Radboud University Nijmegen
Master's Thesis in Artificial Intelligence

An adaptive recipe recommendation system for people with Diabetes type 2

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Abstract

Diabetes type 2 (DM2) is a common lifestyle disease caused by an insufficient amount of physical activity, bad eating habits and possibly some genetic factors. Coaching people on their eating habits and physical activity can help patients to reduce their dependence on medication. My MSc research project, executed at Philips Research, was focused on helping people with DM2 to eat healthier. People are creatures of habit and it is difficult for them to change their eating patterns. For this purpose, we have investigated the use of a content-based recommender system that suggests recipes based on the similarity to past choices of a user. We have taken a user-centered approach in which we collected requirements in a qualitative and a quantitative study. This has led to the development of an adaptive user representation. This profile is used to suggest recipes using a similarity measure. The approach is evaluated in an experimental study. The results showed that personalizing recommendations is effective, but that a simple, baseline personalization is as effective as the more complex adaptive profiling personalization in the current study. An additional qualitative user study showed that people with diabetes appreciated the recipe navigation options we presented them with, and liked the insight in the healthfulness of their choices which the recipe recommender gave them. Research in recipe recommendation by matching recipes to users should be continued.

Preface

This thesis is written as part of an internship conducted at Philips Research Eindhoven. It was interesting to see how different, but also how similar Philips Research is from the university. During my internship I experienced how it was to work at a company focused on actual users. I have experienced the cycle of user-centred research, that is, requirement collection with end-users followed by the development of a system and the evaluation with end-users. I have learned how important end-users are in developing a system.

Many people have helped me during my internship in some way or another. First of all, I want to thank my supervisor at Philips Research, Gijs, for our weekly meetings. I felt that you were always there to respond to questions, by mail or in person, even if you were not at the High Tech Campus. You have made my experience with philips comfortable and inspiring.

Furthermore, I would like to thank my supervisors at the university, Paul and Ida.The meetings with you were also very inspiring and you helped me a lot in correcting my thesis, making it easy for me to be proud of my final thesis.

I would like to thank my fellow interns at Philips Research for the daily lunches, dinner appointments and the conversations when I needed a break. Special thanks goes to Mieke, who helped me a lot in defining the set-up of the experiment(s) and by providing feedback on a first version of my thesis. Additionally, I want to thank everybody that participated in my experiments or helped me find participants.

Finally, I would like to thank Micha for all the dinners he prepared because I traveled so much, and of course for making sure that I set my mind off of this thesis from time to time. I would like to thank my friends and family for their support and their understanding that I did not see them as often as I would have liked to. Thank you all for making this internship such a good experience!

Contents

Chapter 1

Introduction

Over the last decades, the numbers of food products and brands have increased greatly. Supermarkets and (fast-food) restaurants have become continuously available, changing our food environment and behaviour drastically. The time available for preparing meals has decreased, while the number of easy, but often unhealthy food options has increased. This makes it appealing to go for the fast and easy choice, even though it is often not the healthy choice. Health organizations try to increase the awareness of health considerations through advertisements and nutritional information on products. However, these interventions show not to be sufficient since there is still an increase in eating ready-made food and food consumption out of home (FSIN, 2009). These food products are typically high caloric and high in fat. Hence, these changes in eating habits may contribute to obesity, which in turn can cause diabetes type 2 and other lifestyle related diseases. In 2010, the prevalence of diabetes in the USA is estimated at 11.7% of the population, in Europe this is 8.6%. Around 90% of the people with diabetes have type 2, which is related to lifestyle. (International Diabetes Federation). The number of people with diabetes is still growing. This indicates the need for a general adaptation in lifestyle, however providing information is not sufficient by itself. Additional support in improving eating habits is necessary.

In this thesis we will investigate the use of a recipe recommender system for helping people to improve their eating habits. These improved eating habits can prevent or slow down the development of diabetes type 2 with its adverse health effects or help people that already suffer from diabetes type 2 to manage their disease. In this thesis we will describe the development of an easy-to-use recipe recommender system that will provide diabetes type 2 patients with tailored main meal suggestions, in order to help them adopt a healthier diet. These meal suggestions should be healthy main meal suggestions that are likely to be prepared by the patient.

In this chapter, we will first provide background information about diabetes and related lifestyle issues in section 1.1. In section 1.2, current prevention and intervention methods for diabetes will be discussed, showing the importance of eating behaviour in the onset and development of diabetes and the influence of diabetes on the quality of life. Finally, in section 1.3 the implications of the reviewed literature are summarized and the outline of this thesis is given.

1.1 Diabetes and lifestyle

Diabetes is a metabolic disease in which the blood glucose level becomes too high if not treated. Glucose is transported from the blood to the cells by means of insulin. If there is too little insulin in the body, or if the cells are insulin resistant, the body fails to transport glucose to the cells. This causes glucose to build up in the blood and makes the blood glucose level high. High blood glucose levels increase the risk on a wide variety of other diseases including vascular diseases and neuropathy in the long run.

There are two types of diabetes. Type 1 diabetes is generally discovered early in life and is characterized by a total insulin deficiency, the pancreas fails to produce insulin (Wikipedia, 2010). These people need to inject insulin regularly. Type 2 diabetes usually develops at a later age. Unlike type 1 that is caused by genetic factors, in type 2 the disease is usually caused by a combination of genetics and lifestyle. Often diabetes type 2 is found in people that are obese. The pancreas does not produce enough insulin anymore or the body cells have become (partly) insulin resistant. In the first years after diagnosis with diabetes type 2, patients can sometimes postpone the need for medication by changing their lifestyle in terms of eating habits and physical activity. Even in a later stage, a good lifestyle is important for these people, because it makes the disease more controllable (Harris, Petrella, & Leadbetter, 2003). For the remainder of this thesis we will focus on the lifestyle aspects associated with diabetes type 2. When diabetes is mentioned, we refer to type 2 , unless the type is specified otherwise.

1.2 Preventing and Intervening in Diabetes

Diabetes is found to be the most common chronic disease targeted in US primary healthcare. Family physicians promote healthy lifestyles to people with diabetes but these people find it challenging to adapt their lifestyle. Literature describes many services and programs that target lifestyle behaviour change. Harris Petrella and Leadbetter (2003) have conducted a systematic review and found evidence that physical activity and diet are the key areas for intervention in people with diabetes as well as in preventing and managing diabetes. However, changing physical activity levels and diet is complex. Research has been conducted to find ways to help people manage their chronic conditions.

Bodenheimer MacGregor and Sharifi (2005) investigated patient's self management of chronic diseases in primary care. People with chronic diseases make decisions on a daily basis that influence their illness. Traditional education about a disease mainly involves technical or informational aspects, whereas Bodenheimer et al. think that the focus should be on self management, i.e. patient education (including problem-solving skills) *and* collaborative decision making between caregiver and patient. They conducted a literature study on the effectiveness of self-management support interventions. The results suggest that programs teaching self management skills are more effective in improving clinical outcomes than programs with information-only education. Collaborations between patients with varying chronic conditions may improve outcomes. The researchers conclude that self management should be an important aspect in educating people with chronic diseases.

That self management is effective in changing behaviour for people with chronic diseases was confirmed in a pretest-posttest quasi-experimental study by deWalt et al. (2009). They conducted an experiment in which the effectiveness of a goal setting intervention was assessed as a means of helping people manage diabetes. In the experiment, 229 participants with diabetes were enrolled. They were asked to identify an area related to their diabetes on which they were willing to work then. Then action plans (behavioural goal) were generated by the patient. For example "I will walk 10 minutes a day in the next week". Most patients planned actions in the diet and exercise domains. They were provided with a self-management guide to facilitate communication with the caregiver. Their progress was assessed by one in-person session and two telephone calls after 12 and 16 weeks. At the end of the study 93% of the participants achieved at least one behavioural goal, while 73% achieved at least two behavioural goals. The authors concluded that their goal setting intervention with the diabetes self-management guide was able to lead to behaviour change.

A better diet was one of the behavioural goals often set by the participants in the study by the deWalt. This is not unusual, since weight loss is often an important health advice for people with diabetes. Williamson et al. (2009) investigated the effect of a weight management program on the health related quality of life in overweight people with type 2 diabetes. In the study 5145 participants were randomized to two treatment conditions in a multi-site clinical trial (the study was conducted at 16 clinical research centres). Participants of one treatment condition enrolled in the Intensive Lifestyle Intervention program (ILI), while participants in the other condition received the Diabetes Support and Education program (DSE). In the ILI-condition participants were given goals for weight loss or caloric intake, were instructed to self-monitor their physical activity and food intake and were weighted at group meetings. In the DSE program participants took part in three educational group sessions per year about nutrition, physical activity and support. They were not weighted, were not given goals and did not have to monitor their food intake and physical activity. Health related quality of life (HRQOL) was measured by physical health summary scores and the Beck Depression Inventory-II (a measure for severity of depression using a multiple-choice questionnaire). The results showed a significant difference ($p < 0.001$) between HRQOL-scores in the ILI arm and the DSE conditions, in which scores for the ILI condition improved more. The authors concluded that an intensive lifestyle behaviour modification intervention for weight management improves HRQOL more than only giving information as in the DSE group.

1.3 Implications and outline of this thesis

Above literature suggest that self-management and (intensive) lifestyle modification interventions can improve behaviour (and quality of life) in people with diabetes. In the interventions physical activity and food intake play important roles. They are the most important factors for lifestyle improvement.

In this thesis we will focus on improvement of eating behaviour (food intake). Awareness of unhealthy eating behaviour and knowledge about healthful behaviour does not seem to be enough to actually change the behaviour. This leads to the conclusion that it is important to guide people in their food decision process in another way in. Guidance in food decision would be beneficial to people with diabetes or other lifestyle-related diseases in particular, but also to people in general.

As an alternative guidance method this thesis describes a method to promote healthful eating amongst people with diabetes by offering personalized recipe recommendations in a computer system. For this purpose it is important to find out which characteristics of users within the target group of type 2 diabetics and which characteristics of recipes are important for tailored recipe recommendations. It is necessary to be able to identify these characteristics automatically by the system. Knowledge about factors that influence food choice can provide further insight in how recipe recommendations can be optimized. These factors together can be used to find recipes that the user not only likes, but that he or she will actually be likely to prepare.

In the next chapter, a review of literature on factors involved in food choice will be given. Additionally, an interview study with people with diabetes is described in which insight into the target group and their recipe selection process is obtained. In Chapter 3 an internet study regarding food choice constructs is described and requirements for a recipe recommender system are identified. Chapter 4 describes the developed recommendation algorithm, while Chapter 5 and 6 describe the evaluation studies on the algorithm. A discussion on the research in this thesis is found in Chapter 7.

Chapter 2

Food Choice for people with Diabetes

As described in the previous chapter, guidance can be beneficial in changing health-related behaviour. In order to provide guidance in the recipe selection process for people with diabetes, we propose to develop a system that provides tailored main meal suggestions. However, to find recipes that an individual will like *and* prepare, knowledge about the food choice process is necessary. For this purpose we will describe literature on factors involved in food choice as well as the food choice model by Furst, Conners, Bisogni, Sobal and Falk (1996) that models the process of food selection. This review will lead to an adapted view combining the factors and models presented in literature. We use the model presented in Section 2.1.2 in an interview study (Section 2.2). The goal of the interview study was to determine whether the food choice model is sufficient for modeling the food choice process in people with diabetes or whether the model needs to be adapted. Part of the interview study entails the collection of information through a food diary and the food choice questionnaire (Steptoe, Pollard & Wardle, 1995). The purpose of this part is to investigate whether the food choice questionnaire can be used to predict food choices. In the conclusion of this chapter (Section 2.2.3), the findings from the literature, interviews, food choice model and other collected information are translated into requirements for the recommender system.

2.1 Literature

In literature, several influences on food choice are distinguished, grouped into two categories: internal and external. Internal influences come from the person making the food decision, such as motivation to eat healthfully, while external influences are coming from the external world, such as availability of food in supermarkets. However, most influences are a combination of both external and internal factors. For example, the quality of a food product and price of the product are external factors, but the importance values a person assigns to them are internal factors. Several of these food choice factors are described in the following section.

Food Choice

Starting with the question why some people choose more healthy food than others, Cusatis and Shannon (1996) analyzed eating behaviour in American adolescents who often do not eat healthy. The authors sought to explain what influences this non-healthy behaviour. Guided by Bandura's Social Cognitive Theory (1986) they examined relationships between "Pyramid" diversity scores (dietary quality in relation to the recommended diet according to the Food Guide Pyramid), fat and sugar scores and behavioural, personal and environmental variables. In total, 242 high school students participated in several questionnaires in which self-efficacy, self-esteem, body image, conformity to peers/parents, physical activity, participation in school/community activities and meal/snack patterns were assessed. Additionally age, gender, height, weight, and family characteristics were determined. The authors found that pyramid scores were positively correlated to the number of meals they consumed on a daily basis. That is, more daily meals indicated a greater dietary diversity (higher Pyramid scores). The results show that for male participants, meals and snacks obtained from home increased Pyramid scores. For both males and females, fat and sugar scores were positively related to cafeteria meal and overall snack consumption (i.e. more cafeteria and snack consumption results in higher sugar fat and sugar scores). Fat and sugar scores were negatively related to self-efficacy for making healthful food decisions. Self-efficacy in healthful food decision making refers to the belief of an individual in their own capability to choose healthy food. The negative relation of self-efficacy to fat and sugar scores indicates that people with higher self-efficacy do not only believe that they are able to make healthy decisions but actually choose the healthy food (with less fat and sugar). This shows that diet choices and food choices are influenced by the internal factors gender and self-efficacy. The results hence suggest that intervention programs targeting an increase in self-efficacy may positively effect the diet.

Additionally, Neumark-Sztainer, Story, Perry and Casey (1999) investigated concrete food choices in focus-groups with adolescents. Many factors influencing food choice and barriers for eating fruits and vegetables were mentioned. The authors concluded that to help adolescents to eat more healthfully, healthful food should taste and look better and be more convenient to prepare. Furthermore it was suggested that the unhealthy options should be limited or that social norms should be changed making it more socially acceptable to eat healthfully. The authors did not specify how to make these changes.

In terms of the importance of food properties, Glanz, Basil, Maibach, Goldberg and Snyder (1998) investigated the self-reported importance of taste, nutrition, cost, convenience and weight control in food choice. They also investigated whether this was dependent on demographic groups or lifestyle choices that are related to health. There were 2976 participants in the USA who participated in two surveys. These surveys contained questions about the consumption of fruits and vegetables, fast foods, cheese and breakfast cereals. The results showed that respondents found taste the most important factor in food choice, followed by cost. There was a clear influence of demographic and lifestyle differences on the reported importance of the food choice factors. Demographic and lifestyle factors could even be used to predict the consumption of fruits and vegetables, fast foods, cheese and cereal. Lifestyle could also predict the importance attributed to nutrition and weight control. Furthermore, the importance of the food choice factors (taste, nutrition etc.) could be predicted by the types of food consumed. The authors concluded that taste and cost are perceived as more important factors than the healthfulness of the diet. Therefore, healthful diets should be promoted as being tasty and inexpensive in order to induce people to eat healthier.

Since some meals require more experience in cooking than others, cooking experience may also influence meal and food choice. Carahar, Dixon, Lang and Carr-Hill. (1999) reinterpreted data from the 1993 Health and Lifestyles Survey of England to find out how, why and when people use cooking skills. It is easy to imagine that someone who lacks the cooking skills required by a certain recipe will not easily choose to prepare that recipe. Moreover, the authors found that people are unsure of their cooking skills, which has its effect on the meal choices made. This presents another reason why some recipes are favoured over others.

In terms of personal characteristics that influence cooking behaviour, Wansink (2003) has investigated what kind of cooks exist, and how a distinction between them can be made. He found that personality most effectively differentiates between types of cooks. He distinguished four eating behaviours (personality traits) that can be attributed to ten types of cooks (for example, innovative or healthy cooks) that can be related to. The four eating behaviours are social influence (personality trait of giving, innovative, methodical and competitive cooks), inclination toward healthy behaviour (personality trait of healthy and athletic cooks), predisposition to new foods (personality trait of innovative, competitive and stimulation-seeking cooks) and eagerness to learn new ideas, i.e. new techniques or new combinations of food (personality trait of innovative, healthy and methodical cooks). This shows that there is a relation between personality and type of cook, indicating that personality can indirectly influence food choices.

Another obvious food choice factor is the religion of a person. Many religions pose constraints on the diet of believers, such as Muslims and Jews not being allowed to eat pork. Besides these food laws, (conformity to) religion also influences food choice in a social way. Just, Heiman and Zilberman (2007) investigated the influence of religion on family members' food decisions. In his study, 405 individuals who were the main responsibles for doing the grocery shopping (nutritional gatekeepers) that participated in a survey. Their families varied in income and religion (Muslims, Christians and Jews). Their religiousness was determined by a single question in which participants had to choose one of four levels of religious observance. The participants were interviewed about their meal purchases and factors influencing these purchases. Among these factors were income level, the number of family members and each member's food preferences. The results showed that in families with orthodox beliefs the husband and younger children are favoured, while in families with more secular beliefs the wife and older children are favoured. The authors conclude that children do play a role in family decisions but that this role is dependent on religious observance, age of the children, and the gender of the gatekeeper. This shows that there is an interaction between social situation and religion and that conformity to religion indirectly influences food choice.

Monetary considerations is another factor that can influence food choice. Maitland and Siek (2010) investigated how income can influence a user's food choice. They interviewed 17 participants who were primary caregivers about technology and food. Low-income participants were aware of the need for healthy food, but did sometimes not have the means, in terms of knowledge and money to provide healthier meals. Monetary considerations are also influenced by availability in supermarkets (i.e. products that are scarce are more expensive) and by seasonal information (i.e. some products are cheaper in one season than in another).

2.1.1 Food Choice Model

The factors described in the previous section can be formulated into a cognitive model, which has been done by Furst et al. (1996) and is extended by Connors, Bisogni, Sobal and Devine (2001) in the so called Food Choice model. This cognitive model can be used as a base model for the food choice process in people with diabetes.

Furst et al. investigated the food choice process by interviewing 29 adults in a grocery store setting. They asked the participants about how they chose their foods and what influenced their choices. The food choice model they created from this information is displayed in figure 2.1. It distinguishes between the life course, influences and the personal system. These factors lead to an output, the food choice.

The first element in the model is called the life course. It determines and shapes the influences that emerge in food choice situation as well as how and to what extent social and physical context influence the personal system. More concretely, this means that many things in an individual's past influences food choice today. For example, someone who comes from a low income family that watched the price of food carefully may choose food that is cheap even though they have a higher income now.

The life course is connected to the second element, the influences (i.e. factors). Among the influences on food choice Furst et al. mention ideals, personal factors, resources, social framework and food context. The first factor, ideals, depicts expectations, standards, hopes and beliefs about food choices and is rooted in culture. The factor that Furst et al. call personal factors reflect on what is meaningful for people based on their needs and preferences derived from psychological and physiological traits. They shape the boundaries of food choices and include likes, dislikes, cravings, emotions, gender, age, health status and so on. Tangible resources such as money, equipment and space are summarized by the factor that is called resources. Another factor that is identified is social framework. Examples are household food roles, power and conflicting priorities. The final factor in the model is called food context and refers to food availability and the eating situation such as picnic or barbecue. The factors described in the previous section fit in the categories that Furst et al. described.

The food choice influences are the input for the personal system which consists of value negotiations and strategies. Each individual assigns an importance to the five categories of factors involved in food choice. For example some people find it more important that the quality of the food is high and do not mind to pay a little extra for that (thus, quality is favored over monetary considerations), but for other individuals such as students with low income, this may be the other way around. Quality, monetary considerations, convenience, health and nutrition, sensory perceptions (i.e. taste, smell) and managing relationships (wishes of social surroundings) are according to Furst et al. the values that negotiate the influences and lead to an output: food choice. This is mediated by strategies, i.e. general negotiations for situations that occur often which are saved to reduce time and effort.

Connors et al. (2001) elaborate on the personal system in the food choice model. They analyzed 86 interview sessions to see how people managed food-related values. Time, cost, health, taste and social relations are the five primary food-related values. These can be related to convenience, monetary considerations, health and nutrition, sensory perceptions and managing relationships respectively in the food choice model. Variety, symbolism, ethics, safety, quality (related to quality in the food choice model) and limiting factors were also mentioned as values but were less prominent. The authors found that these values varied per person as well as per eating situation. They concluded that there are three main processes in the personal food system:

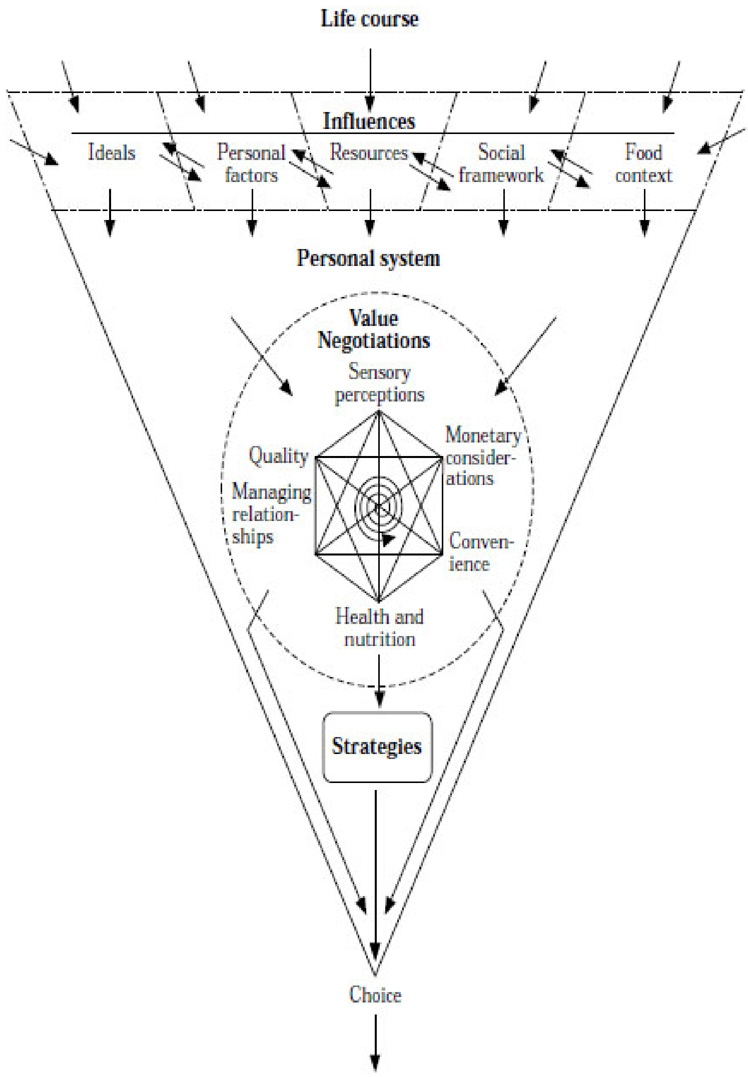

Figure 2.1: Food choice model by Furst et al. (1996)

1. Categorizing foods and eating situations. The categories were based on the food-related values. Foods were typically categorized on multiple dimensions.

2. Prioritizing conflicting values for specific eating situations. Values can be conflicting, for example people tend to think *healthy* food does not *taste* good. Individuals can prioritize one value (i.e. taste) over another (i.e. health) to determine the outcome of the food decision.

3. Balancing prioritizations across personally defined time frames. If values conflicted and one value was prioritized, the next time the other

value could be prioritized to balance the negotiations. For example unhealthy food is often balanced with healthy food over a day or week.

Furthermore, Connors et al. think that participants created prioritization schemes or strategies that tended to be relatively stable. Life changes could bring new food value food conflicts changing the existing prioritizations and balancing strategies, and eventually resulting in a different prioritization scheme for "automated" food choice (or strategy as Furst et al. call it).

This food choice model provides a scheme for how a food choice is derived. Ideally, this model can predict an individual's food choice. This prediction can be interpreted as the likeliness that a food choice will be made and can improve recommendations in a recommender system. However, it is unlikely that all information required in the model is available, as especially the life course is difficult to reconstruct completely. Nevertheless, the model provides us with a way to interpret past recipe choices. This can be exploited to formulate further recommendations.

2.1.2 Food Choice Questionnaire

Some of the influences or factors that are described in the food choice model can be determined relatively easily by collecting the relevant information about an individual (i.e. age, gender, living situation etc), the eating situation for which the choice is made and the characteristics of food items or recipes (i.e. price of a food item). Other elements such as an individual's values are less trivial to derive. Steptoe, Pollard and Wardle (1995) developed the food choice questionnaire (FCQ) that may serve as a method for estimating the values described in the food choice model. Through factor analysis on responses from 359 adult participants, nine factors on motives related to food choice emerged. These are health, mood, convenience, sensory appeal, natural content, price, weight control, familiarity and ethical concern. These can be partly related to the value negotiations in the food choice model by Furst et al. (1996). Health and weight control can be mapped to the health and nutrition value in their model, sensory appeal to sensory perceptions, convenience to convenience, and price to monetary considerations. Quality and managing relationships are not found as factors in the food choice questionnaire. In the questionnaire, people are asked to score items of the form *"It is important to me that the food I eat on a typical day is. . . "* for elements such as *"nutritious"* and *"easy to prepare"* on a six-point scale where 1= strongly disagree and 6= strongly agree. This scale quantifies the values such that they can be used in a mathematical calculation of the negotiations in the food choice model.

2.1.3 Promoting healthy eating

We can conclude from the literature summarized in the previous sections that religion, cooking experience, gender and self-efficacy are only a few of the factors influencing food choice. These factors can limit people in making healthy decisions. Unhealthy food decisions are the cause of unhealthy eating habits in people that develop diabetes. Improving these food decisions will improve the eating habits and may be beneficial for people with diabetes. There are several ways to influence food choice and to improve eating habits, but not all of them are equally effective.

One way to improve eating habits is by providing nutritional information. However, general nutritional education is not sufficient (Bodenheimer, Lorig, Holman & Grumbac, 2002; Bodenheimer, MacGregor, & Sharifi, 2005; Harris, Petrella, & Leadbetter, 2003; DeWalt et al., 2009; Williamson et al., 2009). Unhealthy eating habits usually are a matter of unbalanced nutritional intake. Bouwman (2009) investigated the idea of personalized nutritional advice. She developed a way to personalize nutritional information by assessing the genetic make-up of individuals. The exact needs in terms of nutrition were determined based on this genotype and communicated through an ICT application. However, the contribution of this personal advice to behaviour change has not been investigated.

Another way for improving eating habits is by simplifying the food choice. Gros (2009) reported that the current food environment is particularly challenging if a user has the intention to change towards or maintain a healthy eating behaviour, since there are so many unhealthy, but easy options that it takes much effort to find the healthy options. To model behaviour change in light of this complex environment with many options, she was guided by the theory of planned behaviour (Ajzen, 1991). She argued that a decision support system such as a recommendation system can reduce the gap between intention and behaviour (Sheeran, 2002). She investigated whether a simple colour coded health indicator had a positive effect on eating healthfully. This was done in a longitudinal field study in which 44 participants were asked to use either an electronic agent or the printed cookbook (both with the health indication) to select, prepare and eat healthy meals on a daily basis for two weeks. She found that both tools were successful in improving healthy eating behaviour compared to the self-reported pre-trial measure.

The recipe advice service agent in Gros (2009) presented mechanisms to navigate through the collection of recipes in a meaningful and inspiring way, but did not actively suggest recipes. By adding such functionality, van Pinxteren (van Pinxteren, 2010) changed the system from a recipe search system to a recipe recommender system. The recommendations were aimed at improving variety in main meals. This is based on the finding that people often express the need to have more variation in their evening meals but find this difficult to do because they have busy lives and changing eating patterns costs time and effort (Twigt, 2009). Van Pinxteren developed a similarity measure to rank recipes according to their similarity to past recipe choices. Meals were suggested that were close to the user's normal eating pattern, reducing time and effort in cooking, since the recipe is already familiar. In a small experiment 6 participants were asked to choose between four recipe suggestions every day for a week. Additionally, they were asked to provide reasons why they did or did not choose recipes. The recipe most similar to the normal pattern (according to the measure) was not always perceived as satisfactory. The participants mentioned season, taste, and what was eaten the day before as reasons for not choosing the recipe. However, the most similar recipe was still prepared often. This may mean that the similarity measure is useful but may need some improvements.

This literature has led to some insight in the food selection process. We wish to see whether the food choice model is sufficient for modeling the food choice process in people with diabetes as well as whether we can use the food choice questionnaire to predict food choices of these people. This has been investigated in the interview study described in the next section.

2.2 Interview Study

In this interview study and by the tasks that are part of the interview sessions, we wish to explore whether the food choice determinants/factors found in literature are important for people with diabetes and whether there are additional factors that play a role. Additionally, we try to validate the FCQ as a means of predicting participant's food choices. We expect that the food choice questionnaire gives a reasonable estimation of importance of food choice determinants and can serve as a means to predict food choices.

2.2.1 Method

Participants

On several diabetes-related sources on the internet ads were placed asking for an individual interview session with the nutritional gatekeeper (main responsible person for food choice/preparation) of families with at least one person having diabetes type 2 that would like to eat healthier. Three persons responded to this advertisement, four more candidates responded through word-of-mouth advertising. After additional information was given, such as that the participants were required to fill out a food diary for two weeks, six participants (two men and four women) were included in the research. These participants were the nutritional gatekeepers of their families and had diabetes themselves. They were diagnosed with diabetes 4-9 years ago (between 2001 and 2006). Their ages ranged between 46 and 71. Four of the participants received additional education after high-school (MBO or

HBO). All participants received a reward in the form of a gift certificate of 20 Euros for taking part in this research. They were informed about their right to stop their participation at any time.

Procedure

All participants were visited at their own home. The complete interviews took between 45 and 75 minutes. The interview started with some questions about the influence of medication on food choice, the influence of Diabetes on eating habits, current eating habits and the influence of Diabetes on food choice. These questions were followed by 5 tasks.

In the first task, participants were presented with 17 factors that might influence food choice for the main meal, guided by the food model of Furst et al. (1996). The factors were explained and the participant was asked to sort these factors in three rows. The first row contained the factors they found important in the described situation, the second row contained those that were a bit important and the last row those that were unimportant or irrelevant. Pictures were taken of the ordering of factors. The participants were presented with 5 situations for which they had to sort the factors. These situations were:

1. main meal during the week
2. main meal in the weekends or holidays
3. going out for dinner
4. eating at friends
5. having visitors for dinner

For the second task, each participant received a personal selection of recipe cards (see materials). This was made up of the recipe cards made from the dishes they described in their food diaries, plus for each of those dishes a matching recipe from the Dutch food centre that had a similar price and cooking-time, but an opposite amount of carbohydrates. For example if the own recipe was low in carbohydrates (< 30 grams) the matched recipe was high in carbohydrates (> 30 grams) and the other way around. Some of the own recipes were ill-suited for the task and were excluded. In total 26-28 recipe cards were used in this task (13 or 14 recipe pairs). The participants were given two matched recipes at a time and were asked to pick the one they would like to cook.

For Task 3, 4 and 5, the participants were again presented with a personal selection. These included their own recipes and for each of these recipes the most similar one from the food centre (according to the measure provided by Van Pinxteren (2010)). Some of the recipes were ill-suited for the task and were excluded. Also, for some recipes, the most similar one from the food centre was in fact the same, which further reduced the number of recipes used in these tasks to 22-26 recipe cards per task.

In Task 3 the participants were asked to score the given recipes on a 7 point Likert scale of attractiveness (1=very attractive, 7 = very unattractive). For Task 4 they had to score the recipes on a 7 point Likert scale of healthfulness (1=very healthy, 7 = very unhealthy. Finally, in task 5 the participants were asked to make a meal-plan for the coming week (Monday – Saturday).

After completing the tasks, some final questions were asked about requirements for recipe recommendations and requirements for a system for recipe recommendations. For a complete overview of the questions asked see appendix B (in Dutch).

Material & Stimuli

Before taking part in the interview session, participants were asked to keep a food diary for two weeks. This food diary was a booklet in which participants were asked, for every main meal over a period of two weeks, to describe the dish in terms of its ingredients (see Appendix A for the (short) version of the booklet in Dutch). For every meal they were also asked why they chose this meal. Additionally, They were asked to provide ratings on 7 point-scales (1= not at all, 7 = very much) on whether they liked the dish, whether it was cheap, easy and fast to prepare, how often they prepare the dish, whether it fitted the season, whether ingredients were already available or in discount, and whether they craved for it.

Additionally, the booklet contained some general questions about age, education, how long they have had diabetes as well as eating and shopping habits. The Food Choice Questionnaire (Steptoe, Pollard & Wardle, 1995) was translated into Dutch and included in the booklet and was used to get an indication of the importance of several food choice related factors for the participants. This information was used to predict recipe choices that the participants were asked to make during the interview session(see section Procedure for additional information). Prediction was based on the optimal FCQ-scales for people from Belgium, as described in Eertmans, Victoir, Notelaers, Vansant and van den Bergh (2006)

During the interview participants were asked to choose recipes several times (see section Procedure for additional information). For that purpose 195 recipe cards were created. Of these recipes, 111 came from the Dutch food centre (“het Voedingscentrum”), an organization that stimulates healthy eating. These recipes contained information about the number of calories in the dish, the amount of carbohydrates (in grams) and the amount of fat (in grams). The remaining 84 recipes were collected from the food diaries of the participants. Estimation of calories, carbohydrates and fat for these recipes were made using the “Eetmeter” (food meter) provided online

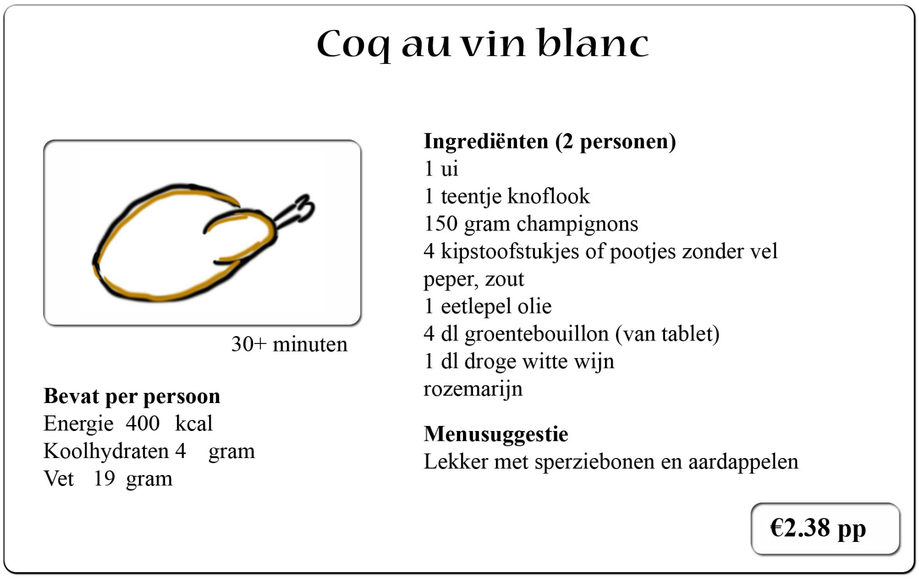

Figure 2.2: Format of the recipe cards in the interview sessions

by the food centre. All recipe cards had the same format, as shown in figure 2.2. Price indications were estimated from the sum of the ingredient-prices found in the webshop of Albert Heijn. The price indicated the price per person of the dish.

Selections of recipes to be presented during the interview were made for each participant individually. The recipes included their own recipes as they described in their food diaries. Each of these recipes was matched to the closest recipe from the set of recipes from the food centre. The distance between recipes was calculated using the similarity measure developed by Van Pinxteren (2010). He used a food ontology and a food hierarchy to automatically parse ingredients into feature values that can be used in the similarity measure. The ontology and hierarchy were adapted such that all ingredients used in the current recipe set were recognized by the parser. The similarity measure was then rescaled and reversed so a score between 0 and 1 was produced, in which 1 means that two recipes contained exactly the same features i.e. are as close as possible to each other and 0 means that all features were opposite to each other.

The interview-sessions were recorded with a Philips voice recorder.

2.2.2 Results

Six people with diabetes took part in the interview. In this section the answers of the participants on the questions asked in the interview are summarized. Additionally, an overview of the results from the tasks is presented.

The section is divided into subsections related to the specific topics of questions or tasks.

Medication

The interview started with some questions about medication. Two of the participants were dependent on insulin injections throughout the day, two of them used pills in combination with insulin injections before going to bed and two of them used pills only. The participants using insulin before/after every meal reported to have a fixed scheme for the injections. One of them sometimes deviates from this scheme when she eats more than usual or when she is more active. The other participants reported that their medication was independent of food intake.

Lifestyle Change

In terms of lifestyle change with regards to eating behaviour, four of the participants actively lost weight after being diagnosed with diabetes. They usually began to eat more vegetables and fruits and less fat. They avoided sauces and tried to use low-fat products. Two of these participants reported to have been told to drink milk (which is said to help in controlling blood glucose levels). Some of them also reported to watch the carbohydrates in their meals. One participant reported that he primarily changed his portion sizes when he learned about his diabetes. He ate less of the carbohydrates and more of the meat and vegetables. He also reported to try to eat less fat. The last participant did not yet know how to cook before learning about his diabetes. He learned from scratch how to cook and plan meals in a healthful way. He joined a dieting-club for learning to cook and also lost a lot of weight.

Most of the participants did not report to have had much difficulty in changing their eating habits. It was a matter of getting used to, they said. All of them reported to like vegetables which made it easier for them to stay away from the carbohydrates and fats. Most of the participants also had an extra motivation for eating healthfully such as a heart problem, a family member with a heart problem or a family member that already had diabetes. One person only started to change his behavior when he had to start injecting insulin (in the evenings).

The participants would advise other people with diabetes to look for things they like and that fit the diabetes prescriptions. They have to find a way to change their eating habits without having the feeling that one is on a constant diet. One person reported that recipes can help with this. Another advice is to start by preparing familiar meals in a more healthful manner. Some of the participants reported that it's all about balancing, so it's okay to take a cookie sometimes as long as you keep the balance throughout the day. Eating fewer carbohydrates is also mentioned, and consulting with a dietician or diet club is said to help.

All participants reported to be quite satisfied with their current eating habits. They think they have enough variation and that they are well aware of the healthfulness of their meals. Two of them saw possibilities for improvement. For example one person reported to want to have more variation in his meals, but that this would be too expensive because only a limited amount of products are affordable in some periods of the year.

Blood glucose and food choice

The participants did not notice any direct influence of their blood glucose level fluctuations on their food choice. Some reported that if they went grocery shopping with a low blood glucose level they were more likely to buy unhealthy products. They tried to avoid that. Low blood glucose levels did affect the "hungry-feel".

Some participants reported that they would choose something that is easy to prepare (for example from the freezer) when they feel less motivated to eat healthy, but that this did not happen very often. One person reported to have observed that people injecting insulin are less motivated to eat healthy since they can easily change their medication. One of the participants who injected insulin indeed reported changing her medication when she wanted to eat something less healthy

Food planning

Most participants would eat the same thing as their partners, although sometimes there was a slight difference in portion sizes (for example fewer carbohydrates for the person with diabetes).

Concerning week plans, most of the participants did not want to eat the same recipe on two consecutive days. For some it is an option to eat the same recipe twice a week (if there are enough leftovers), for some there should be at least a week in between. Most participants said not to have many leftovers and they throw them away if they do. One person reported to have a specific "French fries" day. Some of the participants tried to eat fish at least once a week, but other than that they reported not having such structures in their meal plans.

Most participants reported that they would like a recommended week plan to follow these guidelines:

1. Should be varied
2. Should have enough vegetables
3. Should not contain much saturated fat

4. Should not contain too much carbohydrates (but is also managed by participants themselves trough portion sizes); too few carbohydrates is also not good for people injecting insulin according to one participant

Specific ingredients that should be avoided are also mentioned, as well as preparation constraints for specific days (i.e. "something easy on Tuesdays").

Recipe recommender

Not all of the participants used computers for meal inspiration in the form of recipes. Four of the participants would be interested in a computer system and would use it on a day that they have the time to spare and/or want to try something new.

A computer system should take into account specific activities during the week (planned events) that influence available time to cook. Furthermore, participants would like to give feedback on the recommendations, preferably in natural language (Dutch). Some participants would like a (week) planning feature, others would not use it. Some report that it would be nice to enter ingredients that they want to cook with. The recommendations should not include too much difficult-to-get ingredients or be too complicated. Also it would be nice if it takes the season into account.

Other ideas about a recipe recommender are:

1. It should include a "motivator" to stimulate people to use the system and eat healthy

2. It should be able to adapt recipes or provide suggestions about replacement of ingredients if these ingredients include things they don't like, in the case that they do like the overall idea of the recipe. For example "in this recipe you can replace chicken with tofu".

3. It should be able to keep track of insulin injections

Task 1: Food factor importance

In the first task, participants rated several factors involved in food choice on importance. From table 2.1, we see that overall taste, amount of vegetable and number of carbohydrates are often rated as important. Fat is important to a lesser extent. Number of calories is not found to be important. The season, as well as familiarity of the recipe and how the dish looks is on average rated as a bit important.

We also see that all factors become less important when eating at a friend's house. The scores themselves vary but it seems that the ordering of the factors is relatively stable (i.e. amount of vegetables, carbohydrates and

Table 2.1: Average ranking of factors: 1= important 2= a little important 3= not important/not relevant

	Week	**Weekend**	**Going out**	**Eating at friends**	**Visitors**	**Total**
Time	2.5	2.83	3	3	2.5	2.77
Price	2.33	2.33	2.17	3	3	2.57
Ease of preparation	2.67	2.17	2.67	3	2.17	2.53
Taste	1.5	1.5	1.17	2	1	1.43
Number of ingredients	2.17	2.17	2.67	3	2.33	2.47
Techniques	2.5	2.5	2.83	2.83	2.83	2.7
Familiarity	2.17	2.17	2.33	2.67	1.33	2.13
Family/Friends	2	2	2.67	2.33	1.5	2.1
Scent	2.33	2.33	2	2.5	1.5	2.1
Looks	2.17	2.17	1.67	2.33	1.67	2
Fat	1.67	1.83	1.83	2.5	1.83	1.93
Carbohydrates	1.17	1.33	1	2.5	1.33	1.47
Energy (calories)	2.33	2.33	2.33	2.83	2.33	2.43
Amount of vegetables	1	1	1	2.33	1	1.27
Season	2.17	2.33	2.33	2.5	2.33	2.33
Ingredients in home	2.17	2	3	3	2.67	2.57
Availability in supermarket	2.33	2.5	3	3	3	2.77

taste are in the top of important factors in all situations). Familiarity of a dish seems to become important when visitors come over to eat.

Task 2: Food choice prediction

In the second task, participants were asked to choose, for a series of matched recipe-pairs, their favourite recipe from each pair. The results of the food choice questionnaire (FCQ), that was part of the food diary, showed that healthfulness of a recipe was more important than familiarity for these participants. These were also the factors that were manipulated in the selection of the recipe-pairs and provided us as such with a prediction of what recipe would be chosen. In this manipulation, based on a dietician's advice, a healthy recipe was one with less than 30 grams of carbohydrates per person. In only 48% of the presented recipe pairs the familiar recipe was the healthy recipe, showing the possibility to improve eating habits. In 62% of the pairs the FCQ provided a good base for a prediction of the choice (i.e. the chosen recipe was the healthy recipe) of which 14% was not familiar. However, in 65% of the cases the participant chose the familiar recipe (their own recipe) of which 17% was not the healthy choice, showing a tendency to choose familiar recipes over healthy recipes.

Task 3 and 4: Perceived attractivenes and healthfulness of recipes

In task 3 and 4 the participants were asked to rate recipes on their attractiveness and health, respectively, in a 7-point Likert scale with 1 meaning very attractive/healthy and 7 meaning very unattractive/unhealthy. The results in table 2.2 show that every participant rated familiar recipes as more attractive than new ones. On average, familiar recipes are also rated as more healthful than new ones, but participants' opinions on this aspect differ quite a lot.

Table 2.2: Average scores on attractiveness (A) and healthiness (H) for familiar and new recipes

Participant	1		2		3		4		5		6		Mean	
	A	**H**	**A**	**H**	**A**	**H**	**A**	**H**	**A**	**H**	**A**	**H**	**A**	**H**
Familiar	2.31	2.15	2.07	2.29	2.29	2.29	2.54	2.77	1.71	1.57	2.43	2.85	2.22	2.32
New	2.42	1.77	3.17	3.17	3.00	2.30	3.78	3.44	2.75	2.67	3.18	2.45	3.05	2.63

Food planning

In the final task, participants created a week-plan from the recipes used in task 3 and 4. They used primarily familiar recipes for their plans, half of the participants did not include any new recipes in their plan. Furthermore, most recipe-choices were rated as attractive and healthy (table 2.3). Sometimes concessions were made on the attractiveness of recipes to eat healthful. However, half of the participants made a plan that contained on average more than the advised 30 grams of carbohydrates per person.

For some participants, making the week plan seemed rather arbitrary. It seemed that there was a preference to pick recipes they saw first, rather than to choose recipes that fit a plan of what a week should look like. For some participants specific activities during some weekday influenced the meal choice for that day. Habits and variety of the diet also played a role.

2.2.3 Conclusion

The factor-sorting task (task 1) indicated that the most important factors for people with diabetes are number of carbohydrates, amount of vegetables and taste. These factors can be used as an indication for attractiveness of a recipe. Fat, season and familiarity of a recipe are important to a lesser extent, but should also be included in an attractiveness-indication. This is confirmed by the comments during the recipe-choice task and plan-task.

Table 2.3: Average scores on attractiveness (A) and healthiness (H) in the week plan

Participant	**1**		**2**		**3**		**4**		**5**		**6**		**Mean**	
	A	**H**	**A**	**H**	**A**	**H**	**A**	**H**	**A**	**H**	**A**	**H**	**A**	**H**
Monday	4	1	2	3	1	1	5	3	1	1	1	1	2.33	1.67
Tuesday	4	1	1	2	4	2	2	2	5	1	4	2	3.33	1.67
Wednesday	1	1	2	2	2	3	2	3	2	1	2	4	1.83	2.3
Thursday	1	2	2	2	2	2	2	2	2	1	1	2	1.67	1.8
Friday	2	3	2	2	2	2	3	5	2	1	4	2	2.5	2.5
Saturday	2	4	2	2	2	2	2	3	2	2	1	3	1.83	2.67
Mean	2.3	2	1.83	2.17	2.17	2	2.67	3	2.33	1.17	2.17	2.33	2.25	2.11

From these, we additionally learned that timing, price and calories also play a role. Another important finding for the recommendations is that people do not want to eat the same/similar dish two days in a row. For most people recurrence of recipes is acceptable after more than six days.

Since participants reported that they were satisfied with their current eating habits and the healthfulness of them, they appear to be unaware of any room for improvement. This is corroborated by the strong tendency to favour familiar recipes over new ones. However, the results from the food diaries showed that only half of their own food choices contain a healthy amount of carbohydrates, and the familiar recipes favoured over the new ones are not necessarily healthier. This indicates that current food choices of the participants may be confounded by factors other than objective healthfulness.

With regard to the role of attractiveness in food choice, in the sorting tasks participants often mentioned that they found it difficult to distinguish between (un)attractive and even more (un)attractive, although attractive was easy to distinguish from unattractive. This suggests that a recommender system should focus on learning what is unattractive and filtering that out, rather than trying to find the most attractive choice. Attractiveness in this study is not limited to what is tasty, but whether a recipe is attractive to prepare. A recipe can for example also be attractive because it is easy to prepare or cheap.

Our hypothesis was that the Food Choice Questionnaire could serve as a base for predicting food choices. However, it turned out to be difficult to relate the week-plan choices to the importance values coming from the food choice questionnaire. Although all participants scored relatively low on familiarity in the FCQ, they still chose a familiar recipe in the majority of cases. And again, some participants specifically mentioned to choose certain recipes because they were easy to make although they scored very low on ease of preparation in the FCQ. Although the FCQ provided a higher than chance-level prediction for recipe choice in task 1, the FCQ assumes a consistent ordering in the food choice factors. This seems to be too strong an assumption for prediction of recipe choices in day to day recommendation, i.e. it is not likely that an individual would choose the healthy recipe consistently. It also seems that the FCQ not so much measures the actual food choices people make, but rather what people would ideally want their food to be like. In fact, people overestimate the quality of their choices. For example, they think they eat healthier than they actually do.

An explanation for this latter observation may be provided by construal level theory (Trope & Liberman, 2010). This theory suggests a distinction between abstract and concrete mindsets. Since the food choice questionnaire contains questions about general food wishes and choices, people are in a more abstract mindset, which entails that they think mostly about positive aspects. In the tasks people were asked to make actual decisions. This brings them in a concrete mindset in which they focus more on the concrete limitations of choices. So, for example, people in their abstract mindset may say that they do not mind to cook recipes that take a while to make, but once they have to make the concrete decision they are more aware of barriers such as work or sport obligations that prevent them to actually cook recipes that take more time.

This would mean that the Food Choice Questionnaire is not useful in predicting which recipes a person is actually going to choose to prepare. However, it may still be useful in providing a general indication about what an individual would like their food to be. The factors identified in the FCQ may be used as features in the recommender system.

The recommender system is meant to support healthful eating. Therefore, it seems insufficient to merely model likes and dislikes of a user in a recommender system. The focus in the recommender system will be on providing suggestions that will actually be prepared. In the next chapter we will describe a quantitative study in which we investigated why people do not want to prepare certain recipes. These reasons are translated into features for the recipe and user models in the recommendation algorithm in chapter 4.

Chapter 3

Identifying food choice constructs

By interviewing people with diabetes as described in the previous chapter, we have gained insight in how these people make their food choices. We have learned what they look for in recipes and what makes recipes attractive. We found that the participants found it easier to distinguish between attractive and unattractive recipes rather than between attractive and more attractive recipes. Unattractive recipes are not likely to be prepared by an individual and should thus be avoided in recipe recommendations. However, we do not yet know what other reasons there are that makes recipes unattractive to prepare. In the small scale internet based experiment described in this chapter, we investigate reasons for preparation-unattractiveness of recipes by eliciting negative responses to recipes. We provide participants with potentially unattractive recipes, and ask them to indicate why they would or would not want to prepare the presented recipe. We focus on the reasons why they would not want to prepare a certain recipe. These can be exploited in the recommender system as indicators for unsuitability of a recipe for recommendation.

3.1 Method

3.1.1 Participants

Participants for the experiment were approached trough the personal contacts of the researcher. In total, 34 participants were included in the research. Since the food choice process did not appear to be much different for people with diabetes compared to healthy people, 32 of the participants did not have diabetes. By including healthy participants, more data could be collected in a shorter time. No personal information was collected other than the reasons the participants provided for choosing or not choosing a presented recipe. The participants did not receive any compensation for their participation.

3.1.2 Material & Stimuli

In total, 15 recipes were selected from the recipes provided by the food centre. They were chosen manually and on the basis that they were expected to be unattractive. Their unattractiveness was derived from the food choice model by Furst et al. (see previous chapter). For example, some recipes were very complex with many ingredients or many directions, some took very long to make, contained many calories, fat or carbohydrates or contained ingredients that were out of season (strawberries in the winter).

The recipes contained all relevant information such as the number of calories, grams of fat, carbohydrates, preparation time and of course ingredients and directions. The recipes were created using Adobe Photoshop CS2 and presented as an image on an internet page (see figure 3.1). The internet page was created using php and the data was stored in a MySql 5 database.

Figure 3.1: Screenshot of a recipe presented in the experiment

3.1.3 Procedure

Participants were asked by e-mail to participate. In the e-mail they were provided with the link to the internet page. The 15 preselected recipes were presented in a randomized order. Participants were asked to fill out whether they would want to prepare the recipe for the current day and the reason why or why not. They were asked to imagine that they were responsible for cooking that day, and had not planned anything else yet. Additionally, they had to answer the same question for a day in the weekend if the current day was during the week and a weekday if the current day was a day in the weekend. Examples are "Would you like to prepare this recipe today" and "Would you like to prepare this recipe next Saturday". It turned out that for all participants the current day was a weekday.

3.2 Results

After all data were collected, all negative answers (rejections of recipes) were collected. The reasons for rejecting recipes were manually categorized by the researcher. In total 477 rejections were made, which is 46% of all the decisions. Most recipes were rejected both for the current evening as well as for the day in the weekend. The percentage of occurrence for each reason type is presented in figure 3.2.

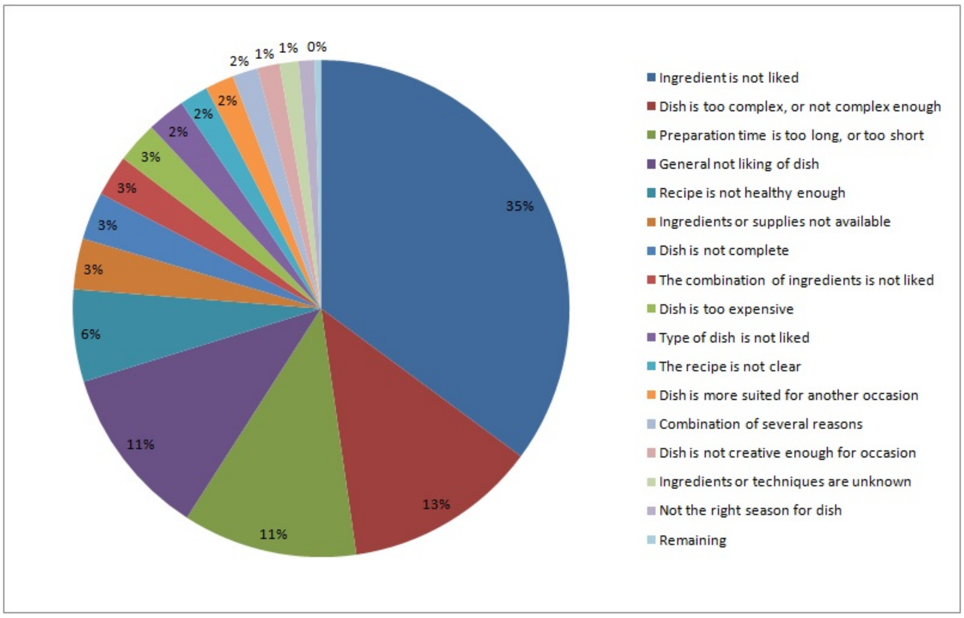

Figure 3.2: Pie graph of reasons for rejecting recipes

3.3 Conclusion

Figure 3.2 shows clearly that the most important reason for rejecting a recipe is the fact that it contains an ingredient that is not liked. Other important reasons are the complexity, preparation time and healthfulness of the dish. For the recommender system this implies that it should account for these reasons. It should be able to model the content and importance of these reasons for each user, and tailor its recommendations accordingly.

Research by Scheibehenne, Miesler and Todd (2007) suggest that it is not necessary to include all reasons for rejecting recipes in a recommendation algorithm. They compared two heuristics that predicted food choice. The first was a heuristic that compared a participant's most important food choice factors to predict the actual food choice, the other was a weighted additive model that included all food choice factors of the participant to predict the actual food choice. They found that the simple heuristic with only the most important factors was as good at predicting a person's food choices as the weighted additive model. This has led us to decide to focus on the most important reasons rather than all reasons in the recommender system: liking of an ingredient, complexity of the dish, time necessary for preparation and healthfulness of the dish. Together these factors explain 65% of the rejections that were made. Although "general dislike of a dish" accounts for another 11% of the rejections, this factor hardly means anything more than "unknown reasons"; it cannot be predicted or measured. Therefore, we will not take it into consideration in the recommender system. This factor does however show that there is a big uncertainty factor in modeling preferences of the user when it comes to recipe selection. If the user does not know why they do not like a certain recipe, how can a recommender system know? On the one hand, this may mean that a recommender recipe system might never be able to give reliable predictions. On the other hand, a recommender system might be able to find relations between recipe choices that the user is unaware of (i.e. the unknown reasons).

As suggested before, there may be a difference between liking a recipe and going to prepare a dish. A limitation of this study is that we did not ask participants to actually prepare the dishes. It is possible that, although we have asked them specifically to report whether they want to prepare the dish or not for a specific day, they were still more focused on the liking of the dish, rather than preparation barriers. This may affect the frequency estimations. Additionally, reasons for not choosing recipes may have been missed if there are reasons that only surface when it comes down to actually preparing the recipes.

3.4 Implications for a recipe recommender

In chapter 2 we learned that a recipe recommender system that promotes healthy eating should recommend recipes that an individual is likely to prepare, rather than merely likes for its presentation or expected taste. It seems probable that there are multiple recipes that can serve as suited recommendations in any occasion. Rather than trying to find the most suited one, it is more important that the recommender system does not recommend an ill-suited recipe, i.e. it should filter those recipes out. One aspect that makes a recipe ill-suited is when the same recipe has already been suggested during the past week.

The factors that seem to be most important in food choice for people with diabetes are the amount of vegetables, the amount of carbohydrates and of course the taste. Additionally, fat, calories, seasonal aspects, familiarity, time and price should also be taken into account by a recommender system. However, seasonal aspects and price will not play an important role in the development of the system, since this information is not readily available for the recipes from the Dutch food centre that will be used in the recommender system.

In this chapter we confirmed that liking of an ingredient, complexity of the dish, time necessary for preparation and healthfulness of the dish are important factors for people in determining whether they want to prepare a recipe or not. This implies that these factors should play a dominant role in a recipe recommendation system.

Additionally, we found that there is a big uncertainty factor in recipe choice, i.e. recipes are rejected for unknown (conscious) reasons ("general dislike of dish" in the figure 3.2). This means that trying to use food choice predictions as a base for a recommender system can pose problems if it cannot take "general dislike of dish" into account. One option for handling this uncertainty is to introduce a random factor in the algorithm that determines the recipe suggestion to represent any unknown reason that can cause a rejection at any time. However this makes suggestions more haphazard. In recognizing the patterns in an individual's eating habits, i.e. the consistent rejection reasons (i.e. health, time etc.), this may have a negative effect. Another option is to ignore the uncertainty and take a certain amount of rejections for granted. Rejections of suggestions can be handled on the go. We will take the latter approach. Roughly, we model the user as well as the recipe in such a way that they can easily be compared in a similarity measure such that recipes can be suggested that are close (similar) to the user representation (i.e. what the user is likely to prepare).

Chapter 4

Recommendation Algorithm

In this chapter we will combine the knowledge gained from literature and the previous studies to come up with a way to find suitable recipes for individual users. Before we describe our own approach, it is essential to see what has already been done in the area of recipe recommendation systems.

4.1 Literature

4.1.1 Collaborative vs. Content-based Recommendation approaches

There are two main streams in recommendation technology. One is collaborative filtering in which recommendations are based on the choices that people with a similar profile have already made, i.e. people with a decision history x tend to choose y, thus if an individual has a decision history similar to x than this individual is likely to choose y. The attractiveness of this approach is that the decision-making data of the whole community is exploited, instead of having to rely on reasoning about the content of the options. A downside is that it relies on the assumption that similarities in decision history lead directly to similarities in new decisions. In some recommendation areas this assumption may not be valid because interfering influences may exist that are not taken into account. Furthermore, when there is not enough decision data, collaborative filtering will produce poor results because people cannot reliably be matched to each other.

In content-based recommendation, a second important approach in recommendation technology, a recommendation is based on the content of the options, i.e. person x thinks y is important, option z satisfies y, so option z is suited for person x. It may be difficult to determine which factors are important for the decision, which is a downside. However, this approach can present an individual with suited recommendations even if there are no decision data.

In this thesis we want to recommend recipes to people with diabetes. Recipe selection is a difficult decision-making process for them which includes many personal factors and is also very much affected by the specific situation. One suggestion can be perfect on one occasion and ever so bad the next day. This is because recipe recommendation is not only a decision on whether you like the dish, it is more importantly a decision on whether you want to, and are able to prepare the dish. Recipe selection is not merely dependent on one person's preferences, but often on the preferences of the complete household. The composition of this household can vary over situations. The question then is, which recommendation approach (collaborative or content-based) is best suited for this purpose.

In collaborative filtering it is assumed that users can be categorized in relatively stable and consistent prototypes with respect to decision history. However, in the case of recipe selection, there are two issues casting doubt on that assumption.

One issue is, as said before, that recipe selection is very much situation dependent, which means that a recommendation should also be situation dependent. In collaborative filtering, influence of situation is typically not taken into account, since this would involve reasoning about the situation, i.e. in situation z, people with decision history x tend to choose y.

Another issue is that in recipe selection, dislikes of ingredients are more important than likes of ingredients (i.e. recommended recipes with disliked ingredients are usually rejected, but recipes with liked ingredients are not necessarily accepted). Moreover, recommended recipes need to comply with likes and dislikes of the complete (possibly varying) household, as well as comply with nutritional needs and wishes and fit the experience of the cook. The composition and values of these dimensions are likely to vary over situations in individuals or households, making it complex to compare them to other individuals and households. Therefore, modelling similarities in terms of similarity in decision history between individuals and households seems too simplistic to capture all the variations that occur within the individuals and households.

Moreover, literature by Freyne and Berkovsky (2010) suggests that content-based methods are better for recipe recommendation in terms of prediction accuracy. They compared several recommender strategies for personalized recipe recommendation including content-based, collaborative filtering and hybrid approaches. Specific strategies were based on food item ratings (ratings of liking of a single ingredient), food item ratings in combination with ratings on food items by neighbours, collaborative filtering on entire recipe ratings, recipe ratings that are decomposed into food item ratings, and two hybrid approaches based on recipe ratings and food decomposition. The methods were evaluated in a leave one out analysis. The methods were trained with actual ratings by users. One user-rating was left out. By predicting the left out rating, comparing it to the actual rating and repeating this process until each rating was left out once, the authors obtained an accuracy of prediction scores. The authors found that collaborative filtering techniques do not have better accuracies than content-based methods and collaborative filtering techniques do not improve results much in hybrid methods.

Additionaly, Svensson, Höök and Cöster (2005) found that only 18% of the recipes recommended by their collaborative filtering approach were actually chosen. They tried their system Kalas which used a combination of recipe recommendation and social navigation in a long term experiment of 6 months with 302 users. They evaluated their recommendation algorithm from the perspective of user acceptance. Although the recommendations should have become better in the end of the experiment, the amount of recommended recipes that were accepted by the users did not increase towards the end of the experiment.

4.1.2 Content-based recommendation for recipes

In light of the limitations of collaborative filtering methods on user and situation modelling with respect to recipe selection we have decided to take a content-based recommendation approach. In content-based recipe recommendation technology most approaches aim at menu-planning or combining meals in daily or weekly plans such that dietary constraints are met. Several algorithms have been investigated for this purpose, a number of which will be discussed concisely below.

Cox and Fox (2000) implemented a nutritional meal planning system in which they exploited the routine decision making algorithm. This algorithm selects a meal plan that fulfills a person's preferences and nutritional needs. Preferences are collected through interaction with the user, who is asked to provide the necessary information. The authors tested their system with three manually defined preference profiles and report that the system creates reasonable plans but that these plans sometimes suffer from undesirable food combinations and repetition in food types.

Valdez-Peña and Martínez-Alfaro (2003) modelled menu-planning as a mixed integer linear problem (MILP) in their Exchange Diet System. The system works by translating daily nutritional requirements intro food group portion requirements which are distributed over the different courses of a menu. Personal preferences are captured by the preference-frequency function. Users are asked to rank menu-items on their taste and their frequency of serving. The sum of the total preferences for every menu-item is maximized. Models were built and solved as a mixed integer linear problem for 4 patients. Preferred items were included in the results, but proposed plans were not realistic because of small servings and incompatibility of menu-items. Therefore, the Exchange Diet System seems to be unsuited for finding plans that an individual will prepare.

Another implementation of long term menu planning was through the use of multi-objective genetic algorithms by Gaál, Vassányi and Kozmann (2005). The weekly menu-planning problem was divided in sub problems such as daily menu planning and meal planning. The fitness function used in the genetic approach entailed criteria on daily nutritional intake. Compatibility of the menu components was described through simple rules about taste and cuisine and how they go or do not go together. These rules, if applicable, provided penalties on the calculated fitness value. Their algorithm proved to be successful in satisfying the numerical constraints and omitting incompatible components.

The menu-planning approach is not focused on single recommendations, but on a series of recommendation, mostly with the purpose to make sure that nutritional constraints are met over a day or a week. A second approach in content based recipe recommendation is not to combine meals, but to adapt individual recipes to fit the needs of the user.

Petot, Marling and Sterling (1998) modelled the reasoning of an expert dietician to assist menu planning. They evaluated and compared a rule-based and a case-based system by running them on a variety of test cases. Both systems were able to adapt menus automatically to suit the user's preferences. Results showed that the case-based system was good in satisfying nutritional constrains, while the rule-based system was more creative in combining food elements. A hybrid system was implemented that proved to combine the strengths of the two systems.

Zhao (2007) interpreted menu planning as a combinatorial optimization problem and used an evolutionary approach for finding good plans. She included as evaluation criteria among others price of the recipe, time necessary to cook and liking. However, the algorithm was not explicitly tested.

Ihle, Newo, Hanft, Bach and Reichle(2009) implemented a rule-based recipe advisor. Their system was built to find single recipes. The system, called CookIIS, modifies recipes according to the user's specification. The system is able to find recipes given specific criteria. If the recipe base is not large enough to provide a recipe for all preferences, the system adapts a similar recipe via a set of rules. This enables CookIIS to find recipes meeting all constraints, however it is unclear how an actual user perceives the recipes.

4.2 Recipe Recommendation Algorithm

We have chosen to take an approach different from menu planning and recipe adaptation. In the research described in this chapter so far, it is assumed that every recipe is suited for every occasion (be it an ordinary weekday or a special occasion) and that one recipe is favoured over another through specified preferences. We do not try to combine recipes optimally; rather we try to find the most suitable recipe for the specified situation. We assume that some recipes are more suited for a specific occasion than others, and that preferences reflect this. This makes our approach different from previous work. We focus on finding a recipe that the user will actually be preparing, rather than finding a recipe that the user likes, but is not likely to prepare. The user profile is learned implicitly, wishes and demands of the user are extracted from the decisions he or she makes for comparable occasions.

For this content-based approach we need to define which aspects of recipes are important. Our original goal was to help patients with diabetes to change their eating habits. Therefore, we need to present them with healthy recipes that fit their preferences and are likely to be prepared. Recommending recipes that are similar to familiar recipes are more likely to be prepared because it reduces the effort to prepare them. Additionally, the studies in chapter 2 and 3 have provided us with the food factors that can represent user preferences.

We have chosen to represent a recipe as a vector of a combination of numerical and binary features. A user profile is represented by seven recipe prototypes, one for each day of the week, in combination with seven weight-vectors, one for each day of the week. The matching algorithm is an adaption of the similarity measure by Van Pinxteren (2010). The matched recipe is the recipe closest to the average of the recipe prototype for that day that also meets the constraints.

In this chapter we will describe in more detail how recipes and users are represented and how they are matched to each other to find those recipes that fit a user's preferences and are likely to be prepared. By recommending only recipes from the Dutch food centre ("voedingscentrum") we ensure that the recommended recipes are also healthy.

4.2.1 Recipe representation

The first step is to create a representation of the recipe. We are guided by the work of van Pinxteren (2010). He developed a similarity measure for comparing recipes. The measure was a Euclidean distance measure that calculated the distance between two feature vectors. The features were selected based on sorting tactics in the recipe sorting task he conducted with 14 participants. This resulted in the selection of 55 binary features (i.e. the feature is present or not) divided over 14 feature groups. For a complete overview of the features the reader is referred to the thesis of Van Pinxteren. The feature values were automatically extracted from the recipes using a recipe parser.

We represent a recipe by a vector of 29 features, divided over 6 feature groups, as shown in table 4.1. Part of the features is a subset of the binary features that Van Pinxteren used for his recipe representation. Our selection is based on the generality of the features; i.e. rice is included as a feature, but the distinction dry-boiled vs. soft-boiled rice has been removed. The choice for general rather than specific features was made to reduce the number of features (and therefore reduce the problem of data sparseness). Additionally, general features are more applicable to the user-model domain. We model a user in terms of a recipe prototype (see next section), which makes it important that the user can be described in terms of the recipe features. Modelling users in terms of how often they choose dry-boiled rice would seem to be overly specific.

On the other hand, several numerical features related to time, complexity and health that were not used in the work by Van Pinxteren are added to the feature set. These features were found to be important during the interviews with the target group and in the determination of the food choice constructs (see chapters 2 and 3).

Table 4.1: Overview of selected features

Group	**Features**	**Feature type**
Time	preparation time	Numerical
Complexity	# ingredients, # direction lines	Numerical
Health	grams of carbohydrates, grams of fat, number of calories	Numerical
Type of dish	soup, salad, stamppot, pastry, rice, pasta, potatoes	Binary
Origin of dish	Dutch, French, Mediterranean, Italian, Spanish, Greek, Eastern, Chinese/Indonesian, Indian, Mexican, Thai, Japanese,	Binary
Main ingredient(s)	meat, fish, poultry, vegetarian	Binary

Although this selection of features does not cover all possible reasons for not choosing recipes, this does not have to be a problem as Scheibehenne et al. (2007) pointed out: *"a simple lexicographic heuristic that only considers each participant's most important factors is as good at predicting food choices as a weighed additive model that takes into account all factors"*.

Definition 1: Let $R = \{r_j\}$ be the set of available recipes. A recipe r_j can be written as a vector of feature values: $r_j = (\ f_0, \ldots,\ f_{28})$

4.2.2 User representation

People in general, and people with diabetes in particular, seem to find it difficult to deviate from their normal patterns in eating. It takes much effort to find new recipes and to add them to their usual repertoire. This is something also found by Twigt (2009). People report to want to eat in a more varied way, but with as little effort as possible; i.e. it has to feel familiar, thus variations on what they normally eat. For this purpose we take the approach to model users according to their eating pattern throughout the week to get an overview of what is familiar. This pattern is determined by the recipes the user accepts (chooses to prepare) and rejects per day. Each user is represented by seven recipe prototypes (one for each day of the week) created from these choices and seven weight-vectors (one for each day of the week) that determine the impact of the recipe features when matching recipes to users.

Recipe Prototype

Each recipe in the set of all recipes can either be accepted or rejected on a specific moment. A recipe prototype is empty, a set of accepted recipes, or a default recipe. A user profile consists of seven recipe prototypes, one for each day of the week. By separating the different weekdays it is possible to model differing situations on specific weekdays. For example, when you go to the gym every Tuesday so you have little time to cook and also want to have a lighter meal, these features will be more prominently represented in the chosen recipes for that day than on other days. Good recipe suggestions need to take these patterns into account, which is made possible by using seven recipe prototypes instead of one.

When determining the recipe prototype for some weekday, the system can encounter the following situations:

1. No data available: When the user has not yet made any choices for that weekday, the recipe prototype consists of a predefined default recipe for that weekday. This recipe is defined by a dietician of the Dutch food centre and is the same for all users. The advantage of this method is that the start recommendation is a healthy recipe from a balanced week plan.

2. Last recipe was accepted: In this case, the recipe prototype provided a good recipe-suggestion. The recipe prototype is the series of (consecutively) accepted recipes for this weekday.

3. Last recommended recipe for that weekday was rejected:

   (a) If less than 3 rejected recipes have immediately preceded this rejected recipe for this weekday, and there is a series of accepted recipes for this day, this means that the user might have moved away from the current prototype and we need to define a new one. This new prototype is initialized as one recipe, the recipe within the current prototype that lies furthest away from the last rejected recipe. This way the knowledge of what suggestions were suited is still exploited, and variation in suggestions and the possibility to deviate from past choices is stimulated.

(b) If this rejected recipe is part of a series of 3 or more consecutive recipes that were all rejected or if there are no accepted recipes for this weekday, the current recipe prototype for that weekday is reset to zero (no recipes in the prototype). An empty profile leads to the suggestion of random recipes. This occurs until a new suitable recipe prototype is found. The reason for this approach is to stimulate variation in suggestions.

These situations for the recipe prototype are formalized in definition 2 below.

Definition 2: Let $L_{u,i}$ denote the set of recipe, decision pairs (decision history) for a user u on a on a day i, $L_{u,i} = \{(r_{i1}, d_{i1}), \ldots, (r_{in}, d_{in})\}$.
Let $P_{u,i}$ denote the recipe prototype for a user u on day i . Then

$$P_i = \begin{cases} \{g_i\} & \text{if } L_i = \emptyset \\ \{r_{ik} \mid (r_{ik}, \text{accept}) \in L_{u,i} \wedge \forall k' \in \{k, k+1, \ldots, n\}((r_{ik}, \text{accept}) \in L_{u,i}) \\ \{r \mid r \in P_{i\_old} \wedge \forall r' \in P_{i\_old}((dist(r', r_{in}) \leq (dist(r, r_{in}))\} \\ & \text{if } P_{i\_old} \neq \emptyset \wedge d_{in} = \text{reject} \wedge \\ & (d_{i(n-1)} = \text{accept} \vee d_{i(n-2)} = \text{accept}) \\ \emptyset & \text{otherwise} \end{cases}$$

where g_i denotes the predefined generic recipe for day i. When the last recipe is accepted, the recipe prototype consists of the last series of accepted recipes.When the last recipe (r_{in}) was rejected, but the previous recipe ($r_{i(n-1)}$) or the one before that ($r_{i(n-2)}$) was accepted, then the recipe prototype consists of one recipe: the recipe in the previous recipe prototype, that was furthest away from the last rejected recipe (r_{in}). The distance between the two recipes is determined using the similarity measure described in Section 4.3.3, Definitions 9 and 10.

Weights

Besides the recipe prototype, each user profile is also defined by 7 weight-vectors, one for each day of the week. These weights are used to increase or reduce the impact a feature has in the matching algorithm. They indicate the importance of a feature value in the choices a user makes. A weight-vector consists of weight values for each feature in the recipe prototype. Initially all weights are equal. As the number of accepted and rejected recipes grows, the weights of the features are adapted. A weight value is updated when a recipe is rejected. This event is taken as an indication that the current recipe prototype or weight for that weekday is not suited any more. In that case, the distribution of values for each specific feature is calculated both for the accepted recipes and for the rejected recipes on that weekday. If there are no accepted or rejected recipes for that weekday, no comparison can be made and the weights are set to the initial value 0.5 If there are accepted and rejected recipes for that weekday, the new weight value for that feature becomes 1 minus the overlap between the two distributions. In this way, features with a similar distribution within the accepted and to the rejected set (high overlap) get lower weights (not good discriminators), while features that have very different distributions (low overlap) between accepted and rejected recipes, get higher weights (important discriminators). This can be formalized in the following definitions:

Definition 3: A weight-vector $w_{u,i}$ for a user u and a day i can be written as a vector of weight values, one for each feature: $w_{u,i} = (wf_{f0}, \ldots, wf_{f28})$.

Definition 4: Let $W_u = \{w_{u,i},\ i\ \in 1, \ldots, 7\}$ be the set of available weight-vectors with u indicating the user and i indicating the day of the week.

Definition 5: Let A_i be the non-empty set of accepted recipes on day i and μ and σ^2 the mean and variance ($\sigma^2 \neq 0$) of feature f in the recipes in A_i, then we assume a normal distribution for the feature f for accepted recipes: $N_{A_i}(f) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(f-\mu)}{2\sigma^2}}$.

Definition 6: Let R_i be the non-empty set of rejected recipes on day i and μ and σ^2 the mean and variance ($\sigma^2 \neq 0$) of feature f in the recipes in R_i, then we assume a normal distribution for the feature f for accepted recipes: $N_{R_i}(f) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(f-\mu)}{2\sigma^2}}$.

Definition 7: If A_i and R_i are nonempty and the variances of feature f are unequal to zero then the weight wf_f in the weight vector $w_{u,i}$ of user u on day i is defined as

$$wf_f = 1 - \mathit{overlap}(N_{A_i}(f), N_{A_i}(f))$$

If A_i or R_i is empty or one of the variances of feature f is zero, the weight wf_f is set to

$$wf_f = 0.5$$

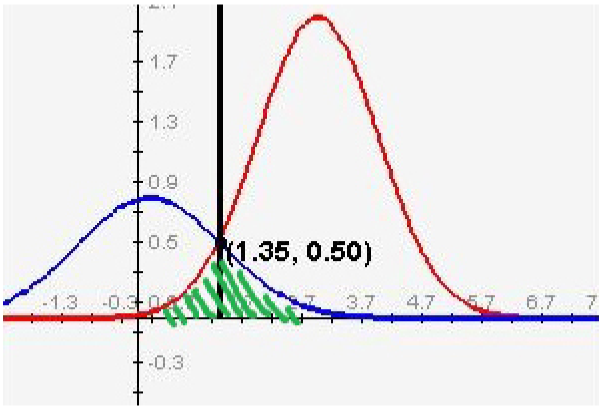

Figure 4.1: Small overlap between two gaussian distributions

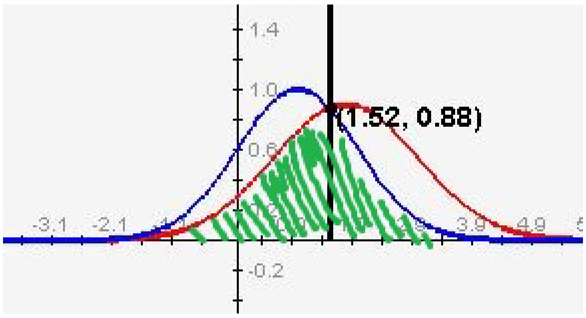

Figure 4.2: Large overlap between two gaussian distributions

With these definitions we can define a user profile as follows:

Definition 8: Let $U_u = ((P_{u,1}, w_{u,1}), \ldots, (P_{u,7}, w_{u,7}))$ be the user profile, where $P_{u,i}$ is the set of recipe prototypes for user u on day i (as defined above), and $w_{u,i}i$ is the weight vector for user u on day i (as defined above).

The average of a recipe prototype for user u with user profile U_u on day i, $\overline{P_{u,i}}$ can be written as a vector of feature values, where each value is the average of the values of that feature in $P_{u,i}$ for user u. The average of the recipe prototype allows for the convergence of accepted recipes to an estimate of wishes for that day in terms of the defined features. This average $\overline{P_{u,i}}$ is used in the matching algorithm described in the next section.

4.2.3 Matching users and recipes

We have defined a recipe and we have defined a user (profile). Now we need to find the best match between recipe and user. The user profile, defined by a set of accepted recipe clusters and a set of weight-vectors, is dependent on the week day (one recipe cluster and weight-vector for each day). The best recipe-match for a week day would be the recipe closest to the recipe prototype of the user for that day. This can be determined by taking a simple Euclidean distance measure. However, there are several problems with the features that can arise.

1. (a) Because we use a combination of numerical and binary features the numerical features can have an advantage. This is because the difference between two binary features can be at most 1, while for numerical features this can be much larger. This way a numerical feature will have a much bigger impact on the total distance
   (b) Because categorical characteristics are represented by multiple (binary) features, while numerical characteristics are only represented by one (numerical) feature, the categorical characteristics would have an unfair advantage, i.e. a bigger impact on the total distance.

How are these problems solved?

1. The first problem is handled by calculating Z-values for the feature values with regard to their distribution in the complete recipe set, and using these as feature values in the distance measure. A Z-value is the number of standard deviations from the mean to the current value. This rescales the differences between feature values to a smaller maximal difference, greatly reducing the difference in impact of a numerical feature compared to a binary one.

2. The second problem is handled by defining 6 factors (groups of features that together represent the value of one characteristic). Distances between a recipe and a recipe prototype are determined per factor and the total distance between a recipe and a recipe prototype is the average of the factor-distances.

We can describe the distance between a recipe r and a recipe prototype $\overline{P_{u,i}}$ with $w_{u,i}$ being the corresponding weight vector in the user model as

$$\begin{aligned} dist(r, \overline{P_{u,i}}) = \; & \tfrac{1}{6}(dist_c(r, \overline{P_{u,i}}) + dist_t(r, \overline{P_{u,i}}) + dist_h(r, \overline{P_{u,i}}) + dist_o(r, \overline{P_{u,i}}) + \\ & dist_y(r, \overline{P_{u,i}}) + dist_m(r, \overline{P_{u,i}})) \end{aligned}$$

where we distinguish 6 partial distance functions for 6 different groups: complexity ($dist_c$), time ($dist_t$), health ($dist_h$), origin ($dist_o$), type of dish ($dist_d$), and main ingredient ($dist_m$). Lower distances indicate a better match between user and recipe. The partial distances are normalized and we distinguish between binary and continuous features. We formally describe their normalized distances functions as follows:

Definition 9: (Distance function for numerical features) Let $dist'_x\left(\overline{P_{u,i}},\ w_{u,i}, r_j\right)$ be the distance between a user on day i described by $\left(\overline{P_{u,i}},\ w_{u,i}\right)$ and recipe $r_j$in terms of *complexity, time and health.* The distance function for numerical features is

$$dist_x(r, \overline{P_{u,i}}) = \sqrt{\frac{1}{M_x}\sum_{f\in x}(\frac{r_f - \overline{P_{u,i,f}}}{\sigma_f} \cdot w_{u,i,f})^2)}$$

where $\overline{P_{u,i}}$ represents the average recipe prototype of user u on day i, $w_{u,i}$ represents the weights of user u on day i, M_x represents the theoretical maximum in the feature-groups *complexity, time and health* and x represents the indices of the features in the recipe related to *complexity, time and health.* $z\left(r_{j_x}\right)$ and $z\left(\overline{P_{u,i_x}}\right)$are the functions in which the z-scores of the feature x in respectively the recipe and the recipe prototype are determined. If $\sigma_f = 0$ and $r_f - \overline{P_{u,i,f}} = 0$ then $dist_x(r, \overline{P_{u,i}}) = 0$.

Definition 10: (Distance function for binary features) Let $dist'_y\left(\overline{P_{u,i}},\ w_{u,i}, r_j\right)$ be the distance between a user u on day i described by $\left(\overline{P_{u,i}},\ w_{u,i}\right)$ and recipe r_j in terms of *origin of dish, type of dish and main ingredient of dish.* The distance function for binary features is

$$dist_y(r, \overline{P_{u,i}}) = \sqrt{\frac{1}{M_x}\sum_{f\in x}(r_f - \overline{P_{u,i,f}} \cdot w_{u,i,f})^2)}$$

where $\overline{P_{u,i}}$ represents the average recipe prototype of user u on day i, $w_{u,i}$ represents the weights of user u on day i, M_y represents the theoretical maximum in the feature-groups *origin of dish, type of dish and main ingredient of dish* and y represents the indices of the features in the recipe related to *origin of dish, type of dish and main ingredient of dish.*

4.2.4 Constraining factors

In the user profile, liked and disliked ingredients are not modelled. All features are based on characteristics of the recipe as such, ignoring relations between user and recipe such as likes and dislikes. However, in the final recommendation process disliked ingredients cannot be ignored, since this is the most important reason for rejecting a recipe. If a recipe contains as little as one disliked ingredient, this influences the entire perception of the recipe and it is likely that it will be rejected.

In the interviews, participants mentioned that they find it difficult to distinguish between attractive recipes and even more attractive recipes. Moreover, food-likes are influenced by many varying factors such as the time of day, activity, and what has been eaten earlier. This makes it very difficult to model food-likes. Therefore, we decided to only focus on the dislikes (i.e. disliked ingredients), however modelling dislikes is again very complex. With a sufficiently large recipe-database it is much easier and much more effective to simply consider the dislikes of a user as constraints, i.e. suited recipes should not contain disliked ingredients.

Another constraint that can be defined is history. Participants in the interview study mentioned that some time has to pass before a prepared recipe is acceptable again. As a constraint this means that recipes that have been prepared during the past 2 weeks are not suitable. This amount of time is based on what participants in the interviews deemed an appropriate intermediate period

In the current approach, health considerations are modelled in the user-profile. However, health considerations can also be modelled as constraints; i.e. a suggested recipe should not contain more than 30 grams of carbohydrates per person. This can of course be interesting when people have specific diet wishes. The reason for not adding these considerations as constraints in the current algorithm is because the recipes that are used in the dataset come from the Dutch food centre and already meet the dietary constraints for people with diabetes.

4.3 Summary

Our recommendation approach is two-fold. On the one hand a constraint-based approach has been taken to meet the dislike and recurrence criteria. On the other hand a content-based approach has been taken in which a user profile is defined. The profile consists of recipe prototypes and weights for the different days in a week. The weights and recipe prototypes are based on the past decisions the user has made and is therefore adaptive. The user profile is compared to a recipe by calculating the distance between them. The closest recipe that meets the dislike and recurrence constraints is suggested.

Chapter 5

Evaluation of the recommendation algorithm

The recommendation algorithm described in the previous chapter is evaluated using a within-subject experiment. We want to know whether personalization of recipe recommendations is effective in improving the satisfaction with and acceptance of the recommended recipes. For that purpose, The MCC-II system with an *adaptive* recipe-profile match(personalized profile, PP) is compared to an *impersonalized* version in which a recipe is matched to a generic profile (GP) that was defined by the Dutch food centre. Additionally, both versions are compared to a version of the MCC-II system that randomly picks recipes as suggestions and does not match recipes to profiles at all (random profile, RP). This latter comparison is added to validate user profiling as a means of personalizing recipe recommendations. The differences between the versions are explained in more depth in section 5.1.3.

We expect that in the adaptive condition the number of rejections will become lower over time and the satisfaction scores will become higher over time as the algorithm learns the user characteristics. Overall we expect that in the adaptive condition the satisfaction scores will be higher and the number of rejections will be lower than in the impersonalized condition, because the adaptive condition learns the user characteristics and adapts its recommendations accordingly. Additionally, we expect that in the impersonalized condition fewer recipes will be rejected and higher satisfaction scores will be given than in the random condition, because in the impersonalized condition the recommendations are based on their similarity to a generic profile, making them more fitting to a regular eating pattern.

5.1 Method

5.1.1 Participants

Participants for the experiment were approached through the personal network of the researcher. They were selected based on their family situation (living alone, living with partner, or having children) and their (high) interest in learning new recipes. In total, 17 participants with varying family situations, ages and gender were included in the research. 5 Men and 12 women took part in the experiment with ages varying between 22 and 69 (mean 38.1, SD 14.9). Of the participants, 8 were nutritional gatekeepers (i.e. the main responsible person for choosing and preparing the family's meals) in a family with children, 6 were nutritional gatekeepers living together with a partner, and 3 were living alone. In total, 2 of the participants had diabetes (type 1 or type 2). Except for three participants, the participants were highly educated (HBO or university level). The participants received a personalized recipe book as a gift for taking part in this research.

5.1.2 Material & Stimuli

Before taking part in the experiment, participants were asked to fill out a questionnaire. The questionnaire involved questions about their living situation, interest and experience in cooking as well as general questions about age, gender and education. This information is used to identify differences between the participants that might have influenced the results (i.e. people with certain characteristics may prefer one condition, while others prefer another condition). Additionally some questions about dislikes and allergies were asked to provide the experimental system with a "blacklist" of ingredients that should not be included in the recipe recommendations. (See Appendix C for the questionnaire in Dutch and table 5.1 for an overview of the answers)

After the questionnaires were returned to the researcher, participants were provided with an instruction guide for the sessions that included log-in information and a link to a modified version of the My Cooking Companion II (MCC-II) service. This experimental version of MCC-II includes 410 recipes provided by "het Voedingscentrum" (food centre). The recipes are said to be "diabetes-friendly" by the food centre (for an example, see figure 5.1). Depending on the experimental condition for the session, the program suggests random recipes (RP) or recipes based on the algorithm (see previous chapter) with either a personalized adaptive profile (PP) or a generic profile (GP). Additionally, the program filters out recipes that contain ingredients reported as unsuitable, as well as recipes that had already been suggested within the last 3 weeks. This latter constraint is a bit more severe than the previous interviews indicated, to ensure that repetition of recipe suggestions

Table 5.1: Overview of the answers in the questionnaire

	Mean	**SD**
How often do you cook from a recipe in a month?	4,32	3,66
How often do you cook with fresh ingredients?	5,38	1,11
How often do you eat ready-made meals?	0,69	0,59
How often do you go to a restaurant?	0,37	0,54
How much time do you spend cooking during the week? (minutes)	42,41	14,78
How much time do you spend cooking during the weekend? (minutes)	48,53	24,77
I prepare meals with more than 3 ingredients	4,29 (Often)	0,77
I make grocery lists	3,41 (Sometimes)	1,50
I plan meals for an entire week	2,12 (Rarely)	1,17
I plan which meal I will prepare each day	2,24 (Rarely)	0,97
I experiment with new dishes	2,82 (Rarely-Sometimes)	0,95

in the experiment is avoided. Normally, avoidance of suggestions repetition within 2 weeks would be enough.

5.1.3 Procedure

The experiment took part in nine sessions of approximately 15 minutes each, divided over three weeks (i.e. 3 sessions a week). The participants were free to choose the days on which they wanted to do the experiment, as long as one of these days was in the weekend, and as long as they used the same days within each of the three weeks. The researcher was informed about the chosen days and the participants received reminders on those days about the experiment through e-mail, text messaging and if necessary, by phone.

Each session consisted of two parts. After the participants had logged on to the MCC-II service, they were asked to describe what they were planning to eat on this specific day, and what they had eaten on this day in the previous week. Additionally, they were asked how much time they usually had available for cooking on this day. These questions were a manipulation to sensitize the participants and make them more aware of possible food choice constraints. By focusing on the current setting and meal choice, we expect that practical considerations around meal choice (available time, people joining for dinner, availability of ingredients) become more prominent.

After the sensitizing phase, the actual experiment started. The MCC-

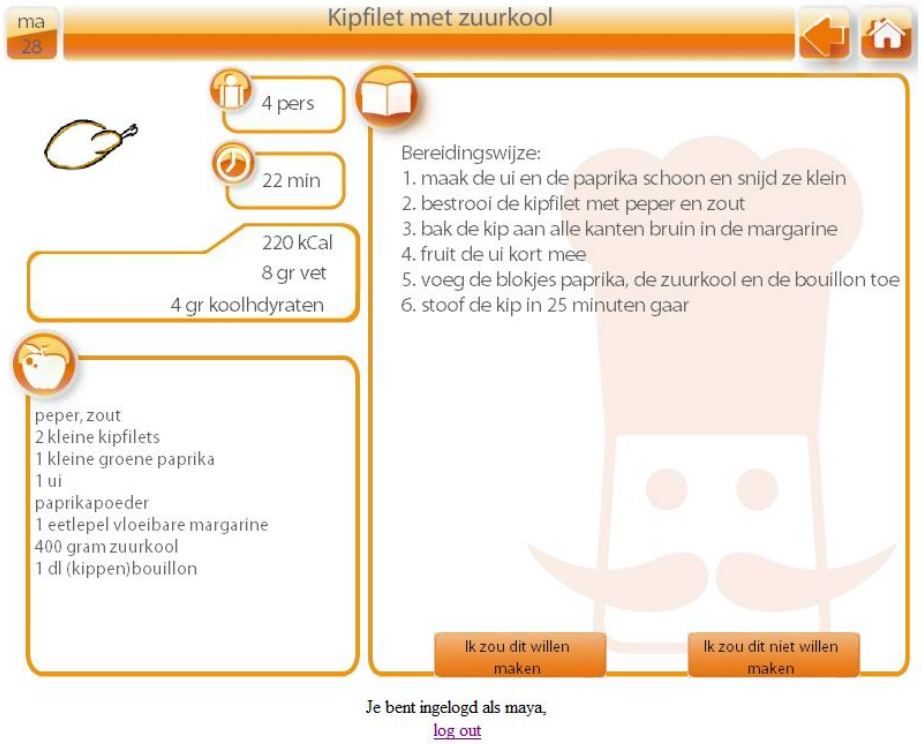

Figure 5.1: Example of the presentation of a diabetes-friendly recipe in the experiment.

II picked an experimental condition for the session randomly until each condition had been assigned 3 times. The three conditions were:

1. random condition (RP); the participant receives random selections from the filtered recipe-set (see Materials & Stimuli) as suggestions

2. impersonalized condition (GP); the participant receives suggestions using the described algorithm but with a predefined generic profile and weights-set that is equal for all participants and is not adaptive

3. adaptive condition (PP); the participant receives suggestions using the described algorithm with an adaptive profile and weights-set

In each session, the participant was presented with 15 suggestions. (S)He was asked to choose whether (s)he would want to prepare this recipe or not. Additionally , the participant was asked to rate how satisfied (s)he is with the suggestion on a 7-point Likert scale and whether it was likely that (s)he will be preparing the recipe in the coming month (on a continuous scale by moving a slider between the values “definitely not” and “definitely”.

At the end of the session the participants were asked to give a rating on their overall satisfaction with the suggestions, again on a 7-point Likert scale.

After the nine sessions, the participants were presented with a funneled debriefing to get some idea about their understanding of the program and the experiment. Additionally, they were asked about how busy they were during the experiment and how much time was available for cooking.

5.2 Results

The data were analyzed for the effect of experimental condition (RP,GP, PP) on the number of accepted recipes and on the rating of the recipes given by the participants. The data were analyzed using a double multivariate repeated-measures ANOVA with experimental condition (RP, GP , PP) as within-subject factor. The dependent variables were the number of accepted recipes and the rating of the recipes given by the participant. No outliers were detected and all data were used. The data on the overall satisfaction with the suggestions were excluded, because of severe incompleteness of this data due to server-issues.

There was a significant main effect of condition: F(4,62) = 3.837, p = 0.008. The univariate tests for the within-subject contrasts showed that, contrary to expectation, the recipes in the random condition were rated significantly higher than the recommendations using the generic profile: F(1,16)=5.905, p=0.027. Also, significantly more recipes were accepted in the random condition: F(1,16)=6.309 , p =0.023. These effects are strong (*eta2* = 0.270 and *eta2* = 0.283 respectively*)*. See table 5.2 for the average rating and acceptance percentages.

As expected, the recipes in the adaptive profile condition were rated significantly higher than the recipes in the impersonalized condition: F(1,16)=13.123, p=0.002. In the adaptive condition there were also significantly more recipes accepted than in the impersonalized condition. F(1,16)=8.168, p=0.011. These effects are also strong (*eta2* = 0.451 and *eta2*=0.338 respectively*)*. See table 5.2 and figure 5.2 for the average rating and acceptance percentages (figure 5.3).

There was no significant difference between the ratings and acceptance percentages of recipes in the random condition compared to those in the adaptive profile condition: F(1,16)=1.310 and F(1,16) = 0.817.

There was no significant difference between the different conditions with regard to the number of consecutively accepted recipes or the number of consecutively rejected recipes.

Influences of the factors age, household composition, education level, use of recipes have also been investigated. There were no significant effects but most factors (Age, Household composition, Education, work situation

Table 5.2: Average rating and acceptance percentages in the different conditions

Condition	Average rating of suggestion on a scale of 1-7	Percentage of suggestions accepted
Random condition	4.56	61%
Impersonalized condition	4.32	53%
Adaptive condition	4.65	63%

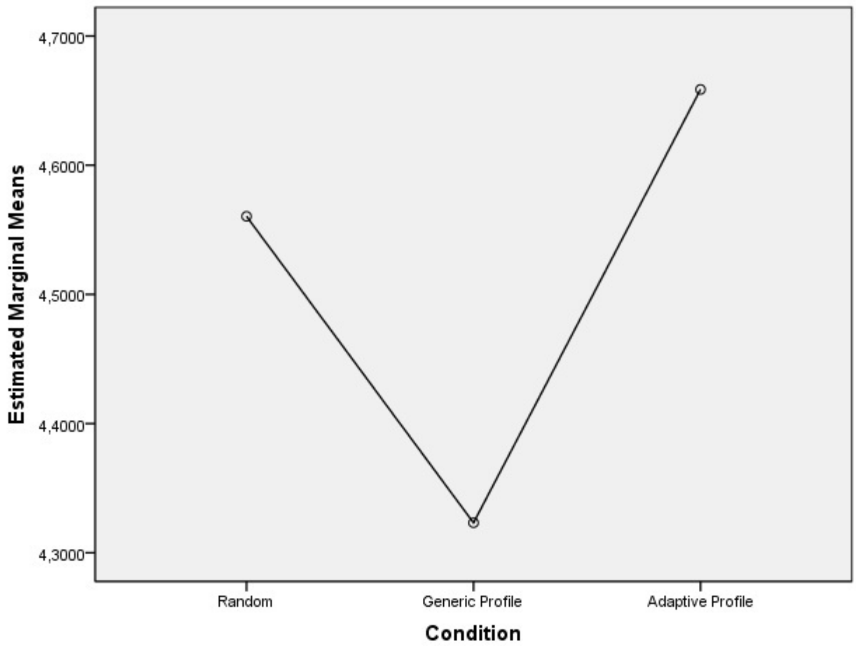

Figure 5.2: Average rating of recipes in the different conditions

(regular, shifts, no work), frequency of recipe use, inclination to experiment in cooking) showed an effect size of *eta2* > 0.1 indicating that an experiment with more participants might well show significance of those factors.

There was a marginally significant, but strong, interaction effect for gender: F(2,14)=3.193, p=0.053, *eta2*=0.516. This effect was significant for the pair wise difference in number of accepted recipes in the impersonalized profile condition compared to the random conditions: F(1,15=12.751 , p=0.003, *eta2* = 0.459, but the other pair wise comparisons did not show significant effects. The means show that male participants accept more recipes in the

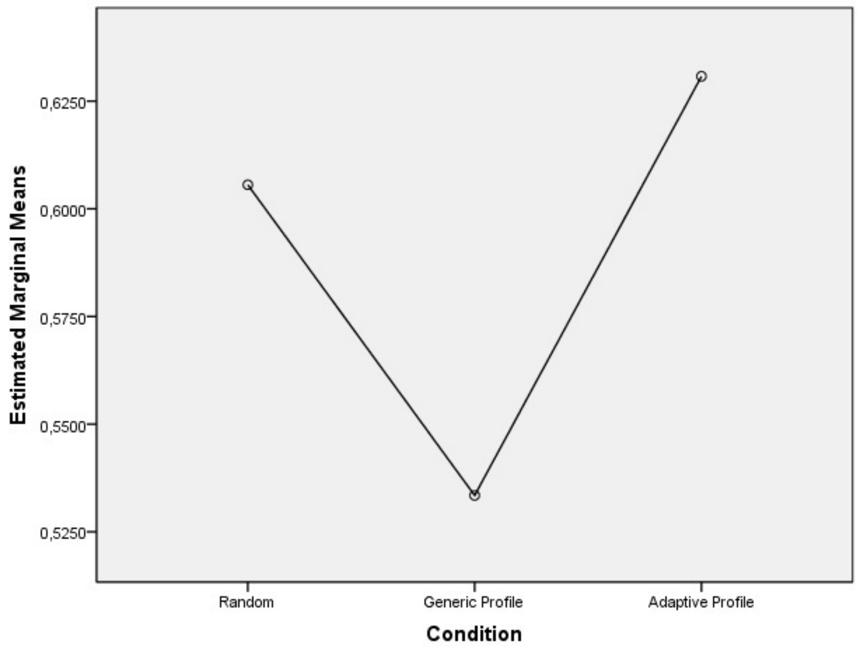

Figure 5.3: Level of acceptance of recipes in the different conditions

impersonalized profile condition compared to the random condition (M= 70% and 65%) whereas female participants accept less recipes in the impersonalized profile condition compared to the random condition (M=46% and 58%) as shown in figure 5.4.

There was no indication for an influence of time (measured by session number; 1-9, week of experiment; 1-3 or session within condition; 1-3).

5.3 Conclusion

The results show that in both the random condition and the condition with the adaptive profile, more of the suggested recipes are accepted and the average rating is higher than in the condition with the generic profile. From these results we can conclude that an approach in which recipes are recommended based on a generic, one-fits-all profile is not effective.

From these results we can also conclude that the adaptive profile method is successful in capturing at least some of the wishes of a participant concerning food choice. This is because both the adaptive profile and the generic profile conditions have the same starting point, but the adaptive profile condition shows significantly higher ratings and acceptance percentages. Since the similarity measure is the same in both conditions, this difference can only

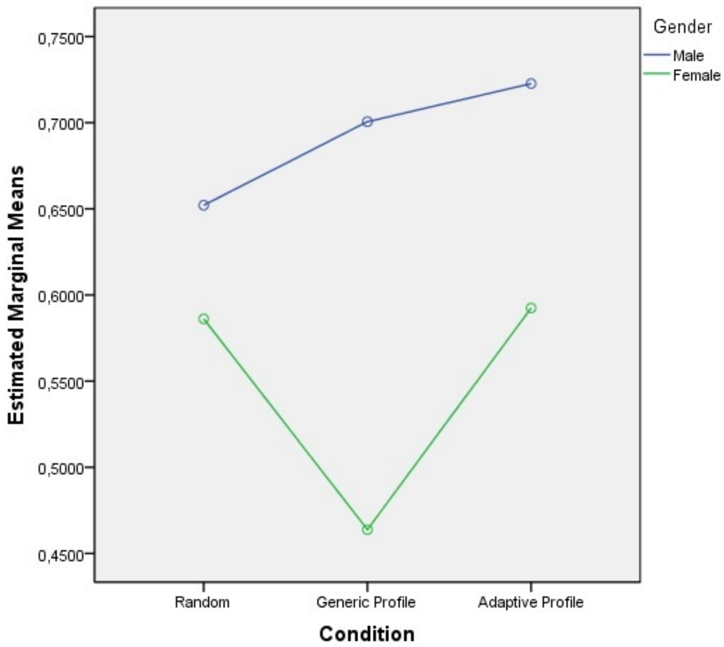

Figure 5.4: Gender effects in acceptance levels in the different conditions

be attributed to the adaptivity of the profile in the adaptive profile condition.

Furthermore, we have seen that there is no significant difference in acceptance percentage or rating between the random and the adaptive profile condition. We expected the adaptive profile condition to have better acceptance and ratings, because this condition presents a more informed suggestion. There are several possible explanations for this lack of significant difference:

1. In the random condition complete randomness of recipe suggestions is suggested, but since the recipes are already filtered according to dislikes and past choices, the random condition does use some knowledge of the user. It may therefore be expected to perform better than a purely random condition (without any pre-selection). The more so because a disliked ingredient is the most important reason for rejecting a recipe.

2. It is possible that the random condition has an overall advantage over the other two conditions through the way the experiment was set up. During the debriefing, several participants reported that they noticed a difference in the variety of dishes that were recommended. In some sessions they noticed less variation. This does indeed tend to happen

in the adaptive and impersonalized sessions since these recommendations are based on similarity to a profile. Because the participants are asked to rate 15 recipes in a row, it is possible that some ratings are influenced by previous recipes (i.e. "I like this fish recipe less than the previous one so I will reject it"). This is less likely to happen in the random condition where (strong) relations between consecutive recipes are less consistent. Of course the influence of past recipes can also be positive, however during the debriefing the influence of past recipes was mentioned mostly negatively. For example, one person indicated that she does not mind eating tofu once in a while, but that she does not like the amount of tofu recipes that was recommended on one day. In a realistic setting only one choice per day will be made, inducing independent ratings rather than comparisons to past recipes. This would mean that in a longer experiment in which only one choice per day is made, the performance of the impersonalized and adaptive condition compared to the random condition may be different.

3. Our requirement study (chapter 2) was focused on people with diabetes that have difficulties in adapting their eating habits. For this target group it is important to start with small changes. That is the reason for the particular design of the recommendation algorithm. In the current experiment however, the participants were selected from a more general audience than this target group. Some of the participants reported to experiment a lot with preparing food (i.e. try out more than 2 new recipes a week), an more than half of the participants prepared one new dish a week, indicating that this particular group may have been more experimentally-inclined compared to what is expected from the target group. These participants are likely to want a lot of variation in their recipe suggestions. Since the random condition offers a lot more variation than the adaptive and impersonalized conditions, this might give another advantage for the random condition over the other two conditions with this particular participant group.

Another finding is that the acceptance percentages and satisfaction rates in the random condition were better than in the impersonalized condition. Both conditions use a recipe set that is pre-filtered on disliked ingredients, which personalizes both conditions to some extent. However, where there is no further reasoning in the random condition, the impersonalized condition tries to assign every participant to the same one-fits-all user profile. It seems that the one-fits-all user profile in the experiment does not represent participants well. It is likely that this profile interferes with the personalized pre-selection of recipes because it reduces the freedom in recipe selection greatly (i.e. it will consistently suggest recipes that take an hour to prepare on Fridays if this is in the profile. Unless all recipes that have a preparation of an hour are rejected, the participant will not be likely to find recipes that do not contain this characteristic). The random condition does not suffer from this freedom limitation, possibly explaining the better results in the random condition.

Finally, we expected that the acceptance percentages and satisfaction rates would improve over time in the adaptive condition. We did not find any such effect. This may be explained by the fact that participants were asked to make as much as 15 decisions within one session. All these decisions directly influence the user model. The acceptance percentages and average satisfaction rates were calculated per session. It is quite possible that the average recipe prototype converged within one session (15 decisions) to a suitable user representation, explaining the lack of difference between sessions.

In hindsight, a problem with the experiment is that people were asked to choose a recipe, but were not required to actually prepare it. As discussed before, there is a difference between recipes that people like and recipes that they are actually going to prepare. Even though participants in this experiment were explicitly asked whether they would prepare the suggested recipes (rather than whether they liked them) and they were sensitized by asking them about what they usually eat and what they are planning to eat on the current day, it still seems that participants were underestimating their constraints in food preparation (i.e. they accepted recipes that take one hour to prepare, while they report to usually prepare something less than half an hour on that day). This side-effect is present in all conditions. However, the adaptive profile is meant to model a user's relevant characteristics and recommend recipes accordingly, and the results from this experiment indicate that the adaptive profile actually capture these characteristics. When it comes down to situation in which users are required to prepare the suggestions, the adaptive profile will still be able to capture the user's characteristics. These become apparent from the decisions the user makes (food decisions that the user also prepares). The random condition, that does not use information from the decision history, only knows about dislikes. This condition will, in a setting where the user is asked to prepare the dishes, still be able to suggest the recipes the user likes, but they will not necessarily be the ones that the user wants to prepare. Recommending recipes that the user likes and wants to prepare was the reason for developing an adaptive profile for a recipe recommender, so the present study might have presented us with a skewed image.

In this experiment we found clearly higher levels of satisfaction and acceptance in the adaptive profile condition compared to the generic profile condition. Additionally, we found a significant advantage of the random condition over the generic profile and a lack of difference between the random and adaptive conditions. This suggests that providing a random suggestion from a set of healthy recipes that are pre-filtered according to disliked ingredients and recurrence of recipes that a user can accept or reject might be equally effective as the adaptive profile in achieving the aim of getting people with diabetes to change their eating habits.

However, as discussed above, there are some issues with the experiment that might have influenced the outcome. This has resulted in a few suggestions for improvement of the experiment. First, the experiment should be limited to one accept-decision a day (rejection may be made more often) and people should be asked to actually prepare the accepted dish. This makes it necessary to run it for a longer period than three weeks for the adaptive profile to be able to sufficiently learn. Furthermore, more participants should be included to investigate whether the working of the algorithm is influenced by specific differences between participants (such as inclination to experiment, gender, household composition etc).

Additionally, it is possible that improvements of the system can be made, i.e. there may be user-profiles, feature sets and weight adaptation methods that are more suited than the one proposed in this research.

Our overall conclusion is that personalizing recipe recommendations, even if only by filtering out recipes that contain disliked ingredients, is a promising area in recipe recommendation that should be further explored.

Chapter 6

Usability study for My Cooking Companion II

In the previous chapters we described an algorithm for suggesting recipes and reported on how we tested this algorithm. However we are not only interested in the technical aspects of such recommendation systems, but are also interested in how the target group perceives such a system. The adaptive version of the algorithm was used as an extension to a system named My Cooking Companion II (MCC-II) with additional functionality besides recommendation as such. We want to evaluate how people with diabetes perceive the extended MCC-II system and if they think it is helpful for them in adapting their eating patterns.

6.1 Method

6.1.1 Participants

Participants were recruited through an advertisement on the internet and trough the physical activity program run by the health center Eindhoven (SGE). They were invited to participate in a study in which they had to do some tasks using MCC-II, and answer some questions in an interview two weeks later. Requirements were that the participant should be the nutritional gatekeeper of the family, are focused on eating healthier and have at least one family member with diabetes type II. Three men and one woman were willing to take part in the study. They were informed about their right to stop participation at any time. All participants had diabetes themselves, which was on average diagnosed 3 years ago. Their ages ranged from 42 to 64. They received payment for their participation in the form of a gift certificate for 50 euros.

6.1.2 Material & Stimuli

Participants were presented with a small questionnaire to assess whether they meet the requirements. It contained questions about age, gender, when the person was diagnosed with diabetes. Furthermore, it contained questions about shopping behavior and dislikes to finetune the system that the participant would try out for two weeks. Recipes were filtered such that recipes containing disliked ingredients or out-of-season products were not recommended. Whether products were out-of-season was assessed using a Dutch vegetable calendar (Vegetable Calender 2011)

The system the participant tried out for two weeks was My Cooking Companion II, extended with the recommendation algorithm described in chapter 4. This system had a flash front end and a groovy & grails back end and was accessed through an internet browser.

The system included a GUI as shown in figures 6.1, 6.2, and 6.3. It contained several functions among which the possibility for the system to suggest a single recipe or a series of recipes (e.g. a week plan). The suggestions were based on the algorithm described in chapter 4.

Figure 6.1: Screenshot of the main menu

Additionally, the user had the possibility to formulate additional constraints

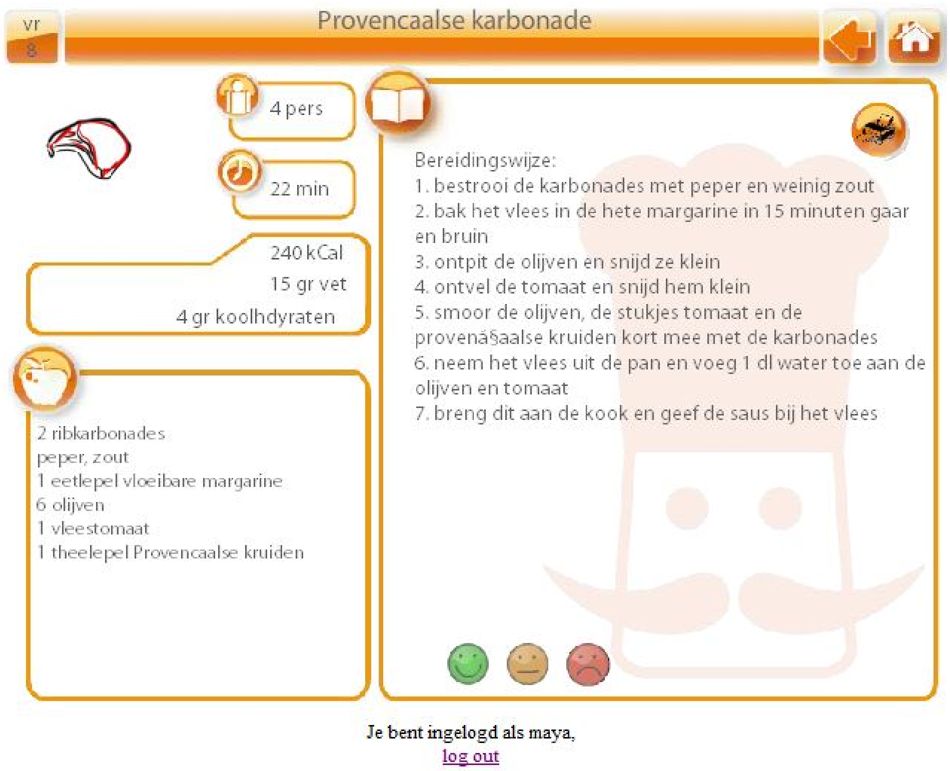

Figure 6.2: Screenshot of the presentation of a single recipe

(figure 6.4) on an already given suggestion. The system then searched for a similar recipe that meets the additional constraints. For example the system suggests something like "vegetable stew", you like this recipe but do not have enough time to prepare it. The system can then search for a recipe similar to "vegetable stew" but that takes less time.

The user also had the possibility to search through the recipe database by selecting the ingredients it should contain (figure 6.5). Selecting these ingredients was done by marking them in an ingredient taxonomy.

Finally, the user had the ability to select ingredients (s)he dislikes, which were accordingly filtered out from the suggestions the system gives.

The interviews were recorded with a Philips voice recorder.

6.1.3 Procedure

The study consisted of two visits from the researcher at the home of the participant, and the actual use of the system in between. Before the first visit, participants received all information and a small questionnaire (Appendix D) in which they were asked about their dislikes in food, shopping behavior and general questions to see whether they fit the requirements.

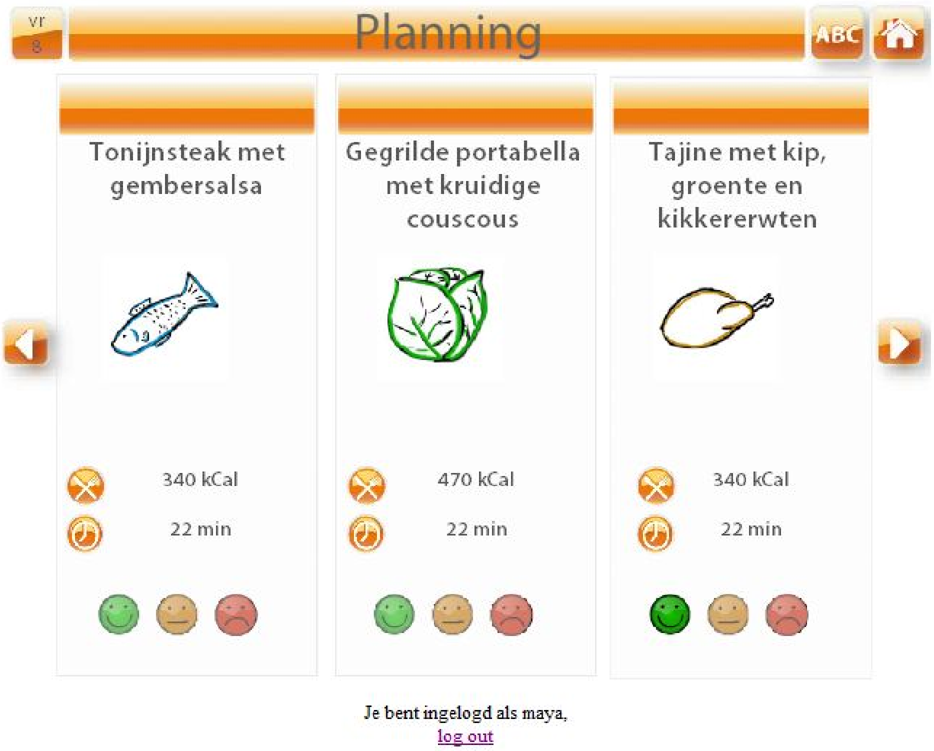

Figure 6.3: Screenshot of the plan function

During the first visit the researcher showed the participant how the system worked and let the participant try it out for themselves. The participant had the possibility to ask any questions (s)he might have. Additionally, the tasks were explained and an informed consent (already sent by e-mail before the first meeting) was signed.

Between the first and second meeting the participants had the possibility to use the system as often as they wished, but they were required to at least do the following task two times over a period of two weeks: The participant was asked to make a suitable meal plan with for an entire week, using the MCC-II. A suitable meal plan was one in which the participant was satisfied with all suggested recipes and was willing to follow that plan (although he/she was not required to actually do so). This was achieved by searching through the recipes by selecting orange (recipe needs additional constraints) and red smileys (recipe is rejected) until all recipes in the plan were saved, which was done by selecting the green smiley.

In the second meeting, the researcher interviewed the participant. This interview was recorded with a voice recorder. The interview sessions took between 15 and 45 minutes. It involved questions about experience with

Figure 6.4: Screenshot of the menu to select additional constraints on a recipe

diabetes, how diabetes affected their eating habits and general questions about food choice. Additionally, questions directed at the several functions in MCC-II and the program as a whole were asked as well as the participant's thought about future improvements of the system and the usefulness of the system for people with diabetes. For a complete overview of the questions asked in the interview see appendix E.

6.2 Results

6.2.1 Diabetes and food in general

Among the four participants, one participant was not yet using medication, but was trying to gain control over her diabetes by adapting her eating habits. One participant used insulin and pills while the remaining two participants only used pill medication. None of the participants adapted their medication to their meals.

For most of the participants it was difficult to get a grip on what they were eating and how it affected their glucose levels. The guidelines for eating that participants had received varied. Two participants were told to primarily watch out for carbohydrates, but also be careful with fat and calories. One participant was only told to watch out for fat and calories. The last one was told primarily to watch out for fat and eat more regularly. Participants

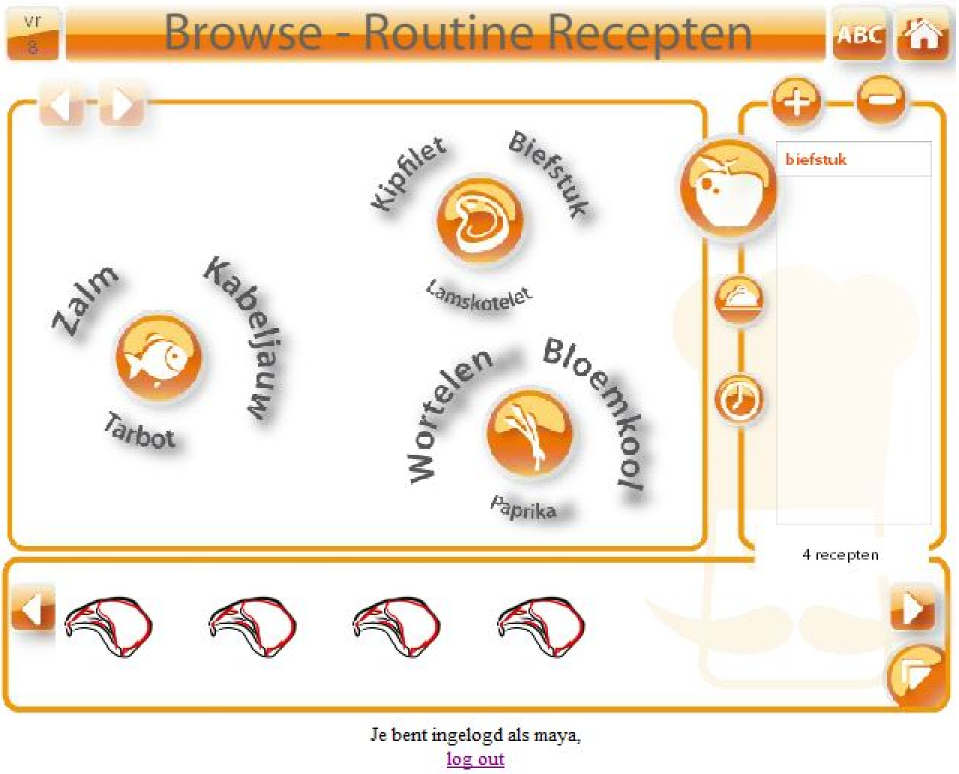

Figure 6.5: Screenshot of browse function

had the most difficulties in following these guidelines when eating out, at friends or in a restaurant. Two participants found that the guidelines were too general for a disease as personal as diabetes; these general guidelines did not seem to help them much.

The participants did not mind eating the same meal on two consecutive days occasionally, but preferred to have a week in between. When they had leftovers of a meal they would usually eat them the next day, but they tried to keep the amount of leftovers as small as possible.

All participants mentioned to eat many vegetables in their meal. One participant reduced the portion size of potatoes compared to his partner, because of his diabetes. All but one participant wished for more variation in their meal pattern. The remaining one was not satisfied with her eating habits but in this case it was because she was still searching what worked for her to gain control over the diabetes, rather than a lack of variation.

6.2.2 Evaluation of MCC-II

Generally speaking, the participants liked the idea of the program, but had some difficulties in using it. Remarks included functions that did not work as expected, ambiguity in what the buttons meant and getting used to "saving" recipes with the green smiley. There were many suggestions on improvements in the interface. One person only used the system once, the other times he could not get access to the program because of browser issues.

For two participants the planning function was not useful since they chose what to eat based on what ingredients were in stock or on discount, i.e. they chose a recipe based on the ingredients instead of buying ingredients based on a recipe. These two participants favoured the recipe search function, although they remarked that it was difficult to find the ingredients using the taxonomy. The other two participants favoured the planning function because they liked the idea of guidance.

All participants liked the overview of calories in the week plan, which they thought gave them better insight in what they were eating. It was suggested that this could be extended with carbohydrate and fat information. The possibility of adding their own recipes to the recipe set was thought to enhance the plan, since this would give a more complete overview of the health information (i.e. when they have prepared an own recipe rather than one from the recommender). Adding own recipes can also enhance the recommendations, since the system can then also use their own (already healthy) recipes as suggestions. Another addition that was suggested was the possibility to define maximum or target levels for calories, carbohydrates or fat. The plan function could also be extended with the possibility to create a grocery list from the recipes selected for preparation.

The function to find recipes similar to the current recipe but with additional constraints was appreciated. Participants thought this was a useful method for searching through the recipes. However, occasionally the newly suggested recipe differed quite a lot from the original recipe. This was probably because of the relatively small recipe set.

Overall, the recipes suggested by the system were liked. Sometimes the preparation time in the recipe seemed to be optimistic. One person did not see much added value of these specific recipes for people with diabetes, but she thought this was to be expected because of the different directions in diabetes guidance (i.e. some were advised to watch carbohydrates, others not).

6.3 Conclusion

Generally, even though this group of participants did not have diabetes as long as the ones in the first interview study, the groups were more or less comparable. For both groups, eating out is the most difficult situation. The guidelines for handling diabetes are not uniform over individuals. This is something that can be confusing sometimes. It seemed that the guidelines are less effective for the current group of participants. This is probably because they are still searching for what works for their specific glucose levels. It is likely that the group of participants in the first interview study had already passed this search phase. Individualization of guidelines seems needed.

Each participant was eager to try out the system and it seems that the overall idea of recipe recommendation is liked. However, because people with diabetes type II are usually relatively old, special care needs to be addressed at designing an intuitive user interface. This was a point of issue in the current user study, since not all functions and buttons were clear.

There seem to be differences between people in what functions they like. Some people like the idea of buying ingredients based on a plan, while others like the idea of planning based on the ingredients they have available. Consequently, the focus they want the system to have is recommendation or navigation, respectively. This should be recognized and the program should accommodate both functionalities at the choice of the user. If not, people may think the system is rigid and that they do not have enough freedom in their choices.

Additionally, the system should be extended with the possibility for users to include their own recipes of which the health information is determined. For people with diabetes in particular, the health information may play a very important role in the week plan. Participants valued that this plan provides an overview of the calories, however, fat and carbohydrates should also be included in the overview. Additional suggestions for this health information include the possibility to define a maximum level and target-level of carbohydrates, calories and fat.

Chapter 7

General Discussion

The main goal of the research described in this thesis was to develop a recommender system that suggests healthy recipes in a personalized manner, specifically for people with diabetes type 2. In the following sections (7.1., 7.2 and 7.3) we will summarize the results of the studies that were executed, describe the algorithm that was developed and reflect on them. In ection 7.4 and 7.5 we present some comments on the future of recipe recommendation and the promotion of healthy eating. We conclude this chapter with a description of an ideal recipe recommendation system for people with diabetes in promoting healthy eating.

7.1 Requirement Collection

In a literature study and a first interview study, the requirements were collected for a recommender system that provides tailored healthy recipe suggestions for people with diabetes were. Qualitative research in the form of interviews with people having diabetes indicated that taste, number of vegetables and number of carbohydrates are important in determining whether a recipe is suited or not. The investigated elements of the food choice model by Furst (1996) seemed to be applicable to people with diabetes as well. Although the Food Choice Questionnaire (Steptoe, Pollard & Wardle, 1995) was developed to measure the importance of several factors regarding food choice, the factor ordering coming from the questionnaire was not successful in predicting the recipe choices participants made during the interviews consistently. An explanation can be found in construal level theory (Trope et al., 2010) which distinguishes between abstract and concrete mindsets. In a concrete mindset, an individual would be focused on concrete short-term considerations of a choice, while in an abstract mindset they would be focused on the abstract long-term considerations. In the Food Choice Questionnaire, people are asked what they generally like their food to be, which can be considered an abstract choice. However, in the interview participants were asked to make actual decisions, bringing them in a concrete mindset in which they focused on concrete considerations such as the time they have available for meal preparation. There may be a difference between what a person wants their food to be (abstract), and what they actually choose their food to be (concrete).

In a second study reasons for *not* wanting to prepare recipes were explored in a web experiment with a general audience. The most important reason for rejecting recipes was the disliking of an ingredient. This was followed by reasons related to complexity, preparation time and healthfullnes of the dish. However, some reasons for not choosing recipes may have been missed. As suggested above, there may be a difference between liking a recipe and actually going to prepare it. In this study, participants were not asked to actually prepare the recipes they selected, so any reasons for rejecting recipes when it comes down to actually preparing them would not have surfaced. Still, these reasons for rejecting recipes gave additional indications for what factors are important in finding suited recipes. Together with the results from the first study, the results from the second study provided the basis for the requirements of the recommender system and the representation of the recipes and users in the system.

7.2 Algorithm

The next step was to develop the adaptive user profile and the algorithm that finds suited recipes for a user. The user profile is gradually learned over time by adapting it according to the recipes the user chooses. The assumption was made that food choices are dependent on the day for which the choice is made. Therefore, the profile consisted of prototypical recipes for each day of the week. The user profile was matched to recipes by calculating the distance between recipes and the recipe prototype for the day of the week the recipe was suggested for. The recipe that was closest to the recipe prototype and satisfied all constraints on taste and reoccurrence was suggested.

In the current study, the parameters in the algorithm have not been optimized. There may be other feature sets that better represent users and recipes. In our study the weights were based on the overlap between the distributions of the last 10 decisions for a day. The determination of these weights in the user profile can be optimized. There may be other methods that are more reliable with so few datapoints, or there may be other settings that work better for weight determination by distribution comparison. Finally, ways of updating the user profile, and ways of learning users' characteristics can be further explored.

A critical note on the determination of a recipe prototype is that when a recipe was rejected, all recipes but one in the recipe prototype were discarded and if more than three consecutive recipes were rejected, the prototype was reset completely. This was based on the assumption that a rejection of a recipe reflects a flaw in the recipe prototype. However, there may be other reasons why the recipe is rejected such as one of the unknown reasons that were mentioned in the study described in Chapter 3. By discarding so much of the recipe prototype, it could be that valuable information is lost, and only short-term learning is possible. Nevertheless, the reason to retain one recipe in the prototype, was exactly to not discard *all* information and still stimulate variation in prototypes. After all, the context constantly changes, so long-term learning does not seem to be valuable anyway. Still, other ways for adapting the profile can be explored in the future. One can think of only discarding the last recipe that was added to the recipe prototype of a day. However, the constantly changing context in food choices should be kept in mind always.

Another problem for the recipe prototype lies in the assumption that accepted recipes are prepared. If the recipe is not prepared for some reason (e.g. for example, the context has changed), this cannot be assessed, and the recipe will still be wrongfully incorporated in the recipe prototype. Also, if a prepared recipe was disappointing, it is important to exclude it from the recipe prototype. Therefore, it may be of added value if people can rate the recipes after they have prepared them, or deselect them when they did not prepare them or did not like them after all.

7.3 Evaluation of the Algorithm

The algorithm was validated in a within-subject experiment in which participants were exposed to several versions of a system:

1. a system that provided random suggestions (random)
2. a system that provided suggestions based on the similarity of a recipe to a generic user representation (generic profile)
3. a system that provided suggestions based on the similarity of a recipe to an adaptive user representation (adaptive profile).

All systems selected the recipes from a pre-filtered set of recipes that complied with taste and reoccurrence constraints. The results showed that an adaptive system is preferred over a system with a generic profile in terms of number of recipes that are accepted and rating of the suggestions. However, contrary to expectation, the random system also performs better than the generic profile, and equally well as the adaptive system. One possible explanation can be that pre-filtering recipes on disliked ingredients is very effective in personalizing recipe suggestions, but the use of a generic user profile depersonalizes recipe suggestions again. Further research on the validation of the algorithm is proposed since there are indications of factors that may have influenced the results, as well as arguments that the random suggestions condition may have had an advantage over the other two conditions through the way the experiment was set up. The experiment showed that personalization of recipe recommendations, even if only by pre-filtering the recipe set on disliked ingredients, is an effective approach in providing satisfying recipe suggestions (i.e. that are accepted and liked).

There are several limitations in the current evaluation study. These include the fact that participants were not asked to prepare recipes. Furthermore, they were presented with multiple recipes at one day of which they were allowed to accept more than one recipe. These experimental design choices may have made the food choice more abstract instead of concrete, possibly influencing the outcome of the research. A suggestion for future research is therefore to better evaluate our approach in adaptive user profiling as a means of learning preferences. This can be done by performing a longer study in which participants can only accept one recipe on a day, which they also have to prepare. The experiment would have to run for a longer period of time to be able to let the adaptive profile capture the user's preferences.

One problem in assessing the performance of the conditions is that we actually do not have an estimation of the a priori chance on how many recipes are expected to be accepted. The random condition had an unexpectedly high acceptance percentage (and rating) compared to the generic profile. The found results may not be (only) due to higher-than -expected random ratings/acceptance percentage, but (also) to lower-than -expected adaptive and generic profile ratings/acceptance percentage. It is possible that the selection of the specific default recipes in this evaluation study caused the generic profile condition to have a relatively low acceptance percentage.

Another issue is that the performance in the three conditions was measured on average recipe rating and percentage of recipes that were accepted. Although the percentage of accepted recipes may be a good measure for comparing the three conditions in the experiment, this indicator does not indicate the performance of the system in itself. This is because the users may reject as many recipes as they like until they find (the most) suited one. Since a user is presented with one recipe at a time, rejecting a recipe does not have to indicate that the recipe is not suited, it may just as well be that it is rejected because the user is curious for the next suggestion. The same goes for the rating of a recipe, but then the other way around. A recipe may be liked, but this does not have to mean that the user is willing to prepare the recipe, and as such rating can be used to compare systems, but not as a performance indicator for a system on itself.

Moreover, the differences between the random and the adaptive profile conditions were not significant. This indicates that the additional effort for generating the profile might not be worthwhile. Simply personalizing recipes by filtering out the ones that contain disliked ingredients is much less complex. In addition, the characteristics used in profiling the user such as health, timing and complexity considerations might be formulated as additional constraints. However, if only recipes that meet all constraints are suggested, it is impossible to deviate from these constraints, reducing the possibility to adapt to changing contexts. The difficulty to adapt constraints when they have been set also makes it more difficult to learn them automatically. It might be difficult for users to determine the constraint values themselves, since it may be hard to formulate (some of) the constraints in concrete values. And of course, the more constraints are formulated, the more complex the filtering process becomes.

In conclusion, although the additional effort in generating adaptive profiles might not seem worthwile in this experiment, an adaptive recipe recommender might stil have enough potential advantage over a purely constraint based system in a more realistic food choice setting (i.e. when one recipe is accepted and the food is also prepared). Additional research on this matter may provide more clarity as to which approach is more promising to be used in a system that promotes healthy eating to people with diabetes.

7.4 Usability Study

The system for recommending recipes to people with diabetes with the purpose of lowering the effort in making healthy food decisions was validated in a small-scale qualitative study. In this study people with diabetes were provided with a working prototype of the recommender system including some additional features for searching through the recipes. After a period of two weeks the participants were interviewed and asked about their experience with the system and their opinion on the usefulness of the system and how it can be improved. Generally, the participants were interested in the system. The option to search through recipes based on similarity on the one hand and additional constraints on the other was appreciated. However, there were differences in the preferred use of the system. Some participants would want to use the system more as a search system, in which they were free to indicate which ingredients a recipe should contain. Others liked the options in which the system took the initiative by recommending recipes (e.g. week plan and single recommendation). This indicates that the system should not only provide personalized recommendations, but also other approaches to recipe selection (e.g. browsing), so users are free to choose which approach they prefer and feel most comfortable with.

In this usability study it was found that general guidelines were ineffective for this group of people with diabetes. Together with the finding from the first evaluation study that a generic profile does not work and may even decrease performance, this implicates that personalization is the key to help people with diabetes. More importantly, collaborative recommendation approaches (i.e. group-wise profiling) seem inadequate for recipe recommendation. However, it is still unclear in what detail the recommendations should be personalized. Possibly, the adaptive profiling method is not yet detailed enough, since it does not outperform the random condition in the first evaluation study, but did outperform the generic profile condition.

In both evaluation studies, participants were presented with one or more recipes in one session, and each recipe was presented individually (one at a time), i.e. they had to reject a recipe before a new suggestion was presented. It should be investigated what the effect is of presenting them with multiple suggestions at the same time. This can provide insight into which of these suggestions will be chosen when there is "competition", and what its characteristics are. In the usability study, some participants perceived the system as too rigid, i.e. they wanted to have more control over the recommendations. Allowing participants to choose a recipe from a set of presented suggestions can improve this perceived control of the user, because the user does not have to explicitly reject recipes when a recipe is not satisfactory or if (s)he wants to see other options first.

People with diabetes in the interview studies often found it difficult to properly assess the healthfulness of their choices; i.e. they thought they were eating healthier than they did. Given this observation, it might be that the recommender system will not be able to improve the health of the meal choices if the system allows for too much freedom in the recipe options. However, if the users feel too restricted, they might not want to use the system, and the recommender system will not be useful. A balance needs to be found such that the system is able to direct users that are misguided about their eating habits, without risking that the users will stop using the system entirely.

7.5 Future of Recipe Recommendation

Currently, the focus in recipe recommendation is on adapting recipes or menus to the preferences of a user. These preferences mostly include nutritional constraints and taste constraints. Although the existing methods have proven to be effective in meeting these constraints, in most methods, users would have to provide a detailed specification of their preferences themselves, which requires a lot of effort for them. Additionally, it may be difficult for users to formulate these preferences in detail. Another weakness of these methods is that they have not been thoroughly tested with actual users. The methods may find recipes or menus that fit the constraints, but if these recipes or menus are not likely to be prepared, then the method is not very attractive to pursue.

The current study provides a method that selects recipes rather than adapts recipes. The advantage of this content-based recommendation approach compared to existing approaches is that it does not involve complex methods for adapting recipes, but exploits existing recipes that can be found on the internet. An advantage of the adaptive-profiling approach described in Chapter 4 is that learning the user's preferences takes place implicitly. This reduces the user's effort, and the method is not dependent upon the capabilities of a user to express his preferences. Additionally, it can capture preferences that the user is unaware of. The evaluation studies have shown that searching for recipes that match a profile is an effective approach for recommending recipes. Users have expressed overall high satisfaction with the recommendations that are based on adaptive profiling as well as those only meeting taste-constraints. Recommendations based on generic profiling were satisfactory to a lesser extent. Future research on recipe recommendation should explore this user-recipe-matching approach further.

Moreover, the strength of a simple personalization, by filtering out recipes that contain disliked ingredients and recipes that have been made during the past two weeks, should be examined. Acceptance percentage and satisfaction of suggested recipes for such a simple personalization method can be compared to, on the one hand, no personalization method at all (no filtering), and on the other hand, elaborate adaptive modeling. Additionally, the effect of additional constraints on for example health, complexity and preparation time can be assessed.

In the usability study (Chapter 6), users were provided with the possibility to browse through recipes by formulating additional constraints on a given recipe suggestion. This is a form of conversation between the system and the user;i.e. the user specifies what the system should look for and the system provides it. The use of conversational recommendation systems can be interesting for recipe recommendation. Such systems might assess the context of the food choice and its corresponding constraints by asking (the right) questions and recommend recipes accordingly. It would not be dependent on consistency in context. This might be useful in a situation where context is so important and changes often such as in recipe recommendation.

Finally, research on recipe recommendation such as it is in existing methods, should become more user-centred. The focus of the research should not only be on finding those recipes that fit the user preferences, as it is now, but more importantly on finding those recipes that both fit these preferences and are also likely to be prepared. Although this latter addition seems very subtle, it may noticeably improve the usefulness of recipe recommender systems, enabling them to be actually used and improve eating habits.

7.6 Future of Promoting healthy eating to people with diabetes

We should not forget that the original goal of this research project was not so much to recommend (personalized) recipes to the liking of individual users, but doing this in order to promote more healthy eating to people with diabetes.

An issue with using a recipe recommender system for promoting healthy eating to people with diabetes is that the current population of people with diabetes may not feel comfortable enough with such seemingly advanced use of computer technology. The current population consists of mostly elderly people that only encountered computer technology at a later age. Some of them have embraced the technology, but many did not. The latter group may use computer systems occasionally, but do not feel comfortable enough to use them on a daily basis. For the promotion of healthy eating using a recipe recommender this is a serious limiting factor.

Apart from their experience with technology, potential users should also be motivated to change their eating habits, since this is the main reason for using the system on a regular basis, which is essential for the healthy eating promotion to be effective. Therefore this approach may only be suited for those who are experienced with computer systems and are really motivated to eat healthier. In the future, when the population consists of people that have grown up with computer systems, the group of people comfortable with technology is likely to grow.

For the group of people with diabetes who do want to use technology and are willing to eat healthier, a recipe recommender seems a promising approach, since it provides them with concrete options that are healthy. However, there are differences between individuals in how high the perceived control over the system should be for them to use the system. Some may like the initiative of the system, others not so much. This may be an issue for further investigation. Additionally, it is interesting to see what the effect is of different persuasion techniques on the effectiveness of the system.

The recommender system described in this study can be improved by incorporating health constraints and health targets. Inclusion of own recipes and the assessment of the health of those recipes might make people more aware of possible improvements and may motivate them to use the system and change their eating behavior. Furthermore, it may be interesting to see whether the current techniques can be adapted in such a way that the healthfulness of an individual's food choices gradually improves. I.e. the recommendations may start with very familiar recipes that need not be particularly healthful just yet, but over time the system might suggest recipes that are ever more healthful, while at all times similar to the previous suggestions (assuming that they were actually prepared). This way, healthy meals are gradually introduced in the eating habits, giving people the time to get used to the new (type of) meals.

For the group that is not used to technology, but is motivated to eat healthier, a more low-tech solution might be an option. Although these people are not comfortable enough with technology to use a recommender system for searching through recipes, they may still use e-mail, internet and text messaging on the mobile phone. These media can be exploited to coach users in healthy eating by sending them personal messages, either from a dietician or automatically generated. Possibly, persuasive messaging can also help people to stay on track in following the guidelines they have been given. Ideally, this approach would be combined with a method for recording food intake for the messages to be more effective. Insight into what they actually eat might stimulate people to change their behaviour, since people tend to overestimate the healthfulness of their food choices.

One step further in promoting healthy eating is weight loss dieting. For some people with diabetes losing weight is necessary. For this study, recommendations for specific dietary regimes has not been a goal. To help people lose weight, a recommender system can be useful, but the system would have to become more complex. For one thing, the system should know what a user eats over the entire day, instead of only knowing what (s)he eats for dinner. Additionally, the health targets and constraints will become more complex, making it more difficult to come up with recipes that a user will be likely to prepare. However, since there is such a big population of people trying to lose weight (even apart from people with diabetes), it can be very interesting to see how recipe recommendation can be used for that purpose.

7.7 Conclusion

Although there are still issues to be resolved, I believe that personalizing recipe recommendations, either by matching recipes to users or by filtering recipes, is a promising approach in recipe recommendation for the promotion of healthy eating. Providing people having diabetes with a continuous tailored guidance in their food choices can help them feel more in control of their disease. It can stimulate them to make week plans, making food choices less dependent on food impulses.

An ideal system for people with diabetes would be a recipe system that provides insight in the actual choices of the users, guiding them in their choices when they want to (e.g. by personalized recommendations) or providing the option to browse through recipes if they want to feel in control. Selection of recipes should be intuitive, and users should be able to reflect on prepared recipes. Browsing should entail the possibility to select the ingredients that the recipe should contain as well as the possibility to select additional constraints, possibly compared to a reference recipe. It should be possible to automatically create a shopping list from selected recipes. The system should provide the possibility to include own recipes, of which the health is assessed such that the overview of meal choices and the corresponding healthfulness can be complete. This health information can be presented by calories, fat and/or carbohydrates, as is preferred by the user. The system should have the possibility to formulate health goals or constraints. And finally, the recipe suggestions should be in line with these goals and constraints, or at least indicate when they are not.

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Appendix A: Food Diary

Enquête

Food Choice Questionnaire
1= niet belangrijk 2= een beetje belangrijk 3= belangrijk 4= erg belangrijk
Het is voor mij belangrijk dat de maaltijd die ik eet op een doorsnee dag. . .

	1	2	3	4
...makkelijk te bereiden is	0	0	0	0
...geen toevoegingen bevat	0	0	0	0
...weinig calorieën bevat	0	0	0	0
...goed smaakt	0	0	0	0
...natuurlijke ingrediënten bevat	0	0	0	0
...niet duur is	0	0	0	0
...vetarm is	0	0	0	0
...bekend voor me is	0	0	0	0
...vezelrijk is	0	0	0	0
...voedzaam is	0	0	0	0
...makkelijk verkrijgbaar is in winkels en supermarkten	0	0	0	0
...waar voor je geld is	0	0	0	0
...me opvrolijkt	0	0	0	0
...lekker ruikt	0	0	0	0
...eenvoudig te koken is	0	0	0	0
...me helpt omgaan met stress	0	0	0	0
...me helpt mijn gewicht te beheersen	0	0	0	0
...een aangename textuur heeft	0	0	0	0
...verpakt is op een milieuvriendelijke manier	0	0	0	0
...uit landen komt die ik politiek gezien goedkeur	0	0	0	0
...zoals het eten is dat ik als kind at	0	0	0	0
...veel vitaminen en mineralen bevat	0	0	0	0

	1	2	3	4
...geen kunstmatige ingrediënten bevat	0	0	0	0
...me wakker/alert houdt	0	0	0	0
...lekker eruit ziet	0	0	0	0
...me helpt te ontspannen	0	0	0	0
...veel eiwitten bevat	0	0	0	0
...weinig tijd kost om te bereiden	0	0	0	0
...me gezond houdt	0	0	0	0
...goed is voor mijn huid/tanden/haar/nagels etc	0	0	0	0
...me goed laat voelen	0	0	0	0
... duidelijk aangegeven landen van herkomst heeft	0	0	0	0
...datgene is wat ik meestal eet	0	0	0	0
...me helpt omgaan met het leven	0	0	0	0
...in winkels gekocht kan worden dichtbij waar ik woon/werk	0	0	0	0
...goedkoop is	0	0	0	0

Als er gasten komen eten is het voor mij belangrijk dat de maaltijd...

	1	2	3	4
...lekker gevonden wordt door mijn gasten	0	0	0	0
...vetarm is	0	0	0	0
...er lekker uit ziet	0	0	0	0
...makkelijk te bereiden is	0	0	0	0
...weinig caloriën bevat	0	0	0	0
...goedkoop is	0	0	0	0
...bekend voor me is	0	0	0	0
...gezond is	0	0	0	0
...lekker gevonden wordt door mij	0	0	0	0
...datgene is wat ik meestal eet	0	0	0	0

Algemene vragen

Wat is uw geboortedatum? ...
Wat is uw geslacht? 0 man 0 vrouw
Wat is uw hoogst afgeronde opleiding? 0 MAVO 0 HAVO 0 VWO
0 MBO 0 HBO 0 Universiteit 0 anders,namelijk: ...
Wie eten er op een normale dag mee? 0 partner, leeftijd: ...
0 kinderen, leeftijd: ...
0 anders,namelijk: ...
Hoe vaak in de week doet u boodschappen? ...
Hoe lang heeft u/uw gezinslid al diabetes II? ...

Maaltijd

Datum:

Wat heeft u gegeten?
Titel van recept...
Welk soort vlees / vis / vleesvervanger?...
Wat voor groenten?...
Wat zat er nog meer bij? (gekookte aardappelen, rijst, spaghetti, etc)...
Saus?...

Wie heeft er gekookt?
0 ikzelf 0 partner 0 iemand anders thuis, namelijk:..
0 ik was uit eten 0 ik at bij vrienden 0 anders:...

Waarom heeft u dit gerecht gekozen?

	Helemaal niet						Heel erg		
Ik vind het lekker:	0	0	0	0	0	0	0	n.v.t.	0
Opmerkingen									
Het is snel klaar:	0	0	0	0	0	0	0	n.v.t.	0
Opmerkingen									
Het is goedkoop:	0	0	0	0	0	0	0	n.v.t.	0
Opmerkingen									
Ik eet dit vaker:	0	0	0	0	0	0	0	n.v.t.	0
Opmerkingen									
Het is makkelijk te maken:	0	0	0	0	0	0	0	n.v.t.	0
Opmerkingen									
Ik had er trek in:	0	0	0	0	0	0	0	n.v.t.	0
Opmerkingen									
Product was in de aanbieding:	0	0	0	0	0	0	0	n.v.t.	0
Opmerkingen									
Omdat het het juiste seizoen is:	0	0	0	0	0	0	0	n.v.t.	0
Opmerkingen									
Omdat ik ingredienten al had:	0	0	0	0	0	0	0	n.v.t.	0
Opmerkingen									

Had u gasten? Ja 0 Nee 0
Zo ja, wat voor invloed had dit op uw maaltijdkeuze? ...
Overige redenen?...

Appendix B: Questions asked in interview study

1. Welke medicatie gebruikt u? (insuline / anders)
    (a) Wat is de invloed van deze medicatie?
    (b) Hoe gaat u om met ergens anders eten/ uit eten gaan, wat zijn de gevolgen voor uw medicatie?
    (c) Wat heeft u verandert qua eten toen u hoorde dat u diabetes had?
        i. Was dit moeilijk en waarom wel/niet?
        ii. Wat voor tips zou u geven aan mensen die hun eetpatroon moesten veranderen?
        iii. Wat zou u erbij helpen/ hebben kunnen helpen?
2. Bent u tevreden over uw huidige eetpatroon?
    (a) Wat zou u er aan veranderen?
    (b) Wat zou u niet veranderen?
    (c) Heeft u behoefte aan variatie?
        i. Zou u twee dagen na elkaar in de week het zelfde willen eten?
        ii. Wat vind u van het eten van een recept 2 dagen achter elkaar/twee keer in de week / Hoe lang moet er tussen twee dezelfde recepten zitten?
    (d) Heeft u vaste patronen, bijvoorbeeld een bepaald recept iedere week/eens in de twee weken/ iedere maand. En is er nog een specifieke dag aan zo' n patroon verbonden?
    (e) Hoe ga je om met kliekjes?
3. Hoe bepaalt u wat u eet bij de hoofdmaaltijd mbt diabetes?
    (a) Speelt uw bloedsuiker (over de dag) hierbij een rol? Wat is de invloed van bloedsuiker op uw honger/trek gevoel?

(b) Speelt motivatie voor verantwoord eten (mbt diabetes) hierbij een rol? (Wat verandert er als u een dag wat meer/minder gemotiveerd bent en hoe komt het dat u meer/minder gemotiveerd bent)

(c) Wat is de invloed van uw partner? Eten u beide altijd hetzelfde? En zo nee, wat is het verschil? Is de portiegrootte voor uw partner anders?

4. (Taak 1) Ik ga u zo 4 situaties voorleggen. Leg de volgende kaartjes op volgorde van belang in die situatie. (3 rijtjes: erg belangrijk, gemiddeld belangrijk, niet belangrijk)

(welke afwegingen maakt u?)

1. (a) Uw normale thuissituatie doordeweeks
   (b) Uw normale thuissituatie in het weekend/in vakantietijd
   (c) U gaat uit eten in een restaurant
   (d) Vrienden gaan voor u koken, wat vind u belangrijk waarop zij letten
   (e) U heeft bezoek

2. (Taak 2) Stelt u voor dat u honger hebt en zo gaat eten. U krijgt steeds twee recepten aangeboden, kies degene welke je zou kiezen en leg uit waarom

3. (Taak 3) Maak een sortering (in 7 stapels) van de volgende recepten op hoe aantrekkelijk het is om te maken (1 = heel aantrekkelijk, 2= aantrekkelijk, 3= een beetje aantrekkelijk, 4= neutraal, 5 = niet zo aantrekkelijk, 6 = onaantrekkelijk, 7 = erg onaantrekkelijk) :

4. (Taak 4) Maak een sortering (in 7 stapels) van de volgende recepten op hoe verantwoord het is voor u (1 = heel verantwoord, 2= verantwoord, 3= een beetje verantwoord, 4= neutraal, 5 = niet zo verantwoord, 6 = onverantwoord, 7 = erg onverantwoord)

5. (Taak 5) Stelt u voor dat u moest plannen wat u volgende week gaat eten. Maak op het vel dat voor u ligt een weekplanning met de volgende recepten. Naderhand kunt u (met behulp van kaartjes eventueel) uitleggen waarom recepten door zijn gegaan/af zijn gevallen en waarom een bepaald recept op een bepaalde dag gemaakt wordt.

6. (Na de taken)

   (a) Als iemand (bijv. Uw dochter/zoon) nu voor u zou bepalen wat u moest eten, waar zou deze persoon dan op moeten letten? (kaartjes met factoren aanbieden)

(b) Als dit nu gedaan werd door een computer die u elk moment kan raadplegen, wanneer zou u deze computer nu wel of niet raadplegen?

(c) Waar zou de computer aan moeten voldoen zodat u deze elke dag zou willen raadplegen?

   i. Wilt u aan kunnen geven dat een recept niet geschikt is? (met een score of aangeven waarom?)

   ii. Wilt u vooraf al aangeven welke ingredienten er wel/niet in moeten zitten?

   iii. Wilt u dat het systeem een weekplan voor u maakt?

   iv. Wilt u dat het systeem rekening houdt met de mensen die mee-eten? (en andere wensen?)

Appendix C: Questionnaire in Experimental Study

Het experiment vind 3 weken lang, min. 1x doordeweeks en min 1x in het weekend plaats. Het is belangrijk dat elke week dezelfde dagen worden gebruikt. Welke 3 dagen wilt u hiervoor kiezen (markeer je antwoorden) ?
0 Maandag 0 Dinsdag 0 Woensdag 0 Donderdag
0 Vrijdag 0 Zaterdag 0 Zondag

Als u wilt kan ik u helpen herinneren aan uw sessies door u een mailtje te sturen, te bellen of te smsen. Hoe wil je de herinnering ontvangen?
0 Mail (op mailadres: .....) 0 Sms (op telnummer:........)
0 Bellen 0 Niet

Wat is uw geslacht?	Man 0		Vrouw 0	
Hoe oud bent u?				
Wat is uw religie?				
Wat is uw nationaliteit?				
Wat is uw hoogst genoten opleiding?				
Hoe ziet uw huidige dagbesteding eruit?	Werk 09:00-17:00 (Fulltime)	Student	Wisselende Diensten	Geen Werk/ Anders, namelijk:
Bent u vegetarier/veganist?	Vegetariër 0		Veganist 0	Nee 0
Wie eten er normaal gesproken met u mee? (bijv. partner, kinderen?)				
Hoe oud zijn de mensen die met u mee eten?				
Hoe vaak maakt u per maand een maaltijd aan de hand van een recept?				

Gedurende een normale week,
Hoe vaak bereidt u een maaltijd met verse ingredienten?
Hoe vaak eet u een kant-en-klaar maaltijd of afhaalmaaltijd (bijv. Chinees)?
Hoe vaak gaat u naar een restaurant of snackbar?
Hoeveel tijd besteedt u aan het koken van ma-vrij?
Hoeveel tijd besteedt u aan het koken in het weekend?
Deze ingrediënten gebruik ik liever niet (wegens smaak of allergie) ? Denk hierbij ook aan degenen die met u mee eten.

1 Nooit [0% - 20% van de tijd]
2 Zelden [20% - 40% van de tijd]
3 Soms [40% - 60% van de tijd]
4 Vaak [60% - 80% van de tijd]
5 Altijd [80% - 100% van de tijd]

	1	**2**	**3**	**4**	**5**
Als ik kook, maak ik . . . maaltijden die meer dan 3 ingredienten bevatten	0	0	0	0	0
Ik maak . . . een boodschappenlijstje	0	0	0	0	0
Ik plan . . . maaltijden voor een hele week	0	0	0	0	0
Ik plan . . . . welke maaltijden ik welke dag ga maken	0	0	0	0	0
Ik experimenteer . . . met nieuwe gerechten	0	0	0	0	0

Appendix D: Questionnaire in Usability study

Wat is uw geboortedatum? ...
Wat is uw geslacht? 0 man 0 vrouw
Wat is uw hoogst afgeronde opleiding? 0 MAVO 0 HAVO 0 VWO
0 MBO 0 HBO 0 Universiteit
0 anders,namelijk:...
Hoe lang heeft u/uw gezinslid al diabetes II? ...
Wie eten er op een normale dag mee? 0 partner, leeftijd: ...
0 kinderen, leeftijd: ...
0 anders,namelijk:...
Waar let u normaal op bij het kiezen van de maaltijd?

0 Tijd	0 Technieken	0 Vet
0 Prijs	0 Bekendheid	0 Koolhydraten
0 Gemak	0 Gezin/Partner	0 Energie
0 Smaak	0 Geur	0 Groente
0 Hoeveelheid ingredinten	0 Uiterlijk	0 Seizoen
0 Aanbod supermarkt	0 Ingredinten in huis	0 anders, namelijk: ...

Hoe vaak in de week doet u boodschappen? ...
Op welke dagen doet u meestal boodschappen? ...
Voor hoeveel dagen doet u de boodschappen? ...
Heeft u/ uw gezinslid een voedingsadvies gekregen en zo ja, wat is dit advies?
...
Welke ingredinten gebruikt u niet? (bijvoorbeeld omdat u ze niet lekker vindt
of er allergisch voor bent)
...

Appendix E: Questions asked in usability interview

1. Welke diabetes medicatie gebruikt u? (insuline / anders)
   (a) Wat is de invloed van deze medicatie?
   (b) Hoe gaat u om met ergens anders eten/ uit eten gaan, wat zijn de gevolgen voor uw medicatie?
   (c) Wat heeft u veranderd qua eten toen u hoorde dat u diabetes had?
      i. Was dit moeilijk en waarom wel/niet?
      ii. Wat voor tips zou u geven aan mensen die hun eetpatroon moesten veranderen?
      iii. Wat zou u erbij helpen/ hebben kunnen helpen?
2. Houdt u elke maaltijd rekening met uw diabetes?
3. Wat vindt u de voordelen van de diabetes eetrichtlijnen? En de nadelen?
4. Wat zijn momenten dat u het moeilijk vindt om verantwoord te eten?
5. Bent u tevreden over uw huidige eetpatroon?
   (a) Wat zou u er aan veranderen?
   (b) Wat zou u niet veranderen?
   (c) Heeft u behoefte aan variatie?
      i. Zou u twee dagen na elkaar in de week het zelfde willen eten?
      ii. Wat vindt u van het eten van een recept 2 dagen achter elkaar/twee keer in de week / Hoe lang moet er tussen twee dezelfde recepten zitten?
   (d) Heeft u vaste patronen, bijvoorbeeld een bepaald recept iedere week/eens in de twee weken/ iedere maand. En is er nog een specifieke dag aan zo' n patroon verbonden?

   (e) Hoe gaat u om met kliekjes?

6. Hoe bepaalt u wat u eet bij de hoofdmaaltijd mbt diabetes?
   (a) Wat is de invloed van uw partner? Eten u beide altijd hetzelfde? En zo nee, wat is het verschil? Is de portiegrootte voor uw partner anders?

7. Wat vond u van het programma MCCII?
   (a) Wat vond u er goed aan?
   (b) Wat vond u er niet goed aan?
   (c) Was het programma intutief?
   (d) Liep u nog tegen problemen aan?

8. Zou u het programma gaan gebruiken?
   (a) Op welke momenten wel? Waarom? Welke functies?
   (b) Op welke moment niet? Waarom? Welke functies?
   (c) Welke functies mist u? Bijvoorbeeld: zoekfunctie, bladeren door recepten.

9. Wat vond u van de mogelijkheid om een enkele suggestie te krijgen?
   (a) Zou u deze functie gebruiken / wanneer?
   (b) Wat vond u van de suggesties?
   (c) Wat vond u van de groene smiley functie?
   (d) Wat vond u van de oranje smiley functie?

10. Wat vond u van de rode smiley functie?

11. Wat vond u van de mogelijkheid om een plan voor meerdere dagen te maken?
    (a) Wat vond u van de voorgestelde recepten in het meer-dagen-plan
    (b) vond u het moeilijk om recepten te vinden die (beter) geschikt waren
    (c) Maakte u gebruik van de mogelijkheid om een recept te zoeken met bepaalde eisen? (de oranje knop)
    (d) Vond u het uiteindelijke meerdagenplan realistisch (zou u het ook echt bereiden)
    (e) Zou u deze functie gebruiken/ wanneer?

(f) Wat kan er verbeterd worden aan de recepten die voorgesteld worden in het weekplan?
(g) Wat kan er verbeterd worden aan het weekplan functie (weergave en dergelijke)?

12. Wat vind u van de zoekmogelijkheid die het programma biedt?
    (a) Heeft u de functie gebruikt?
    (b) Zou u de functie vaker gebruiken? Wanneer? Waarom wel/niet?
    (c) Vond u de functie intutief?
    (d) Wat vond u er goed aan/ wat slecht?
    (e) Wat kan er aan verbeterd worden?
13. Hoe zou uw ideale systeem met receptsuggesties eruit zien?
    (a) welke functies?
    (b) wat voor recepten?
14. Mogelijk: Ingaan op de specifieke recepten die ze hebben gekozen en waarom ze die gekozen hebben