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# ANALYSING PHYSICAL ACTIVITY BEHAVIOUR WITH SELF-ORGANIZING MAPS – A RCT STUDY WITH POLAR ACTIVE

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## Abstract

*Physical activity (PA) is a major contributor for both physical and mental wellbeing, and it is also needed to maintain our working capability. PA is not only about sports and exercise, but also being active at work, home, in commuting and during leisure time. According to WHO physical inactivity accounts globally for more than 3 million deaths annually. Evidence-based interventions to understand and increase our PA behaviour are therefore important. Activity monitors provide a means to set targets for daily activity and to follow the intensity, frequency, and duration of PA. Monitoring daily activity has been shown to motivate for PA but more information is needed to understand our daily PA behaviour. Our daily PA is correlated to our daily habits such as steps and calories burned and sleeping time. The current randomized control trial study try to understand by visualising and clustering daily PA (>3.5 MET), steps, calories and sleep of the baseline and the week 8 in working days, from Monday to Friday. The data analysis is based on self-organizing maps (SOMs) technique. The data clusters reveal changes and differences the intervention has occurred between men and women in their PA behaviour.*

*Keywords: Physical activity, behaviour change, visualization, clusters, self-organizing maps*

# 1 INTRODUCTION

Digitalization and medicalization have changed our life substantially during the past few years. Digitalization of healthcare from enterprise architecture to electronic health records, from telemedicine to mobile health applications both challenge the delivering of treatment or services and embower individual's responsibility of their own health (Varshney, 2009). In medicalization a previous human conditions are defined as medical problems in need of medical study, diagnosis, prevention, or treatment. Medicalization can be driven by new evidence or hypotheses about conditions; by changing social attitudes or economic considerations; or by the development of new medications or treatments (Conrad, 1992). From one point of view this is a fruitful situation, more tools and gadgets for more diseases, and more business possibilities. But, on the other hand, there is a challenge as we should find different ways to reduce the growth of healthcare expenses at least public ones.

Preventive healthcare has been suggested as one solution for resource savings. However, they need careful cost-benefit analysis to identify evidence-based opportunities for more efficient delivery of health care, prevention or treatment, after that the system needs to restructuring and incentives that encourage the effective interventions (Cohen et. al, 2008). At the same time, there are convincing evidence that a sedentary and unfit way of living increase the risk of numerous chronic diseases and conditions and even decreases longevity (WHO 2009). A physical inactivity has been one of the highest leading global risks for mortality in the world already for some time. Globally, around 31% of adults aged 15 and over were insufficiently active in 2008 (men 28% and women 34%). Physical inactivity causes an estimated 3.2 million deaths globally (WHO 2015).

Physical activity (PA) is defined as any bodily movement produced by skeletal muscles that requires energy expenditure (WHO 2015). PA is a major contributor for both physical and mental wellbeing, and therefore needed to maintain public health. Evidence-based interventions to increase PA are important. Being physically more active in today's society is challenging. Activity monitors provide a means to set targets for daily activity and to follow the intensity, frequency, and duration of PA. Monitoring daily steps has been shown to motivate for PA (Dena et al. 2007).

The primary research question of the current study is how digital intervention impacts on individual's daily PA. Secondary we are interested in whether there are any differences between men and women. This explorative study use self-organizing map (SOM) technology which is one type of artificial neural networks. The applications of artificial neural networks are very popular in various fields, such as finance, manufacturing, information systems, marketing, operation management, social behaviour analysis, and so on (Turban et al., 2010). In this study we cluster and visualize with Viscovery SOMine® application what are the changes in PA, steps, calories, and sleep of working days induced by Polar Active (Polar Electro Oy, Kempele, Finland) activity monitor during a 10-week randomized controlled trail.

The structure of the paper is organized as follows. Section two focuses on resent research in PA interventions. In section three the research design, materials and methods are described. Key findings and conclusions together the future research directions end the papers.

## 2 PHYSICAL ACTIVITY AND DIGITAL INTERVENTION

Regular physical activity such as walking, cycling, or participating in sports has significant benefits for health and weight-loss maintenance (Ekelund et al. 2011). Although, the nature between objectively measured of physical activity and abdominal fat distribution has not been well characterized (Philipsen et al. 2014), previous studies have firmly shown that PA reduces of the risk of diseases and reduce mortality and extend life expectancy (Vanhees et al. 2012, Wen et al. 2001). But the challenge is: How do we change our way of living? How can we be more physical active in modern information society? We need to find solutions how digital interventions could help us to change our behaviour.

Many persons want to be more physically active, but achieving sustainable changes in lifestyles can be challenging (Sherwood and Jeffery 2000). ICT-embedded health and wellness services have suggested empowering people to manage their health (Honka et al 2011). People may use their own health related data for promoting their well-being. For example, electronic activity monitors contain a wide range of behaviour change techniques typically used in clinical behavioural interventions (Lyons et al 2014). The increasing availability of health information technology enables people to measure, store, and manage their health related data. Indeed, numerous of gadgets and applications are available for use by consumers and researchers (Lowe and Ólaighin 2014). However, little is known about how these monitors effect on our physical activity in normal non-diseases settings. Our review on more than two hundred research articles revealed that most of the studies so far have focus on treatment of some disease or achieving recommended levels of exercise and physical activity (e.g. Tudor-Locke, 2009). In order to increase the PA of population we need to understand how the digital intervention effects on the PA behaviour of different population segments. Our focus is in sedentary workers aged 35-55.

Cole et al (2015) explored desk-based office workers' perceptions of factors that influenced sedentary behaviour at work and to explore the feasibility of using a novel mobile phone application to track their behaviours. Study participants stated that recording data using the phone application added to their day's work but the extent to which individuals perceived this as a burden varied and was counter-balanced by its perceived value in increasing awareness of sedentary behaviour. Grande et al (2015) argues that engaging in workplace exercise has a significant positive effect on health behaviour and willingness to become more physically active.

In an intervention study designed to increase moderate to vigorous physical activity, participants who increase their time spent exercising will obtain much of this time by reducing their sedentary behaviour (Siddique et al. 2015). The data was measured with accelerometer. Martin et al. (2015) found that an automated tracking-texting intervention increased physical activity with, but not without, the texting component. A meta-analysis of changing physical activity behaviour suggest that multi-component goal setting interventions represent an effective method of fostering physical activity across a diverse range of populations and settings (McEwan et al. 2015). In our literature review we have not found any research that analysis the behaviour change of the intervention study based on pattern analysis method based on self-organizing maps. Our aim is with this kind of unique approach to explore whether we able to find some hidden patterns or interesting clusters that could help us to understand and promote physical activity among sedentary workers aged 35-55.

### **3 MATERIALS AND METHODS**

The data for the study was collected with Polar Active activity monitor. Polar activity technology detects and filters activity intensity, and calculates it to MET (Metabolic Equivalent of Task, or simply metabolic equivalent, a physiological measure expressing the energy cost of physical activities) values. In Polar activity technology METs are used to accumulate time in the five different activity zones: very easy (1-2 MET), easy (2-3.5 MET), moderate (3.5-5 MET), vigorous (5-8 MET), and vigorous+ (>8 MET). The activity is measured 24/7 and activity bar shows the target and achieved time in moderate to vigorous+ activity zones. It measures and displays steps, burned calories and time spent of each activity level.

Our study group consist of almost 120 white-collar workers. 60 females and 54 males were randomized into an intervention (30 females, 28 males) and control group (30 females, 26 males). Inclusion criteria for the study subjects were: age 35-55, BMI < 30.1, no sports engagement, reported daily PA challenging, wanted to increase everyday PA.

During a 1 week run-in period all subjects used a blinded PA monitor for baseline PA recording. During the following eight week period the intervention group used PA monitor with display and diary functions while the control group continued with the blinded PA monitor. The activity target for the test groups was set on one hour per day. All subjects downloaded their PA data biweekly via an internet interface. All they got biweekly remainder about this downloading. No physical activity counsel-

ling was given at the beginning of the study, only technical support to use the Polar Active and the downloading procedure.

The current study visualises and clusters daily PA (>3.5 MET), steps, calories and sleep of the baseline and the week 8, test line, from working days, from Monday to Friday. This daily PA (>3.5 MET) was displayed in test group's monitor and therefore selected to further analysis. Indeed, both groups increased this PA but there were no significant difference between the groups during the week days (Koskivaara et al. 2013).

The data was analysed with Viscovery SOMine® application which visualization is based on self-organizing maps (SOMs) technique. It is a tool for explorative data mining, visual cluster analysis, statistical profiling and classification. SOM is a type of artificial neural network (ANN) that is trained using unsupervised learning to produce a low-dimensional, typically two-dimensional, discretized representation of the input space of the training samples, called a map. Self-organizing maps are different from other artificial neural networks as they apply competitive learning as opposed to error-correction learning (such as backpropagation with gradient descent), and in the sense that they use a neighbourhood function to preserve the topological properties of the input space. This makes SOMs useful for visualizing low-dimensional views of high-dimensional data. The artificial neural network introduced by the Finnish professor Teuvo Kohonen in the 1980s is sometimes called a Kohonen map or network (Kohonen, 2008).

SOM is very useful tool for exploratory data analysis. SOM also has the advantage to dig out inner relations of unstructured data, dig out possible patterns hidden in the data, and detect features inherent to the problem. It can be put into use in such common problems as clustering, categorization, visualization or hidden factor analysis. Before the SOM algorithm starts, the map will be randomly initialized and each neuron will be assigned a parametric reference vector. Afterwards, the SOM algorithm will begin by taking two steps. In the first step, the best matching neuron will be found by using some certain distance function. In the second step, the neurons adjacent will learn from the input data. After repeating step one and step two for all input vectors for a predefined amount of times, the network will be fully trained and show some groups of vectors. After completing the SOM algorithm process, a landscape with representative colours will be created to show the results and classified groups. By using different colours the maps will be clearly visualized. The distances will also be represented by various colour labels such as light and dark colours.

## 4 KEY FINDINGS

Table 1 shows the numbers of clusters for baseline (BL) and test line (TL) for female test (FT), female control (FC), men test (MT) and men control (MC) groups.

Cluster	FT_BL	FT_TL	FC_BL	FC_TL	MT_BL	MT_TL	MC_BL	MC_TL
1	33	48	50	59	41	31	30	19
2	29	24	43	25	29	25	22	16
3	15	14	4	10	16	18	11	16
4	12	7	3	6	7	12	13	15
5	7	4			3	10	10	13
6	2	3			2	2	8	10
7	1				1	1	2	10
8	1				1	1	2	1
9							2	

Table 1. Numbers of clusters and their frequency portion in per cent.

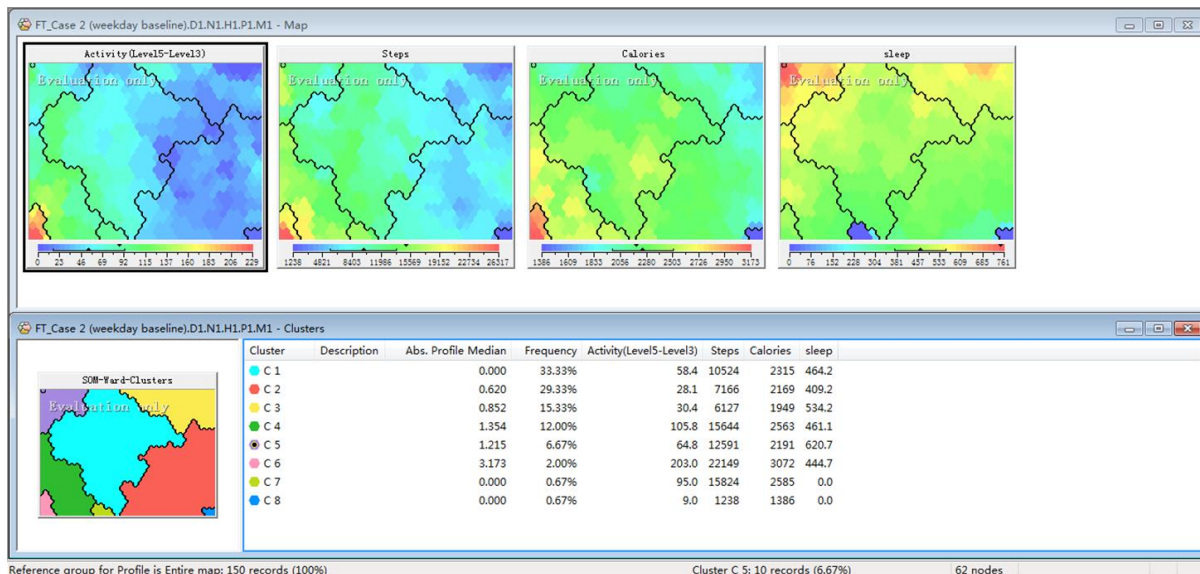


Figure 1. The clusters and maps of female test group data from baseline.

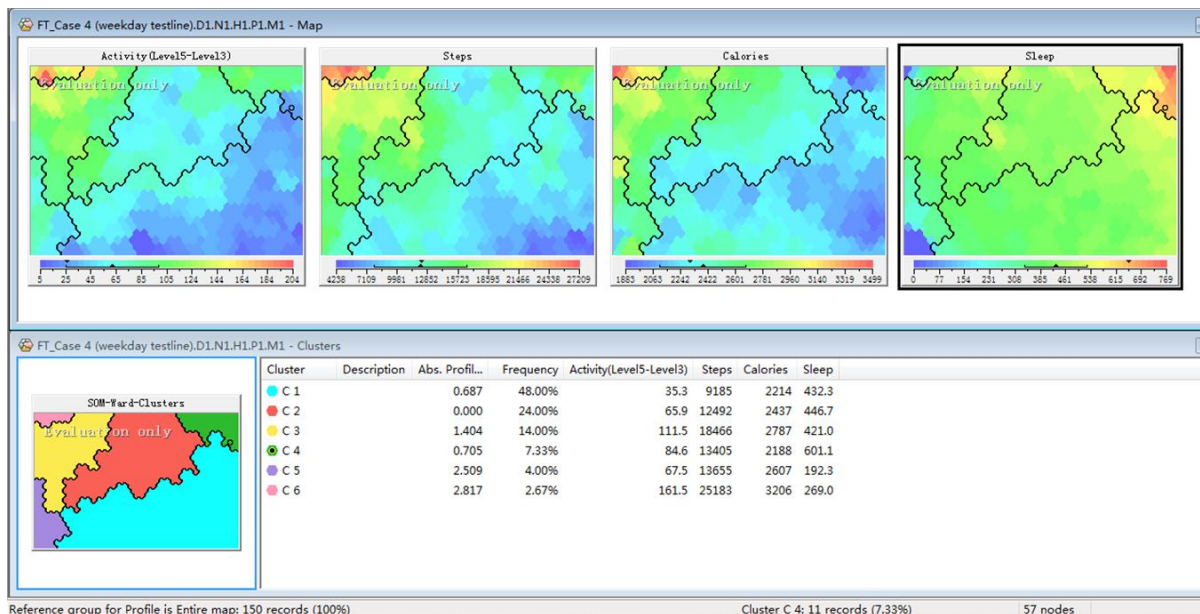


Figure 2. The clusters and maps of female test group data from test line.

As the biggest change seem to occur in women's test group, we will start analyse the SOM-map of women's test group more thoroughly. When analysing the map of women's test group from the baseline (FT\_BL) (Figure 1), we were able to find following patterns:

- Cluster 6, pink colour on the left down corner in the small maps, seems to be really physically active. Their activity level is 203 minutes per day which is almost double more than next cluster 6, green one.
- In 5/8 clusters (1, 4, 5, 6, 7) the daily steps in more than 10 000 steps which in some researches has been the daily recommendation.
- Clusters 7 and 8 are very small ones and their sleeping is zero which indicates that these study subjects have not used the activity monitor during the night time.

When analysing the maps of women's test group from the test line (FT\_TL) (Figure 2), we were able to find following patterns:

- In almost every cluster the daily steps are 10 000 or more. In cluster 6, pink colour, the daily steps are almost double to the others.
- In the biggest cluster, cluster 1, the activity level is lowest, about 35 minutes per day, when comparing the other clusters in this study group.
- Each clusters have values for sleep, but e.g. in cluster 6 the average sleep amount is about 3,5 hours per day which indicates some stressful situation.

When comparing the cluster maps of women test group between baseline (BL) and test line (TL) (Figure 1 and Figure 2), we were able to find following issues:

- Less clusters on test line map.
- One strong cluster (light blue), which increased from 33 percent to 48 per cent.
- Size of three biggest clusters increased with 10 per cent, i.e. some kind of concentration happens in behaviour.

Table 2 describes the behaviour change in three largest clusters of each study groups. The following analysis is based on these clusters. In female's test group it means about 86 per cent of population at the test line, and in female's control group it means about 94 percent at the test line. Equal frequencies for men's groups were about 74 percent for the test group and 51 percent for men's control group at the test line. When we combine the three largest clusters in each group the only positive change in *frequency* occurred in the female's test group. In the *activity* level the female test group increased their activity with 96 minutes whereas the female control group declined it 49 minutes. Both men's groups increased their activity level, the test group with 17 minutes and the control group with 82 minutes per day. In daily *steps* each study group increased the total amount of daily steps although both female's groups the daily steps decreased the largest clusters. Only in the women's control group the *calories* burned change was negative, each other group manage to increase their calorie consumption. In 10/12 clusters in these study groups the *sleeping* time decreased. In cluster three in the women's control group the information is bias as the recorded sleeping time on test line in this cluster was zero.

	Cluster	FT	FC	MT	MC
Frequency	1	15	9	-9	-11
	2	-5	-18	-4	-6
	3	-1	6	2	5
Activity	1	-23	-28	29	30
	2	38	56	41	33
	3	81	-77	-53	19
Steps	1	-1339	-3019	4513	3498
	2	5326	7484	4818	4860
	3	12339	8233	6046	2929
Calories	1	-101	-146	450	335
	2	268	347	519	283
	3	838	-705	-699	332
Sleep	1	-32	13	-23	-73
	2	38	-10	-21	-17
	3	-113	-443	-6	-17

Table 2. Change of frequency, activity, steps, calories, and sleep in three largest clusters from baseline to test line in different study groups.

## 5 CONCLUSIONS

The impact of the digital intervention in this study are as follows. Pretty light digital intervention, a wrist-worn activity monitor and a biweekly email reminder together with activity data downloads did increase the PA (>MET 3.5) in both intervention and test group. The increase of physical activity is in line with other similar studies (Dena et al. 2007). Such increase, if durable, has a positive impact on health.

The theoretical contribution of the study is on the novel approach to analyse the physical activity behaviour and its' change with self-organizing map. We manage to profile different type of clusters among users. This kind of finding can be a contribution for design requirements for technologies that encourage physical activity (Consolvo et al. 2006). The visualization of the group results shows that that the effect of daily monitoring seems to have different effects on female and male. It seems that female start to behave more similar and that man's behaviour starts differentiate. But then there are also different types of clusters in each study groups. Recognition of the different types of PA persons and support them with tailored digital intervention at work might increase satisfaction at work. Indeed, understanding the digital interventions effect on PA related behaviour would be a significant assets to prevent many chronic diseases.

There is a need to study how to design and implement digital interventions to achieve durable and sustainable achievement in encouraging physical activity on individual, organizational or even society level.

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