NUTRITION ASSISTANT APPLICATION

ABSTRACT:

Healthy nutrition contributes to preventing non-communicable and diet-related diseases. Recommender systems, as an integral part of mHealth technologies, address this task by supporting users with healthy food recommendations. However, knowledge about the effects of the long-term provision of health-aware recommendations in real-life situations is limited. This study investigates the impact of a mobile, personalized recommender system named Nutrilize. we provide a deeper understanding of how our nutrition application affects the users' physique, nutrition behaviour, system interactions and system perception. Our results show that Nutrilize positively affects nutritional behaviour measured by the optimal intake of each nutrient. we discuss general knowledge acquired on the design of personalized mobile nutrition recommendations by identifying important factors, such as the users' acceptance of the recommender's taste, health, and personalization.

OBJECTIVE:

The research in recommender systems has been recently interested in food recommender systems addressing, among others, nutritional health with different approaches . These systems have the potential to help users navigate the growing amount of multimedia food content while fostering healthy eating patterns. Conventional recommender systems learn the users' preferences and try to cater to them, which might enforce recommendations for unhealthy food as well. Thus, health-aware recommender systems need to also incorporate different parameters related to taste and health into their systems . The use of nutrition assistance systems is promising since previous studies have shown that persuasive technologies can help people to eat healthier.

PERSONALIZED NUTRITION:

Food recommendations for nutrition personalized according to individual health requirements are a major research gap identified by several food recommender system surveys. One of the most prominent studies on personalized nutrition is the Food4Me study Over an intervention time of six months, 1607 participants across multiple European study-centres received four types of advice via e-mail: 1) a control group receiving conventional advice, 2) a group receiving personal advice based on dietary intake, 3) a group receiving personal advice based on dietary intake and phenotype, 4) a group receiving personal advice based on dietary intake, phenotype, and genotype. Similarly, a second evaluation focused on the improvement of the Healthy Eating-Index shows that participants receiving personalized feedback consumed less red meat, less salt, less saturated fat, more folate, and had higher Healthy-Eating-Index scores at month six than the control arm , with no significant difference between the personalization branches. In line with these insights, the Nutrilize system is integrating personalization according to intake history, phenotype, and blood measures.

HEALTH RECOMMENDER SYSTEM:

Formal nutrition models need to cover the user profile, food information, and advice functions. The user profile variables that were considered are: (1) the BMI (BodyMass-Index) calculated from the user’s height and current weight, (2) the waist to hip ration calculated from the hip-measurement and waist measurement, (3) the user’s basal metabolic rate calculated from age and gender, (4) the total energy expenditure calculated from the physical activity level and basal metabolic rate, and (5) the user’s risk for diseases based on blood values. The variables from the user profile are later used to weight different nutrients in a personalized way. While BMI and WHR (waistto-hip ratio) influence the recommended portion sizes, gender and age are parameters used in the advice functions. The food diary builds a bridge between pure food and pure user-related information. It is a crucial part of the personalization to consider previous dietary intake. Regarding the information on food items, two types of input need to be distinguished. The most critical decision for accurate nutritional feedback is the choice of a nutritional database.

EVALUATION:

The first wave is important to note the difference to a control group and to see the long-term effect of both groups. The application group of this wave could furthermore volunteer for an interview at the end of the study. The second wave consisted only of application users and had a duration of 2 months. Part of the participants had previously conducted the control group of the first wave and thus gave detailed insights into changes of users over time. The second wave of participants had to additionally conduct an interview after four weeks and another one after the full eight weeks. We thus call this group the qualitative group (Q) or, if previously in the control group and the control qualitative group (CQ). We expect the application group to show higher improvements than the control group. At the same time, we monitor the system interactions, the nutritional behaviour, and several questionnaire based outcome measures of all participants. We expect the interview data to give more background information and input on the rationale of the quantitative analysis of the data.

CONCLUSION:

In summary, our study shows different challenges that health-focused nutritional assistance systems face when being used in the long term. Our findings can be used to improve future system regarding their impact in the long-term and to postulate more long-term evaluation of recommender approaches.

REFERENCES:

[1] P., Weber, I.: Extracting food substitutes from food diary via distributional similarity (2016). arXiv preprint arXiv:1607.08807.

[2] Alrige, M., Chatterjee, S.: Easy nutrition: a customized dietary app to highlight the food nutritional value. In: Chatterjee, S., Dutta, K., Sundarraj, R.P. (eds.) Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics). LNCS, vol. 10844, pp. 132–145. Springer, Berlin (2018). https://doi.org/10.1007/978-3-319-91800-6_9.

[3] Baecke, J.A., Burema, J., Frijters, J.E.: A short questionnaire for the measurement of habitual physical activity in epidemiological studies. Am. J. Clin. Nutr. 36(5), 936–942 (1982).

[4] Brooke, J.: SUS-A Quick and Dirty Usability Scale. Usability Evaluation in Industry, pp. 189–194. CRC Press, Boca Raton (1996). https://doi.org/10.1002/hbm.20701.