An Application Framework for Personalised and Adaptive Behavioural Change Support Systems

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Keywords: Behavioural Change Support System, Systems to Encourage Healthy Behaviour, Nudging, Mobile Health, Personalisation, User Modelling, User Adaptation, Meta Modelling.

Abstract: The paper analyzes current weaknesses of behavioural change support systems (BCSS) such as the failure of adequately taking into account the heterogeneity of target users. Based on this analysis the paper presents an application framework that comprises various components to accommodate user preferences and to adapt system interventions to individual users. Among these components is a goal hierarchy which can be set up to represent the goals a user wants to achieve. The higher-level goals can be broken down into more specific goals that can be measured and associated with appropriate activities. Furthermore, our BCSS framework includes components for adapting its interactions according to a user's observed behavioural preferences as well as his or her previous reactions to system interventions. User adaptation also takes into account the preferences of similar users by employing a collaborative filtering approach. Thus, overall user acceptance should be improved and motivation for behavioural change sustained. The framework is currently being implemented and will subsequently be evaluated.

1 INTRODUCTION

One of the greatest challenges to health systems all over the world is the growing number of people with (multiple) chronic conditions such as diabetes, asthma, cardiovascular disease and obesity. According to the WHO chronic diseases nowadays account for about 80 % of the burden of disease (World Health Organization, 2012). Most of these are lifestyle-related and the risk factors are well-known, including the lack of physical exercise, smoking, a diet rich in fat and sugar, and the excessive consumption of alcohol. Although people are generally aware of the long-term negative consequences, they often lack the motivation as well as the social and emotional support that is required for changing one's behaviour. Besides, we tend to discount long-term gains such as a higher life expectancy and better quality of life in the long run in favor of short-term rewards like the one offered by some delicious cookies. Whilst the majority of the chronically ill may well agree with their doctors' or caregivers' recommendations and fully intend to adhere to them, e.g. engage in regular exercise and change their diets, they fail to do so.

Behavioural economics is an approach that promises to ameliorate the shortcomings of traditional healthcare management, especially with regard to chronic disease (see e.g. (Cabinet Office, 2010; European Commission, 2014)). Behavioural economists use knowledge from behavioural science as well as motivational psychology and neuroscience to study how individuals make decisions which are often non-rational, and biased by a series of mental shortcuts, for instance, the so-called "status quo bias" (Kahneman, 2011). Apart from the status quo bias, people's behaviour is also susceptible to the influence of default rules, framing effects and starting points. Consequently, persuasion strategies can involve changing the way options are presented, e.g. by adapting the rules that drive user interaction.

The philosophy of behavioural economics is also called "libertarian paternalism", namely that people should not be forced to act in certain ways, but rather encouraged to act in ways that are better for them or help them stopping bad habits formed over time. This idea of a "gentle push", or "nudge" favours invitations to change behaviours, rather than the introduction of constraints and sanctions to obtain behaviour change (Thaler and Sunstein, 2009).

It has been shown that frequent and immediate feedback is very helpful to nudge people towards healthy behaviour (Loewenstein et al., 2013; Maier

Reimer, U. and Maier, E.
An Application Framework for Personalised and Adaptive Behavioural Change Support Systems.
In *Proceedings of the International Conference on Information and Communication Technologies for Ageing Well and e-Health (ICT4AWE 2016)*, pages 152-159
ISBN: 978-989-758-180-9

and Ziegler, 2015). Mobile devices including smartphones and wearables such as smartwatches offer great opportunities because they can be used for measuring vital parameters such as heart rate, skin conductance or blood pressure but also the number of steps or sleep patterns. Most mobile health solutions, i.e. mobile devices connected to medical applications or sensors, as well as pure lifestyle apps actually include some kind of support for the users to achieve their goals. However, these nudges tend to be hardwired, i.e. they do not adapt to user preferences and needs and on the whole they are not grounded in behavioural change theory (see e.g. (Lister et al., 2014; Patel et al., 2015)).

Our recent research therefore focuses on how to use digital technologies to support behavioural change in a systematic way and to allow adaptation to what works best for an individual user.

2 CHALLENGES OF BEHAVIOUR CHANGE SUPPORT SYSTEMS

Nudging for healthy behaviour using mobile technology has to be viewed in the larger context of so-called behaviour change support systems (BCSS) as introduced and defined by (Oinas-Kukkonen, 2010):

> *"Behavior change support systems (BCSS) are information systems designed to form, alter, or reinforce attitudes or behaviours or both without using coercion or deception."*

The persuasive systems design (PSD) model, a framework for designing a BCSS introduced in (Oinas-Kukkonen and Harjumaa, 2009), draws from the seminal work by Fogg on persuasive technology (Fogg, 2002). It distinguishes two major design steps: first, analyzing the *persuasion context*, second, designing the *BCSS features*. The persuasion context is defined by the *intent*, the type of change to be achieved, e.g. if it is a one-time or a permanent change, the *event*, which includes the use context as well as the user's goals, and the *strategy*, which determines what kinds of message are to be delivered via which route to the user. The BCSS design features consist of four categories:

Primary Task Support. distinguishes various principles of how to support the user, e.g. by reducing complex behavioural goals to smaller goals that can be achieved by simple tasks, or by personalizing the system to the user's specific behaviour and preferences;

Dialog Support. deals with how to set up the dialog with the user;

System Credibility. addresses the issue how to make the system credible for the user;

Social Support. deals with how to improve motivation and adherence by including social influence, e.g. via the peer group, into the system.

While the model suggested by Oinas-Kukkonen already mentions *personalisation* as one of many design principles, it plays a more important role in more recent work on persuasive systems. Target user groups are typically very heterogeneous so that it is nearly impossible to design a "one-size-fits-all" system. (Kaptein et al., 2010) examines individual differences in persuadability in the health domain and concludes that the intervention of a persuasive system needs to be tailored to the persuasion profile of the specific user. For example, some users react best to strongly persuasive messages while other users respond adversely to too strong an intervention and would require a more low-key suggestion. (Prost et al., 2013) build upon these results and describe a system that employs personalisation based on factors such as persuadability of the user, social-emotional attitude and behaviour history. The results of an empirical study on the relationship between personality and the effectiveness of persuasive technologies is presented in (Halko and Kientz, 2010).

Laverman and his colleagues (Laverman et al., 2014) present an approach to personalizing communication in a BCSS (which they call "self-management support system"). The authors argue that the system should provide information in a way that is "relevant to the user's situation and match[es] the user's preferences and abilities to understand and be persuaded by [it]". The effect of personalising short text messages to reduce snacking behaviour was investigated by Kaptein and his colleagues and the results reported in (Kaptein et al., 2012). A more general overview of the possible roles personalisation can play in persuasive systems can be found in (Berkovsky et al., 2012).

Behavioural change starts with motivation and intent and requires the setting of clear and measurable goals which direct attention and effort toward goal-relevant activities (Locke and Latham, 2002). Therefore, BCSS include mechanisms for goal setting as well as measuring goal achievement to give appropriate feedback. Many of the smartphone apps that have come into existence as part of the quantified self movement for tracking and measuring all kinds of activities, support goal setting and typically offer support for achieving these goals, e.g. by giving feedback on current goal achievement, by drawing on peer group support, or by playful competition. In these cases, while goal setting is supported, the types of goals a user can set are very limited due to the specific focus each of these apps has, e.g. on measuring physical activity, calorie intake, or stress level.

Consequently, while there are many theoretical models available for guiding the proper design of a BCSS and for designing mobile systems for supporting behavioural change in particular, in the end each application has to be hand-crafted and tailored to a specific domain and application scenario. When designing a system, developers make assumptions about what will work for the target user group, but once the app has been completed, maybe even evaluated with a focus group, one cannot but hope that the app will be effective in supporting the intended behaviour changes. Should this not be the case, it will be very difficult to identify the reasons. Thus, despite the theoretical guidelines available, the actual task of creating a BCSS is more an art than a systematic development process.

One way to tackle this challenge is to devise a more generic BCSS which can be easily configured to meet the needs of a specific user. Ideally, the users can carry out the necessary configurations themselves. In this way, fewer assumptions need to be made about the functions that a user actually wants to have.

To this end, we propose mapping the existing theoretical concepts to an application framework for creating mobile persuasive systems that can be easily configured to accommodate a wide variety of user requirements without the need to reimplement parts of the system. Additionally, we propose that the framework includes components for automatic user adaption during system runtime.

In our current research we focus on those aspects of the framework which we deem most important for a mobile BCSS. Our framework will

- remedy the limited goal setting capabilities of existing apps by including a *goal network* that can be set up and edited by a user according to his or her specific needs (maybe together with a person acting as a coach or therapist for the user);
- distinguish between the ultimate goals a user wants to achieve and more concrete *operationalized sub-goals* whose achievement can be measured, e.g. with sensors;
- offer a variety of persuasive interventions (*nudge types*) a user can choose from according to his or her preferences;
- include *automatic adaptation mechanisms* that monitor user behaviour, correlate system interventions with user behaviour and determine which kinds of system interventions work best for a specific user and then adapt its intervention strategy;
- permit users to configure a system according to their needs.

Throughout the paper we use the term “nudge” in the following meaning:

> Definition:
> A *nudge* is a brief persuasive intervention that encourages a specific behaviour.

In the following section we will describe our framework in more detail.

3 APPLICATION FRAMEWORK FOR BEHAVIOURAL CHANGE SUPPORT SYSTEMS

3.1 Goal Hierarchies

At the heart of any BCSS, which also includes mobile health apps, are the goals a user wants to achieve. An application framework for creating a BCSS therefore needs to include some mechanism for specifying goals or target behaviours. Many of today’s mobile health apps support the setting of user-specific goals but fail to consider the larger context within which these goals are embedded, i.e. what the higher-level goals are. For example, an app might allow users to specify the number of steps per day to make. The higher-level goal behind walking a certain amount of steps per day could be to keep healthy or to lose weight. Walking 10000 steps per day is only one possible way to achieve this; other possibilities could be to go swimming or cycling. Consequently, in order to give users more flexibility in how to achieve their goals, a *goal hierarchy* is needed which represents the users’ higher-level goals as well as how to reach them. This enables a user to achieve a higher-level goal via (a combination of) alternative sub-goals, e.g. a combination of walking, running, cycling and swimming. Goal hierarchies originally go back to cognitive psychology (e.g. (Schank and Abelson, 1977)) and play an important role e.g. in interactive systems that create and maintain models of their users’ goals and plans.

Our BCSS application framework therefore includes a construct for specifying one or more goal hierarchies for the targeted application domain of a BCSS. A goal hierarchy starts with a top goal which represents a target user’s primary goal. The top goal tends to be *long-term*, it may be measurable, e.g. “body mass index of below 30”, or be more generic, e.g. “keep healthy”. It can usually be achieved by a variety of different ways, e.g. by engaging in physical activity, lowering the stress level, by eating regular

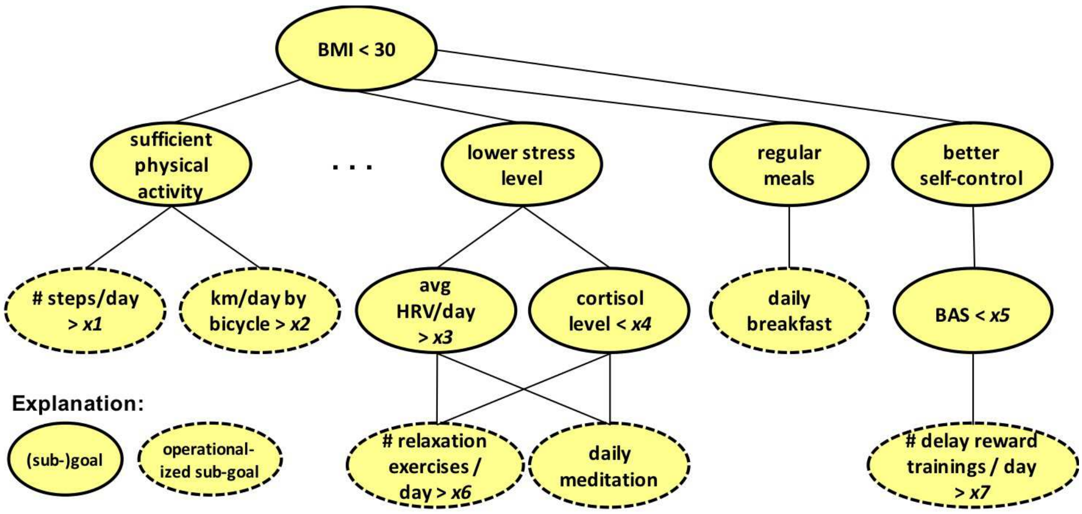

Figure 1: Example of a goal hierarchy (application model level).

meals or a combination thereof. Each option is represented by a sub-goal, together with an indication if the sub-goal is sufficient for reaching the higher-level goal or if several sub-goals need to be reached. Sub-goals can be broken down into further sub-goals until these can be associated with a measurable activity. We call such goals operationalized:

> Definition:
> An *operationalized goal* is short-term and is associated with a measurable activity to reach the goal.

Figure 1 shows some examples of operationalized goals. Activities associated with operationalized goals can e.g. be measured via sensors or diary entries. An activity detection module using a 3D accelerometer and state-of-the-art algorithms can automatically determine if the user is e.g. walking, running, cycling, or climbing stairs, and thus can help to keep track of the achievement of alternative goals for physical activity (see e.g. (Slim et al., 2016)).

Operationalized goals are parameterized so that they are not yet goals but rather *goal types*. An example of such a goal type is "physical activity $> x$ steps per day" (cf. Fig.1). The user, possibly together with a coach or a therapist, selects goal types and sets values for the goal parameters to obtain specific (operationalized) goals.

We will implement the application framework by adopting a meta modelling approach (Karagiannis and Kühn, 2002; Atkinson and Kühne, 2003). The *meta model* defining our application framework (cf. Fig.2 for its main part) introduces all constructs that can be used to create a specific BCSS. One example of such a construct is the goal hierarchy we have already introduced. A specific BCSS application is then represented by an *application model* that is an instance of the meta model. A specific goal hierarchy with parameterized goal types would be on this model level (cf. Fig.1). The parameters of the goal types are set by a user during runtime to create concrete goals. Thus, the *runtime system* is essentially an instance of the application model.

Users are not only allowed to set the parameters in the goal types but they can also delete parts of the goal hierarchy so that only the goals they wish to pursue are left. For example, a user who does not like running would delete the associated sub-goal. However, we do not permit a user to add sub-goals because this would essentially lead to a new application model, which then would require additional implementation effort, e.g. to provide the means to measure the achievement of the added goal. Therefore the goal hierarchy in the application model provides the set of all possible goals for the intended application, from which users pick the ones they like. Modifying the goal hierarchy is a task for the developers.

3.2 Adapting Nudges to Users

In the course of our research we have conducted extensive interviews with potential end-users which confirm the findings of other researchers (Halko and Kientz, 2010; Kaptein et al., 2010; Prost et al., 2013) namely that behaviour is influenced by a variety of factors, e.g. age, sex, socio-economic status, attitudes, personality, social environment and peer group. Thus, the fixed set of interventions (or nudges) that existing BCSS have implemented do not take into account the *heterogeneity of target users*. This results

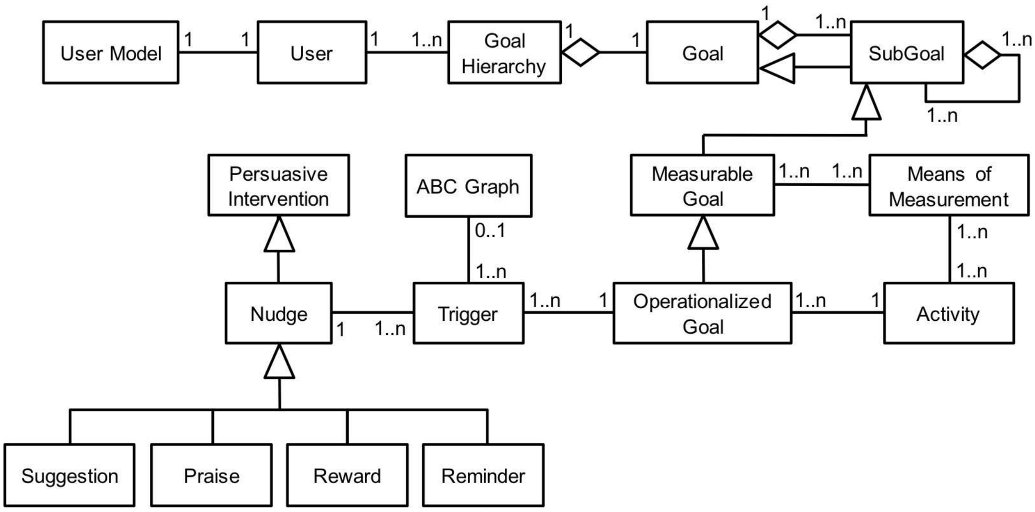

Figure 2: Core fragment of the BCSS meta model.

in low intervention efficacy and low user acceptance. In our framework we therefore provide for a variety of *nudge types*, such as suggestion, praise, reminder, reward, and we devise different means to control the user-specific selection of nudge types and their timing. The corresponding constructs of our framework are defined in the meta model (cf. Fig.2), just like the construct of goal hierarchies.

The simplest way to adapt nudges to users is to have them select the preferred nudges. However, as shown by our interviews the average user will shun the additional effort and finds it difficult deciding which choices to make. We therefore aim at enabling the system to choose the nudge types using a threefold approach – a) user modelling, b) collaborative filtering, and c) progress-dependent adaptation.

3.2.1 User Modelling

Our framework includes a *user modelling* component (Kobsa, 2001) which allows to monitor user behaviour and keep track of the user's preferences with regard to nudge types, choice between alternative goals, and schedule of activities. To deduce these preferences, the system starts by selecting nudge types randomly and monitoring which of them work best for a user. Once the system has identified the nudge types that are more successful in terms of triggering intended behaviour, the system uses those types more often. However, according to our framework the system does not completely stop using the other nudge types so that possible future changes in user behaviour can be detected and the user model adapted accordingly.

For example, if a user often follows a suggestion made by the system, this is a good indicator that the user responds well to suggestion nudges. Also, whilst some users might respond well to reminders or feedbacks that they are falling behind their peer group, other users might simply ignore such messages.

Additionally, the system keeps track of the timing of different kinds of activities performed by the user and adjusts the timing of nudges, such as suggestions and reminders accordingly. The user model also keeps track of the alternatives that a user prefers to achieve a higher-level goal, e.g. cycling instead of walking.

Although the user preferences derived by the user modelling approach can never do justice to the enormous complexity of human behaviour, we nevertheless expect our approach to result in superior system performance with higher user acceptance rates.

3.2.2 Collaborative Filtering

For the purpose of user adaptation our framework will also make use of *collaborative filtering* (Adomavicius and Tuzhilin, 2005). This approach implies that the system primarily uses those nudges that work best for similar users. Similarity is determined with respect to the user profile, i.e. what the user initially said about himself or herself, and the user model. For example, collaborative filtering might indicate that showing the user's achievements compared to those of the peer group works poorly for female users in a certain age range and with a low activity profile.

With collaborative filtering we are able to identify user preferences much faster than with user modelling because it can draw on the collected evidence from all the other users of the system, provided this evidence has already been collected. Within our BCSS framework initial preferences are determined by collaborative filtering and are then continuously fine-tuned using the user modelling approach described above.

3.2.3 Progress-Dependent Adaptation

As already described above, in our BCSS framework the user modelling component keeps track of a user's typical activities as well as their timing and adjusts the timing of suggestions and reminders accordingly. Another important mechanism to adapt the time and type of nudges consists in monitoring the progress of achieving (operationalized) goals. Plotting goal achievement along the time axis produces a rectangular area which we divide into the three sub-areas A, B and C (see Fig.3): Area A signifies good progress, area B indicates slow progress, while area C indicates that considerable effort is required to achieve the corresponding goal.

For example, a first, still rather simplistic selection of nudges could work as follows: As long as a user's progress lies in area A, no nudges are generated because the user is performing well. When progress falls within area B, unobtrusive, low-key nudges are appropriate, e.g. a suggestion or a discreet reminder. When goal achievement moves into area C, the user is at risk to miss the goal and stronger nudges may be called for than in area B. On the other hand, if the user catches up and moves back into area B or from area B to area A, a praise message could be generated. More elaborate algorithms could fine-tune the system responses and e.g. consider if the user just crossed into a new area or is already deep inside it.

In our application framework each operationalized goal can be associated with nudge types and corresponding trigger conditions (cf. the meta model in Fig.2):

- A nudge is generated when progress crosses from one area into the neighbouring one, independent from the percentage of achievement and the elapsed time, e.g. from A to B or from B to C or back.
- A nudge is generated when a predefined amount of time has elapsed and the user's progress is located in area A, B or C. For example, when 70% of the time available for reaching a goal is over a praise message is generated if progress is in area A, a reminder if progress is in area B, and a prompt or a challenge is generated if progress is in area C.
- Similarly, a nudge is generated when a predefined percentage of achievement has been reached and the user's progress is in a specific area.

The boundaries between the areas in the ABC graph are initially defined according to the user profile, e.g. taking into account if a user is an early riser or a night owl. The system monitors a user's achievement pattern for each goal and adapts the boundaries to fit with his or her typical daily routine. For example for a user who likes to go running early in the morning, area A would be far to the left and small. On the other hand, for a user who usually goes running in the afternoon, area A would stretch far to the right.

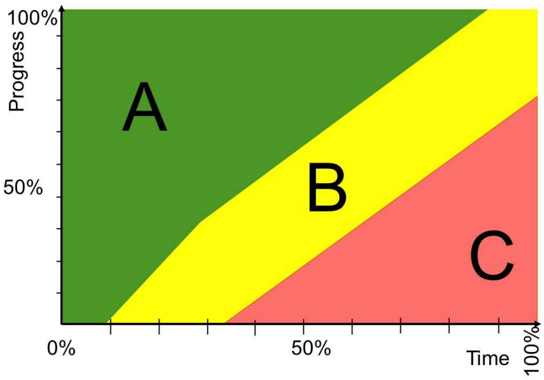

Figure 3: An ABC graph for progress-dependent nudges.

4 EVALUATION

We are currently implementing the BCSS framework. Subsequently we will conduct an evaluation with people who wish to reduce their weight or maintain their previously achieved weight loss. To this end, we will develop a smartphone app which is based on our framework and offers a variety of weight-related goals, including physical activity, self-weighing, eating behaviour and calorie intake. We will distribute the app via social media platforms and utilize the Apple ResearchKit to take care of issues such as seeking informed consent and giving participants control over what data they want to share.

The study will randomly divide participants into two groups. One group will get the version that allows customizing the goal hierarchy and which automatically adapts to the individual user. The other group will get a version with predefined goals and with fixed interventions. Our hypothesis is that the former version, which makes full use of the capabilities of our framework, is more effective in terms of achieving one's goals.

5 CONCLUSIONS AND OUTLOOK

In this paper, we have presented an application framework for behavioural change support systems (BCSS) that comprises various components for tailoring a BCSS to users' needs and preferences. One of these components is a goal hierarchy which can be set up to represent the goals a user wants to achieve. The higher-level goals (e.g. reaching a BMI below 30) can be broken down into more specific goals that are operationalized, i.e. can be achieved by associated measurable activities. Furthermore, our BCSS framework includes components for adapting its interactions in line with a user's previous reactions to system interventions (nudges) and with observed behavioural preferences, whilst at the same time taking into account the preferences of similar users by employing a collaborative filtering approach. The adaptation components do justice to the heterogeneity of target user groups, which tends to be ignored by most of the current systems.

We are planning to embed our framework into a more general approach where the activities associated with operationalized sub-goals are chosen from the predictors of a predictive model. For example, long-term studies have shown that regular self-weighing and having breakfast regularly are strong predictors for weight loss and weight-loss maintenance (see e.g. (Feller et al., 2015)). Such predictors would therefore be included as *evidence-based goals* in the goal hierarchy. In this scenario, a therapist familiar with such predictors co-decides with a user which goals to set.

Furthermore, we are planning to develop a decision support system which utilizes a combination of predictive models to predict a person's health outcomes in the near future based on various input data, such as genetic, physiological, psychological, and behavioural data. The decision support system will be able to analyse the influence of each predictor in the predictions. The predictors shown to have the most impact on the desired health outcomes are good candidates for evidence-based goals because they are likely to be most effective in terms of improving the corresponding person's future health.

Whilst we consider our approach very promising and conducive to adopting and maintaining a healthy lifestyle, we are aware of the ethical issues involved (see e.g. (McGrady and Nelms, 2010)). Above all, it is important that users should always stay in control, participate in all decisions, and can grasp the implications of a prediction, on what it is based and that it is only a likely but not a certain outcome. Besides, it is absolutely essential to guarantee the privacy and confidentiality of health-related data. We will develop measures and guidelines that assure users' autonomy, privacy and right of control whilst making sure that the decision support system really supports and motivates them in their every-day lives.

Furthermore, we are considering applying our BCSS framework to domains other than health, e.g. to mobility. By encouraging users to use public transport or cycle to work, they will achieve the predefined goal of causing a smaller ecological footprint (Maier, 2012).

ACKNOWLEDGEMENTS

The research presented in this paper has been made possible by a grant from Gebert Rüf Foundation. Our thanks go also to the members of the student group for their contributions to this research: M. Eggenschwiler, S. Frigg and R. Zuberbühler. We further thank the reviewers of an earlier version of this paper whose feedback helped to improve it.

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