An Approach to Improve Physical Activity by Generating Individual Implementation Intentions

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ABSTRACT

Daily physical activity not only empowers the body, but it also invigorates the mind and helps people cope with the struggle of everyday life. A balanced amount of moderate to vigorous physical activity is recommended. Major barriers that lead to low levels of physical activity are lack of time and motivation. The objective of this paper is to generate individual recommendations to improve physical activity by using if-then plans - so called Implementation Intentions. We developed a mobile application named DayActivizer to collect all the necessary activity data by the user. Based on the collected data, the application automatically recommends activities within if-then plans with an increasing degree of physical effort to counteract insufficient physical exercise concerning individual daily routine. To evaluate our approach, we conducted a field study (N=8) and qualitative interviews in which every participant was asked to examine the validity of the individual recommended implementation intentions.

CCS CONCEPTS

• **Human-centered computing** → **User models**; *Smartphones*; • **Social and professional topics** → *Seniors*; • **Applied computing** → *Consumer health*; Psychology;

KEYWORDS

User Modeling, Activity Recommendation, Daily Routine, Physical Activity, Markov Chains, Implementation Intentions

1 INTRODUCTION

In the process of growing older, the human body is more vulnerable to diseases such as diabetes and various types of cancer which can be prevented by strengthening the immune system by doing physical activity [2, 11, 21]. Despite knowledge of these benefits, people have difficulties in pursuing any kind of physical activity. Lack of motivation and lack of time are main causes for this phenomenon [3, 22]. A regulated daily routine is essential for many people. A structured daily life helps to master the everyday challenges. Due to that facts we developed a concept for a mobile application to support more physical activity by generating individual recommendations that can be integrated into the individual's everyday life an form new habits.

A habit is defined as a specific activity which is performed regularly and repeatedly by someone. The process of performing an activity happens automatically and sometimes unconsciously which is called as chunking [6]. It is the basis to establish new routines [6]. A behaviour is characterized as a repeating learning process, which is triggered by a setting [24]. Furthermore a habit is a three-stage process which consists of the components cue, routine and reward. The cue is defined as a trigger which activates an action or a routine under specific conditions. A routine can be a physical activity or even an emotion. On the basis of the reward, the brain finally decides whether the routine is accepted or not. If the reward after performing an action is accepted, the subject will maintain this which will be automated by multiple repetitions [24]. To form a new habit discipline and willpower is needed. It takes about 66 days on average to adopt a new habit [12]. As a precondition to form a new habit successfully one have to identify the three components clearly and execute the routine very often. Moreover the success increases if the demand for a concrete purpose is defined [6]. Changing a habit works in four steps: First, an identification and understanding of habits is needed. Secondly, a reward which can be changed, thirdly, a focus upon the cue associated with an action is important. Cues can be categorized in the following five categories:

- Location
- Time
- Emotional state
- Present of other persons
- Immediately precding action

Lastly, using the knowledge of the previous three steps, the creation of a schedule or plan is necessary to change the analyzed behaviour. There is a wide breadth of approaches for creating such plans, however this paper focuses upon the strategy of implementation intentions. Therefore recommendations are expressed as

UMAP'17 Adjunct, July 09-12, 2017, Bratislava, Slovakia

ACM ISBN 978-1-4503-5067-9/17/07…$15.00
https://doi.org/10.1145/3099023.3099101

action plans. Action plans, so-called implementation intensions, are a psychological construct for the establishment of new routines, in order to bring about a desired change in behaviour. The construct was introduced by the psychologist Gollwitzer [7] and examined according to its efficacy [9, 13, 19, 23]. The strategy serves to achieve a specific long term goal, which is declared as If situation x arises, then I will initiate the goal-directed response y! [7]. The if-component describes a detailed critical situation whereas the then-component is defined as a behaviour or an action [8, 9]. The use of implementation intentions successfully meets two criterions: on the one hand the plan needs to be formulated as precisely as possible and on the other hand the plan should be viable. As described above the if-component can stay for a specific situation with specific time and location but it can also be an emotional situation which shows how someone feels. So the if-component represents the cues of a habit whereas the then-component expresses the wanted and goal-directed response to the given cue. The following plans are examples to show how action plans could look like:

- If it is sunday at 5 o'clock in the evening, then I will go by bike.
- If I am feeling stressed, then I will do 20 push-ups.

According to the results of some studies [9, 13, 19, 23], people who use Implementation Intentions can pursue their goals longer and carry out their action plans in the long term than people who do not use implementation intentions. In order to generate acceptable recommendations, our concept is based on a digital representation of user's acitivity behaviour. We developed a mobile application named DayActivizer to collect all the necessary activity data and used Markov Chains to extract the user's daily routines. Concerning individual daily routines and according to a desired behavior change the application automatically recommends activities within a plan with an increasing degree of physical effort.

The contribution of this paper is to offer a smart approach to assist the user in creating implementation intentions. This is done by modelling routines based on tracked activity data which are then used to identifiy timeslots or situations that are suitable for the 'if' part of an implementation intention. In the next step an activity for the 'then' part is suggested based on one of four different strategies. The goal is to create useful implementation intentions to increase the physical activity of a user in everyday life, so that he meets a certain threshold value of activity. The calculation of individual recommendations for the activity goal level is not part of this work. Some related work, the basics of the concept, the concept itself, the development of the application and a field study to evaluate the recommendations are explained in more detail below.

2 RELATED WORK

In the last decade, several persuasive systems were developed to support a healthier lifestyle and thus numerous applications which are commercial as well as based on scientific research appeared in app stores in the category Health and Fitness. Bort-Roig et al. (2014) [4] reviewed 26 studies with focus on influencing physical acitvity with smartphone technology. Concerning the strategies to influence the user's physical activity the results show that the majority of studies only use verbal or graphical feedback to represent the current state of physical activity. Stawarz et al. (2015) highlight the importance of habit formation support when pursuing long-lasting behavior change. As a means to support habit formation the use of implementation intentions is emphasized. Support could be given by helping the user to select cues and trigger situations to create implementation intentions, assisting the user to identify and learn to automatically connect these cues with a certain action and, to a smaller extend, positive reinforcement. The authors reviewed 115 commercial apps that aim to help the user to develop new habits. The results show that most apps focus on tracking behavior, setting goals and showing progress, but only few use strategies to support habit formation [20]. An example for a commercially available but science-based app that makes use of implementation intentions is WOOP [14]. WOOP is an acronym for Wish, Outcome, Obstacle and Plan. The app leads the user through a dialog that asks him to reflect on these constructs and create an implementation intention based on this. The progress of reaching the goal can be tracked manually by the user, there are no reminders or automatic tracking. Pinder et al. (2016) use the context-aware functionality of smartphones to create an app that identifies triggers that are based on time, location or movement to remind users of these cues and their corresponding implementation intention. The implementation intentions are set by the user [15]. So, to date only few apps offer habit formation support in general, even though it is a promising method to assist behavior change. Furthermore, the review of related work did not show any app that offers support in creating implementation intentions other than by leading through a self-reflection dialog. Recommendations for both the 'if' and 'then' part could be useful though: The user may not be fully aware of his routines and thus, of which timeslots and situations are suited best to integrate implementation intentions into everyday life. Apart from that the user could get further support by combining tracked data about everyday routines with implementation intentions, so that, for example, the user gets informed about how active or inactive certain weekdays are in general and gets recommendations for activities with a duration and intensity enough to reach a certain activity level. Smart activity recommendations based on user preferences and context are another approach to follow. Concerning the development of recommendation systems in the field of health Schäfer et al. (2017) [17] identify several key challenges to face. They emphasize the importance of using intelligent user models to filter user needs, to personalize recommendations based on user's context, history and goals and to assist users in the implementation of them. Works from Servia-Rodríguez et al. (2017) [18] and Reimer et al. (2016) [16] deal with user modelling based on past activity data in the domain of health applications. Former authors use smartphone sensor and communication data to derive routines for weekdays and weekends concerning the environment, activity and sociabilty of the users. In latter work user modelling is used to determine the choice of persuasive techniques for behavior change. Moreover the authors use collaborative filtering to recommend kind and target altitude of activity goals by comparing similar users. Nevertheless, so far none of these works aim to derive detailed daily routines with context data to identify appropriate time slots and activities for implementation intentions.

3 CONCEPT OF GENERATING INDIVIDUAL RECOMMENDATIONS

In order to generate acceptable recommendations to support users in the achievement of a goal, in this case more physical activity, the concept is based on a digital representation of the user's activity behaviour, i.e. his so-called user model. The user model is learned from data logged by the user in his / her everyday life. With the smart phone application DayActivizer (Figure 1) the user is given the opportunity to log his or her daily activities manually and to collect and store contextual information on his everyday routine both manually and automatically.

The data collected by the apps are: collection of everyday activities, their start and end times, information on the degree of effort in MET-Minutes[1], the number of steps the user takes during an activity, the location of the performance, the current weather during the performance, and how the user feels after performing an activity. Because there was not enough context data produced in the test phase of DayActivizer, in this prototypical phase the user model graph is generated only from the logged activities and learned as a Markov chain as a representation of his daily routines.

3.1 Extracting knowledge and generating recommendations

According to Figure 2, a graphical representation of the activity behaviour of one weekday learned as a Markov Chains, which contains different paths while each path represents potentially a daily routine. According to the graph and to take account of frequently occurring routines that are common to habits, we looked for the path with the highest probability.

Based on Figure 2, we begin with the vertex 'drive to work' and go the next vertex depending on the value of the edges. In this case, we take the edge with the highest probability. The path ends if a vertex has no outgoing edges. However, the result is a list of sequences of activities. This calculation we did for every weekday. As a next step, we evaluated all resulting paths in the previous step concerning the two components of an action plan. To identify the if-component, we developed two strategies:

- *Free time.* Within this paper, free time is described as an unrecorded time slot and can be used to create a new habit by performing a recommended physical activity. One must consider that after a strenuous activity, the user should be allowed to pause. The period of a free time shall also be sufficient to perform an activity including preparation time and travel time, in this work at least more than 10 minutes.
- *Replacing light-intense activities.* The other strategy is to look after a light-intense physical activity which can be replaced by a recommended physical activity which requires more effort. At this point, physical activities with less than 3 METs are not always that bad. If the user executed a physical activity with more than 3 METs, then he should be able to take a break or execute a light-intense or relaxing activity. This must be taken into account. Users can also clarify activities as essential, for example working or sleeping. These activities are not replaceable so they are ignored in this algorithm.

Regarding the then-component, recommended activities should be on the one hand adaptable to the user and on the other hand they have to meet the requirements to improve physical activity. Before calculating recommendations we calculate the MET-minutes which are reached by the user in average and if the MET-minutes reached are below the guidelines, then we decided to increase the MET-minutes by 30 MET-minutes per day which is actually a physical activity with moderate intensity done in 10 minutes. The reason for that decision is, according to [5], a moderate-intense workout with a duration of 72 minutes per week has an enormous effect on your personal fitness and health. It should be pointed out that the focus of this work is not on the identification of an individual target level, but rather on the integration of adaptable action plans into individual everyday life. To make the action plans and the activity recommendations more adaptable to the user, we developed four strategies for the then-component:

(1) **Most frequent activities**. The first strategy for individual activity recommendation deals with the frequency of the executed activities. We consider that users who often perform a physical activity are likely to do this activity on another time, too. Based on this assumption, we counted all the collected physical activity data above 3 METs.

(2) **Similar sports activity**. Our assumption is that users would accept recommendations with a sports activity which is similar to their known sports activity. For example, a user plays Badminton regularly. Badminton is a racket sports. Tennis and Table Tennis are also racket sports, so that the user might be interested in these new sports activities. The similar sports activities are derived from the sports type-classification from an online overview of different sport disciplines[2].

(3) **Favoured activities by age**. Although physical activities are not specific to age groups, but for fitness levels and personal preferences, there are investigations that certain age groups prefer certain activities. Therefore another recommendation strategy is based on a survey that investigates which physical activities are liked by people depending on their age [22]. According to the results of the survey we recommend an activity randomly.

[1]The Metabolic Equivalent of Task describes the rate of energy consumption of an activity to measure the physical effort [1]. Moreover, physical activities are classified by MET. So activities between 3 and 6 METs are described as moderate-intensity physical activities whereas physical activities above 6 METs are vigorous-intense. Light-intense activities are less than 3 METs. The World Health Organization recommends at least 600 MET-minutes a week but other studies recommend to obtain more MET-minutes due to the proven dependence to lower risk of several diseases [11, 25]. Based on the duration and entered type of activity the application determines the total MET-Minutes from a corresponding table.

[2]https://de.wikipedia.org/wiki/Liste_von_Sportarten

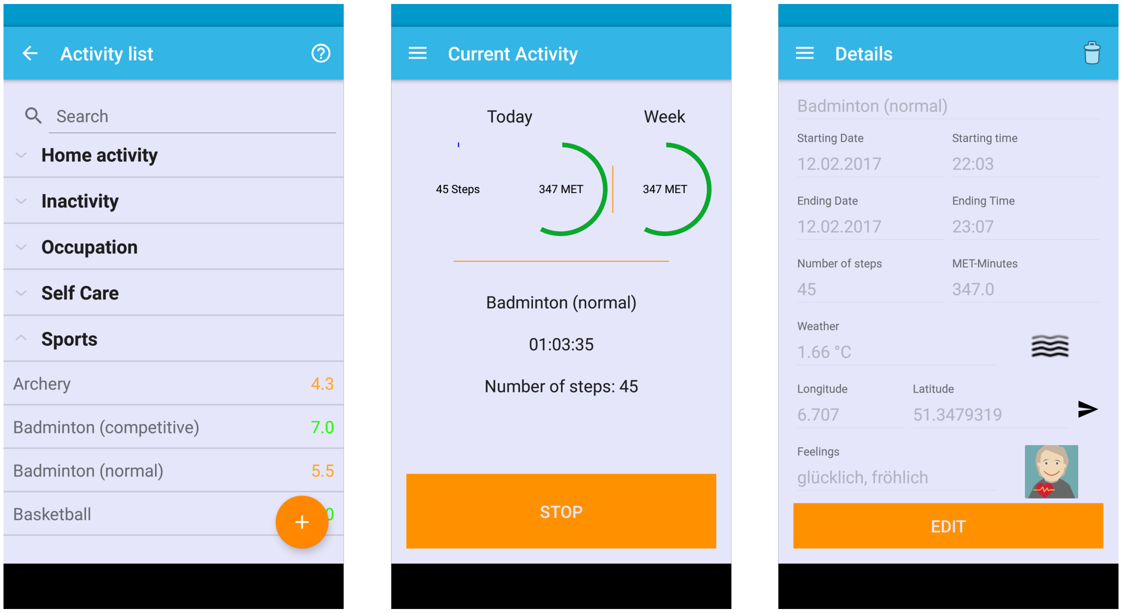

Figure 1: Screenshot of the selectable activity list, main page and tracked detail view of DayActivizer.

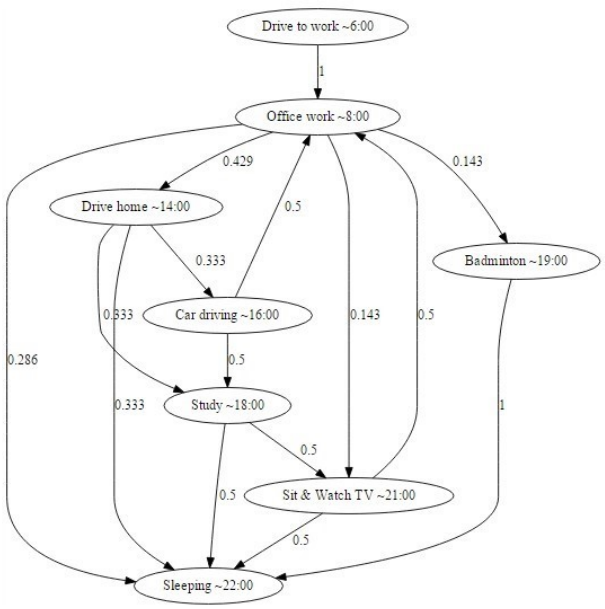

Figure 2: A graphical representation of the activity behaviour of one weekday using Markov Chains.

(4) **Good feeling activity**. The next strategy suggests that if you feel pleasantly after performing a physical activity, then there is a high probability that you will perform this again. In order to implement this strategy, we used the collected emotion data to each physical activity and recommended the most pleasant physical activities with at least moderate intensity.

After calculating a recommended activity using one of the strategies above, we generated an if-then plan with all the information we gathered. Therefore, we used the following template:

If I have finished (activity), then I will perform (recommended activity) every (weekday).

4 EVALUATION

The implementation of DayActivizer was followed by a two to four week field study with 8 participants. We investigate the user's acceptance of the individual recommended if-then plans.

4.1 Method

Eight participants from the age between 20 and 34 years were acquired. The participants were advised to use their own smartphones as test devices. All participants were instructed to detect their daily routine as detailed as possible after they installed DayActivizer. All relevant data was collected within a schedule of at least two up to four weeks. The gained data of all participants were uploaded on a server afterwards. After evaluating the data, several recommendations with regard to the individual daily routines of the participants were automatically generated and presented. Some recommendations were designed to create new habits during free time periods whereas other recommendations were designed to replace old habits. To evaluate the generated recommendations all participants were invited to take part in qualitative interviews. These interviews consisted in open discussions on key topics, e.g. which of the recommendations were considered appropriate by the participants and why.

4.2 Results and discussion

Most of the users entered their activities after execution or retrospectively at the end of the day, so we could identify missing context information within the collected data. Despite an individual alarm for inactivity, several participants obviously ignored or deactivated this provided service. Two out of eight participants only delivered dissatisfied or no results at all. Both of them only recorded about 36 activities in two weeks. Other participants recorded about 50 activities and two participants even recorded about 245 activities in four weeks. Nevertheless routines were detected out of the remaining user data from six participants. Based on the daily routines, several recommendations were established with respect to the calculated free time and for the replacement of activities. Most of the participants said that they could imagine implementing most of the recommendations. Nevertheless some of the recommendations were rejected by the user. Reasons were unsuitable time and inappropriate or non-executable activities. Illustrated as an example, participants do not like to do some physical activity in the morning or in the evening. Although some participants accepted the if-component of the generated plan but they decline the activity which was recommended because they do not like to do this. This is our first field study to test the automatically generated recommendations of DayActivizer. To examine the routine of a user, DayActivizer needs to have sufficient recorded data. This field study was very time-consuming to every participant because it is hard to record every activity during a day. Some of the generated recommendations are refused by the user. We identified two categories of reasons that we called individual reasons and context-based reasons. Individual reasons cover all kind of reasons which arise from personal preferences and dislikes. To solve this problem, we plan to integrate a survey into DayActivizer to find out some information about the user's dislikes and preferences. According to the tracked data, participants tended to record their activities afterwards, mostly at the end of the day. This problem caused missing context information which is important to generate individual recommendations. The reason wrong recommend activity is caused by this missing information. Due to limited knowledge of activities, which depend on time and location, recommendations were not advantageous. Those problems are covered by context-based reasons. Thus, in the future it is planned to substitute a majority of the manual user entries by automatic activity recognition to reduce the burden on the users and to ensure that less data is missing due to left out user entries. Furthermore, the automatically gathered context data can be used to improve activity recommendations based on user context.

5 CONCLUSION AND OUTLOOK

We presented an approach for supporting users being more physically active by building a user model to analyze their daily activity behaviours and give them individual recommendations for implementation intentions for long term goals to generate new activity habits. To realize this proposed approach, we developed an Android application called DayActivizer. We outlined two strategies for identifying the if-component and four strategies for identifying the then-component of action plans to be able to generate individual recommendations. To evaluate the generated recommendations, eight participants in two to four weeks collected data through a field study. Afterwards, we conducted a qualitative interview with each participant to find out what kind of recommendations generated by DayActivizer is useful for the participants. Our findings show that our user model is built successfully with the recorded data by the user but lack of context information and information about users dislikes and preferences caused some inacceptable recommendations. In future work, we aim to implement an activity recognition within DayActivizer to avoid record of data manually using ActivityRecognitionApi provided by Google which can already detect activities as walking, running and not moving [10]. So, we aim to record and update routines automatically as far as possible to reduce the burden on the user. The user should also be allowed to set and adapt implementation intentions manually whenever he wants to, but it is planned to give him smart suggestions for appropriate timeslots, situations and activities that fit context and personal preferences. Furthermore the tracking of the adherence to the implementation intentions, as well as their adaptation in case of no adherence, is a task for future work.

ACKNOWLEDGMENTS

This research is part of the project PAnalytics of the University of Duisburg-Essen and was funded by the German Federal Ministry of Education and Research (BMBF).

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