Nutrilize a Personalized Nutrition Recommender System: an *enable* study

Nadja Leipold*
Technical University of Munich

Mira Madenach
Technical University of Munich

Hanna Schäfer
Technical University of Munich

Martin Lurz
Technical University of Munich

Nađa Terzimehić
University of Munich (LMU)

Georg Groh
Technical University of Munich

Markus Böhm
Technical University of Munich

Kurt Gedrich
Technical University of Munich

Helmut Krcmar
Technical University of Munich

ABSTRACT

A nutrition assistance system gives feedback on one's dietary behavior and supports behavior change through diverse persuasive elements like self-monitoring, personalization, and reflection implemented e.g. with visual cues, recommendations or tracking. While an automated recommender system for nutrition could provide great benefits compared to human nutrition advisors, it also faces a number of challenges in the area of usability like efficiency, efficacy and satisfaction. In this paper, we propose a mobile nutrition assistance system that specifically makes use of personalized persuasive features based on nutritional intake that could help users to adapt their behavior towards healthier nutrition. In a pilot study with 14 participants using the application for 3 weeks we investigate how the different features of the overall system are used and perceived. Based on the measurements, we examine which functions are important to the users and determine necessary improvements.

CCS CONCEPTS

• **Applied computing → Health care information systems**; **Health informatics**;

KEYWORDS

Recommender Systems; Personalization; User Interaction; User Experience; Nutrition Behavior; enable-Cluster

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1 INTRODUCTION

In recent years, the need for personalizing dietary recommendations became more and more apparent. Until today, dietary recommendations are mostly aimed at the general population to decrease the overall occurrence of malnutrition. However, looking at an individual level, people are very different in relation to their dietary needs. This can be due to the phenotypic or genotypic traits of a person, or the individual diet and lifestyle of that person [5].

At the same time, mobile applications that support people in healthier lifestyles reach increasing awareness among society and industry as well as in research. In combination with intelligent recommender systems and persuasive designs, they offer a way to face unhealthy lifestyles [20] like unhealthy diets, smoking and lack of physical activity, that are related to an increasing number of noncommunicable diseases (NCDs) such as cardiovascular diseases, cancer, chronic respiratory diseases and diabetes [24].

Smartphone applications have already been used as an intervention tool (e.g. [3]), but focus mostly on the weight loss of participants. There are also several popular commercial weight loss applications like MyFitnessPal, MyNetDiary and Lifesum. [7] analyzed the most popular mobile applications in this context and concludes that they generally lack personalized nutrition with individualized feedback as well as nutrition education.

In contrast to these approaches, our nutritional recommender system *Nutrilize* combines personalized recipe recommendations, visual feedback and other persuasive measures, as presented by [21], by considering the personal characteristics and the nutritional status of 26 macro- and micronutrients.

In this paper, we present the characteristics of the *Nutrilize* system as well as a pilot study of this system. We analyze the interaction with and perception of this system over a period of 21 days considering data from 14 participants.

2 BACKGROUND

This section provides insights into the status of recommendations in the food domain, in the health domain, in the nutrition science domain and within existing applications in general.

Even though research in the area of *food recommendation* for healthier nutrition becomes more popular due to social relevance, the number of existing systems is relatively low. [23] as well as [22] provide state-of-the-art reviews of approaches and systems in the area of food recommender systems. Various approaches exist to recommend food and recipes based on different methods that elicit user preferences using user ratings, scores and tags. For example, approaches utilize recipe information and offer recommendations from individual scored ingredients contained within a single recipe that got formerly rated positively [8] or negatively [12] by users.

*Email: nadja.leipold@in.tum.de

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Besides user preferences in certain foods, health becomes more important as a factor in a food recommendation system due to the increasing problems with unhealthy eating habits and their related diseases. Recently, efforts to incorporate health into so-called *health-aware recommender systems* have been done by a number of researchers [20]. [10] developed for example a function to derive the balance between calories needed by the user and contained by the recipe. [6] addresses the problem of finding the balance between users' taste and nutritional aptitude. [23] investigated the possibility to integrate nutritional facts into their recipe recommendations. Nevertheless, literature on research covering the topic of incorporating health is limited until now.

There are several national and international dietary guidelines [17] that provide important standard sources for nutritional information. However, they are based on population rather than individual needs. Recent approaches to personalized nutrition show promising insights into the effectiveness of *personalized nutrition recommendations*. For example, [25] investigated individual aspects, which influence the post-prandial glucose response (PPGR) of a person to a certain food. They showed, that the PPGR for the same meal differs greatly between individuals. Using machine-learning techniques and creating an algorithm based on individual aspects, such as dietary behavior, anthropometrics, blood biomarkers and gut microbiome, they were able to accurately predict the PPGR to certain foods. The effectiveness of personalized dietary recommendations for multiple nutrients was also examined in a European web-based Proof-of-Principle (PoP) study, the Food4Me study [4]. The aim was to compare the effectiveness of personalized nutrition advice (based on dietary, phenotypic and genotypic information) with population-based advice to improve dietary behavior. In the 6-months study, personalized dietary advice proved to be more effective than conventional dietary advice in improving nutritional habits [18]. Food4Me was not solely created for overweight participants to lose weight, but their main aim was to enhance a healthy diet. In [21] we design a mobile system *Nutrilize* that offers personalized nutrition advice similar to Food4Me and combines it with new approaches such as recipe recommendations. *Nutrilize* supports users with recommendations based on the estimated personal nutritional needs and combines them with principles of persuasion

[19] developed MyBehavior, a mobile application that supports users with different personalized feedback in terms of actionable suggestions. These are based on algorithms from decision theory that learn users' physical activity and dietary behavior. They include users' preferences as well as behavioral change strategies to give appropriate personalized feedback on diet and physical activity. Besides scientific approaches, commercial food diaries and/or diet coaches with incorporated physical activity trackers, mainly focusing on reduction of calorie intake such as MyFitnessPal, MyNetDiary, Lifesum, etc. offer various forms of visual and textual feedback (e.g. overview charts on calorie intake and expenditure, and the macronutrients' distribution of consumed foods). According to a review on nutrition-related mobile applications in the UK [7], the analyzed applications lack personalization and educative aspects. Partially, they include individual aspects like age, gender, weight and other phenotypes. However, the information used to generate user feedback is primarily based on macronutrients and activity. Intake tracking or feedback on a micronutrient level, is not considered within the analyzed systems.

3 NUTRITION RECOMMENDER SYSTEM

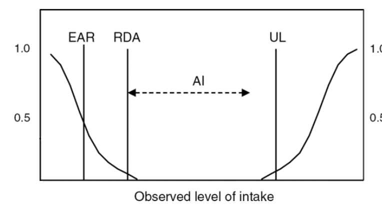

Figure 1: Nutrient response curve of the DRI concept [16]

To provide meaningful recommendations, we implemented a knowledge-based, personalized nutrition recommender system. This recommender system relies on four main components: An accurate nutritional food database, a user nutrition profile, a recipe database, and a knowledge-based utility function for each nutrient.

We compared 3 different sources of food item databases: BLS, FDDB and Fatsecret. In the end, we selected the BLS (Bundeslebensmittelschluessel) database [11] due to its high number of accurately represented nutrients. The BLS is used to record the user's intake as well as to calculate the recipes nutritional profile. During the pilot study 26 different micro- and macronutrients were derived from the BLS for both the user's intake and the recipes profile.

The user profile has several components. The main influence on the recommender system is represented by the user's intake history. We chose a three-day-average to represent the users nutritional profile. We decided on using an average to avoid contradicting advices within one day (e.g. less/more calcium). At the same time, we did not want to extend the average further than three days to be able to react to changes in the users diet. Furthermore, the recommender system integrates gender, age, and BMI to personalize the recommendations.

The recipes are obtained from KochWiki[1], which is licensed under Creative Commons Attribution - ShareAlike 3.0[2]. We combined the recipe database with the nutritional information for each food item in the BLS database using an adaptation of [13]. Overall, 240 recipes are provided during the study.

For the recommendations, each recipe is rated by comparing its nutritional profile with the nutritional needs of the user. The user's needs are derived using the dietary reference intakes (DRI) from the Institute of Medicine [15] and from the D-A-CH reference values [9]. The dietary reference intake [16] is divided by age and gender and structured as shown in figure 1. For the purpose of estimating the nutrient intake status of a person, intakes below the EAR (estimated average requirement) are categorized as insufficient intake, intakes above the UL (upper limit) are categorized as a likely overdose, and intakes between EAR and RDA (recommended daily allowance) are categorized as possibly insufficient intake, while intakes between the RDA and UL are categorized as optimal intake. Based on these

[1]www.kochwiki.org
[2]https://creativecommons.org/licenses/by-sa/3.0/

reference functions, the user's needs are described as a vector of 26 advice values. To derive a recipes utility (u) to improve a user's nutritional profile, the nutrient profile of the recipe (r) is multiplied with the need/advice profile of the user (a), resulting in a rating score. During this multiplication, some nutrients (p_i) are weighted (w) higher based on certain input parameters of the participant:

$$\begin{bmatrix} r_{p_1} \\ \vdots \\ r_{p_n} \end{bmatrix} \circ \begin{bmatrix} w_{p_1} \\ \vdots \\ w_{p_n} \end{bmatrix} \circ \begin{bmatrix} a_{p_1} \\ \vdots \\ a_{p_n} \end{bmatrix} = \begin{bmatrix} u_{r,p_1} \\ \vdots \\ u_{r,p_n} \end{bmatrix} \tag{1}$$

Finally, all recipes are ranked per meal by the sum of their ratings and shown to the user. In addition to the recipes, the users received an explanation on which nutrient influences the ranking of this recipe the most and which benefits this nutrient provides.

4 *NUTRILIZE* INTERFACE DESIGN

The developed mobile smartphone application, which is used for this study, is based on the intervention tool presented by [21]. It consists of three main components in terms of a food diary, visual feedback and recipe recommendations.

4.1 Food Diary

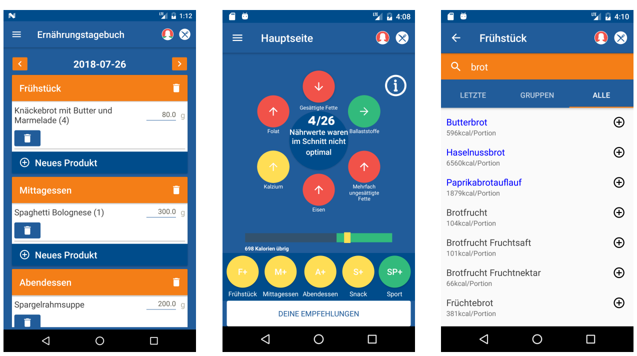

Figure 2: Diary (l), home screen (m) and food search (r)

In order to provide personalized feedback and recommendations, the application needs regular input of the user's nutrition behavior. This can be tracked via the integrated *personal food diary* supplied by nutritional information from the BLS database (Figure 2, left). We added the meal categories "Breakfast", "Lunch", "Dinner" and "Snacks" for better structuring. The diary can be filled by clicking the plus button at each diary section or by using the shortcut on the home screen (Figure 2, middle). When adding food to the diary, a search dialog is opened (Figure 2, right), where users can search their meals in the database. After selecting a result, the user can adjust the amount of the food item before adding it into the diary or change the amount afterwards in the diary view. For the purpose of a quick access of previous chosen meals and related quantitative disclosures the user is offered a *Recent* tab below the search bar.

4.2 Visual Feedback

Information graphics are generated for different *visual feedback* screens. The home screen (Figure 2, middle) provides an overview of the current nutrient status. Feedback calculations here are based

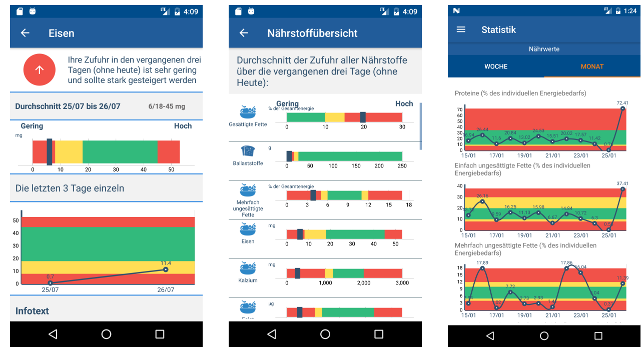

Figure 3: Nutrient details screen (l), nutrient overview (m) and statistics overview (r)

on the average of the three previous days of consumption. The six most critical nutrients (regarding the highest aberration from the suggested intake amount) are shown. The color coding used in the application consists of a traffic light color scheme that provides a high association for the users [2]: red (for warnings), yellow (for attention) and green (for go on). In case of optimal behavior, even the six most critical nutrients would show a green symbol. Additionally, the arrows in the circles in the home screen indicate recommended behavior (pointing up: increase intake; pointing down: reduce intake). On the bottom of the home screen we added four circular buttons for easy diary access to add new meals. When using the sports button, the user can fill out a questionnaire to estimate the physical activity level [14]. Finally, users can access their recommendations through the white button on the home screen.

Through clicking on a nutrient on the home screen, an information page is shown (Figure 3, left). There, the current nutrient status is visualized via a colored horizontal bar, showing the current value as a blue vertical line and the areas of intake represented with the same color coding as in the home screen. Furthermore, the intake development over the last three days is visualized. In addition to the visual feedback some information is given in textual form, such as information on the nutrient, its importance for the human body and possible adverse effects caused by over- or under-consumption. Below the nutrient description, the main food sources for this nutrient are listed as well as the personalized reference values for the consumption of this nutrient.

By clicking on the middle circle in the home screen, the user can access the personal nutrition overview (Figure 3, middle). It lists all 26 nutrients with their current status, visualized through a horizontal bar as on the nutrient detail screen. Users can furthermore access detailed statistics on their previous nutrition behavior through the applications menu (Figure 3, right). This visualization allows the user to see the progress within a week or a month.

4.3 Recipe Recommendations

The *recipe recommendations* offer ranked lists of recipes (as described in section 3) for each meal, based on their nutrient content and the user's nutritional history of the last three days. They are provided in separate tabs for each of the four meal categories, as shown in Figure 4. The traffic light color scheme is used here as well and represents the overall "health benefit" of the recipe according to the user's current nutrition status. Each recommendation consists of a recipe title, a picture and a coarse overview of the recommended amount and relative content of macronutrients. Additionally, users can click on the explanation button to receive insights into why this recipe is recommended to them.

All additional information on the recipe, such as a detailed list of ingredients and the preparation instruction can be viewed when clicking on the recipe item within the list (figure 4). The users can view the ingredient list for one portion or with the recommended sizes for the user (based on their caloric requirements). They can immediately add the consumed portion of a recommended recipe to their diary, saving the time of entering each single ingredient.

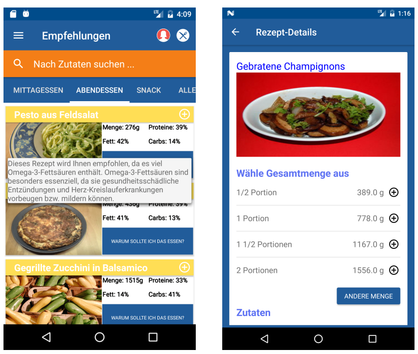

Figure 4: Recommendation list (l) and recipe screen (r)

5 USER STUDY

This study represents an exploratory pilot study of the *Nutrilize* system. We focused on study group, system interaction, system perception and reported dietary behavior. The study protocol was approved by the ethical committee of the Faculty of Medicine of the Technical University of Munich in Germany (no. 477/16 S).

5.1 Study Procedure

Participants were recruited from the *enable* research participation database [3] with approx. 120 invitations. The study consisted of four distinct steps. First, all participants completed a screening questionnaire that checked for medical (e.g. allergies, pregnancy, etc.) and technical constraints (e.g. Android phone, Internet access, etc.). Second, if participants matched study constrains and gave their consent, they received a link to the first survey (time point 0). In this survey, we collected data on dietary habits using a food frequency questionnaire (FFQ), on activity habits using the Norman questionnaire [14] and on their anthropometric measures. The anthropometric measures included self-measurements of the body height, bodyweight and waist/hip circumference. Third, one day after the first survey all participants received the *Nutrilize* application and an instruction manual. Fourth, after 3 weeks of using the application, the participants received the final survey (time point 3) asking for feedback on the system. They received no payment for participation. Out of 31 participants, who finished the first screening, 20 were both suitable for participation and finished the first survey. The final survey was concluded by 18 participants. Overall, only 14 of the 20 participants concluded all measurements. Those 14 users are further examined in this paper.

5.2 Measures

We had three different types of measurements in this study. First, we measured the *nutrient intake* of participants. In the beginning and end we derived the users' dietary intake from a food frequency questionnaire using 150 common food items. Afterwards, we let the participants track their nutrition within our application for 21 days. Based on their input, we were able to derive daily nutritional information. Second, we measured the *participants' usage behavior* within the application using an open analytics and tracking tool named Matomo [4], formerly Piwik. The tracking tool allowed us to measure the time and number of actions within each application session. It furthermore tracked predefined goals, such as accepting a recommendation. Third, we measured the *participants' self-reported attitudes and perceptions.* In a pre-study questionnaire we asked them about their background, cooking habits, their health attitude, and their technology attitude. In a post-study survey, we assessed the overall usability using a System Usability Scale (SUS) questionnaire [1] and specific feedback for each application feature.

6 STUDY RESULTS

This section shows the results of our user study for the different measurements. First, we look at the characteristics of the study group. Then we analyze the system perception by the participants and how they used it during the study. Finally, we analyze the nutritional data retrieved from both the application's diary and the food frequency questionnaires. Our goal is to get an understanding of the needs of our participants, the effects of the system and the required changes for the system.

6.1 Study Group

Table 1: User characteristics of 14 participants. Health and technology attitude are measured with 6 questions each on a 5 point Likert scale (0 disagree - 5 agree)

	Age	Height	Weight	BMI	Health Attitude	Tech. >=50y	Tech. <50y
Min	23	152	52	18,4	3,3	1,8	2,8
Max	65	183	113	36,1	4,5	3,5	5,0
Avg	45	170	77	26,6	3,9	3,0	4,3

Table 1 shows the user characteristics, the health attitude, and the technology attitude of the participants below and above an age of 50 years. The gender ratio is slightly biased with 8 female and 6 male participants. This tendency is lower than expected. The balance can be explained by the recruitment target, which is already balanced and interested in healthy nutrition in general. The age of the participants ranges from 23 to 65 years. With an

[3] http://enable-cluster.de/index.php?id=198&L=1

[4] https://matomo.org/

average age of 45 years, the study group is significantly older than expected. In part this leads to different attitudes towards technology in general. We furthermore see a full range of BMIs. One participant is underweight, five participants are of normal weight, four are overweight, and three are obese. Finally, all participants have very similar health attitudes. The majority (12 out of 14) feels unwell with their current diet, but they believe they can keep up the changes required of them, even if a transition would be difficult.

6.2 System Interaction and Perception

The first aspect of the system perception is the overall usability of the application. The SUS [1] feedback resulted in a score of 52, which shows that the application is not a basic prototype anymore, but also not on an average usability level yet. Next, we tracked the user's interactions within the application. Most of the interactions (on average 85%) are focused on filling in the dietary diary of the users. Among the features the application is offering to the users, the patterns are less uniform. As visible in figure 5 some users prefer the visual feedback given in retrospective (user 1,5,10), while others focus almost entirely on the recommendations (user 2). A few users are even putting their emphasis on the calorie overview (user 12). During the final questionnaire, the feedback shows that

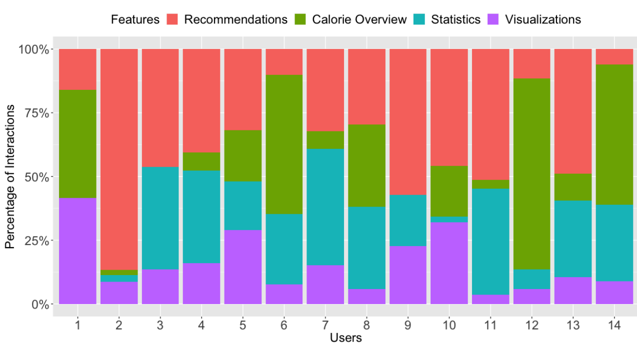

Figure 5: Percentage of interactions within the application

the system still needs to improve. The single nutrient visualizations are perceived very well for all visual representations. Other features however, such as the recommendations, were not perceived as well. In general, feedback on the recommended recipes included missing variety, difficulty of recipes, and missing personal adaption of the recommendations (e.g. raw food or vegetarian). The explanations within the recipes on the other hand were perceived as helpful by most participants, possibly because they link back to focusing on the single nutrients from the visualizations. Finally, the diary function of the application was clearly (12/14) preferred over the FFQ input method, even though it is more time consuming.

Besides the current perception, we also inquired the wishes for our future system. The users suggested easier entry methods for the food diary, detailed sports tracking, greater recipe variety, more positive feedback and better general performance and design.

6.3 Nutrition Behavior

The nutrition behavior can be analyzed on different levels. First, we can look at the eating habits of the participants. Second, we can analyze the caloric behavior during the study and third, we consider the health measurement represented by a sufficient nutrient intake according to the reference guidelines. The eating and input tracking habits can be viewed by looking at the different consumed meals. The data shows that breakfast and dinner are very similar with an average number of 70 tracked food items during the 21 days. Lunch is only reaching 58 tracked items. This difference might be due to the limited time for systematic tracking during lunch. Finally, the snack category was used very differently amongst the participants ranging from 0 to 66 items.

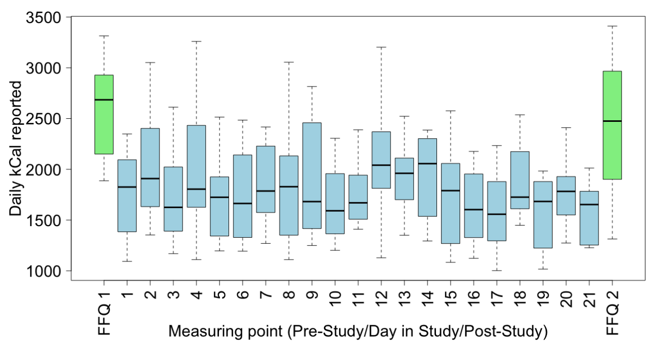

Figure 6: Comparison of reported daily energy intake (kCal) calculated based on FFQ (green) or on the application based dietary tracking (blue)

The caloric behavior during the study shows that the intake tracked within the application is systematically lower than the one derived from the FFQs. In figure 6 the tracked intake is shown as a box plot for every day (blue). Additionally, the measurement with the standardized food frequency questionnaire before and after the study is shown. For most participants, the daily intake is about 1000 kCal lower when tracking with the application. At the same time, the calories calculated from the FFQs stay in a similar range with a slight tendency to less intake after the study.

The healthiness of nutrition in this study is defined by the number of adequately consumed nutrients over the past three days, which were calculated and presented as nutrient intake per day. The highest number of optimally ingested nutrients (22 out of 26 nutrients) is reached by one participant after 11 days of intervention. The average number of adequately ingested nutrients is 13, which is only half of the tracked nutrients. This might in part be caused by the underestimation of food intake.

7 DISCUSSION OF RESULTS

One of the main challenges, that can be drawn from the results is usability. As working with a prototype system this is not surprising. Nevertheless, important next steps could be extracted from the feedback, which are crucial for an improved usability and for an application which is supposed to be used daily.

The first feature that should be improved are the recommendations. Although we included a recommendation system, which produces highly personalized and individual recommendations, the users are facing many constraints in real life situations that were not modeled. These factors include the availability of certain food (e.g. seasonal fruits), personal preferences (e.g. vegan) and group constellations (e.g. a mother who should cook for her family). Moreover, additional recipes seem to be necessary since the current recommendations were often perceived as repetitive.

An additional learning for the personalized recommender system is the high dependency of some advice functions on accurate user input. When some meals are tracked or the amount of a food item is underestimated (which seemed to be a trend in the pilot study), the users do not reach the recommended consumption values of the macronutrients. This can result, for example, in suggestions to increase the user's intake of fat and thus providing recipe suggestions of high fat foods. To prevent such inverse advice, we suggest excluding total amounts of carbohydrates and fat while including proportional advice on specific types of fat and on sugar.

Besides improvements, the users also reported the missing of some functionalities. For example, some users wished for the ability to track their physical activity manually (instead of with a questionnaire). This would suggest a sports diary comparable to the current food diary with the option to integrate data from popular fitness trackers. Furthermore, the home screen was perceived to be discouraging. Some UI changes might easily improve this perception. One possibility could be to show a progress on the optimization of nutrients in the center circle on the home screen.

Finally, the high amount of time spent on the intake tracking (85%) might offer a chance. Instead of giving only support for retrospective or perspective actions, some visual cues might be integrated within the action of tracking itself. Furthermore, the subsequent implemented system addresses this issue by offering fast access to favorite foods for use in the longitudinal study.

Overall, the system still needs some improvement, but already 43% of users stated that they would use the system frequently. Of the 14 participants 9 used the system for more than 17 days. This shows that the general idea and purpose of the system are relevant to the study group. However, further adjustments might increase the number of users willing to use the system frequently and might consequently create an effective tool for nutrition behavior change.

8 CONCLUSION AND FUTURE WORK

Mainly, this study shows the need for improvements in several aspects of the application, such as the recommendations, performance and ease of intake tracking. Still, 43% of the participants would use the application regularly and most (85%) prefer the daily dietary tracking to a weekly food frequency questionnaire. Some major challenges remain open, such as integrating contextual and social information as well as the accuracy of the received input data. In future, we will improve *Nutrilize* according to the given feedback and evaluate the long term (3 months) effect of using the application against a control group. Finally, this works provides starting points about the integration of nutritional recommender systems into more holistic persuasive mobile systems for daily usage.

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