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Preliminary results from a study of the impact of digital activity trackers on health risk status

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Abstract. Digital activity trackers are becoming increasingly more widespread and affordable, providing new opportunities to support participatory e-health programs in which participants take an active role. However, there is limited knowledge of how to deploy these activity trackers within these programs. In response, we conducted a 7-month study with 212 employees using a wireless activity tracker to log step count. Our results suggest that these devices can support improving physical activity levels and consequently reduce diabetes risk factors. Furthermore, the intervention seems more effective for people with higher risk factors. With our work we aim to contribute to a better understanding of the issues and challenges involved in the design of participatory e-health programs that include activity trackers.

Keywords. Activity trackers, participatory health, e-health, risk factors

Introduction

There is growing evidence on the harmful consequences of having a sedentary lifestyle [3,6]. These negative outcomes not only affect individual health but also have a significant economic impact. Healthcare costs due to physical inactivity are estimated to be almost $1.5 billion in 2006-2007 in Australia [4].

In response, a growing area of interest has been the use of sensing technology that supports users collecting data about their own physical (in)activity, as it is believed this could enable users to take a more active role in improving their own health. In particular, wearable digital activity trackers have emerged as a tool for real-time data collection and sharing (e.g. Fitbit, Nike Fuelband). However, it is not clear yet how some of the features of these new devices could be used to motivate wearers to be more physically active, in our case to meet physical activity guidelines. Prior work suggests the use of game mechanics [7], social networking [9] and remote coaching [2]. We aim to complement this thinking by highlighting the opportunity that comes with the large volume of sensed data these digital activity trackers generate. In particular, we see an opportunity to use this data as a central feature of participatory e-health programs.

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1. Description of the Study

To explore this opportunity, we conducted a 7-month pilot study with employees of the Australian Unity group. A total of 556 employees were invited, of which 212 (38,1%) were willing to participate in the pilot study. Most of the participants worked in the same location (82%), but we also included people that work off-site. The intervention consisted of offering participants an activity tracker (Fitbit Ultra) at a subsidised price (20% of the retail price). We selected this device because of its wireless synchronisation ability, relatively long battery life, physical unobtrusiveness and the availability of social features including the ability to develop online communities using the Fitbit website.

We assessed the participants' health risk status at commencement and completion of the study using the Australian Type 2 Diabetes Risk Assessment Tool (AUSDRISK), which stratifies participants into three levels of risk—high, intermediate and low—of developing type 2 diabetes within 5 years [1]. We also undertook two questionnaires (at first month and completion; response rate of 56% and 77% respectively) and three ad-hoc focus groups (at fifth month; between 5-10 participants each) in order to gain additional insights about participants' experiences. We also received monthly downloads of activity data directly from Fitbit after receiving written consent from participants.

2. Results and Discussion

A summary of results is set out in Table 1, showing the split between participants based on their AUSDRISK score at commencement. Comparing with risk levels at end (response rate of 66%), we found promising health outcome results with 23% of participants reducing their AUSDRISK score over the period of 7 months. This self-reported data was strengthened by the data captured by the trackers: the users that moved from high to a lower risk had the highest average number of steps (Table 2).

The average monthly dropout rate was 15% (i.e. every month, 15% of the users with any activity in the previous month stopped using the device), with a peak of 23% of dropout on Month 3 (corresponding to January), that may be associated to the main Australian's holiday period. In total, a 36% of the participants remained using the device during the entire pilot (Table 3).

We found that the participants with high AUSDRISK scores at commencement seemed to be the most motivated to increase activity levels and continue using the device over the period of the study (Figure 1). Surprisingly, this group had the highest average steps per day over the pilot (8,588 compared to 7,836 for medium risk and 7,878 for low risk) and the highest mean number of months engaged (5.7 months compared to 4.4 month for medium risk and 4.2 months for low risk). These results are promising considering that high-risk groups are arguably the most important target of these programs. However, self-selection bias may have influenced these results as participants joined the study voluntarily. Further, prior work suggests that awareness of high-risk levels can improve motivation to adopt preventive lifestyle changes [5], such as starting using an activity tracker as part of our study after getting a high AUSDRISK score.

Table 1. Summary of Results

	AUSDRISK Score at Commencement				
	High	**Medium**	**Low**	**Total**	**%**
Total	45	86	81	212	100%
%	21.2%	40.6%	38.2%	-	-
Males	26	40	14	80	37.7%
Females	19	46	67	132	62.3%
Age					
Under 35	8	29	52	89	42.0%
35 - 44	16	32	26	74	34.9%
45 - 54	10	19	3	32	15.1%
55+	11	6	0	17	8.0%
Completed AUSDRISK at End	38	50	54	142	67%
AUSDRISK Score at End					
High	21	4	0	25	17,6%
Medium	15	31	7	53	37,3%
Low	2	15	47	64	45,1%
Number improved	17	15	-	32	23%
Number declined	-	4	7	11	7%

Table 2. Average Steps per Risk at Start/End

	AUSDRISK Score at Commencement		
	High	**Medium**	**Low**
AUSDRISK at End			
High	8173	9607	-
Medium	10059	9515	8494
Low	12294	8950	9025

Table 3. Monthly Engagement/Dropout

	Total	**%**	**% Monthly Dropout**
At Start	212	100%	-
Month 1	198	93%	12%
Month 2	174	82%	11%
Month 3	154	73%	23%
Month 4	118	56%	14%
Month 5	102	48%	17%
Month 6	85	40%	11%
Month 7	76	36%	-

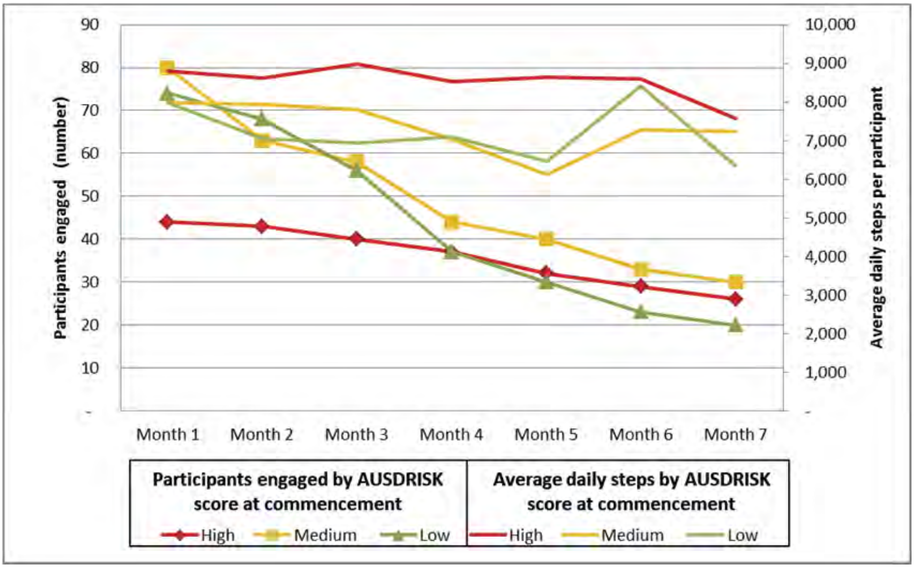

Figure 1. Engagement and Average Steps by AUSDRISK score at Commencement.

The questionnaires and focus groups provided insights into the main reasons for different levels of engagement and activity levels. Low engagement was predominantly driven by device issues (including broken, lost or forgotten devices) while low activity was explained predominantly due to lack of time and insufficient motivation to change habits. These results suggest that the device in itself may be insufficient to drive behaviour change in a large proportion of participants. On the other hand, we found anecdotal evidence in the focus groups that high-risk participants were already thinking about making a change. This could explain the better results in this particular group in both engagement and activity levels, where the intervention may have acted as a trigger of their willingness to change. In terms of the Transtheoretical Model of behaviour change [8], for some of the participants the program provided an excuse to finally move from contemplation and preparation stages to action.

In order to get a deeper understanding of the different types of users, we classified participants in four groups according to the number of months engaged (i.e. months where participant activity was null in more than 25% of the days), and number of months active (i.e. most of the days with less than 7500 steps, insufficient average steps to meet physical activity guidelines [10]) (Figure 2). We found that a large group of the participants (43%) were not able to meet physical activity guidelines for more than one month or be engaged for more than 4 months with the device. The survey results for this group show that a large number of its members would be willing to try something different like "Playing games that encourage physical activity" (46% agree/strongly agree). These results suggest that the problem for this group might not be a lack of willingness to change, but the need of an additional source of motivation. In contrast, 1 out of 4 participants (24%) were both engaged and active most of the months. According to the survey, members of the "active–engaged" group would prefer to have more goal-oriented functionalities like smart reminders of physical activity (77% agree/strongly agree) or normative information about the appropriate levels of activity (84% agree/strongly agree) rather than playing games (30% agree/strongly disagree). These results highlight the relevance of considering different approaches depending on the different target groups of users.

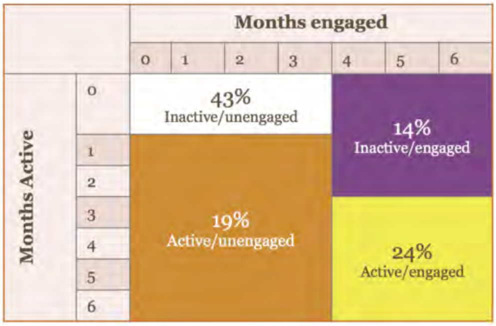

Figure 2. Distribution of Participants According to Engagement and Activity Level

Finally, in order to examine the impact of social support and competition from friends or relatives midway through the pilot we offered an additional device to all the participants at the same subsidised price. A total of 101 participants elected to purchase an additional Fitbit. The participants that purchased the additional device had both higher activity levels and engagement duration; however, this appears to be the result of self-selection as those with higher average activity levels were more likely to take-up the offer.

In sum, these results suggest that there is high potential in designing interventions that target high risk users, firstly helping them to get convinced about making a change and, secondly, triggering and sustaining the new behaviour using activity trackers in engaging, meaningful ways; however, each target group of users may require a different approach according to their particular level of risk and self-motivation.

3. Future Work

To extend this research, we are currently trialing the use of activity trackers with 90 users with no pre-existing relationships that have 2 or more health risk factors. This will examine if these results change in a different setting (distributed vs. co-located users). We are also testing the use of a semi-public display that shows the number of steps of teams of 6 members in near real-time. With this new system, we aim to foster playful competition within a smaller groups, in this case, 24 colleagues that are co-located. For both systems, we are accessing the data directly using the Fitbit API, which enable us to get on-going results and create real-time feedback loops that can boost both users' motivation and the participatory dimension of these interventions.

Finally, in order to ascertain if engagement levels can be improved by using a different device, we are planning a small trial with wristbands trackers. With these new studies and trials, we aim to learn more about new ways of participatory e-health interventions to encourage greater activity and foster engagement.

4. Conclusions

The results from this 7-month study that examined 212 employees' experiences using an activity tracker suggest that these devices can support improving physical activity levels and consequently reduce diabetes risk factors. Furthermore, the devices seem more effective for people with higher risk factors (older, less physically active). Our results are limited by the fact that our participants are from a limited cohort that may be subject to self-selection biases (e.g. voluntary participation in the intervention and surveys). Moreover, we acknowledge that knowing how many steps participants take before using the device could strengthen our argument.

Overall, our results indicate our approach could be effective for those with health risk factors, particularly if the intervention targets the right user groups.

With our work we aim to contribute to a better understanding of the potential of activity trackers to improve participants' health risks together with insights about the challenges and issues involved in the design of health programs that include activity trackers.

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