolic terms.

Overweight and obese users should be interested in weight reduction. Lean users should focus expending enough calories every day to counter-balance the excess calories taken in through food (weight maintenance). Any imbalance in this metabolic equation will result in weight gain [13]. To help in this respect, our app provides the user with a personalized caloric estimate that s/he needs to expend on a daily basis. This estimate is calculated according to the methodology used by NIH [12]. Specifically, the app asks the user to provide her/his age, gender, height, and weight during the registration process. Next, the app requests the user to provide an estimate of her/his mean caloric food intake per day (Fig. 4). The help button in this view links the app to the calorie count website (www.caloriecount.com), where the user can estimate her/his typical food intake value.

The user's inputs are then plugged-in to Eq. (1a) to compute the calories that need to be expended in the weight reduction plan, and Eq. (1b) to compute the calories that need to be expended in the weight maintenance plan:

$$Calories_{weightloss} = Calories_{intake} - (1.2 * BMR). \quad \text{(1a)}$$

$$Calories_{maintain} = Calories_{intake} - (1.1 * BMR), \quad \text{(1b)}$$

BMR (basal metabolic rate) for male and female users is calculated through Eq. (2a), and Eq. (2b), respectively [11]:

$$BMR_m = 5 + 10 * weight_{kg} + 6.25 * height_{cm} - 5 * age, \quad \text{(2a)}$$

$$BMR_f = -161 + 10 * weight_{kg} + 6.25 * height_{cm} - 5 * age. \quad \text{(2b)}$$

Finally, the expended physical activity $Calories_{expend}$, as measured by the app, is normalized for the relevant iPhone body location (e.g., jacket pocket, pants pocket, or waist) according to the method reported in [5].

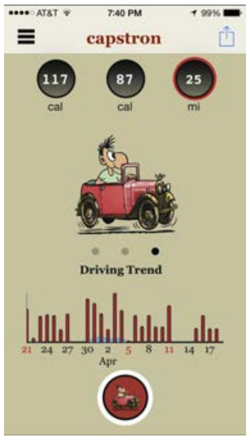


Figure 3: New iBurnCalorie app - Driving mode.

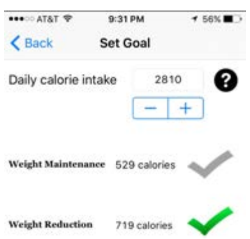


Figure 4: New iBurnCalorie app - Personalized goal settings.

Social Trending and the User
Humans are social animals and care not only how well they do in terms of personal goals, but also how they fare with respect to others. For this reason, the new iBurnCalorie app provides the user with trending information. The trending graph at the bottom of the home screen gives an overview of the user's physical activity vs. group physical activity (Fig. 2a). The former is tracked via the individual percent goal completed (green bars), while the latter is tracked via the group's median percent goal completed (blue curve); the group is the app's user base. The user can toggle between weekly and monthly views by tapping on the trend graph.

Methodology
We wanted to investigate if the design principles embodied in the new iBurnCalorie app (Fig. 2a) had any significant effect on usage patterns with respect to other designs. We chose the old iBurnCalorie app (Fig. 1b) as the comparative yardstick because it put exclusive emphasis on social competition - a strategy that is antithetical to the new app and we believe merits further scrutiny.

Data Collection
The study was approved by the local Institutional Review Board (IRB) of the University of Houston. For the comparative analysis, we used the old iBurnCalorie app (aka social competition app) data from February 14, 2014 to April 2, 2014 and the new iBurnCalorie app (aka personalized goal app) data for the same period in 2015. Thus, the observation period for each app was 48 days long. The selection of this period was constrained by the release of the personalized goal app in early February 2015; the apps were freely available in the App Store during the respective periods and user enrollment was free-flowing. Thankfully, the user base of both apps was concentrated in southern states, where early spring is ideal walking weather - an important covariate in this case.

We targeted habitual users only, excluding all transient users representing noise. Based on the bimodal usage distributions (non-noise vs. noise), we identified as habitual users those who expended at least 10 calories per day (i.e., a few minutes walk) for at least 10 days during the observation period (i.e., $\sim$ once per week or more). The user base of the social competition app was $n = 54$ users out of which $n = 9$ users (17% of the user base) met the habitual user criteria. The user base of the personalized goal app was $n = 42$ users out of which $n = 12$ users (29% of the user base) met the habitual user criteria.

To ensure that the datasets were comparable and further analysis would be valid, we performed a series of statistical tests on key covariates including age, gender, and body mass index (BMI). The tests revealed no significant mean differences between the two datasets in terms of age and BMI ($p > 0.05$, t-test in both cases), as well as male - female composition ($p > 0.05$, test of proportions). We also found no correlation between physical activity and driving patterns ($r^2 = 0.005$, Pearson correlation).

Data Normalization
Since the caloric goal ($Calories_{goal}$) and caloric expenditure ($Calories_{expend}$) vary by user, we normalize the raw calories expended towards the daily goal:

$$Goal_{complete} = (Calories_{expend}/Calories_{goal}) * 100. \quad (3)$$

The personalized goal app explicitly records the caloric goal in conjunction with the caloric expenditures. Hence, computing the percent goal completed for this app was straightforward. The social competition app, however, recorded caloric expenditures only. Hence, we had to reverse-engineer the caloric goal for it. In order to do this, we first calculated each user's BMR according to Eq. (2a) for male users and Eq. (2b) for female users. For each overweight and obese user (BMI > 25), we computed her/his target weight by assuming the BMI of a lean person (BMI $= 23$). This target weight was then used to compute the target BMR according to Eq. (2a) and Eq. (2b). The difference between the current and the target BMR values was the reverse-engineered ideal caloric goal ($Calories_{goal}$) for the user.

Our apps focus on caloric monitoring. In this sense, users with lean BMI (BMI < 25) and normal food intake are not required to do much, as they are in an optimal caloric state. Hence, we had to come up with a light goal for them, instead of the zero goal reported by the formulas. We set this goal to 100 calories per day. It was the closest memorable number to the mean daily expenditure of normal users in the old app (88.12 calories, $n = 19$ normal users). Hence, it appeared to represent the daily behavior of the normal user based on the dataset we could sample at the time.

Data Analysis

Activity Patterns

Figure 5 illustrates boxplots of the daily percent caloric goal completed for every user in the datasets. We ran the Welch two sample t-test on the number of active days. The test revealed ($p < 0.05$) that the habitual users of the personalized goal app (aka PGA) logged more active days than the habitual users of the social competition app (aka SCA) - an indication that the personalized goal design was engaging.

Figure 6 illustrates the activity patterns via spatiotemporal plots. The y-axis represents the users, the x-axis represents the observation period, and each cell in the plot represents activity intensity, with darker shades corresponding to more intense activity. Empty cells represent no activity

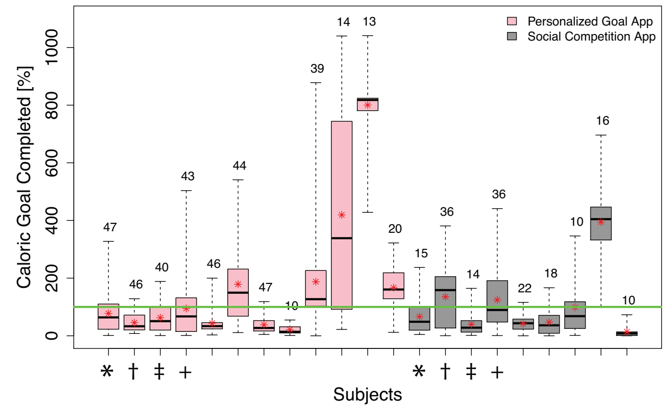


Figure 5: Boxplots representing daily percent goal completed for every user. The number of active days appears on top of each boxplot. The green line indicates 100% goal completion. The four shared users, who lasted through SCA and PGA as habitual users, are annotated with the symbols $*$, $\dagger$, $\ddagger$, and $+$.

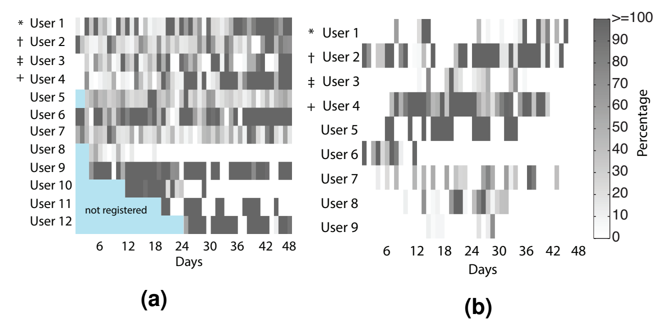


Figure 6: Percent goal completed via (a) PGA and (b) SCA.

on a particular day. This visualization clearly demonstrates higher usage consistency for PGA (Fig. 6a) with respect to SCA (Fig. 6b).

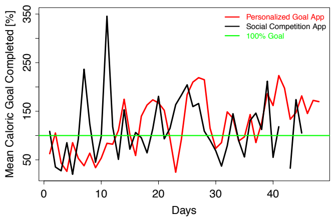


Figure 7: Signals representing mean percent goal completion over time for the two groups.

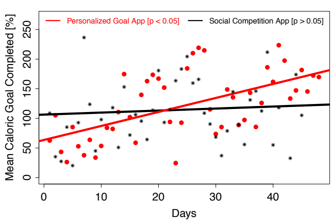


Figure 8: Linear regression shows improvement in percent goal completion over time for PGA.

Next, we computed the mean of the percent goal completed over the observation period for each user and ran the Welch two sample t-test on the mean values. The test revealed that the mean percent caloric goal completed (i.e., activity intensity) did not differ between the two designs ($p > 0.05$).

Usage Cycle

Next, we investigated if there were any underlying behavioral pattern characterizing each group. Specifically, we were interested to compare the usage cycle between PGA and SCA. The usage cycle refers to the average consecutive days of app usage before a break day. First, we computed the evolution of the mean percent goal completed over time for the two groups (Fig. 7). Next, we performed wavelet analysis on the signals per the method in [3]. The analysis computed each signal's dominant frequency, which is indicative of the corresponding usage cycle.

The usage cycle of PGA's user base was 6.25 days, while it was 3.75 days for SCA's user base. This means that it took a PGA user almost an entire week before having a low or no activity day, that is, twice as long as an SCA user. These results along with the raw signals in Fig. 7 indicate that in comparison to PGA's user base, SCA's user base used the app for short periods with irregular activity patterns - abrupt high activity for a few days and then quickly dropping to low or no activity period. In contrast, PGA's user base exhibited a longer and more gradual pattern that is healthier [19].

Goal Completion

Figure 8 shows the linear regression analysis on the mean signals presented in Fig. 7. The analysis shows significant increase in percent goal completed over time for PGA's user base in comparison to the SCA's user base ($p < 0.05$). This is true for both subsets: the four shared users ($p < 0.05$), and the remaining unshared users ($p < 0.05$).

Discussion and Conclusion

We tested a simple design with emphasis on personalized goal, against a design based exclusively on social competition. Comparison between two user samples that were equivalent in terms of covariates, showed that with the design emphasizing personalized goal achievement habitual users tended to be physically active for longer consecutive stretches (almost double), before taking a day break. And, while the intensity during these active days did not differ significantly between the two groups, the group following the personalized goal design exhibited a significant ascending trend, which suggests that it is bound to overtake the legacy group given more time. All in all, the personalized goal design clearly contributed to increasing the frequency of physical activity, having the average user taking just one break day per week. Since behavior is highly defined by habit, and since the ideal physical activity habit is to 'do something every day', the personalized goal design appears to work as an effective orthotic.

The major limitations of this study are the small sample sizes, which are ameliorated, however, by the significant longitudinal horizon (one and a half months).

In fact, this was an observational study comparing a pure social competition with a personalized goal + social competition design, based exclusively on objective measures. We plan to expand and deepen our investigation on the behavioral effects of personalized goal and competition designs, by running a controlled longitudinal study covering all possible combinations: pure personalized goal vs. pure social competition vs. personalized goal+social competition vs. social competition+personalized goal. This comprehensive controlled study will use both objective and subjective (surveys) measures to complement the initial results reported here.

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