Improving the Recommendations of Meals in the PROMISS Application

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Abstract. The PROMISS application is specifically built to let older adults keep track of their diet and protein intake. To improve the user-experience of this application, we study how machine learning algorithms can be used to recommend meals and products based on historical data. An intelligent workflow is designed which combines five different algorithms that recommend suitable meals and products. These algorithms are trained and tested using data from a previous user study with the PROMISS application. The change in user-experience is measured by the numbers of clicks needed to enter a meal in the application. Two different variants of the new application, namely, one using only the two new recommended meals and the other using both the two new recommended meals plus the old recommended meal, are compared with the old application. It was found that both new applications reduce the number of clicks and thus increase the user-experience of the application.

Keywords: Recommender systems · Diet tracking · Machine learning · Association rule learning

1 Introduction

Over the last few years, the usage of technology in the lives of older adults has increased significantly. An example of this is PARO: the famous seal that is used in elderly homes as a companion robot and a therapeutic tool. Research showed that the older adults were willing to interact with PARO and that this interaction improved their physical activity [12].

Technology can also be used in order to stimulate a healthy lifestyle, for example meal planning systems. Such an application has been created for the diet trial of the PROMISS project [17]. The PROMISS diet trial aims on increasing the protein intake of older adults with a relatively low protein intake [19]. One of the risks of a low protein intake is a rapid loss of muscle mass [10].

The PROMISS application is meant for daily usage during the diet trial. For each user, the application is personalized with the help of their personal diet plan created by the dietitians of the PROMISS project. Using a progress bar,

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the total amount of protein consumed by the user is visualized throughout the day, helping the user complete their daily protein intake.

The PROMISS application that was used in the diet trail included meal recommendations based on the user's diet plan and previous input [17]. In this project the possibility of improving the user-experience by reducing the number of necessary clicks to enter a meal is studied. This can be achieved by creating an intelligent workflow using machine learning algorithms that personalize meal and product recommendations on regularities in historical data of users. Furthermore, it has been shown that using computer tailored information personalized on the user, is more effective in promoting a nutritious lifestyle, than general non-computer tailored information [11]. Thus, recommending meals in a more personalized way improves the user-experience not only by increasing the efficiency but also by making the recommendations more personalized.

First, background information about the PROMISS application and meal recommendation is discussed in Sect. 2. Second, the research methodology, including a description of the data, is described in Sect. 3. Third, the different algorithms are described in Sect. 4, together with an overview on how they work together. In Sect. 5 it is discussed how the training data has been determined. Finally, the conclusion and discussion can be found in Sect. 6.

2 Background

First, more details on the PROMISS application are discussed. Furthermore, an overview of related work on meal and product recommendation is given.

2.1 PROMISS Application

As mentioned in the introduction, the PROMISS application is a system to improve diet compliance for elderly users [17]. Protein points were used as a way to represent the protein value of products and meals. The users of the application could keep track of their diet by means of their protein points. The goal was to stimulate users to eat enough protein each day by providing them with a progress bar of the protein points they have gotten on a specific day or moment.

Before the diet trial, the eating habits of participants were monitored. Based on this information a diet plan, including the personal protein need, for each user was composed by a dietitian. For most participants, there were six eating moments per day: three main meals and three snacks. The diet plan consisted of one meal for each eating moment of the day, and it was the same for each day. The users each received a tablet with their personalized application. They were instructed to fill in meals they have eaten for each eating moment for a specific period of time. The original application contained three ways of entering meals:

- The user can enter a meal via the meal composer. They can replace, remove or add products from the recommended meal. When the user has switched a product for three times or more for the same product, the meal plan for that eating moment is adjusted by replacing the product.

– The user can directly enter the number of protein points eaten, without filling in the products of the meal.
– The user can use the additionally provided foodbox to register intake of specific products.

This system also had disadvantages. Firstly, each day the recommended meal was, in essence, the same. Secondly, when the user chose to deviate from the recommended meal, (s)he had to enter this meal manually. This can be a time depending task.

2.2 Meal and Product Recommendation

Technology is growing each day and is playing an increasingly larger role in our lives. Whether needed for work, sharing pictures on social media or downloading useful applications to make life easier, nearly everyone owns a mobile device [2]. Another thing that keeps growing is the problem of obesity and poor health. Being obese causes the death of over four million people each year [4]. However, it has been shown that obesity and health related problems can be prevented or even reversed in some cases through good nutrition [18]. Because of the growing use of technology and health problems due to obesity, there are quite some food recommender tools on the market which all try to stimulate a healthy lifestyle.

Elsweiler and Harvey presented an approach to integrating nutrition in a recommender system by grouping items, which together present a balanced meal, rather than recommending individual items [13]. During this experiment Elsweiler and Harvey gathered a taste profile of the participants, using data including recipes and nutritional properties, which users could rate. One potential pitfall was that the users did not rate enough breakfast recipes, and it has not been further researched how to improve the recommendation for breakfast meals.

Furthermore, the approach of Elsweiler and Harvey did not contain any research on the usage of the application by older adults [13]. The system 'Nutrition for Elder care' (NutElCare) by Espin, on the other hand, has been especially designed for older adults [14]. In the last few years, the usage of technologies among older adults has increased substantially. Which caused a higher willingness of using these kinds of technologies, such as food recommender systems, in their daily lives [14]. NutElCare uses knowledge-based techniques and requirements of the user to generate a recommendation of items. Furthermore, the user can rate meals which are used to calculate similarity scores between meals.

Many food recommender tools rely on the input from users. See, for example, work by Freyne and Berkovsky, whose recommender system use ratings on both recipes and food items [15]. Or the food recommender system from Professor Aberg, whose system uses collaborative filtering to predict a user's taste opinion on a recipe that the user has not yet rated based on other ratings [8]. Disadvantages of these systems are the lack of willingness of rating meals and the lack of rated meals for specific categories. No examples are found of systems that rely purely on historical data on eating habits of the users.

3 Method

This research studies whether personalized recommendations improves the user-experience of a diet tracking app. To do so, data from the PROMISS application used in the PROMISS diet trial is used. This data is described in the next section. The evaluation of the designed algorithms is explained in Sect. 3.2.

3.1 Data Usage

The data that is used has been gathered from the users that participated in the PROMISS diet trial [16]. The data has been anonymised in order to maintain the anonymity of the participants. When designing the five algorithms, the data of the protein products, the activity logging of the user and the day totals of the protein points is used. From the activity logging data, especially the data where the user fills in a meal using the meal composer are important for this research. This data contains all information (e.g. product and portion size) on the meals that are entered in the meal composer.

Furthermore, not all data of all participants is used. In the tablet study of the PROMISS diet trial, 36 participants were considered active users [16]. The data varies from 27 days as the least amount of data and 240 days as the most amount of data. However, some people did not use the meal composer for the majority of the time. They entered the number of protein points without the products their meal consisted of. Therefore, the percentage of meals entered using the meal composer has been calculated for each participant. It has been decided to use a threshold of 70% and only use data of users above that threshold. Further in this research, the 11 remaining participants are referred to as active users.

Subsequently, the period of training data has to be established. There needs to be a balance between having enough data which can lead to logical recommendations and containing the satisfaction of the user. During the training period there cannot be personalized recommendations based on historical data and thus this also needs to be taken into consideration. Until enough data is present, users are considered ‘new users’. In the results section is explained how the training period has been established.

3.2 Evaluation of the Task Completion Time

When evaluating the task completion time, the number of clicks when entering a meal using the old application is compared to the number of clicks using the new application. As mentioned, this new application is improved through the use of five different algorithms which are explained in Sect. 4.

In Fig. 1, a screenshot of the meal composer in the old application is shown. On the left all products in the recommended meal are shown. When clicking on the blue button below the meal (‘add a new product’), the categories of products appear on the right. By clicking on a category, the top 5 most used products for that user appear followed by all products in alphabetical order. By clicking on a product, this product will be added to the meal and the right part of the

Fig. 1. Screenshot of the meal composer

screen is emptied again. Moreover, if a user wants to replace a product in the meal, (s)he can click on that product and all products from the same category will appear, with the right amount so that it contains the same protein value as the original product. In Algorithm 1 it can be seen how the number of clicks is acquired using the old application.

For evaluating the number of clicks for the new application, the test data is used to acquire the chosen meal. From the logging data of the user, it can be determined what products have been added or deleted to the recommended meal, this way the chosen meal can be acquired. Furthermore, the two personalized recommended meals obtained using the newly created algorithms are used. For the evaluation, the meal that resulted in the least number of clicks is used. A difference between the old and the new application can be seen in Algorithm 2: adding a product can also lead to two clicks when a product is chosen from the predicted product list which is acquired using a machine learning algorithm named association rule learning. When comparing the number of clicks

Algorithm 1. Pseudocode number of clicks old application

```
Initialize a recommended meal for user
if user replace/add product then
    if product can be replaced with product from same category then
        Clicks += 2
    else
        Clicks += 3
    end if
end if
if user removes product then
    Clicks += 1
end if
```

Algorithm 2. Pseudocode number of clicks new application

```
Initialize recommended meals for user
if user replace/add product then
    if product can be replaced with product from same category then
        Clicks += 2
    end if
    if product is in advised product list then
        Clicks += 2
    else
        Clicks += 3
    end if
end if
if user removes product then
    Clicks += 1
end if
```

between the old application and the new application, a two-sided test for the null hypothesis that two independent samples have identical average expected values is conducted. The test assumes that the samples have identical variances.

4 Implementation

Five different algorithms have been designed and composed together such that it creates an intelligent workflow. The code of the algorithms and the evaluation of the algorithms can be found on GitHub [1]. The algorithms are implemented in Python 3.7.6 [5]. In this section, an overview of the general workflow and a description of the five algorithms is given.

4.1 Overview and General Flow

The basic working of the five algorithms is as follows:

- The **preset algorithm** computes the 10 most used presets from all active users. In this context, a preset is a combination of categories which often occur together. From these categories the algorithm creates a meal by looking at the most used products within these categories.
- The **protein points algorithm** is only used for meals filled in for dinner and the evening snack. The algorithm looks at how much points the user has still left for that day and recommends a meal within a range of these points.
- The **core + addition algorithm** considers products which are often used together in one meal. From this, one core of two products is chosen. Furthermore, the additions are products that appear in the same meal as the core. Combining the core and some additions, one meal is created.
- The **preference algorithm** is used to recognize people with a vegetarian or a pescatarian diet. Where vegetarians exclude both meat and fish from their diet, pescotarians do eat fish but not meat. This knowledge can be used to match their recommended meals with their preference.

– The **association rule learning algorithm** is used when the user decides to add or replace a product. Machine learning is used to discover relationships between the products from the current composed meal and all products in the database. These relationships can be used to predict the next product.

Figure 2 shows how the five algorithms are combined into one intelligent workflow. The colors which appear in the flowchart each advocate a different algorithm. The preset and protein algorithm have been combined together, which later is explained in detail.

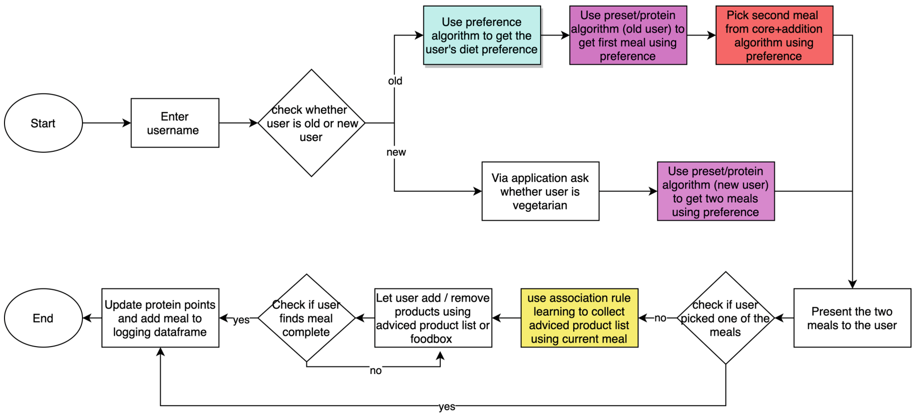

Fig. 2. Flowchart of general workflow

The first step of the flowchart is to enter a username to decide whether the user is an old or a new user. This is a crucial step, because the data used in the algorithms is different for new and old users. New users do not have historical data which can be used by the algorithms. In total there are two recommended meals. First, for old users, the preference algorithm is used to acquire the diet preference of the user. Then the two meals are deducted using a combination of the preset/protein and the core + addition algorithm. Both algorithms take into account the diet preference. The preference algorithm cannot be used for new users, hence the question whether the user's diet is vegetarian or pescatarian is asked. The two meals for new users are deducted using only the preset/protein algorithm and taking into account the diet preference.

Subsequently, the two meals are presented to the user. The user can add, replace or remove products from the recommended meal. In order to speed up this process, products are predicted using the association rule learning algorithm. This algorithm is used to acquire relationships between the products present in the meal and all the products in the database of the application. Based on these relationships a product is recommended to the user.

4.2 Preset/Protein Algorithm

The preset/protein algorithm is used to recommend the first meal to old users and to recommend both meals to new users. However, the working of the algorithm is slightly different for old and new users. Figure 3 shows the workflow of this algorithm. The first step in the flowchart is to retrieve the eating moment which the user wants to enter a meal for, this is due to the fact that for the eating moment 'Avondeten' (dinner) or 'Tussendoor avond' (evening snack) the protein algorithm is used and in other cases the preset algorithm is used.

Assume the flow for the protein algorithm is followed, both the data of the user's day totals of protein points and the protein need is used in order to gather the amount of protein left. If this amount needs to be split between the two eating moments, then 'Avondeten' uses 75% of this amount and the 'Tussendoor avond' 25%. Afterwards the check whether a user is old or new occurs, because if the user is old, their own meals are used in order to gather all meals for the specific eating moment. If the user does not have this data, meaning the user is a new user, the meals of all active users is used.

The meals for the specific eating moment are divided into clusters using K-means clustering. This machine learning algorithm clusters data by trying to

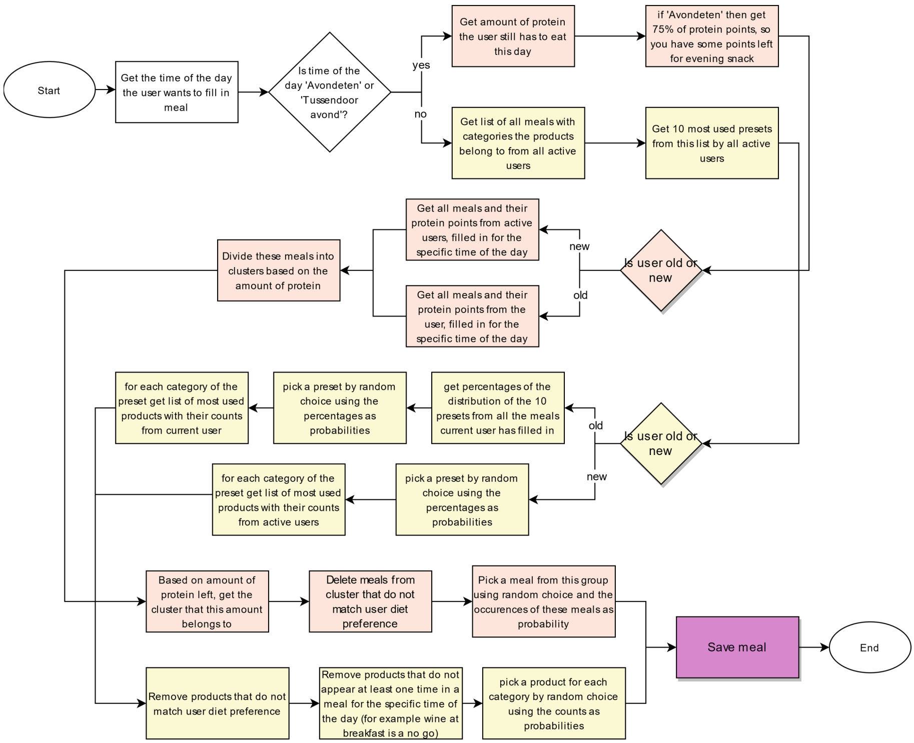

Fig. 3. Flowchart of preset/protein algorithm

separate samples in groups of equal variances (using [7]). It requires the number of clusters to be specified, therefore a range between 2 and 40 has been chosen and for each number of clusters k-means is used. The best silhouette score is commonly used as a factor to determine the appropriate number of clusters. For each cluster number the silhouette coefficient is calculated and plotted (using [3]). Using this plot, the highest silhouette coefficient is determined and therefore the appropriate number of clusters. Subsequently, based on the amount of protein left, it is decided which cluster is closest to this amount. The meals from this cluster are then examined whether they match the user's diet preference, and the occurrences of the meals are gathered. These occurrences are used as probability in order to choose a recommended meal using a random choice method [6].

For the other eating moments, the flow from the preset algorithm is followed. Presets are categories of products which often occurs together in the eating pattern of each user. For a Dutch person this could be the standard AVG (Aardappelen - starch, Vlees - meat but also includes fish/veggie, Groenten - greens) meal. The algorithm transforms each meal from all users for a specific eating moment into a list of the categories of the products. The 10 most used presets are selected. The approach on how to retrieve the recommended meal is different for old and new users.

If the user is old, the distribution of the presets in their own meals is calculated. The distributions are used as probabilities in order to choose a preset using the random choice method. For each category of the chosen preset, the most used products are gathered from all eating moments. Next, with a similar method a product is chosen for each category. The products that do not match the users diet preference are deleted. The products that do not appear at least one time in the specific eating moment are also deleted. Using the occurrences of the most used products in the meals from the user, one product for each category in the preset is chosen using the random choice method again. By adding all products together, the recommended meal is assembled.

If the user is new, so the user has not finished their training period yet, the distribution of the presets in all the meals of all users is used in order to choose a preset using the random choice method. Subsequently, the most used products for each category are gathered using all active users. From this moment, the algorithm continues the same as before. This way, users without historical data also receive a recommended meal.

4.3 Core + Addition Algorithm

The core + addition algorithm is used to recommend the second meal to old users. The preset algorithm can be used for new users, using data from all active users, however the core + addition algorithm is not modelled to be able to do this. Therefore, this algorithm is only used for old users.

According to the flowchart in Fig. 4 the first step in this algorithm is to collect all unique meals the user has filled in for a specific eating moment. From the unique meals, all unique two-product combinations are gathered. The combinations that do not match the user's diet preference are deleted. For each unique

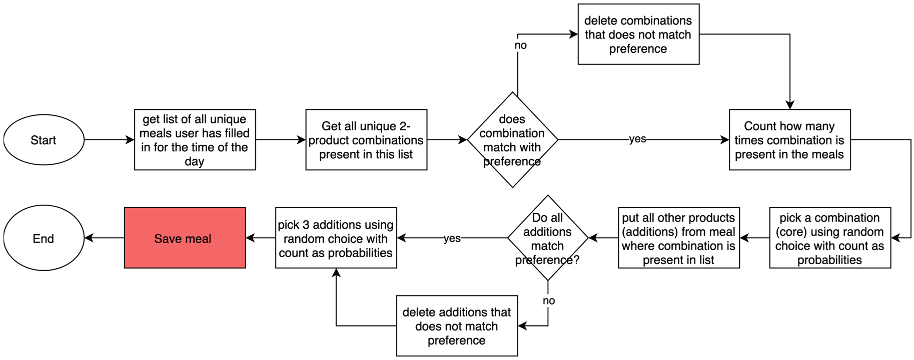

Fig. 4. Flowchart of core+addition algorithm

two-product combination, the occurrences in all meals from the specific eating moment from the user is collected. Using the occurrences as probabilities, one core is chosen using the random choice method. Subsequently, the algorithm goes through each meal from the specific eating moment where the core is present and gets the occurrences of all additions (consisting of one product) from these meals. The additions that do not match the user's preference are deleted. At last, three additions are collected using the random choice method and their occurrences as probability. The three additions and the core together form the recommended meal.

4.4 Preference Algorithm

The preference algorithm is important for both the preset/protein algorithm and the core + addition algorithm. The algorithm predicts the diet preference of the user and therefore prevents that recommended meals for people who eat vegetarian or pescatarian contain meat or fish products. This algorithm can only be used for people who have historical data, namely the old users.

First, as is shown in Fig. 5, the algorithm collects all the meals the user has filled in and checks for every meal whether all products in the meal are vegetarian or pescatarian. Beforehand it has been decided for every product in the protein products database whether a product is vegetarian, pescatarian or neither. If the percentage of vegetarian meals is above 99%, then the user's preference is vegetarian, this is the same for a pescatarian preference. The threshold of 99% is chosen because it would be a pitfall if the threshold is not high enough and thereby will wrongly delete meat or fish products from a user's recommended meal who mainly but not entirely eats pescatarian or vegetarian. However, 100% is not used, as sometimes participants might eat something that does not match their diet preference, but still have this as a preference.

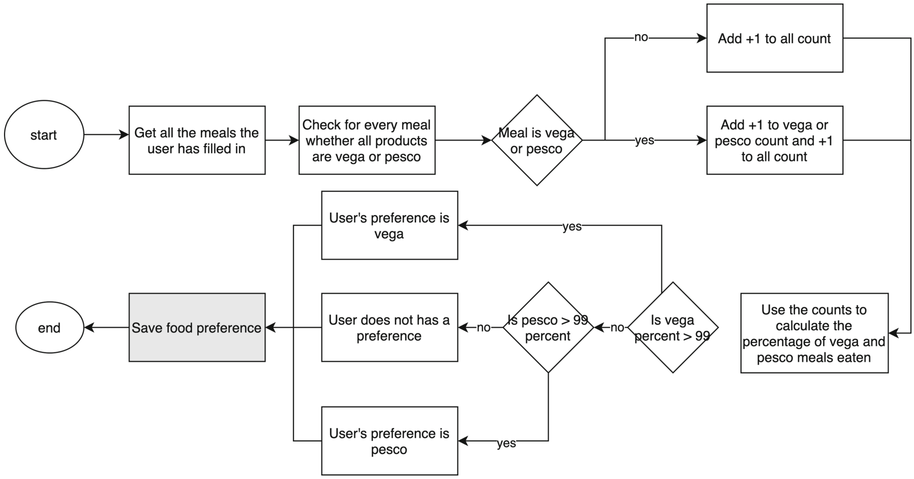

Fig. 5. Flowchart of preference algorithm

4.5 Association Rule Learning Algorithm

The application is not only improved on the part of recommending meals, but also when the user chooses to alter the recommended meal by adding products. As can be seen in Algorithm 1, it takes the user three clicks for adding a product which is not from the same category as the product the user wants to replace. In order to reduce this to two clicks, the association rule learning algorithm is used. In Algorithm 2 it can be seen that when a user wants to add a product which is in the advised product list, it takes the user only two clicks.

There are different software implementations of the association rule algorithms. This research uses the Apriori association rule algorithm created by Christian Borgelt [9]. It proceeds by identifying the frequent individual items in a database, hence it is chosen to use this algorithm in order to improve the addition of products. The Apriori implementation uses transactional data and generates frequent item sets from within this data in order to create association rules from these item sets [20]. An antecedent is an item found within the data, in this case a product or combination of products, a consequent is an item found in combination with the antecedent. In the algorithm where Apriori has been implemented, a list is created including all consequents with a minimum support of 0.05. The support is then used as probability and using random choice two consequents are collected. For at most 5 randomly chosen products present in the current meal, their 5 consequents are collected and presented to the user, which can help them choose products for their meal.

5 Results

As mentioned in Sect. 3, the available data has been split into training and test data. This section discusses how the training period has been established.

Furthermore, the number of clicks of both the old application and the newly created algorithms are presented.

5.1 Training Data Duration Results

As previously has been discussed, a balance between having enough data which can lead to logical recommendations and containing the satisfaction of the user needs to be taken into consideration when establishing the training period. In this research the preset algorithm has been used in order to find this balance. The data of all users has been used to calculate the presets from week 0 until week 35. Week 35 being the number of days all users have used as a maximum. For each week the presets were compared to the final preset, which uses all the data from all users. The percentage of matching presets has been calculated and visualized in the graphs in Fig. 6. It has been calculated for three eating moments, for 'Ontbijt' (breakfast), 'Lunch' and 'Avondeten' (dinner). This shows that for each eating moment 80% is quickly reached, afterwards the increment goes slower until it reaches 100%. For both lunch and dinner, the 100% mark takes a lot of time to reach. It makes sense in order to maintain the satisfaction of the user, to not choose 100% as a threshold. Taking lunch into consideration it is best to continue to 80%. It can be concluded that 80% is the right percentage, according to the graphs each eating moment quickly increases until 80%. Therefore, it has been decided to use 80% as a threshold, which means the training period is 10 weeks since the presets for lunch reaches this threshold at 10 weeks. Because of this, not all data can be used to evaluate the number of clicks, since some participants did not fill in meals for the whole training period. Moreover, some participants are excluded as bugs in the application makes their data unreliable. Thus, the remaining data that is used in for this study are from 7 users.

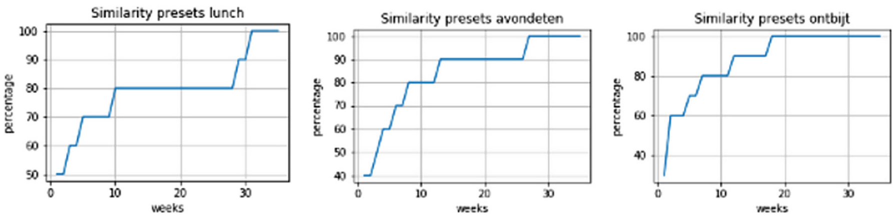

Fig. 6. Similarity scores for presets 'Ontbijt', 'Lunch' and 'Avondeten'

5.2 Results on the Number of Clicks

Algorithm 1 and Algorithm 2 show how the number of clicks can be calculated for the old and new application. In this section the results of the number of clicks are shown. For the new application, two different approaches have been used. First,

Table 1. Comparison number of clicks old application and both new applications.

	Breakfast (n = 81)	Morning snack (n = 61)	Lunch (n = 41)	Afternoon snack (n = 13)	Dinner (n = 43)	Evening snack (n = 12)	All meals average
Old	4.8 (SD = 4.32)	6.7 (SD = 5.06)	10.1 (SD = 6.81)	5.4 (SD = 3.11)	9.62 (SD = 4.55)	3.66 (SD = 3.60)	6.71 (SD = 4.57)
New (2)	2.8 (SD = 3.47)	4.1 (SD = 5.56)	7.88 (SD = 5.56)	4.8 (SD = 3.26)	7.15 (SD = 4.18)	4.08 (SD = 2.33)	5.135 (SD = 4.06)
New (3)	2.16 (SD = 2.77)	3.72 (SD = 4.94)	7.2 (SD = 5.54)	4.6 (SD = 3.36)	6.33 (SD = 3.86)	2.9 (SD = 1.76)	4.48 (SD = 3.71)

Table 2. Comparison p-value and t-test old application and both new applications.

		Breakfast (n = 81)	Morning snack (n = 61)	Lunch (n = 41)	Afternoon snack (n = 13)	Dinner (n = 43)	Evening snack (n = 12)	All meals average
New (2)/Old	p-value	0.004*	0.026*	0.126	0.627	0.093	0.74	0.269
	t-test	2.904	2.247	1.545	0.492	1.698	−0.336	1.425
New (3)/Old	p-value	8.715^{-}05*	0.004*	0.048*	0.475	0.005*	0.325	0.142
	t-test	4.028	2.969	2.01	0.726	2.87	1.007	2.298

the new application including the two meals resulting from the preset/protein algorithm and/or the core + addition algorithm. Secondly, a new application including three meals is evaluated. The third meal is the meal recommended in the old application and the two meals are the same as in the other new variant.

In Table 1 the mean average and the standard deviation of the number of clicks are shown. In the first row, the number of evaluated meals is presented. Looking at this table, it can be concluded that for each eating moment, the new application results into a lower number of clicks. Except for the eating moment 'Tussendoor avond': only the new application using three meals is lower than the number of clicks of the old application. Furthermore, the number of average clicks (M = 4.48, SD = 4.06) is even lower using the application using three meals than the application using two meals.

In Table 2 the results from the t-test comparing the new and old applications are shown The p-values which are significant ($p < 0.05$), are indicated with an asterisk. The majority of the p-values of the new application using three meals are statistically significant. For example, the participants who filled in a meal for 'Ontbijt' (breakfast) and used the new application using three meals (M = 2.16, SD = 2.77) compared to the participants who used the old application (M = 4.8, SD = 4.32) demonstrated significantly better scores (p-value = 0.004).

6 Conclusion and Discussion

To improve the user-experience for a diet tracking app, this research aimed to reduce the number of needed clicks to enter a meal in the application. As a use case we used the application that is used in the PROMISS diet trial and the data that is gathered during that study. The results show that it is possible to reduce the number of clicks by improving the recommendation of meals/products. For most of the meals, this reduction is significant. The application using three recommended meals performs even better than the application using two recommended meals. Logically this can be explained by the fact that because it includes the same meal as the old app, the number of clicks can never be higher.

However another explanation of why the application using three meals performs better is the case that the chance of a recommended meal which matches the users meal, increases when the number of recommended meals rises. It could be that adding more meals even reduces the number of clicks further because of this chance. However, displaying this in a user-friendly way is challenging due to the limited screen size of a tablet or smartphone. With the previously studied version of the application [16] it was found that the elderly users were successfully able to use the application. With only a limited change to the lay-out of the meal composer, to include three menus instead of one, we do not think that this will change. However, it is important that, before using it in a live setting, we test the new lay-out with users from the target group.

In this research historical data from a previously performed study was used. However, using live data might give different results, for example for the association rule learning algorithm. For example, the order of deleted or added products could not be taken into consideration in this research, but this could lead to a different list of advised products, which could lead to a higher or lower number of clicks. Furthermore, it could be interesting to take the time of scrolling for products into consideration. This is also an important factor for the time spend on the task of entering a meal, and thus could further effect the user-experience.

Moreover, when the new application will gain users, the number of active user's needs to be set to a specific number of users which represent the whole population. When dealing with new users, both the protein and the preset algorithm uses data from active users in order to create a recommended meal. When the number of active user's rises, this could take too much time. Further research could investigate an appropriate number of users which represent the whole population of users.

This research shows that an intelligent workflow for recommending meals and products within a diet tracking app reduces the number of clicks needed to enter a meal. Although other measures such as time needed for scrolling could not be taken into account due to the lack of a live experiment, this research provides a first step in making a more intelligent diet tracking system that can be used in interventions or trials.

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