Evolutionary approach for 'healthy bundle' wellbeing recommendations

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ABSTRACT

The purpose of this paper is to introduce an Evolutionary Recommender System focused on promoting a healthy lifestyle through suggestions that jointly consider meals and physical activities, based on users' aims and their preferences. Our solution considers a Genetic Algorithm as the main driver of the recommendation process. An experimental study of algorithmic performance is conducted on users with different goals, along with a cohort study to analyse how real users perceive the recommendations suggested to them.

CCS CONCEPTS

• **Information systems** → *Decision support systems*; *Information retrieval*; • **Applied computing** → **Health care information systems**.

KEYWORDS

Recommender system, Genetic algorithms, Food recommendation, Exercise recommendation

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1 INTRODUCTION

Recommender Systems (RS) have been developed in numerous domains due to their capabilities for building a personalised experience for users, e.g. in online shopping [13], video and audio streaming services [7], tourism [9], wellbeing [6] and dating [16]. RS for wellbeing generally provide end users with suggestions to either improve or maintain their physical exercising [1] or dietary habits [2]. A sedentary lifestyle or unhealthy nourishment might cause serious chronic diseases such as obesity and diabetes. Thus, RS approaches are being recently investigated to support users in preventing such conditions by improving their lifestyle.

Some studies contributed to developing RS solutions for wellbeing purposes. For example, Berndsen et al.'s work in [5] focuses on non-professional runners who want to train as professional athletes. Another study conducted by Agapito et al. [2] recommends suitable food for people suffering from chronic diseases predicated on their health status. Regarding approaches to recommend food, Trattner et al. [21] provide a concise review of solutions and applications from a dietary perspective. By investigating these and other related works in the aforesaid domains, we identified various challenges which have not been dealt with yet. Firstly, a healthy lifestyle can not be holistically adopted if each of the foundations for wellbeing, e.g. nourishment, exercising, etc., is considered in isolation. For instance, eating and exercising habits are strongly interrelated when it comes to maintaining a healthy weight or preventing physical problems. Thus far, no research studies have still focused on the interrelationship between these two aspects for the sake of improving people lifestyle through RS solutions.

Another notable aspect in the landscape of RS refers to the sheer presence of AI techniques across models and domains, yet some AI techniques have still been scarcely investigated by the RS scientific community. One of them is Evolutionary Computing, which has been used for some specific steps within recommendation processes, however its potential in *leading* such processes has not been fully discovered yet. For instance, Kilani et al. [12] uses a Genetic Algorithm (GA) as a supplementary tool to help enhancing performance of a Matrix Factorisation-based model [15]. Their GA implementation refines the preliminary outputs produced upon Matrix Factorisation, but it does not partake in the core recommendation process. Due to their potential to represent personalisation problems as an optimisation problem (as considered in this work), GAs could potentially yield a new approach for RS design and operation due to its flexibility, adaptability and robustness, with ample possibilities to implement such systems.

This paper proposes a novel RS model for wellbeing, founded on a GA implementation which objective is to help users improving or preserving a healthy lifestyle via personalised suggestions on eating and exercising. These two wellbeing elements have been chosen inasmuch they both together regulate numerous aspects of people health needs. When working towards a wellbeing goal, both the nutrients in the food consumed and the exercise activities undertaken can jointly influence such a goal. Our proposed methodology takes the users' preferences and their wellbeing goals as the inputs for building "bundles" composed by a set of food items (a meal) and an exercising suggestion. A bundle plays the role of an item being recommended. Our primary contributions are threefold.

- We introduce a novel RS model in which the recommendation process is led by a GA, with highly configurable items, i.e. meal-exercise bundles, being created and "evolved" to suit the user's preferences and goals.
- We propose an item modelling approach in which food-activity bundles are created and evolved. Unlike other RS domains such as movie or hotel recommendation where

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items are static non-configurable entities, in our approach highly configurable bundles are dynamically built.
- We conduct an experimental study with performance analyses and a real user evaluation.

2 RELATED WORK

This section reviews relevant literature concerning RS for wellbeing and existing RS models incorporating GAs.

2.1 Recommender Systems in wellbeing

Research efforts on RS for wellbeing are relatively recent. Notwithstanding the foregoing studies entail recommending either physical activities or dietary habits.

Achananuparp et al. [1] adopt in their research the assumption that foods consumed in the same context can be seamlessly replaced by each other, thereby allowing for greater diversity in healthy daily meals. Two natural language processing techniques were applied on their data: PPMI (Positive Pointwise Mutual Information) and SVD (Singular Value Decomposition). Based on food similarity, their method produces top-10 food substitute candidates for each target user.

Akkoyunlu et al.'s research [3] present another study based on food substitution, by constructing a graph where nodes represent meals from the database. Nodes are connected if two different meals have at least one food item in common. Adjacent nodes are within the same context and therefore replaceable, thus forming a clique. The Bron-Kerbosh algorithm is applied to find the maximum clique and calculate replaceability score, i.e. some items are more suitable than others to be substituted.

Caldeira et al. [6] stated that meal recipes can be recommended by considering their nutritional value, harmony of ingredients and coverage of pantry. Using the NSGA II algorithm, a list of suggested meal recipes is found considering the number the portions, quantity of ingredients and tastiness. Their approach also makes it possible to set a specific type of food styles.

Regarding personalisation approaches for recommending physical activity, Reimer et al. [19] advocate encouraging users to change their habits for the sake of reaching exercise goals in a tailored manner. The authors' approach to motivate a user consists in using "nudges". There are various types of nudges: suggestions, praise and rewards. The accepted nudges by the user are used to create a personalised profile which is used to encourage the user to reach the goal.

Furthermore, recent research focused on recommending workout videos: Ezin et al. [7] use a hybrid filtering approach to create diverse recommendations. Their model firstly builds a user profile based on the user preferences on types of workout. A Content-Based Filtering produces apreliminary set of recommended videos, whose diversity level is measured. If the recommendations are not diverse enough, a Collaborative Filtering process is iteratively triggered for achieving more diverse recommendations based on similar users' views and likes.

2.2 Genetic Algorithms in Recommender Systems

Evolutionary Computation techniques have been used in numerous Computer Science domains and other disciplines such as Biology, Architecture and Chemistry. In the area of RS, GAs (one of the primary Evolutionary Computing techniques) have still been very scarcely investigated to date. Below we review some works in which GAs have been applied in recommendation processes.

Lv et al.[13] present a research based on combining a GA and an ontology whose objective is to recommend websites. Each item is mapped as a concept in an ontology. User-item similarities are calculated, and a GA is applied on top of a collaborative filtering process to estimate the weights of the related attributes. Another study employs GAs as a metric to calculate similarity [4] between items. The proposed algorithm, called "SimGen", uses training data as a fitness function and test data to check the resulting similarity. Each candidate solution (individual) in the GA is represented by a two-dimensional array indicating the similarity between users.

GAs have been also applied as a optimisation step within a multi-criteria RS in [10], along with a comparison between well-known methods and GA-based methods. They used three variations: Standard GAs, Adaptative GAs and Multi-heuristic GAs. The results show that GA-based approaches could outperform some well-known ones. In another multi-criteria based study, Islem et al.[11] show that a GA can suggest a suitable set of neighbours in a Collaborative Filtering RS, in which both high similarity and considerable diversity are achieved.

Despite the extant efforts on using Evolutionary Computing techniques in the RS domain, their role has been limited to a smaller step inside the recommendation process, thus their potential has not been fully explored yet. Moreover, existing approaches based on GA assume items of static nature, however meal and exercise recommendation demands items that are highly configurable, e.g. physical exercising workouts. Our proposed solution fully relies in a GA in an effort to bridge this research gap. Furthermore, we unify physical activities and meal suggestions into bundles to capture the close interrelationship between nourishment and a physical activity to sustain wellbeing and prevent chronic diseases.

3 METHODOLOGY

This section introduces the main elements of our proposed GA-based approach for personalised wellbeing. The RS workflow is broadly illustrated in Figure 1.

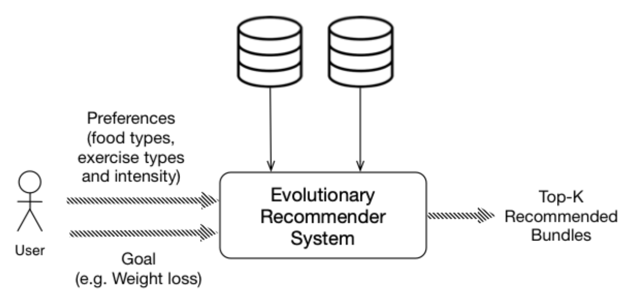

Figure 1: Model of Evolutionary Recommender System

3.1 Dataset and ontology

Our proposal considers a unified approach in which the recommendations contain a set of compatible food items together with a physical activity suggestion. For the scope of this study, the food information (food items and nutritional values) is adopted from [18], and the physical activity information is from [17]. Both data sources have been stored in a database. The following food item attributes are considered: *Food id, Name, Type, Serving size, Calories, Protein, Carbohydrate, Sugar, Fat*, with nutritional values measured in grams. Exercising items have the attributes: *Exercise id, Name, Type, Intensity, Burned calories.* This information is referenced against one hour of activity by a person who weighs 58.97 kilograms. A set of compatible food items is called "meal". A meal plus an exercise item is called "bundle". Both meal and exercising instances are strongly interrelated via the calorie intake balance. For instance, if a meal has a certain amount of calories, then its associated exercise's duration and intensity should burn a sufficient number of calories with respect to the meal (depending on the user's goal, as explained in the next subsection). Thus, bundles are the primary output in our wellbeing RS. This is illustrated in Figure 4. Bundles are used to define each individual or chromosome (candidate solutions in a GA) during the evolutionary process, as explained below.

3.2 Definition of Individuals

A GA works through a population conformed by a group of individuals or candidate solutions to evolve. Each individual represents a possible solution in the problem domain. Individuals are randomly initialised in order to broadly cover the search space. As the GA progresses and explores the initially wide search space, it gradually narrows down the search: this is done based on the actual user's preferences. The initial GA exploration also allows for more diverse and serendipitous, yet less repetitive recommended solutions.

Based on existing coding schemes to represent individuals [8], we encode food item attributes and exercise features into individuals describing meal-exercise bundles (Fig. 4). Each bundle or individual in the GA is, therefore, equivalent to a candidate item for recommendation.

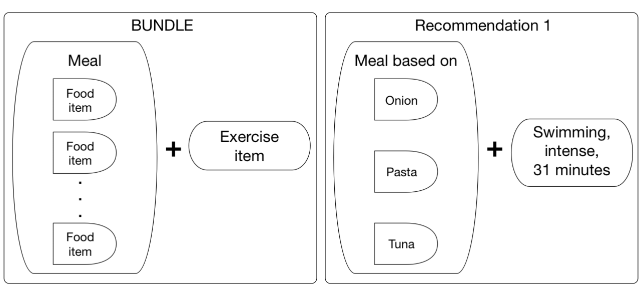

Figure 2: Structure and example of bundle (individual).

3.3 Fitness function

A key element in any GA is the fitness function, as it evaluates "how good" each individual is. This function allows to select those individuals with better aptitude, so as to improve the population throughout an iterative evolutionary process [8]. In order to provide suitable and consistent recommendations that meet (i) the user's preferences and (ii) her wellbeing goals, we define the fitness function upon a set of restrictions. Let $\mathcal{R} = \{\rho_1, \rho_2, \ldots, \rho_N\}$ the set of all possible restrictions to consider. A fitness function FF_i associated to a user $u_i \in U$ with a goal $\mathcal{G}_i \subset \mathcal{R}$, is defined based on a subset of restrictions from $\mathcal{R}$ and her individual food-exercising preferences Ψ_{u_i}. It assesses "how much" a recommended bundle meets $\mathcal{G}_i$ and the user preferences.

$$FF_i = FF(\mathcal{G}_i) = \phi\left(\Psi_{u_i}; \Gamma_i(\rho_{i,1}), \Gamma_i(\rho_{i,2}), \ldots, \Gamma_i(\rho_{i,M})\right) \quad (1)$$

with $\mathcal{G}_i = \{\rho_{i,1}, \rho_{i,2}, \ldots, \rho_{i,M}, \}$. $\Gamma_i(\rho_{i,j})$ is an *aptitude* function describing the degree to which restriction $\rho_{i,j}$ is satisfied by the individual, Ψ_{u_i} is a restriction that measures how much u_i preferences are met, and ϕ is a combination function, e.g. an averaging operator. For instance, given u_1 whose selected goal $\mathcal{G}_1$ is diabetes control, we consider reducing sugar, moderate exercising and a limited amount of calories per meal as its associated restrictions. Therefore, her fitness function FF_1 is defined as follows:

$$\phi(\Psi_{u_1}; \Gamma_1(\rho_{sugar}), \Gamma_1(\rho_{ex-mod}), \Gamma_1(\rho_{cal-lim}))$$

Let u_2 be another example user whose goal $\mathcal{G}_2$ is to lose weight. The fitness function FF_2 is:

$$\phi(\Psi_{u_2}; \Gamma_2(\rho_{fat}), \Gamma_2(\rho_{carb}), \Gamma_2(\rho_{ex-high}), \Gamma_2(\rho_{cal-lim}))$$

Some of the restrictions in wellbeing goals are related to nutrient components. For instance, there is a restriction to regulate the fat levels per meal, another one linked to the carbohydrates and sugars per meal, etc. Figure 3 shows how the fitness function is defined.

3.4 Genetic Operators

Genetic operators are another essential part of a GA. Their objective is to modify the structure of the individuals in order to widely explore the search space. The most common genetic operators are *crossover* and *mutation* [8]. The genetic operators for our evolutionary RS model have been defined in close accordance to the domain problem, hence they are adapted versions of the classically defined ones.

3.4.1 Crossover. This genetic operator needs two individuals for the crossover process to take place. Essentially, it randomly combines a part of each individual to create two new ones, with the aim of further exploring a specific (and sometimes promising) part of the search space. Algorithms 1 and 2 describe the crossover process between meals. For exercising suggestions, each of the new individuals inherits each of the original individuals' activities.

Algorithm 1 Crossover Operator between meals

$random\_crossover \leftarrow random(0.1, 1.0)$
if $random\_crossover < crossover\_probability$ **then**
  $individual_A \leftarrow population[random\_index_1]$
  $individual_B \leftarrow population[random\_index_2]$
  $create(individual_A, individual_B)$
  $create(individual_B, individual_A)$
else
  add $individual_A$ *to new population*
  add $individual_B$ *to new population*

The purpose of $build\_meal$ (Algorithm 2, line 6) is to randomly create a meal by selecting food items from the two original individuals. This new meal forms, together with an exercise option, a new bundle treated as a new individual by the GA. Without loss of generality, let $crossover\_probability = 0.9$ and $bundle\_probability = 0.75$.

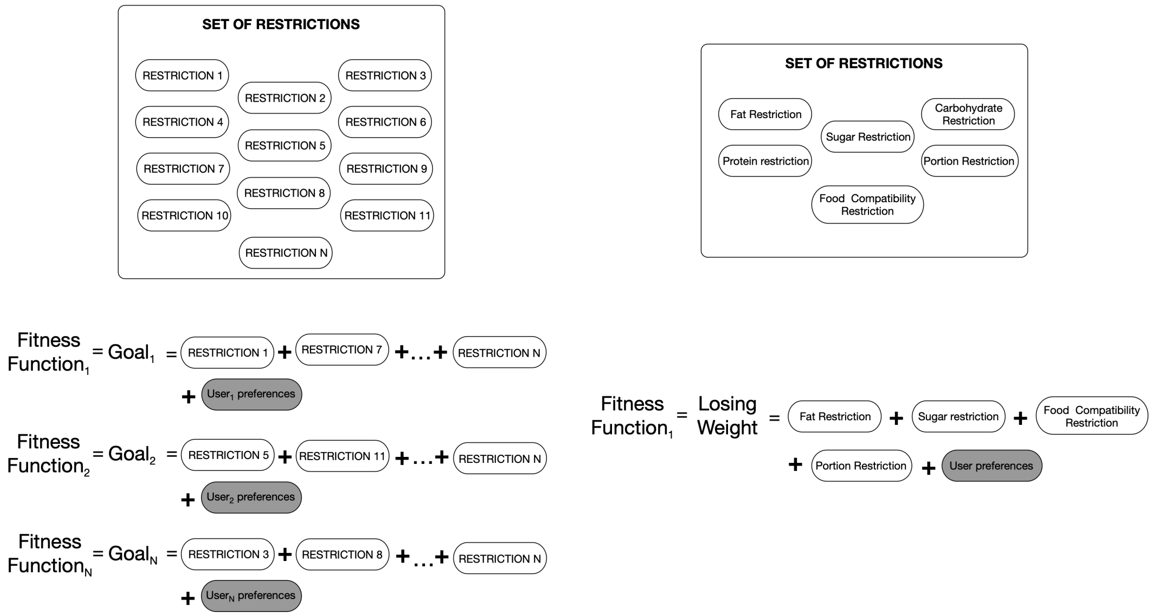

Figure 3: Definition and example of fitness function based on a selected wellbeing goal, its associated restrictions and the user preferences.

Algorithm 2 Function $create(individual_A, individual_B)$

$new\_individual_A$
$random\_bundle_A \leftarrow random(0.1, 1.0)$
if $random\_bundle_A < bundle\_probability$ **then**
  $meal_A \leftarrow bundle_A$
  $meal_B \leftarrow bundle_B$
  $new\_meal \leftarrow build\_meal(meal_A, meal_B)$
  $activity_A \leftarrow bundle_A$
  $new\_bundle \leftarrow Bundle(new\ meal, activity_A)$
  add new bundle to new individual$_A$
else
  add individual$_A$ *bundle to new individual*

3.4.2 Mutation. This genetic operator requires one individual, and it is only applied on meals in our current model. It randomly takes two food items in the meal and swaps their calorie values, thereby exploiting a specific part of the search space. Algorithm 3 illustrates this process. The objective of the *swap_calories* procedure in line 8,

Algorithm 3 Mutation Operator

1: $random\_mutation \leftarrow random(0.1, 1.0)$
2: **if** $random\_mutation < mutation\_probability$ **then**
3:   $individual \leftarrow population[consecutive\_index]$
4:   $random\_bundle \leftarrow random(0.1, 1.0)$
5:   **if** $random\_bundle < bundle\_probability$ **then**
6:     $food\_item_A \leftarrow meal\_bundle$
7:     $food\_item_B \leftarrow meal\_bundle$
8:     $swap\_calories(food\_item_A, food\_item_B)$

is to swap the calories data of two random items in the meal, and then accordingly recalculating the nutritional values of each food item and therefore, the item proportions in the meal. The constant *random_probability* is set as 0.5, and *bundle_probability* is equal as in the crossover operator.

4 EXPERIMENTAL EVALUATION

This work introduces a new type of RS modelling based on a GA. Our model is also the first to jointly recommend meal and exercise activity. For these reasons, there are no baseline models available to reasonably compare against. Instead, the core of this model, which is a GA, is evaluated. We also evaluated our model by conducting a cohort study with users who volunteered to supply information describing their food preferences and exercising habits. We elicited (i) basic demographic information: gender and age; (ii) their height and weight; (iii) their preferences on a sample of food categories on a 1-5 rating scale; (iv) their preferences on four types of exercise (cardio, strength, team sports, balance); (v) their preferred intensity for such exercises, from low to moderate and intense; and (vi) their main fitness goal $\mathcal{G}_i$ out of: losing weight, maintaining weight, gaining weight, diabetes control, building muscle.

This study considers only current user's preferences, with no prior history of their preferences or eating/exercising history (incorporating historical information constitutes one of our future work directions). Owing to this, and due to the meta-heuristic nature of GAs and absence of previous baseline approaches for 'healthy bundle' recommendation to compare against, no offline RS evaluation metrics are used. Instead, we conduct (1) an online user-satisfaction evaluation; and (2) an experimental analysis of the GA performance. Reference values for calorie intake per meal are calculated for each user based on their age, weight and height, by using a revised version of Harris-Benedict equation [14].

4.1 Algorithm Performance

For the GA performance analysis, we consider two performance metrics typically used to evaluate GAs [20]:
(1) *Likelihood of optimality*: Let k be the number of generations for which an GA execution is made, n the number of consecutive executions of the GA algorithm, and $m \leq n$ the number of executions in which an optimal solution is found in the population after k generations. The likelihood of optimality at kth generation, $Lopt(k) \in [0, 1]$, is given by:

$$Lopt(k) = m/n \tag{2}$$

(2) *Average Fitness Value*: Let k and n be as above. The average fitness value at kth generation, $\overline{FF}(k) \in \mathbb{R}^+$, takes per execution the average of the best individual's fitness values found along k generations, and averages them for the n executions:

$$\overline{FF}(k) = \frac{\sum_{j=1}^{n} FF_j^*(k)}{n} \tag{3}$$

We measured $\overline{FF}(k)$ and $Lopt(k)$ for five users, each of whom provided their food/exercising preferences and selected one of the five different wellbeing goals described above.We ran $n = 100$ executions of the GA per user, with $k = 100$ generations per execution. For every user and execution , we measure (i) the average aptitude of the resulting population at k, and (ii) the best aptitude found.

The results are summarised in Table 2. Average fitness values were calculated first, with FF being a function to be minimised, i.e. closer aptitude values to zero are better. Evaluating aptitude values is usually a non-trivial comparison task, as they greatly vary between domains or depending on the search space: our user with a weight gain goal expressed a positive preference towards all food and exercise types, hence his search space is larger and reported fitness values were, on average, higher. Therefore, we suggest relying on $Lopt(k)$ in order to objectively assess the GA performance. This metric requires a reference value, such that *optimality* is achieved at an execution if it finalises finding either an individual with lower aptitude value than the reference or an individual with the same aptitude value than the reference.

The reference value is obtained by firstly calculating, for each execution, the average of the aptitude associated to the best individual found at each generation. Resulting average values per execution are then averaged, leading to the reference value. Furthermore, we set an optimality threshold at a 5% above the reference value found at the end of an execution, i.e. at its 100th generation. For each execution j we take the best individual's aptitude value at the end of the execution, $FF_j^*(100)$. If $FF_j^*(100)$ is lower or equal than the optimality threshold, then the execution achieved optimality. Figure 4 shows how the two metrics are used to measure the algorithm performance.

The results in Table 2 indicate, for instance, 82 out of the 100 executions for the user aiming to lose weight are optimal. Overall, optimal bundle recommendations can be found after k generations in at least 80% of the cases, except for the *build muscle* user whose $Lopt(k)$ is comparatively lower, 0.64. A possible cause for this could be the need for more expert knowledge on the nutritional and exercise requirements for this type of wellbeing goal, which strongly

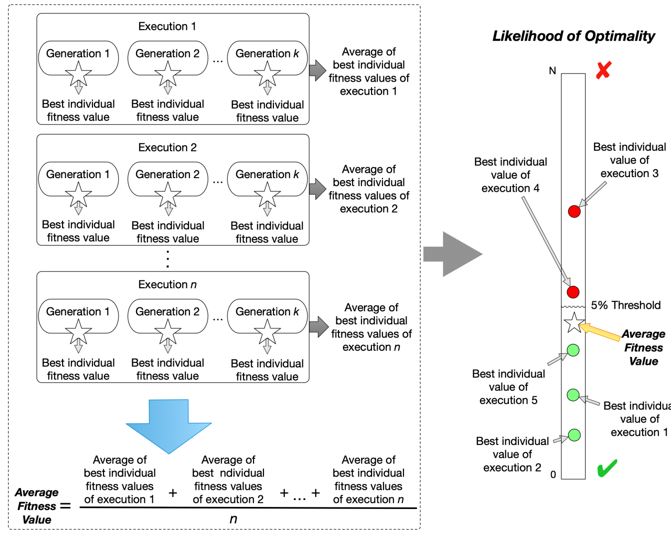

Figure 4: Average Fitness Function is first calculated and then is used to calculate the Likelihood of Optimality.

User goal (n = 100)	$\overline{FF}(100)$	$Lopt(100)$
Lose weight	232.54	**0.82**
Maintain weight	222. 36	**0.86**
Gain weight	3141.29	**0.99**
Diabetes control	1126.40	**0.80**
Build muscle	121.13	**0.64**

Table 1: Average fitness value $\overline{FF}(k)$ and likelihood of optimality $Lopt(k)$ for five sample users, with $n = 100$ and $k = 100$.

motivates future work with experts and data providers from these disciplines.

4.2 Online Evaluation

A group of 54 volunteers were provided with personalised lists of recommended bundles, for the purpose of collecting user feedback on them. Each volunteer was sent four meal-exercising recommendations: two of them are "true" bundles generated by our model *for* her/him, whereas the other two are randomly picked items from a generic user with the same goal and neutral preference information. The following questions have been asked to each volunteer:
[*Q1*] From these four recommendations numbered R1 to R4, please select your two favourite ones.
[*Q2*] What was the main reason for your choice? (With five possible answers to this question, see Figure 5).
[*Q3*] On a scale from 0 (worst) to 10 (best), how satisfied are you with the four options provided?
[*Q4*] On a scale from 0 (worst) to 10 (best), how satisfied are you with the two options you selected?

The results for Q1 are as follows. For an 88.9% of the volunteers, at least one of the two generated recommendations for them was picked, which we deem as promising in terms of end user satisfaction and relevance of recommendations. From these, 25% (12 persons) correctly guessed both of their recommendations. Figure 5 summarises the response rates for Q2. The majority of users chose

	Average	Std. Dev.	Min	Max
Q3	7.28	1.71	4	10
Q4	8.22	1.43	5	10

Table 2: Summary statistics for answers on a 0-10 scale

answer (c) "I liked those meal-exercise bundles the most", which hints at the importance of the interrelationship between eating and exercising for supporting wellbeing (as stated in the introduction). Finally, the results for Q3 and Q4, indicating subjective satisfaction scores on a 0-10 scale, are analysed in Table 3. On average, most users tended to be highly satisfied with the list of four recommended bundles (Q3), particularly with the two options each of them picked (Q4). A final observation on Q1 results is that all of the 11.1% users who did not pick the right bundles chose *build muscle* as their goal, which again suggests that further extensions of this prototype study are required in collaboration with nutritional domain experts for making more granular recommendations, considering another nutrients such as saturated fat, omega3-fatty acids, fibre, etc. We finally note again that instead of purely preference-driven solution, our RS model tries to produce recommendations that balance what the user *likes* and what she *needs* to reach her set goal.

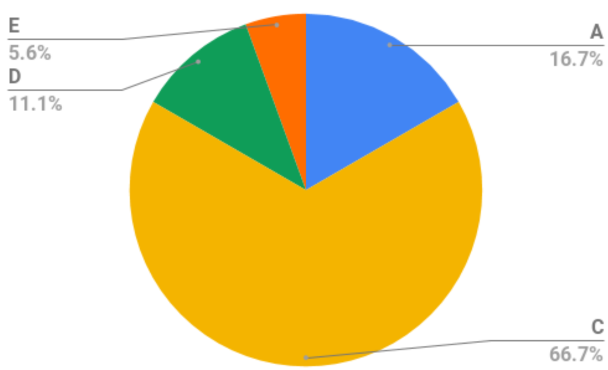

Figure 5: Answers for [Q2]: 'What was the main reason for your choice?'. (A) I liked those meals the most, (B) I liked those exercises the most, (C) I liked those meal-exercise bundles the most, (D) I prefer some variety, (E) Other.

5 CONCLUSION

This contribution presented a novel evolutionary model for recommending wellbeing bundles comprising meals and physical activity, predicated on the users' preferences and goals. A genetic algorithm is defined to lead the recommendation process, and its primary components are described. An empirical evaluation and online study with a volunteer cohort, are conducted to measure the optimality of recommendations and their relevance to the participants involved. To our knowledge, this is the first health recommendation approach that (i) is primarily driven by a genetic algorithm (ii) jointly suggests meals and physical activity as part of an unified recommended item, hence there exist multiple directions for future work, specifically along with nutrition and exercising domain experts. For instance, introducing *collaborative filtering* to consider the preference and behaviour from similar users, and incorporating past user data from e.g. meal diaries and wearables to implicitly build their preferences, would be interesting aspects to investigate.

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