Can an Automated Personalized Nutrition Assistance System Successfully Change Nutrition Behavior? - Study Design

Research-in-Progress

Nađa Šahinagić
Technische Universität München
Chair for Information Systems
Boltzmannstrasse 3
85748 Garching, Germany
nadja.sahinagic@in.tum.de

Nadja Leipold
Technische Universität München
Chair for Information Systems
Boltzmannstrasse 3
85748 Garching, Germany
nadja.leipold@in.tum.de

Hanna Schaefer
Technische Universität München,
Chair for Applied
Informatics/Cooperative Systems
Boltzmannstrasse 3
85748 Garching, Germany
hanna.schaefer@in.tum.de

Mira Madenach
Technische Universität München,
Chair for Nutritional Physiology
Gregor-Mendel-Str. 2
85354 Freising
mira.madenach@tum.de

Markus Böhm
Technische Universität München
Chair for Information Systems
Boltzmannstrasse 3
85748 Garching, Germany
markus.boehm@in.tum.de

Georg Groh
Technische Universität München,
Chair for Applied
Informatics/Cooperative Systems
Boltzmannstrasse 3
85748 Garching, Germany
grohg@in.tum.de

Kurt Gedrich
Technische Universität München,
Chair for Nutritional Physiology
Gregor-Mendel-Str. 2
85354 Freising
kgedrich@tum.de

Helmut Krcmar
Technische Universität München
Chair for Information Systems
Boltzmannstrasse 3
85748 Garching, Germany
krcmar@in.tum.de

Abstract

Despite a multitude of existing dietary guidelines, the rise of the number of people suffering from a diet-related disease occurs on a yearly basis. Studies show that the response to different diets varies individually, calling for more personalized measures available at any time in any context. Therefore, this paper proposes a research design based on a smartphone app, that delivers automated, personalized dietary recommendations, to encourage a healthier nutrition lifestyle. Founding on previous research in computer and nutritional science, we propose 6 different intervention factors: (1) type of dietary recommendations, (2) dietary assessment, (3) tracking of physical activity via smartphones or smart activity trackers, (4) feedback with visualization of personal nutritional data, (5) feedback with textual explanations behind recommendations, and (6) dietary recommendations including blood values. In an extensive 6-month field study, we plan to examine which of the factors influence a healthier behavior change and long-term app engagement most.

Keywords: M-Health, Personalized nutrition, Behavior change, Healthy eating, Visualization, Recommender systems, Study design, Experimental design

Introduction

According to the World Health Organization (WHO), about 38 million people annually die due to Non-Communicable Diseases (NCDs) (WHO 2014). The most frequent diseases are cardiovascular diseases (48%), cancer (21%), chronic respiratory diseases (12%) and diabetes (3.5%) which share the same four behavioral risk factors: tobacco use, unhealthy diet, physical inactivity and harmful consume of alcohol (WHO 2014). There are two main reasons for the existence of these risk factors: (1) missing knowledge about the consequences of beneficial or negative behavior, and (2) missing motivation or habit for the beneficial behavior. Therefore, any successful strategy to improve diet and lifestyle is expected to pay off with improved health in the long term (Celis-Morales et al. 2015). Despite the large amount of available nutritional guidelines, obesity and chronic diseases such as diabetes record an annual continuous growth (Borrelli et al. 2012; Brinks et al. 2012).

So far it was assumed that standardized recommendations about healthy nutrition would be suitable for everyone. In recent years, however, evidence became stronger that the response to nutrition is very individual. In 2005, a clinical randomized controlled trial by Dansinger et al. (2005) investigated four popular diets in terms of their ability to stimulate weight loss and reduce cardiac risk factors. After the 1-year trial, the response of each individual deviated substantially, with some participants even gaining weight. These results indicate a individual response to diet, leading to the concept of individually-tailored nutrition advice. In order to achieve this personalization, the relation between user profiles and their optimal diet needs to be defined. A more recent study by Zeevi et al. (2015) investigated the factors of the Post-Prandial Glucose Response (PPGR), an important risk factor for type 2 diabetes (Vrolix and Mensink 2010), by using a machine-learning algorithm to predict accurately the PPGR according to physiology, blood and behavior. They succeeded in learning a personalization strategy for this single parameter, indicating such relations exist and can be modelled.

The Food4Me study made a first step in investigating behavioral changes for personalized nutrition guidelines (Celis-Morales et al. 2015). Food4Me was a multi-centered, web-based, proof-of-principle study of personalized nutrition (Celis-Morales et al. 2015). The aim was to compare the effectiveness of personalized nutrition advice, based on different dietary, pheno- and genotypic information, against conventional population-based advice to improve eating patterns and health outcomes. They proved the effectiveness of personalized nutrition advice compared to general advice in a 6-months trial (Poinhos and Almeida 2015).

Building on the efforts of the Food4Me study, our research aims at presenting a persuasive and easily accessible guidance system. The accessibility will be provided by developing a mobile application that seamlessly integrates into the everyday contexts of the user and eases information retrieval by using the data retrieved via smartphone. Persuading users with technology is not a newly founded concept. Fogg et al. (2002) teach us how technology, through its triadic role as a tool, a medium, and a social actor that creates relationships, changes our actions and thoughts. Building on Fogg's work, Oinas-Kukkonen and Harjumaa (2009) postulate that "information technology is never neutral" and present the Persuasive System Design (PSD) framework that helps improving a system's design, in order to strengthen the desired persuasive effects and eliminate persuasive side effects.

According to the PSD framework elements, our steps towards an automated personalized nutrition assistance system are: (1) automated on-demand generation of personalized advice and recommendations on a mobile device, (2) easy or automated digital input of contextual information such as dietary intake and physical activity (PA), (3) motivation by integration of gadgets and blood characteristics, as well as (4) clear communication of the given advice by visualization and explanation.

Theoretical Background

The upcoming section describes the extent and rationale of each theoretical component from which the intervention factors are derived, how it complies to the PSD framework, its relevance to the investigation and how it is rooted in previous work. We start with describing the digitalization and automation of user input, proceed into details about personalized recipe-based dietary recommendations and the personalization by blood metabolite values and finally cover the feedback optimization via explanations and visualization. Table 1 depicts the intervention factors and its compliance to the PSD.

Digitalization and automation of user input and dietary recommendations

The sharp rise in smartphone usage in recent years provides an excellent new communication channel. Their ubiquity and personal character has led to a large number of apps about healthy diet that benefit the lifestyle of users (Wang et al. 2016). Most of these applications request some form of data tracking related to PA and nutrition. Information about PA became accessible, thanks to built-in smartphone sensors (i.e. accelerometers, GPS) and modern activity tracking smart gadgets (i.e. FitBit, JawBone etc.). Additionally, using these devices leads to a perceived increase in PA levels as Shih et al. (2015) show. Keeping a food diary on the other hand is rather time-consuming and thus decreases people's long-term adherence (Carter et al. 2013). Both types of data input, nutrition and PA, have mainly been used for self-monitoring (Andrew et al. 2013; Matthews et al. 2016). There is a lack of research on how people would adhere to daily diet-logging with the awareness of receiving individually-tailored recommendations. Up to the best of our knowledge, the only similar approach, focusing on personalization as a persuasion element, is the one by Rabbi et al. (2015). Their proposed MyBehavior smartphone app delivers automated personalized, actionable guidance on nutrition and PA based on simple life-logs. In contrast to Rabbi et al. (2015), we strive to suggest automated personalized advice based on missing nutrients, PA and user's food preferences. By studying the effectiveness of several intervention factors in a factorial experiment, we aim at answering what factors influence users most in changing their nutritional behavior.

Personalized recipe-based dietary recommendations

In traditional nutritional interventions patients are guided by in-person consultation and stationary or session based medical interventions. Depending on the type of behavior, more medical or psychological input might be needed. Disadvantages of those interventions are, for example, the lack of adherence to sessions (Dombrowski et al. 2012) or the maintenance of changes after returning to everyday life (Meister et al. 2016). Impediments and constraints when trying to adopt nutritional advice at home, such as limited time, limited availability of food and missing transfer knowledge between the abstract guidelines and the actual decisions stop patients from fostering their new lifestyle. Using a context aware recipe based recommendation would reduce the cognitive load of transferring the given information and ease the decision making process. Transferring utility from ingredients to recipes has been investigated and tested with different recommender approaches (Freyne and Berkovsky 2010). It is thus possible to reach users in their everyday situations with a directly applicable recipe recommendation instead of complex, textual nutritional advice.

Personalization by blood metabolite values

The Food4Me study included blood metabolite values in its personalized nutritional advice. After a 6-months trial the eating patterns of the groups receiving personalized nutrition advice were healthier, with respect to the chosen criteria, than in the group receiving conventional nutrition advice (Poinhos and Almeida 2015). Thus, by including blood metabolite values into our study, we expect to improve the nutrition recommendations due to a higher degree of personalization. The blood metabolite values add a certain positive or negative weight in the recommendation algorithm to some of the nutrients that should be consumed, depending on the nutrients' relation with the metabolite. To determine the blood metabolite concentrations, the Dried Blood Spots (DBS) method will be used. The method presents an easy, non-invasive way to collect blood. Sakhi et al. (2015) showed that it delivers comparable results to fresh blood analysis.

Feedback optimization

Explanations When giving recommendations to users there are two critical influences on the outcome. One is the quality of the recommendations, which will be improved by personalization, blood value integration and accurate input measures. The second factor is the adherence of users to the recommendations. Here visual feedback and textual explanations based on the different recommendation criteria are important. Tintarev and Masthoff (2012) compare different strategies for explanations and their effect on the adherence. They conclude that personalized explanations of recommendations may increase user satisfaction and thus reduce drop-outs. They also warn, that this may only be the case in meaningful and feature based explanations. Since none of the listed domains were correlated to the domain of nutrition, we find this to be an interesting aspect to survey.

Personalized visualization Existing research on information visualization (IV) as form of feedback denotes its significance in understanding the underlying information in various ways. Its branch, personalized visualization (PV), follows several fundamental criteria of the promoter-inhibitor-motivation-model (Sprague and Tory 2012), which stresses the benefit of personal relevance of the displayed data and its existing context. Hermsen et al. (2016) indicate a more disruptive nature of visual feedback, compared to tactile and auditory feedback. Research on visualization of personalized nutrition and nutrient intake data are rarely found yet (Wenger et al. 2014), but have potential for a healthy behavior change in nutrition as already proven for other personal casual contexts (Sprague and Tory 2012). IV finds its applicability in healthcare, but with its focus being rather on large-scale datasets (West et al. 2014). PV and visual analytics techniques for data spreading over long-term might present an appropriate decision support system, as well as a self-monitoring tool, from a self-centric perspective in terms of healthier nutrition behavior.

Research Design

Concluding the theoretical background, we derive six intervention factors of interest. Their effectiveness will be examined in an experimental study in Germany starting in the beginning of 2017. We aim to compare the effects of our intervention factors on health-related and app-engagement outcomes. The following chapters describe the study in detail.

Intervention factors

Type of dietary recommendations Typical dietary recommendations, e.g. given from the German Nutrition Society (DGE), target the population and not individuals. They occur in form of food-groups, occasionally accompanied with optimal quantities, such as "one cup of low-fat milk" or "vegetables 5 times a day". Recommending recipes to the participants as a translation of required food-groups, might stimulate stronger behavioral changes. Research lacks evidence as to how recipe-based recommendations, composed of multiple food-groups that make up a complete meal, influence participants' dietary behavior and app adherence. We therefore aim to investigate the difference in the nutritional behavior change when providing recipe based and food-group based suggestions.

Dietary assessment The user enters his food intake through a diary by logging complete meals or a selection of food items. The app matches the items with a food database, estimating its nutrients. Manual, meal-based food logging on a daily basis from the participant indicates to become a burden over time (Burke et al. 2009). For this reason, we aim to investigate the balance between accuracy loss and adherence gain when using a 7-day recall FFQ. Users receiving both treatment levels will initially log food intake daily. In case of insufficient entries, the app prompts a notification to encourage users to fill in the 7-day-recall.

Tracking of physical activity All participants' monthly expended calories, are estimated from the results of a PA questionnaire (Norman et al. 2001) and their resting metabolic rate, as calculated from Mifflin St. Jeor equation (Mifflin et al. 1990). Additionally to the questionnaire, half of the participants' physical activities will dynamically get tracked by smartphone or, when available, contemporary activity tracking gadgets (i.e. FitBit, Jawbone etc.). The final TEE outcomes as the result of leveling data from all two, i.e. three sources.

Table 1. Theoretical background components and their corresponding PSD elements

Component	**PSD element**	**Example in our research**
Digitalization and automation of user input and dietary recommendations	Reduction	Food diary for logging daily food intake divides logging into small steps. Automation of PA tracking removes the task of manually logging PA.
	Personalization	Automated nutritional advice is personalized to user's anthropometric measures, food preferences, previous dietary intake and blood metabolite values.
	Self-monitoring	Food diary for recording daily food intake enables the user to check upon what he/she has been eating previous days.
	Reminders	Notifications are sent in case the user does not log his food in a week to get him back on track.
	Suggestion	Dietary suggestions based on several personalized criteria are being made towards a healthier nutrition behavior.
Personalized recipe-based recommendations	Personalization & Suggestion	Personalized dietary suggestions are given in form of full meal recipes.
Personalization by blood metabolite values	Personalization	Dietary suggestions are personalized, among others, to user's blood metabolite values.
Acceptance of dietary recommendations by explanations	Suggestion & Personalization	The recipe suggestions are accompanied by a personalized explanation on why these recipes were suggested.
Personalized visualization	Self-monitoring	Previous dietary intake is presented in form of graphical visuals over a time span.
	Simulation	The diary shows how the health status and nutrient intake might change when food is being logged.
	Suggestion & Personalization	The opening screen shows which nutrients are not in the optimal range and suggests whether to reduce or increase that nutrient's intake.

Table 1: Theoretical background components and their corresponding PSD elements

Feedback with visualization Participants within study groups receiving visualization, will be presented a graphical overview of their nutritional and physical activity status instead of plain textual data. By providing visual feedback we expect to engage users in the app, provide support in making nutritional decisions and make users become more aware of their behavior.

Feedback with explanations Additional comprehensive information on the reason for a given recommendation is said to increase motivation and adherence in users, due to the added feeling of control (Tintarev 2007). Such explanations will be based on the knowledge based recommender algorithm and provide a description of why a recipe is ranked as healthy. The explanation will contain the nutrient or factor giving the highest contribution towards the ranking and the reasons for why this is an important contributor. As an example such a contributor could be a high value in iron, which is suitable for the user due to his lack in iron intake and his blood value indicating iron deficiency.

Dietary recommendations including blood values Personalizing the recommendations given to participants based on their blood profile, is expected to be a major motivational effect. In addition to the resulting increase in adherence, the risk estimation of different NCDs and the nutrient status can be linked to several indicators in the blood measurements. Using this information enables us to increase weight for the effect of different nutritional aspects such as the intake of fat, if it is connected to the identified risk group. Thus for a pre-diabetes participant, the low intake of sugar is far more important than the appropriate amount of Vitamin A and should have a stronger influence on the suitability of recipes.

Study design

Procedure A pilot experimental study will be conducted in autumn 2016. The main study is planned to start in the beginning of 2017 and last for 6 months. Both will be conducted in Germany. To minimize the effects of drop-out, participants will be given a 1-week warm-up phase to acquaint with the app and its features before the actual start of the study. To evaluate the long-term effect of the mobile app and the sustainability of the healthy eating behavior, a follow-up will be performed 3 months after the end of the main study.

Participants Adult German residents, with a BMI >= 25 willing to improve their nutritional status are eligible to apply to the study. Applicants with the diagnosis of any cardiovascular disease, nutrition-related disease (e.g. diabetes), food allergies or intolerances will be refused to participate due to ethical reasons. Pregnant or lactating women will also be excluded from the study. Participation requires exclusively Android smartphones in possession of mobile internet. The final sample will be checked to quotas for age, gender, education and activity level to represent the German population. Participants' distribution to study groups will be randomized, but balanced in terms of being representative of the German population within reasonable bounds.

Factorial Experiment The first intervention of our experiment uses a full-factorial design with five intervention factors: (1) type of dietary recommendation: food-based, recipe-based or both; (2) dietary assessment with a meal-based food diary, a 7-day-recall Food Frequency Questionnaire (FFQ) or both; (3) dynamical tracking of PA via mobile phone/activity tracker gadgets additionally to a TEE questionnaire versus questionnaire only; (4) feedback with visualization of recommendations and users' nutritional status versus none; and (5) feedback with textual, analytical explanations on the reasoning behind the proposed diet counseling versus none. Putting these factors into a matrix, we receive a 3x3x2x2x2 dimensional setup, which leads to 72 experimental component combinations in total. The full-factorial nature of the design enables us, additionally to the calculation of main effects of the factors, the calculation of the interactions between factors uniting both efficacy and cost-effectiveness (Collins et al. 2014).

Regression Analysis To obtain the effects of blood metabolites on participants' healthy eating behavior, we will execute a second experiment in parallel to the factorial. This part of the study uses the maximum app-version from the factorial experiment, meaning all factors are included in their maximum shaping: (1) dietary recommendations include both food and recipe recommendations; (2) dietary assessment follows by both a meal-based food diary and a 7-day-recall FFQ; (3) PA tracking happens dynamically; (4) visualized feedback is included; and (5) feedback with explanations is included. Additionally, a sixth factor will be included in this design: the blood metabolite values. Their values influence the recommendation algorithm, marking it to be the highest level of personalization. An extensive regression analysis of the results will be made (Chittaranjan et al. 2011; Sykes 2007).

Sample Size A first sample size calculation using the mean Healthy Eating Index (HEI, 84.8) and the standard deviation (9.8) from the German National Consumption Study II resulted in a sample size of 157 participants in the intervention with the maximum app version (i.e. version where all intervention factors are included in its maximum shaping). With this number we can detect a difference of 2.6 %, which was the difference in the Food4Me study between the control and the intervention groups, with a power of 80 % and alpha = 0.05.

Study outcomes

Healthier nutrition behavior Measurements for a healthier nutrition behavior depict whether the intake of the necessary nutrients has been increased. These will be primarily measured with an improvement of the HEI (Guenther et al. 2013; Kennedy et al. 1995) and the increase of dietary intake of individual nutrients after 3 and 6 months. Secondary outcomes include a reduction in the anthropometric measurements (i.e. body weight, body mass index (BMI) and waist-to-hip ratio), an increase of PA and an improvement of metabolite levels in blood (i.e. triglycerides, cholesterol, iron, homocysteine and omega-3 fatty acids).

Mobile app usage engagement Measurements for engagement of individual users, with focus on long-term engagement, present an important determinant of our study goals and outcomes. The primary outcome is the adherence of usage, i.e. the dropout-rate from the study, prospectively defined as the participant not providing any data for a month. Frequency of app usage, frequency of data input, duration of usage per single view within the app and acceptance (i.e. motivational perception) of the dietary recommendations comprise the secondary outcome measures. Additionally, we plan to enquire into the motivational influence of the lone intervention factors on the participants' adherence. All over, we observe and track each intervention's dropout rate to gain insights on users' behavior corresponding to the attached intervention and its shaping criteria.

Assessment of Study Outcomes

Applicants interested in taking part in the study, must initially assent to self-report all measures using the app. Additionally, they must agree to the continuous monitoring and collection of app analytics data on servers, i.e. tracking common user interactions: performed interactions with the app, used features, as well as time spent on individual screens. Participants assigned to the group comprising blood metabolites, must send requested DBS samples by mail. Detailed instructions on the DBS collection will be provided.

The applicants' inclusion criteria to the study will be verified with questionnaires covering social-demographic information (age, gender), anthropometric data, pregnancy and lactation, diagnosis of cardiovascular-diseases, diabetes and cancer, food intolerances, allergies or prescribed diets.

At the start of the study, included applicants will self-measure and self-report their weight, height, waist and hip circumferences in the app. Randomly chosen participants will be asked to perform the self-measuring process via a skype call in order to validate the method. Each participant will be given the in-app FFQ developed for the Food4Me study (Forster et al. 2014) to quantify dietary habits. Estimated nutrient values provide the recommendation algorithm cold start data. To determine participants' activity level before any data provided by the app, the TEE questionnaire will be used. Participants assigned to the intervention including blood analysis, will collect and dispatch their DBS samples.

Participants report their self-measured anthropometric data each month during the study, as well as their TEE from PA. Furthermore, in the middle of the study (i.e. 3-months point), participants will again complete the FFQ to verify the food log entered in the app. For the purpose of a qualitative estimation and evaluation of user experience and users' subjective attitudes against the system, we will benefit from Pu and Chen's (2010) user-centric evaluation framework (UCEF) of recommender systems, initially raising it at the 3-months point.

Finally, all measures, including DBS, will be collected once more at the 6-months mark. A follow-up study, conducted 3 months after the main intervention, aims to indicate how sustainable the dietary behavior change is. Accordingly, all data, except DBS and UCEF, will be collected.

Design of Intervention Tool

To prove the effectiveness of the intervention factors pointed out in the previous section, in terms of an improvement in the nutrition behavior and user engagement with the app, we will design, develop and evaluate a smartphone app covering a randomized combination of those factors.

The app is designed to emulate nutritional expert knowledge within a recommendation algorithm (Hecktor 2015), generating personalized dietary recommendations based on several sources of personal data: (1) previous food intake, (2) PA level, (3) anthropometric measures (i.e. age, gender, body weight, height), (4) dietary preferences, (5) history of diet-related illness in participant's immediate family, and (6) blood markers. The app disposes with several feedback techniques for the purpose of self-reflection and persuasion. Five main constituents compose the app: (1) opening overview, (2) food diary, (3) dietary recommendations, (4) personal statistics, and (5) account screen. Some of the screens are presented in Figure 1.

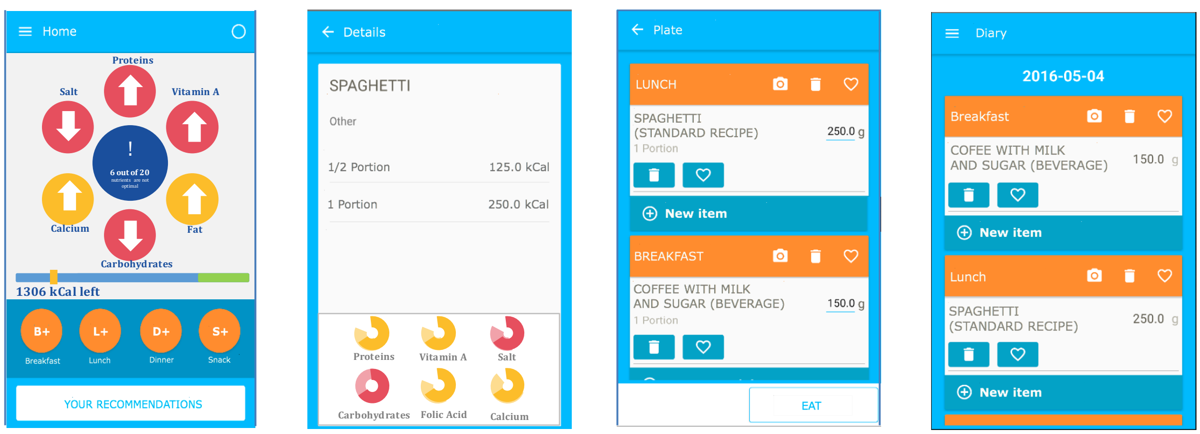

Figure 1. Design of the Home, Details, Plate and Diary screens (in progress)

The initial “Home” screen provides a centrally-located, visual overview of the user’s lacking behavior, as a reflection-on-action mechanism (Hermsen et al. 2016). The missing nutrients are variable in nature and adapt to those falling short to achieve user’s average daily needs. Additionally, the main screen comprises of several shortcut buttons. First, to start the task of dietary intake logging for a specific meal type or snack and second, to view recommendations. In this way the main screen provides quick access to all the major functionalities right after the app’s startup.

Food-logging can be conducted meal or item based. The user can search for food items or recipes within the search screen. Food items, containing both single items (e.g. apple, chicken) and recipes, together with their nutritional value, are provided by a mash-up of the German Nutritional Database (BLS) and several recipe resources. The user can either use a general search or find an item by browsing a category-tree. Recently selected items and favorites are available as shortcuts for frequently repeated food choices. Each item provides a "Details" screen, for specifying the quantity of the food and reviewing visual information on the items characteristics and its healthiness degree. A color code presents the general healthiness of the item, gradually moving from red to green, while an arrow indicates in which direction health will be influenced. Thus, the user gets direct information on the food item choice in the reflection-in-action manner (Schön 2002), receiving a chance to modify the food choice. Before ending the entry of one meal, the user is given an overview of all the food items he selected to constitute the meal, with the appropriate message of how it affects the daily amount of nutrients and calories, in a textual and visual form. After marking the meal as "eaten", the user returns to the main screen, where his weekly overview adapts accordingly to the previously logged meal.

Users obtain dietary advice personalized to their needs by entering the "Recommendations" screen. Utilizing user's food intake data from the previous week, the system generates 20 recommendations for each category in breakfast, lunch, dinner and snacks. Dietary recommendations occur in form of food groups or complete meal recipes. Distinct textual explanations uncover the rationale behind the recommendations. Furthermore, visual graphics, equal to the ones in the diary entry overview screen, enable the user to pictorially realize the alterations of the nutrients, supposing the recommendation gets accepted. For that matter, the food becomes logged into the diary. Users are able to reject a recommendation, making it no longer appear. Additionally, the app offers the possibility of explicitly re-generating recommendations.

The "Statistics" screen collects a bundle of statistical and introspective views based on personal nutrition intake, micronutrients and PA in different temporal intervals (i.e. daily, weekly, monthly). Furthermore, we plan to offer a comparative view between different meal types such as breakfast, lunch and dinner based on their healthiness over time. The design of the screen aims at providing a quick analysis of the current nutritional status and a meaningful self-reflection tool on previous behavior.

Finally, food preferences are expressed in the "Personal account" section. There are several ways for the user to influence his dietary recommendations. The strongest effect is dedicated to the so called no-goes. Those are a list of ingredients that the users will never want to eat. For example, a vegetarian could add meat. Any of those keywords will be completely filtered from the list of recommendations. Other user preferences are expressed within the recommendation screen or the search screen where users can give ratings and tag meals and components they like.

Far from users' sight, the app employs the smartphone's accelerometer and its global positioning system sensors to continuously record users' PAs, distinguishing between a sedentary state, a walking state or physically active state (e.g. running, cycling). Calculating the expended energy amount during tracked activities grounds on the standard of Total Energy Expenditure (TEE), which is calculated by multiplying the basal metabolic rate with the Physical Activity Level (PAL) (Butte et al. 2012). The average level of PA over the past week will be utilized to calculate the TEE value, which can be used to replace the general amount of calories per day that are recommended to the user. In addition to the smartphone tracking, integrating a handful of the most popular smart gadgets for activity tracking will be provided within the app.

Conclusion

As the mortality rate caused by diet-related illnesses rises on a yearly basis, new prevention strategies going beyond the "one size fits all" approach become a worldwide priority. By using modern information and communication technology (ICT) strategies to investigate the concept of personalized nutrition approaches, this research aims at identifying the most important ICT factors that demonstrate promising effects on a dietary behavior change. Drawing from previous research on personalization and behavior change interventions with mobile apps, we identify and investigate six intervention factors, presenting personalization either as the shaping of personal data itself, the input method of the personal data or as a self-reflecting feedback tool. We premise these factors having a positive impact on the dietary behavior and long-term app engagement. This research-in-progress paper presents the core personalization strategies to foster healthier food choices and the experimental study design, which we plan to conduct over 6 months starting in the first quartile of 2017.

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