Smart Self-Management for Better Working

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Abstract: Work intensification and blurring boundaries between private and professional life constitute major challenges in today's society. High working pressure and imbalances between life domains can cause serious physical and mental health problems. Thus, personal self-management becomes increasingly important to cope with high work demands while considering personal resources. In recent years, sensor technology has become ubiquitous and enables new kinds of data collection. This PhD research proposal discusses how information technology can be used to support the enhancement of self-management competencies. The proposed approach considers a wide range of data from several sensors that will be analysed to provide the user with comprehensive feedback. By using smart devices, it will be possible to give situational feedback even in a mobile context.

Keywords: Self-Management, Sensors, Assistance, Work Organisation, Stress Prevention.

1 Introduction

Mobile devices such as smartphones or tablets are widely used and help us to work, learn, and manage our social relationships. All this can be done independently of location and time. While there are many benefits, the boundaries between life domains can become vague with a high flexibility. Furthermore, the increasing usage of information and communication technology can cause a high intensity of work. Resulting stress threatens motivation, performance, wellbeing, and health [LGC04, BS05]. Especially for the increasing proportion of knowledge-intense work [Ru17], these challenges are amplified greatly since this kind of work goes along with a high self-responsibility. Therefore, it is a major challenge to carefully deal with individual freedoms and resources in order to avoid overload. In this context, individual self-management becomes increasingly important. In a recent study, 55% of the respondents indicated a need to develop competencies in this field [Ru17]. Self-management comprises the willingness and ability to manage the own life responsibly and to shape it in such a way that productivity, motivation, well-being, and balance in life are promoted and maintained over the long term [Gr12]. As sensor technology and smart devices are increasingly integrated in everyday life, these technologies may serve as a remedy to support people in self-management. The aim of the presented PhD project is to develop a concept for an assistance system supporting the diverse aspects of self-management. The next section describes the key features of the proposed approach. Section 3 presents potential components of an assistance system and Section 4 describes the next steps.

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2 Proposed Approach

Enhancing self-management competencies may include the need to observe one's everyday behaviour, recognise necessary development steps, consequently drive the development through concrete actions, and perform progress checks. Performing all these actions may be challenging. The key research question for the described PhD project is, how the potential of sensors and smart devices can be used to assist individuals in their self-management. By using devices that are easy to integrate in daily life, a wide range of data can be collected continuously and at runtime. Collecting data over the long term and combining data from several sources will enable providing comprehensive feedback for self-management. Moreover, the use of smart and wearable devices allows to remind the user of taking actions or to intervene in certain situations unobtrusively even in a mobile context [MW15]. In summary, the proposed innovative approach for self-management assistance comprises the following central aspects:

- Consideration of several areas and individual factors of self-management
- Use of mobile and unobtrusive devices with built-in sensors
- Data collection at execution time
- Aggregation and analysis of data from multiple sources
- Feedback on development over time
- Situational guidance and interventions at execution time

3 Potential Components

A central point of the project is to bridge the gap between research in self-management and sensor-based assistance systems. As a first step, the literature was analysed to find features that are relevant for self-management and that can be supported by the use of technology. The development of the system concept follows the core idea that information systems essentially acquire or receive information, process it, and deliver relevant results to the user. Therefore, potential components for the steps data collection, data analysis, and feedback generation are identified and described in the following. At the current phase of the project, a prototypic implementation of data collection and storage is developed.

Data Collection. To assist users in everyday work, data needs to be collected mainly without user intervention and in an unobtrusive way. As *smartphones* and *personal computers* are already widespread and integrated in daily life, these devices easily lend itself to collect data. Furthermore, wearables such as *smartwatches* are unobtrusive, light-weight, and do not interfere the user in daily processes. Smartwatches have numerous built-in sensors [KMM17] and deliver more accurate physiological data than smartphones [Sh15]. To consider especially the wellbeing and health aspects of self-management, relevant data can comprise the *user's activity level* (e.g. walking vs. sitting) and *physiological data* (e.g. heart rate). To detect the environmental context, for example, if a user is currently in the office or in a public park, *outdoor positioning* (via GPS) and *indoor positioning* (e.g. via Wi-Fi, Bluetooth, or ultrasonic [Ly15]) can be used. Finally, it is possible to identify *software-based work* and to monitor contents related to used applications via additional software running on the devices. The software could then run in the background and record all types of events. By doing so, information from digital calendars, mailing programs, writing tools, web browsers, or other tools can be retrieved. Such information shows, for example, if the user currently is in a meeting, works on a document, browses for information on the web or is engaged in organising and communication. Selected data will be stored in a database. As data shall be collected and analysed over time, the open source time series database InfluxDB[2] is chosen for implementation. It is then possible to efficiently analyse the time series data.

Data Analysis. The retrieved variety of data has to be aggregated and combined in order to provide the user comprehensive feedback. Therefore, complex data analysis will be necessary to detect patterns, to recognise the need for interventions, and to analyse developments over time. Four important components of complex information are identified yet. The first component is intended to analyse *time spent* on certain activities. Using the broad range of collected information such as location, appointments, and motion of a user, even activities where no operations on a device are performed could be monitored. The second component focuses on *workload*, because a high workload in the long-term can lead to decrements in performance, motivation, wellbeing and health [Ho97]. To determine the general workload, the amount of tasks, appointments, emails, opened files, and physical activity could be considered. In regard to individual workload, changes in a user's cognitive performance caused by mental workload can be estimated by considering heart rate variability [Ts17]. *Biological rhythms* as the third component considers the human's circadian rhythms that drive the patterns of cognitive, behavioural, and physiological processes (e.g. activity, sleep, and mood). Individual rhythms should be considered, because rhythm disruption can lead to negative effects like reduced motivation, performance, and health [FK14]. Biological rhythms could already be associated with patterns of smartphone app use [Mu16]. Thus, the data collected from background software on the personal computer and smartphone could be used for this component. Furthermore, physiological and activity data would add high further value in order to determine these rhythms or their disruption. The fourth component is conceived for analysing the *productivity status* with respect to individual resources. For example, if decreased cognitive performance is recognised, taking a break for recovery may be productive, but randomly surfing the internet when performance is high may be not. Therefore, information from time-consuming activities, workload, and biological rhythms could be combined in order to analyse productivity over the long term.

Feedback Generation. The system is envisioned to support the user in reflecting behaviour as well as in taking action for development. For the first, *information on development over time* that is delivered from data analysis will be presented to the user. Furthermore, users shall have the opportunity to define goals related to the information presented, for example, to work on high-leverage tasks at performance peaks. In order to encourage the user to take action for self-development, the system is envisioned to give

[2] https://www.influxdata.com/

situational feedback by providing recommendations on carrying out or omitting activities together with a reason for the certain recommendation. The feedback could be delivered by personal computers in a stationary context and by smartphones or smartwatches in a mobile context. In the following, possible recommendation features are described. The system could, for example, recognise a conflict of activities to a user defined goal and *remind to pursue the goal*. Furthermore, the assistance could *recommend a next task*, e.g. according to an urgent deadline recognised through an appointment. Similarly, the system could *intervene distracting actions* like randomly browsing the internet. Regarding wellbeing and health it is considered important to have *recommendations of breaks and relaxation*. Generating such feedback could depend on workload and biological rhythms. The system could recommend a break, e.g. if decreased cognitive performance is predicted. Finally, existing mechanisms of digital calendars that warn the user when appointments overlap could be extended to also regard workload and biological rhythms. The system could then *recommend a suitable date and time of an appointment* according to these factors, when the user is about to plan it.

4 Next Steps

The development of the system concept is seen as an iterative process by which relevant features are identified, selected components are implemented prototypically, and the concept is evaluated and possibly adjusted. Currently, a prototypical implementation of the identified data collection components is carried out for a first experimental run. In this process, an important step will be to develop an appropriate interaction of the proposed devices and technologies. Furthermore, the suitability of retrieved data has to be examined. Physiological data from current smartwatches, for example, may be more accurate in workload monitoring, if user activities are characterised by little movement [Bi16]. If higher accuracy will be required, approaches to filter misleading data could be used [Ra17]. Sensor data could additionally be contrasted against answers from psychology questionnaires. These can, for example, reflect a person’s experiences of positive or negative moods [QKK09]. Considering not only measured data, but also subjective appraisal will have an impact on the quality of system feedback to enhance individual self-management skills. Next, the main focus of situational feedback will be specified in order to determine which analysis components actually will be part of the project. To this end, requirements will be determined from empirical studies. When components for data analysis are selected, their prototypical implementation will be arranged. After collecting first practical experiences, it will be possible to elaborate the system components.

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