Smart Health Systems for Personal Health Action Plans

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Abstract— **Smart health systems such as networked activity trackers, scales, or sports watches allow monitoring many aspects of a healthy lifestyle. Nevertheless there is a semantic gap between these systems' measurements and the users' personal health action plan that is not bridged by existing health data aggregators. We describe representative types of health data as measured today and suggest a simple classification of data based on temporality of the data. We present a mapping of physical devices to health action plans that is device-agnostic and bridges this semantic gap. A key concept is the mapping of logical devices to primary health features that translates measurements to a meaningful health concept. We describe a prototype system implementing our mapping and providing lessons learned. The approach shows to be feasible to describe typical personal health action plans.**

Keywords— wellbeing, prevention, pervasive computing, smart health systems, personal health action plans

I. Introduction

The general interest in healthy living is continuously increasing. Public health campaigns aim to prevent behavior related and non-communicable diseases and reduce the burden incurred on the health systems. Individuals want to increase their quality of life, be fit and attractive, and stay healthy. Key elements of a healthy lifestyle include, but are not limited to increased physical activity and sports, a balanced diet, and proper sleep. These behaviors help preventing a broad range of potential health problems such as obesity, hypertension, diabetes, cardiovascular diseases, or back pain, but also mental health aspects such as depression or burn-out.

Products such as activity trackers, sports watches, or sleep monitors aim to support a healthy lifestyle. In the last years we've seen the raise of networked health products consisting of a physical device that is connected to an internet service and that jointly implement monitoring, feedback and coaching for certain aspects of health. These products are lifestyle devices advocating the positive aspects of healthy living and helping to sustain healthy behaviors. They currently receive a major public interest, and it is generally assumed that they offer tremendous opportunities for promoting healthy living.

Nevertheless we argue that the users' needs in smart health are complex and involve numerous daily habits and formal or informal behavior goals. They go considerably beyond today's systems' possibilities and their fairly simple measures such as step counts. We therefore identify a gap between the products' abilities and the users' needs for flexible and personalized health action plans. After an overview over related work and a description of the data collected and provided by the devices, we suggest and discuss a concept to close the identified gap by providing a data aggregation and mapping from smart health systems to personalized health action plans.

II. Background and Challenge

A. Smart health systems

In this paper we focus on what we subsequently call "smart health systems". By this we mean systems fulfilling three characteristics:

- They monitor determinants – behaviors or vital parameters – that are relevant for health, e.g. daily physical activity or weight.
- They are a combination of a physical device for monitoring and direct feedback, and an internet service where the device's data is uploaded and further services are offered.
- And the systems are by design primarily lifestyle oriented focusing on the healthy person and advocating a healthy lifestyle, rather than the sick person in need for managing a chronic disease or following a strict regimen.

Examples of smart health systems include activity trackers such as the various Fitbits, Nike Fuelband, Jawbone UP, or Basis B1, sleep trackers such as Zeo (abandoned), the Withings Aura or Beddit (both announced), or networked body fat scales such as the Wtihings Smart Body Analyzer or the Fitbit Aria. Sports watches like the various Garmin Forerunner or Polar watches may also be understood as smart health systems if their data can be uploaded to portals such as Garmin Connect, or to third-party portals such as Runkeeper. With the same argument a smart phone with the appropriate sensing and monitoring app connected to an internet service can also be part of a smart health system.

The core services offered by the smart health systems are the monitoring of certain health determinants by the physical devices' sensors and their storage in the internet services. This naturally allows further services such as visualization of past and current values, various types of analyses, or identification of trends and changes. Often some intervention or coaching programs or some persuasive technologies such as goal setting, competition, or social networking are also included. Many internet services provide an API that allows accessing a user's data from a third-party service.

B. Recommendations for healthy living and personal health action plans

A healthy lifestyle to prevent diseases such as cardiovascular diseases, back pain or mental health problems requires regarding multiple aspects of behavior simultaneously. We will subsequently focus on cardiovascular diseases (CVD) as our use case. But many aspects of cardiovascular health such as physical activity also contribute to the prevention of other types of diseases including back pain and depression. Moreover our argumentation will be independent of concrete behaviors or diseases and can therefore be generalized.

Guidelines for the prevention of CVD are published e.g. by the different cardiac societies. They include recommendations on physical activity, sports, and nutrition, and they advise ranges for vital parameters such as body mass index or blood pressure. While there is a strong agreement on the general direction, the individual recommendations may in detail vary or be formulated differently. Table 1 gives an example by comparing recommendations on physical activity from three different cardiac societies. Other recommendations that may not (yet) have made it into the guidelines are supported by further studies. E.g. [1] discusses that lack of or disturbed sleep increases the risk of cardiovascular diseases and suggests that 6-9 hours of sleep correlates with the least risk of cardiovascular diseases.

TABLE I. RECOMMENDATOINS ON PHYSICAL ACTIVITY

German Cardiac Society [2]	**American Heart Association [3]**	**European Cardiac Society [4]**
>=30min of activity on medium level, total 3000-3500 kcal per week	>=30min of activity on medium level	2.5 – 5h of moderate intensity physical activity per week
Short phases of training on increased level improve the maximum fitness	3-5 times a week 20-40min of increased activity are advantageous	OR: 1-1.5 h/week of vigorous-intensity activity, or combinations of multiple bouts of >=10min each.
Additional resistance training, 20% of training time, advantageous	Resistance training >= 2 times a week, 8-10 exercises, 1-2 sets, 10-15 reps	

While the recommendations are suitable for ex-post analyses of achievements, they usually must be translated into more concrete actions for an individual to become operative: 30 minutes of daily activity may be translated into e.g. "go for a walk each day", or "cycle to work". Activity on an increased level may become "go to the gym three times a week", or "run 10 miles once a week". Operative goals may also be enabled by technical equipment. For example if the person uses a pedometer the daily activity goal may also be "walk 10.000 steps each day". This is in line with Consolvo's design recommendation to "give proper credit" [5], and it is also confirmed by our own studies showing that it's important for the users to see their achievements as directly and concrete as possible.

A person may have multiple goals contributing to the same recommendation, e.g. "cycle to work at least four times a week AND go for a walk on weekends AND go to the gym every Thursday". There may at the same time be other goals contributing to other recommendations, such as following a consistent bed time and following an appropriate diet. While many, if not most people may not make these goals explicit, the goals will often be part of daily and regular routines that people implicitly aim to follow as part of their normal lives. We will call this set of a person's explicit or implicit health goals a Personal Health Action Plan.

C. The gap between smart health systems and personal health action plans

We see two reasons why today's smart health systems are not yet suitable for monitoring personal health action plans: an inter-device gap, and a semantic gap.

1) The inter-device gap

Today's smart health systems are not device-agnostic: Most devices are tied directly to exactly one internet service that the user must use for uploading and reviewing data. Therefore the user is not flexible in which device to use. Wearing e.g. an unobtrusive Fitbit One pedometer in the pocket during work and a Basis B1 on the wrist for richer data in the free time would require the user to use two different internet services simultaneously. Moreover buying one device results in a "vendor lock in": Pedometer data collected over years in one internet service cannot be moved to another one, losing the possibility to observe long term changes.

Data aggregators collecting the data from multiple services would be a solution, and a number of aggregators exist (see section 3.2). But these collect data primarily on a syntactical level and fail to close the second gap.

2) The semantic gap

The devices' measurements do not always match the users' health goals. The internet services are usually designed for a specific set of use cases and interventions, with achievements and measures being defined accordingly. Once the user's health goals are different the user has to revert to secondary goals and interpret the data. This puts the work load onto the user and makes misinterpretations and errors likely.

Moreover the smart health systems usually present measurements only, leaving the interpretation and the implementation of behaviors to the user. E.g. all activity trackers advocate the step count as the basic measure and present the number of steps walked per day. However the user's health goal may not be to achieve a specific number of steps but to go for a 20 minute walk each day. From the user's point of view the step count is only a secondary goal, and monitoring the achievement of his primary goal would require further analyses and reflection.

What is therefore needed is a semantic mapping of measurements from the smart health services to the user's individual health goals that interprets the user's data and makes achievements of goals explicit and directly understandable by the user.

III. Related work

A. *State of the art*

While using mobile devices for health behavior change is researched since more than a decade already, most of the work has focused on fairly short-term interventions of up to a few months, and towards specific health issues such as lack of physical activity. Long-term use has been discussed later only [6]. The authors suggest the need for customization of health goals and that it is necessary to "adjust the system as [the user's] needs change". Wellbeing as an ongoing status of being and staying healthy is now identified as a related but distinct field [7]. It is suggested that users will choose their level of support based on their current needs, accepting more obtrusive sensors as more assistance is needed, but reducing efforts in times of safe and stable health.

Data fusion for monitoring is researched in many projects. E.g. [8] fuses data from a sensor network for semantic event detection. [9] as well as [10] use ambient sensors in a person's own home for monitoring and activity recognition. And [11] suggests an architectural approach for integrating multiple sensors to offer various health related services. These approaches rely on fairly well-known sensors that provide data of quite high quality. However, we aim to be device-agnostic, using data of lower quality that is just good enough for a given purpose.

Models are used in multiple contexts in health, but with different meanings. In epidemiology models describe e.g. spreading of diseases [12]. On a personal level a "virtual physiological human" aims to describe excerpts of an individual's health state from a physiological point of view to enable predictions of health developments and enable personalized medicine. From a psychological point of view health behavior models describe relevant factors influencing a person's motivation [13]. And the inherent models of a health care plan are in [14] used for a model-driven development of personal health care applications. These different models have some, albeit sometimes vague relation to our understanding of a Personal Health Action Plan and our concept is inspired by these different notions of health models.

B. *Platforms for health data aggregation*

Aggregating health data in a single platform is an obvious idea, and there are numerous systems doing just that. Most systems are implemented as web platforms, but others such as Tactio (http://www.tactiosoft.com/tactiohealth), Nudge (http://www.nudgeyourself.com), or OptimizeMe (http://www.optimizeme-app.com) are apps working on a smart phone or tablet. Many platforms aim to support physical activity and integrate multiple activity trackers and sports trackers, e.g. Runkeeper (http://runkeeper.com), EveryMove (https://everymove.org) or EarndIt (http://earndit.com). Platforms aiming at weight control put a focus on nutrition diaries and nutrition monitoring, e.g. Lifesum (https://lifesumcom) or Nutrino (http://www.nutrino.co). Such platforms are defined with one health goal in mind, and they are difficult to use in other contexts.

Other platforms aim to be more generic. Examples are HumanAPI (http://humanapi.co), QuantID (http://www.quantid.co) or TicTrac (https://tictrac.com). These systems are fairly flexible in defining individual goals based on multiple behaviors, or calculating scores on how well particular goals are fulfilled. They may also allow correlating various behaviors and parameters, supporting "life hacking" where users aim to understand how certain behaviors or observations influence others.

Nevertheless all these systems still work on measurements only and don't support defining operational higher-level health goals. E.g. "cycling to work" as an operational measure cannot be defined as a goal in any of these apps, and the user would have to revert to "cycle for 20 minutes each day". The existing aggregators therefore still do not close the semantic gap between the devices' measurements and the user's personal health action plan.

IV. Data from smart health systems

The data measured by the smart health system's devices and delivered by the internet services is the key ingredient of our concept. We briefly describe some typical health determinants frequently measured today and characterize them with respect to one key property for our concept, their time-reference.

A. *Measured behaviors and parameters*

1) *Continuous physical activity*

Activity trackers continuously monitor the user's physical activity throughout the day. Unlike traditional pedometers that just sum up the steps, all modern activity trackers count activity per time interval, e.g. steps per minute. This results in a potentially infinite stream or time series of time-discrete measurements. Most trackers provide steps per time interval, most also offer derived measures such as calories per time. Some trackers additionally use an abstract activity measure such as Nike's "FuelPoints".

2) *Discrete physical activity*

Discrete physical activities are for example a workout, a walk or a bike ride. They have a defined start and duration and a level of intensity. Discrete activities can be monitored by e.g. a sports watch or an activity tracker. The level of intensity is defined implicitly by the type of activity and possibly by further measures such as speed, pace or heart rate. Metadata such as the heart rate may be observed. Further metadata may be included, e.g. a GPS track, pace for running, or cadence for cycling.

Discrete and continuous activities are two complementary views on physical activity. A discrete activity may be a subinterval of the continuous activity: A walk is a period of time where the number of steps per minute is above a threshold of e.g. 50. And a discrete activity contributes to the continuous activity.

3) Sleep

Sleep is described by start, duration, and optionally sleep type phases (deep, light, REM sleep, wake phase). Some trackers rate sleep quality in a sleep efficiency score. This rating is not always well-defined, though, so it's not necessarily identical between different devices.

4) Weight and Body Composition

Networked body fat scales measure the body weight and use a body impedance measurement to estimate the body fat percentage. Some scales also estimate the amount of body water. While weight is usually very precise, body fat and water are based on models that are known to vary considerably for some individuals, so the measurements between different devices may be inconsistent and the precision is unclear.

5) Heart Rate

Most sports watches measure heart rate by using an ECG belt that is worn around the breast during work out and that transmits the current heart rate to the watch. This method has shown to be reliable and provide precise measurements also during vigorous activity. Some devices including the newly announced Samsung Galaxy S5 smart phone or the Wihings Pulse activity tracker use optical blood flow analysis to measure the heart beat based on subtle color changes of the skin. This method requires several seconds of good optical contact to the skin and usually requires the person to be calm during the measurement. The Basis B1 uses optical blood flow in a wrist worn device and is able to measure the heart beat by the minute. The aforementioned announced sleep monitors Withings Aura and Beddit will use ballistocardiography.

6) Other behaviors and vital parameters

Our list of possible measurements is not exhaustive. E.g. various other vital parameters such as blood pressure, temperature, or blood sugar can also be measured by networked devices. And we can expect more and improved devices in the future like devices for continuous blood pressure monitoring. However for our concept as described below these types of measurements seem to be representative enough to make for a thorough argumentation and deliver feasible results.

B. Time-reference of measurements

From a user's point of view the measured data may have one of three different types of time-reference, single point, time limited, and consecutive.

Single point data such as body weight is taken at a given time and doesn't have a duration.

Time-limited data has a starting time and a finite duration. Discrete physical activity and sleep are inherently time-limited and therefore result in time-limited data. While this may contain series of data, e.g. the heart beat measured during a run, this series is a finite component of the one complex data set about the discrete physical activity.

Consecutive data is provided by repeated discrete measures and results in an ongoing stream of measurements. The step-count per minute is one example of consecutive data. Unlike discrete activities and sleep that inherently have a duration, consecutive data doesn't have a natural start and end point.

To be meaningful for a user to describe health behaviors consecutive data must be aggregated over a period of time. E.g. the steps measurement is usually aggregated over a period time to count e.g. the steps per day. Aggregation adds a time reference to consecutive data and limits the data to a defined duration.

V. USING SMART HEALTH SYSTEMS FOR PERSONAL HEALTH ACTION PLANS

In this section we present a concept to map the data from smart health systems to personal health action plans. Our concept is device-agnostic and bridges the semantic gap between measurements and health goals. We suggest a four step process that we subsequently describe from the device to the user's health action plan.

A. Decomposing physical devices to logical devices

The first step decomposes the smart health system's devices to Logical Devices representing exactly one type of measurement each. This decomposition implements the device-agnosticism of our concept.

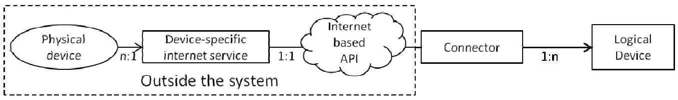

Fig. 1. Decomposing physical to logical devices

A connector provides the link to the smart health system's internet service. For each internet service exactly one connector exists in the system. Multiple physical devices may be linked to one connector, e.g. both the Withings scale and the Withings activity tracker are connected via the Withings internet service. The connector is service specific and uses the service's API. It translates the device's proprietary data into an internal format that is independent of physical devices and specific for each logical device.

One physical device is decomposed into one or multiple logical devices, e.g. an activity tracker can be decomposed into both a pedometer and a sleep monitor. One logical device is fed by exactly one connector. But multiple logical devices of the same type may exist, e.g. multiple pedometers, representing the fact that the user uses multiple different pedometers simultaneously. In these cases fusing the data happens in later steps. Multiple logical devices of the same type may have different parameters such as a different resolution of a continuous measurement, or sub-sets of possible metadata. This dealt with in subsequent steps.

Examples of logical devices are:

Pedometer: A pedometer delivers consecutive step data with a resolution that is dependent on the physical device's limitations and will often be by the minute.

Workout Monitor: A workout monitor delivers a time-limited dataset describing a discrete physical activity. Core data includes the type of activity; optional data includes the heart rate as a time-limited data set, a GPS track, or possibly activity specific metadata such as running pace.

Sleep Monitor: A sleep monitor delivers a time-limited dataset describing one sleep. Optional data includes the sleep phases. Since the smart health system's sleep quality assessment is device-dependent it is not included here.

Body Fat Scale: A body fat scale delivers a single-point measurement with weight, height and body fat.

A logical device need not be the direct representation of a physical device:

Dead Man's Button: A dead man‘s button delivers a single-point measurement with just the time and no further data. A dead man's button is connected to a system that the user interacts with, such as a scale: Whenever the user steps on the scale he also triggers the dead man's button. Also every step monitored by a pedometer triggers a dead man's button. The dead man's button therefore represents that the user is in some way active. It may be used as input in later stages e.g. to identify periods of sedentary behavior.

B. Mapping and enriching logical sensors to primary features

In the second step the data delivered by the logical sensors is mapped and enriched to what we call Primary Health Features. Primary health features represent one aspect of the user's health, i.e. one type of behavior or one vital parameter; therefore each type of primary health feature has at the most one instance for a user. They are the smallest meaningful bit of a user's health data and the atomic building blocks for a user's health goals. Mapping from logical devices to primary health features is one key point of our concept. It converts a device's measurements into observations about a user's health, thus raising the data to a higher semantic level.

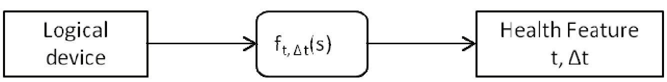

Fig. 2. Mapping logical devices to primary health features

All health features have a finite time-relation (i.e. $\Delta t < \infty$). Single-point and time-limited data already have a natural time-relation. Continuous data must be limited to a finite period to be sensible for describing a user's health determinatn. Often this will be done per day, which seems to be a natural basis for a human health rhythm. It can e.g. be the number of steps per day.

The mapping from a logical device to a health feature may be canonical, e.g. when a device already delivers a measurement that is directly used as a health feature. It can also become very complex, e.g. when signal analysis methods are used on a pedometer's step data to identify cycling.

Multiple logical sensors of the same type may be mapped to one primary health feature, e.g. when the user uses multiple pedometers alternately. Here the mapping also resolves ambiguities and duplicates. Also different types of logical sensors can be mapped to one primary health feature. E.g. a discrete physical activity may be monitored by both a pedometer and an activity monitor, and the mapping merges both data sets to one feature.

Examples of primary health features are:

Step count per day: This is one of the most frequently used measures to describe a user's physical activity. Related primary health features would be the calories burnt per day, or the active minutes on at least mild to medium level per day. Larger time periods such as step counts per week are dealt with later in our concept. Step count per day is measured by a (logical) pedometer. However active minutes per day as well as calories burnt per day might also take into account e.g. measurements from a workout monitor.

Discrete activity: Discrete activities are activities of a given type performed in a defined time-period. They can be of a mild to medium intensity such as a walk or cycling in a moderate speed. Or they can be a vigorous workout such as running. Discrete activities are usually monitored by activity monitors, but can also, with some limitations, be observed by e.g. pedometers.

Sedentary behavior: Sedentary behavior is an interval where the user performed no physical activity. This would be derived from the dead man's buttons as an interval where no activity has been observed.

Sleep: Sleep is described by start time and duration plus optional quality measures such as time in deep, light, REM sleep. Sleep is usually monitored by a sleep monitor. If no sleep monitor is used, a long phase of sedentary behavior from the evening to the morning could also describe the maximum duration of a night's sleep, although the precision and reliability are obviously lower than when using a real sleep monitor.

Body composition: A body fat scale's measurement of body weight and body fat percentage in conjunction with the user's height is canonically translated into BMI and various other measures of body composition such as lean body mass.

Cycling to work: Unlike the aforementioned ones, this health feature would be person-dependent. It is a specific cycling that could be identified by having a "typical" start time and duration (every morning at about 8:30 for about 20 minutes) and following a "typical" GPS track, where "typical" would be learned as part of a machine learning procedure. It is worthwhile to notice that this health feature could be identified solely relying on GPS measurements e.g. from a smart phone tracking, thereby omitting the need to use a body-worn sensor such as a pedometer.

C. *Aggregating primary to secondary health features*

In the third step the atomic building bricks as identified in the primary health features are aggregated to Secondary Health Features, specifying a user's individual health behaviors over multiple occurrences and a longer period of time, thus describing the user's health goals as described in section 2.2. .

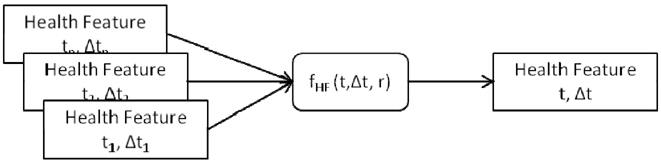

Fig. 3. Aggregation of primary to secondary health features

The aggregation is a function over all occurrences of the same type of primary health feature that fall within a given time interval [t, t + Δt] and fulfill a condition r. This definition is not a limitation, since the aggregation function can be any function, the interval [t, t + Δt] can be arbitrarily large, and r can be true. However, many typical parameters of healthy living, as outlined in section 2.2, can be described using fairly simple combinations. Frequent aggregation functions are sum, count, average, minimum, and maximum.

Some examples of Secondary Health Features are (in pseudo-formal description):

Total calories burnt in last week:

CaloriesPerWeek(t) = sum(caloriesBurnt([t-7,t], true))

Number of runs in last week of at least 30 minutes duration:

NumberRuns(t) = count(activity running([t-7,t], duration>=30min))

Count of cycling to work in last week:

CyclingToWork(t) = count(cyclingToWork([t-7,t], true))

D. *Operationalizing health goals*

Finally the health features can be compounded to describe a user's health. The vector space $(HF_1, HF_2, \ldots, HF_n)$ of different health features describes all the health aspects that a user is interested as part of her or his personal health action plan. For a user interested in calories burnt, cycling to work and regular running this could e.g. be *(CaloriesPerWeek, CyclingToWork, NumberRuns)*. We might call this a Health Profile.A person u's health feature's values at a time t, $hf_u(t)=(hf_1, hf_2, \ldots, hf_n)_u(t)$ is a person's Health Status in respect to the Health Profile, e.g $hf_u(today)$ = $(CaloriesPerWeek_u(today), CyclingToWork_u(today), NumberRuns_u(today)) = (14338, 4, 3)$ describing that the user burnt 14338 calories in the last week, cycled to work 4 times and did three runs. Lastly we can also describe a targeted health status $hg_u = (hf_1, hf_2, \ldots, hf_n)$ formally representing a user's personal health action plan, e.g. $hg_u(today) = (15.400, 5, 3)$ indicating that the user wants to burn 15400 calories, cycle to work 5 times and do three runs per week. We may call this a user's Health Goal. Then e.g. $hf_u(t) - hg_u$ decribes the deviation between the intended and the actual health state. In our aforementioned example this would be (-1062, -1, 0) meaning that the user burnt 1062 calories less than planned and cycled to work one time less than planned. More general a functionmay e.g. be used to calculate an adherence score.

VI. Discussion

A. *Proof-of-concept implementation HeartAware*

We implemented a simplified version of the concept in a proof-of-concept system (see Figure 4) demonstrating some key features of our concept. The system integrates four smart health systems, namely Fitbit, Jawbone UP, Runkeeper, and – as long as it existed – Zeo. This system uses a mapping of these physical to logical devices and implements three hard-coded health goals: 7-9 hours of sleep per night, three workouts of at least 30min per week, at least 30min of mild to medium physical activity in bouts of at least 10 minutes each. Some informal user tests show that users basically appreciate the concept of presenting health data in an integrated system. We identified particularly two challenges:

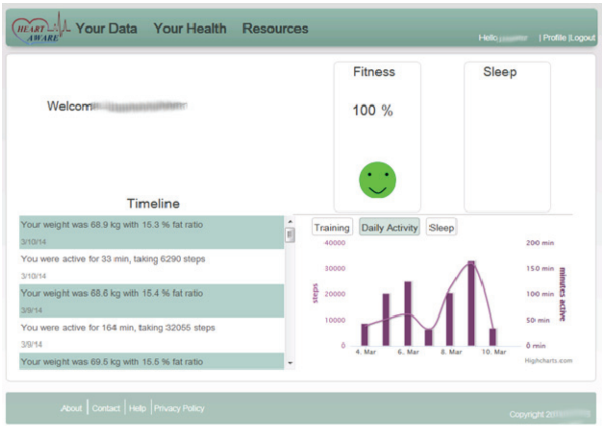

Fig. 4. The HeartAware System

First, accessing the data may be not just technically tricky, but also systematically limited: Some internet services may be restrictive with gaining access to a user's data or, like the Basis internet service, may not have an API at all. This is not just a challenge for implementation, dealing with different and often only incompletely defined APIs. It is also a consequence of the open question about ownership of data. Some service operators try to make themselves the keepers of a user's data by forbidding third party services the access.

Second, aggregating data from multiple systems is inherently complex, and usually too complex for the average user with average health interest. Our concept to bridge the semantic gap between smart health systems and personal health action plans allows defining fairly detailed plans. However users who are new to self-monitoring often are excited by a pedometer's step count, and may not yet see the necessity for more complex plans. Bringing the user "beyond" the smart health system's portals is therefore challenging.

B. Limitations

Our discussion is focused on data analysis, aggregation and describing differences between actual health status and intended health goals. We did not discuss HCI topics such as interaction or feedback, or the use of the concept in behavior change interventions. Interaction would be important for a real-life use of the system e.g. for manual input of data when device-based sensing is not feasible. Defining personal health action plans may be done by the user himself, by a health professional, or automatically by a coaching system based on user data. Such topics are highly relevant, but beyond the scope of this paper.

C. Strengths and weaknesses of the concept

Our concept implements a device-agnostic mapping of smart health systems' data to a personal health action plan. It opens the path for innovative ways of monitoring activities. E.g. analyzing step data from a pedometer allows identification of periods of physical activity in bouts of at least 10 minutes each, a measure that is important in some contexts only. And the mapping from logical devices to primary health goals may also take into account user-specific features such as "typical behaviors". This allows e.g. learning a user's behavior to improve activity recognition.

A key question is whether our system is powerful enough to describe realistic personal health action plans. Obviously, it is not possible to derive arbitrary health features from any given set of physical devices. Ultimately the user's health goals must be reflected in the use of appropriate devices, and the mapping must support these devices and goals. The more detailed the user's health goals are, the more powerful the devices have to be. If number of steps per day is an issue the user needs to wear a pedometer, and if weight is an issue a scale is required. Our concept, however, allows the user to define more "relaxed" goals that may be easier to monitor. Identifying "cycling to work" may be easier to detect than "30 minutes of mild to medium intensity physical activity per day".

VII. Conclusion

By bridging both the inter-device gap and the semantic gap, our approach allows balancing between the unobtrusiveness of monitoring devices for daily use on the one hand, and the precision of data required for personal health action plans on the other. It is therefore particularly feasible for long term monitoring e.g. for primary prevention, when the user is not willing to accept wearing obtrusive and complex devices but still wants a minimum level of health support.

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