Exploring the Effects of Natural Language Justifications in Food Recommender Systems

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Users of food recommender systems typically prefer popular recipes, which tend to be unhealthy. To encourage users to select healthier recommendations by making more informed food decisions, we introduce a methodology to generate and present a natural language justification that emphasizes the nutritional content, or health risks and benefits of recommended recipes. We designed a framework that takes a user and two food recommendations as input and produces an automatically generated natural language justification as output, which is based on the user’s characteristics and the recipes’ features. In doing so, we implemented and evaluated eight different justification strategies through two different justification styles (e.g., comparing each recipe’s food features) in an online user study (N = 503). We compared user food choices for two personalized recommendation approaches, popularity-based vs our health-aware algorithm, and evaluated the impact of presenting natural language justifications. We showed that comparative justifications styles are effective in supporting choices for our healthy-aware recommendations, confirming the impact of our methodology on food choices.

CCS Concepts: • Information systems → Recommender systems; • Computing methodologies → Natural language processing.

1 INTRODUCTION

How do people choose what to eat? The answer is not straightforward, as research has shown that food choice motivations span from sensory appeal, convenience, and health, to ethical concerns and familiarity [23, 29, 38, 43]. Factors that affect food choices can be divided in food-related features (e.g., perceptual features and nutritional information) [35], individual differences (e.g., knowledge, skills, and anticipated consequences), and society-related features (e.g., norms and values) [9]. In this context, food recommender systems (RS) have emerged as an effective solution to drive and support people’s food choices. Early technologies that generate meal recommendations to users date back to 1986 (e.g., CHEF [18]), while applications use ML techniques to automatically generate recipes that match user preferences [55].
In recent years, the idea of exploiting personalized recommendations to aid people to nourish themselves more healthily has spread [12]. This intuition is investigated by the research line regarding health-aware food recommender systems [41], which consider user information, such as dietary preferences and constraints (e.g., allergies) to generate a suitable meal plan. The main issue at hand is that most of the popular internet-sourced recipes used in recommendation approaches are unhealthy [53], and are, as a result, preferred by users. However, most RSs are still ill-equipped to effectively support a shift towards healthier (or more sustainable) eating habits [35, 45, 47].

In parallel recommender domains, the developments in natural language explanations and justifications strategies are promising [50]. Explanations can make the recommendation process more transparent, increasing users’ trust and affecting their decision-making processes [36]. This paper fits this research theme, for we introduce a methodology to generate a natural language justification that supports recommendations generated by a food recommender system. Preliminary food recommender research shows that the interface context (i.e., how recommendations are presented) could affect user preferences [47, 52]. Our strategy aims to encourage people to make healthier food choices by providing them with a justification of the recommended recipe, emphasizing nutritional facts, risks, or benefits related to food consumption. Our conjecture is that justifications allow users to make better-informed and healthier food choices.

To this end, we present a framework inspired by knowledge-based Natural Language Generation [39] strategies. It takes a user and two food recommendations as input and produces an automatically generated natural language justification as output, which is based on the user’s characteristics and the recipes’ features. Moreover, general knowledge about health risks and benefits related to food consumption is considered to generate our justifications. Within the framework, we implement and evaluate eight different justification strategies through two different justification styles, based on the combination of different informative content and features. In particular, we generate comparative justifications of recommendations, which compare the main characteristics of two recipes into a single natural language sentence. For instance, such a justification could compare the fiber content of two recipes. This taps into consumer research on the effectiveness of comparative evaluations of item attributes [3], compared to a separate representation of that information (i.e., a 'Single' justification).

The strength of the current work lies in its novelty. Generating food recommender systems with explanatory messages is a poorly investigated research topic, nor is there much empirical evidence on the support of healthier food choices. We evaluate our framework in a user study (N = 503), examining whether natural language justifications steer user food choices towards healthier recommendation. We posit the following research question:

[RQ]: Do natural language justifications affect user choices for healthy recipe recommendations, compared to popular ones? As we will show in the following, it emerged that users preferred healthier recipes over popularity-based recommendations, when comparative justifications are presented.

We summarize our contributions as follows: (i) We introduce a methodology to automatically generate a natural language justification to support personalized food recommendations; (ii) we design and (iii) evaluate several justification styles (i.e., None, Single, or Comparative styles) and strategies in a user study, where each justification leverages different user characteristics and recipe features. Section 2 presents an overview of related literature, while section 3 introduces our framework to automatically generate natural language justifications supporting food recommendations. Finally, we discuss the outcomes of our experimental session in Section 4, and sketch conclusions and future work in Section 5.

2 RELATED WORK

The idea of providing intelligent information systems with explanation facilities has been studied since the early 90s [24], and it was introduced in the area of recommender systems since 2000s [19]. It re-gained attention due to the recent
General Data Protection Regulations (GDPR), which prescribed to increase the transparency of underlying algorithms. This particularly applies to RSs, since explanation strategies have shown to positively affect both a user’s acceptance of and trust in presented recommendations [10, 44]. The community’s interest in the topic is shown across several studies, which each discuss the merits of explanations for recommender systems [16, 26].

We frame our current work by identifying persuasiveness (i.e., to promote healthier food choices) as the main goal of our justifications, which has not been investigated in other food RS research. This explanation aim is highlighted by Tintarev and Masthoff [50] and used in other domains to convince users to try or buy a recommended item. For example, [17] present a preliminary study of the persuasive power of explanations in a movie recommendation scenario.

With respect to the information content, which is exploited to generate justifications, we frame our approach as being at the intersection between content-based and knowledge-based methods (cf. [22]). Our methodology is based on the exploitation of user characteristics and food features, along with general knowledge on food consumption that is used to justify our health-aware recommendation by emphasizing health risks and benefits. This is related to a study where health risks are highlighted in a smoking cessation application [20], but, unfortunately, no evidence concerning the effectiveness of such information is provided in the article. Conversely, our work fills this knowledge gap, by evaluating the impact of justifications, including health risks and benefits, on user food choices.

Another hallmark of the current work lies in the development of a justification framework, designed specifically for the food domain. As discussed in [51], studies that evaluate the impact of explanations and justification in the food domain are scarce, even though they could encourage users to stick to better eating habits. A preliminary attempt to introduce explanation mechanisms in a food RS is presented by Leipold et al. in [27], where a very simple explanation strategy based on food features is integrated with a food recommender system. However, the authors did not evaluate its impact on users’ food choices. Another simple explanation interface is presented in [11], where users’ food preferences are linked to the ingredients of the recommended recipe, generating explanations such as ‘Because you want food containing X’. We go beyond [11], designing and evaluating a more comprehensive set of justification strategies.

Furthermore, the novelty of this work also lies in the automatic generation of comparative natural language justifications that emphasize similarities and differences between two alternative recommendations. Consumer decision-making research has shown that how two alternatives are compared (e.g., separately or comparatively) affects user preferences [3]. A remotely similar approach is presented by Chen et al. [8], who introduce a user interface where different recommendations are presented together with their distinctive features, obtained automatically from user reviews. However, in contrast with [8], rather than developing a completely novel user interface, we designed a framework to automatically generate a single natural language justification that compares two alternatives.

To conclude, we frame our approach with respect to the taxonomy of explanation strategies introduced in [15], labelling it as a black box methodology. Hence, the explanation strategy is not aware and independent of the underlying recommendation model, generating a post-hoc explanation that is not linked to the recommender algorithm. Post-hoc explanations provide reliable and effective explanations that are typically preferred by final users [32, 33]. We evaluate this framework by implementing two food recommender approaches: one that identifies popular recipes and one that selects healthier recipes. More details about the algorithms will be provided in the upcoming section.

Finally, we emphasize that the term justification is used, instead of the ‘traditional’ explanation. Even though both concepts appear to be synonymous, we follow the definition provided by Biran [4]: an explanation focuses on how the suggestion is generated, while justifications describe why a user would be interested in an item. This supposedly provides users with a means to make a more informed decision about consuming an item or not, fitting seamlessly to the current study’s goal, for we evaluate whether and how natural language justifications affect users’ online food choices.
3 METHODOLOGY

This section outlines our methodology to generate natural language justifications supporting food recommendations. We first introduce our workflow. Next, we focus on the generation phase, by introducing the different strategies we designed to justify a recommendation, along with the motivations that led to their implementation.

3.1 Description of the Workflow

The general workflow carried out by our framework is depicted in Figure 1. As shown in the figure, the methodology takes as input a user and two food recommendations, producing as output a natural language justification. The workflow is based on three main components: a Profiler module, whose goal is to collect information about the user, a Recipe Analyzer, which extracts the main features of the recommended recipes (e.g., nutrients, calories, ingredients), and a Generator, which builds the final justification based on user characteristics, food features, and knowledge about risks and benefits related to food consumption. As for the final output, we designed two general justification styles and eight different justifications strategies, each of which emphasizes different recipe characteristics or user features.

The Profiler module initiates the process to obtain information on a user. It implements a profiling strategy based on the holistic user modeling paradigm [5–7, 34], which has already been used in previous studies concerning food recommendations [35]. Table 1 outlines the seven user aspects used, which are encoded in each user profile: demographics, preferences, goals, affect, behavioral data, health data, and domain-related information.

Along with a user’s characteristics, the workflow also acquires food features. These are, for example, the total amount of calories, macro-nutrient content (e.g., carbohydrates, fibers, fats, proteins), a recipe’s preparation difficulty, cooking time, and its popularity on a recipe website. Some of these features are used to obtain the healthiness of a recipe based on the United Kingdom Food Standards Agency (FSA) Health Scores [37], which has been introduced by [47, 53] as a reference score related to food recommendations and food search. Generally speaking, all these features can be obtained by exploiting online resources, such as food communities. More details about the data collection procedure will be provided next. For our research goals, we can assume that all the above-mentioned information is available.

Table 1. User characteristics obtained by the Profiler Module in our natural language justification workflow.

<table>
<thead>
<tr>
<th>User Aspect</th>
<th>Factors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Demographics</td>
<td>Gender, Age, Height, Weight</td>
</tr>
<tr>
<td>Preferences</td>
<td>Food Preferences and Restrictions (lactose-free, vegan, etc.)</td>
</tr>
<tr>
<td>Goals</td>
<td>Losing Weight (binary)</td>
</tr>
<tr>
<td>Affects</td>
<td>Mood (positive, negative, neutral)</td>
</tr>
<tr>
<td>Behavioral Data</td>
<td>Level of Physical Activity</td>
</tr>
<tr>
<td>Health Data</td>
<td>Lifestyle, BMI, Amount of Sleep, Stress</td>
</tr>
<tr>
<td>Domain Knowledge</td>
<td>Cooking Experience, Available Time, Cost Constraints</td>
</tr>
</tbody>
</table>
3.2 Generating Natural Language Justifications

After obtaining user characteristics and food features, the Generator module comes into play. This component’s goal is to generate a natural language justification that supports the recommendation by emphasizing a recipe’s nutritional facts, risks, or benefits, in order to encourage people to make a more informed and, possibly, healthier decision.

First, it is important to emphasize that the generation process follows the principles of Natural Language Generation systems [39], thus it is completely automated and unsupervised, and does not require any human intervention. Given this general setting, our framework can generate its output by following two different justification styles: single and comparative. As a reminder, our framework takes as input two different recipes: by following the first justification style, both of them are processed separately and each recipe is provided with a different justification. In contrast, a comparative justification compares the characteristics of the recipes, which is generated automatically by the algorithm.

To generate justifications, the algorithm also relies on general food knowledge. Our approach uses a food knowledge base that comprises facts related to the daily intake of macro-nutrients, as well as food consumption risks and benefits. This knowledge is based on general guidelines concerning food consumption, such as government publications, academic studies, and commonsense knowledge. In particular, for each of the main nutrients (i.e., carbohydrates, sugar, proteins, fats, fibers), around 10 facts are encoded. For example, “Consuming too much sugar increases the risk of diabetes”, “High sodium intake increases health pressure”, and “High protein intake improves muscle development”. In total, we have encoded around 150 facts in our knowledge base, which are used in several justification strategies.

3.2.1 Overview of the Justification Styles and Strategies. Based on the above-mentioned setting, eight different justification strategies are implemented in the framework, across two justification styles. These strategies exploit different information sources and focus on different aspects. Regardless of the specific strategies, justifications are generated by exploiting a template-based structure. Each output follows a fixed structure and is dynamically filled in, based on: (i) characteristics of the user; (ii) features of the recipe; (iii) facts extracted from the food knowledge base. These aspects of the justification are generated separately and are concatenated to each other by using adverbs and conjunctions. In the following, we provide an overview of the eight justification strategies. Table 2 summarizes the output produced by the different strategies, along with details of the features they rely on, using ‘Spaghetti Cacio and Pepper’1 and ‘Vegetable Soup’ as running examples, providing an overview of the behavior of the framework.

**Description.** This justification strategy is based on a textual description of the recipe, which is gathered from online sources and is stored in our dataset as food feature. In this case, single and comparative justifications do not differ. The goal of this strategy is to provide the user with very general information about the recipe.

**Popularity.** This justification strategy is based on the popularity score of the recipe. This information is obtained as a food feature. For single justifications, we map the popularity score to a categorical popularity feature. In particular, we rank all the recipes based on their popularity scores and split them into four bins of equal size. When the explanation is generated, labels of the bins are used to provide information about the popularity of the recipe. Conversely, when a comparative explanation based on popularity is generated, popularity scores of the recipes are compared, and the one with the higher popularity score is emphasized. In this case, the justification provides information about how much popular is the recipe in the community, based on the fact that people often use this criterion in food choices [13].

**User Skills.** This justification is grounded in the construct of self-efficacy, which is defined as “beliefs in one’s capabilities to organize and execute the courses of action required to produce given attainments.” [2]. As hypothesized by Bandura [1, 13], people having high levels of self-efficacy belief tend to undertake more difficult and challenging tasks

1https://www.gimmesomeoven.com/cacio-e-pepe/
Table 2. Recap of the available Justification Strategies. We present examples for ‘Single’ and ‘Comparative’ justification styles.

<table>
<thead>
<tr>
<th>Just. Strategy</th>
<th>Information Source</th>
<th>Single Justification</th>
<th>Comparative Justification</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Description</strong></td>
<td>none Recipe Description</td>
<td>Spaghetti Cacio and Pepper are one of the dishes of the Roman Tradition: grated pecorino and peppercorns, a quick and tasty recipe.</td>
<td>n.a. (same as single)</td>
</tr>
<tr>
<td><strong>Popularity</strong></td>
<td>none Recipe Popularity</td>
<td>Spaghetti Cacio and Pepper is very popular in the community.</td>
<td>Spaghetti cacio and pepper is more popular than Vegetable Soup in the community</td>
</tr>
<tr>
<td><strong>User Skills</strong></td>
<td>Cooking Experience Level of Difficulty</td>
<td>Spaghetti Cacio and Paper has a medium level of difficulty. It might not be adequate to your cooking skills, which are low.</td>
<td>Vegetable Soup is very easy to prepare. The recipe seems adequate to your cooking skills, which are low.</td>
</tr>
<tr>
<td><strong>Food Goals</strong></td>
<td>Diet Goals Calories</td>
<td>Spaghetti Cacio and Pepper has 491 calories. Please consider it, since your goal is to lose weight. Vegetable Soup has 462 calories. Please consider it, since your goal is to lose weight.</td>
<td>Spaghetti cacio and pepper has more calories than Vegetable Soup (491 vs. 462). Past of vegetables can better help to reach your goal of losing weight.</td>
</tr>
<tr>
<td><strong>User Lifestyle</strong></td>
<td>Personal Lifestyle FSA Healthy Score</td>
<td>Spaghetti Cacio and Pepper is an unhealthy recipe according to FSA Score. Please consider this, since you aim to have a healthy lifestyle.</td>
<td>According to FSA Score, Vegetable Soup is healthier than Spaghetti Cacio and Pepper. Please consider this, given the importance you give to a healthy lifestyle</td>
</tr>
<tr>
<td><strong>Food Features</strong></td>
<td>Preferences and Restrictions Nutritional Information, Ingredients</td>
<td>Spaghetti Cacio and Pepper has 8.7gr of saturated fats and 2.3gr of fibers. Vegetable Soup has 4.55gr of saturated fats and 7.3gr of fibers.</td>
<td>Spaghetti Cacio and Pepper has a higher amount of saturated fats (8.7gr vs. 4.55gr) and a lower amount of fibers (4.55gr vs. 7.3gr) than Vegetable Soup.</td>
</tr>
<tr>
<td><strong>Health Risks</strong></td>
<td>BML Mood Sleep, Stress, Physical Activity, Nutritional Information, Ingredients</td>
<td>Spaghetti Cacio and Pepper has 8.7gr of saturated fats and 2.3gr of fibers. To intake many saturated fats increases the risk of heart diseases. Given your high BMI, you should take into account this fact.</td>
<td>To intake many saturated fats increases the risk of heart diseases. Given your high BMI, you should take into account this fact. On the other side, to intake many fibers increases the risk of constipation.</td>
</tr>
<tr>
<td><strong>Health benefits</strong></td>
<td>BML Mood, Sleep, stress, Physical Activity Nutritional Information, Ingredients</td>
<td>Spaghetti Cacio and Pepper has 8.7gr of saturated fats and 2.3gr of fibers. To intake many saturated fats improves your energy supply. Given your current stress level, this can be helpful.</td>
<td>Spaghetti Cacio and Pepper has a higher amount of saturated fats (8.7gr vs. 4.55gr) and a lower amount of fibers (4.55gr vs. 7.3gr) than Vegetable Soup.</td>
</tr>
</tbody>
</table>

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than people with low levels of self-efficacy. In this perspective, this justification strategy aims to match users’ beliefs in their own cooking skills with the difficulty of the recipe execution. People who rate themselves as being low-skilled are matched to easy recipes, while users with high self-perceived skills are shown challenging recipes, an intuition that is rarely applied in (food) RS research [42, 46, 48]. Specifically, we compare the ‘cooking experience’ feature encoded in the profile to a recipe’s ‘level of difficulty’. Single justifications first present the recipe’s level of difficulty of (e.g., high, medium, low), which is compared to the user’s self-reported cooking skills afterwards: if a user’s skills are lower than or equal to the recipe’s difficulty, a string indicating that the recipe is adequate for the user is concatenated to the justification. Vice versa, the opposite information (e.g., Recipe X is not adequate) is shown. As for comparative justifications, the levels of difficulty of the recipes are compared. If the self-reported cooking skills of the user are low, the easiest recipe is emphasized. Otherwise, the justification first shows the most difficult one.

User Goals. Food choices are often driven by specific goals of users, such as losing weight. Goal-setting theory [28] shows that people make decisions and take action in line with their set goal, particularly if that goal is important to the individual (e.g., self-set rather than assigned) [31]. Accordingly, this explanation strategy links a user’s self-set goals to the total amount of calories of the recipe. For single justifications, we generate a sentence presenting the calories of the recipe, along with the suggestion to consider this information in a user’s food decision. For single justifications, sentences are filled in by using the amount of calories of each recipe. As for comparative justifications, they contrast the calories of the two recipes in the format (‘X has more calories than Y’). Furthermore, if it is the user’s goal to lose weight, we generate a second sentence that indicates the recipe with fewer calories.

User Lifestyle. Users’ personal values, such as the importance of maintaining a healthy lifestyle, can strongly influence food choices. The value-attitude-behavior model explains that both values and attitudes impacts on behavior [54]. In this perspective, research has shown that people’s health values have a positive effect on both their attitudes towards low-fat or low-calories menu items and their behavioral intentions to choose healthy menus [25]. Accordingly, this justification strategy links users’ health values to a recipe’s healthiness, which is computed based on the popular FSA Health Score [53]. In single justifications, our template fills in a recipe’s name and a categorical label (unhealthy, quite healthy, healthy), based on the FSA Health Score of the recipe. Moreover, in line with the previous justification strategy, we generate a new sentence that suggest the user to interpret this information in line with their lifestyle self-assessment. Comparative justifications work in a similar way, by first comparing the recipes’ FSA scores and subsequently, generating a sentence that emphasizes the healthier recipe if that is in line with the user’s self-health assessment. If not, a simple comparison between the recipes is presented (e.g., ‘X is healthier than Y’).

Food Features. The goal of this strategy is to inform the user about the ingredients of each recipe. Research highlights that nutritional knowledge contributes to better food choices and a more adequate nutrient intake [21]. Moreover, people with higher food knowledge are more likely to meet the current recommendations for fruit, vegetable and fat intake than individuals with lower knowledge levels [56]. For single justifications, our framework compares the amount of macronutrients (e.g., protein) and salt in a recipe to the recommended daily intake [30]. Next, two randomly selected nutrients that in the top-3 in terms of % of the recommended daily intake are used to fill in the template. Comparative justifications compare the nutrients by automatically generating a lexicalization of the characteristics, such as ‘X contains more protein and fats than Y, but fewer carbohydrates’.

Health Risks. This justification strategy can be seen as an extension to the ‘food features’ strategy, linking information about macronutrients to health risks. Justifications are based on the health belief model, which posits that health behavior is affected by the perceived susceptibility to illness or health problems and the perceived severity of the consequences associated with the state or condition, the sum thereof is called perceived threat [40, 49]. Based on this
theoretical foundation, we generate risk-aware (single) justifications that are split into three parts. First, we follow the food features strategy by presenting the main macronutrients of each recipe. Second, this is linked to the previously mentioned food knowledge base. In this case, we retrieve facts that match the main characteristics of the recipe. For example, if ‘saturated fats’ has been previously selected by the algorithm, a fact describing health risks related to overconsuming saturated fats is randomly retrieved among those available in the knowledge base (e.g., ‘the intake of too many saturated fats increases the risk of heart disease’). Finally, the third part of the justification links some characteristics of the user to further health risks. For instance, if the user’s self-reported features indicate that she is overweight or do not do engage in sufficient physical activity, our framework could highlight a risk related to heart diseases. For comparative justifications, the algorithm first compares the different levels of macronutrients, presenting two different sentences that each link food characteristics to health risks. ‘Health Risks’ is our most comprehensive strategy, for it links information about food, risks, and user characteristics into a single natural language justification.

Health Benefits. This justification strategy is analogous to the previous one and is also based on the health belief model. The key difference is that the current strategy focuses on health benefits rather than health risks, which is also highlighted by the health belief model: the perceived benefits of a health behavior are also an important determinant [40, 49]. Apart from this aspect, the justification follows the same structure as the previous one. It presents nutritional information and food characteristics first, after which it selects a number of recipe aspects that are linked to food facts encoded in our knowledge base. Similar to the Health Risks strategy, a randomly selected fact that matches the selected characteristic of the recipe is chosen. Finally, the fact is linked to a user’s characteristics. If a further match emerges, a new sentence is introduced in the justification. This setup applies to both single and comparative justifications.

4 EXPERIMENTAL EVALUATION

We examined whether natural language justification affected user preferences for healthy recipe recommendations, compared to popular ones. In the following, we described the setup of our online user study, introducing the dataset, participants, and the research design. Subsequently, we compared our main conditions (i.e., a single justification and a comparative justification) to our no explanation baseline. Moreover, we explored which specific justification strategies (e.g., health benefits) affected food choices the most and the examined the underlying choice motivations.

4.1 Method

4.1.1 Dataset. Recipes were sampled from a database of 4,671 recipes, which is available online;\(^2\). Recipes were obtained from a popular food community platform\(^3\), and translated to English. The recipes contained information about their name, category, preparation difficulty, as well as their ingredients, (macro-)nutrients, calories, rating count, and average website rating. Moreover, they also included several binary tags, such as vegetarian, vegan, lactose-free, and low-nickel.

4.1.2 Food Recommendation Algorithms. Recipes were retrieved using two different personalized food algorithms. In the following, we refer to our recommendation algorithms as health-aware or healthy, and popular or popularity-based. For the former, we obtained healthy recipes based on user characteristics, goals, and constraints, retrieved through our healthy-aware food recommendation algorithm [35]. In the second case, a popular recipe was identified by the algorithm. We wish to reiterate that the algorithms were entities separate from our natural language justification framework, and were thus considered as independent parameters in our analyses.

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\(^2\)https://tinyurl.com/recipes-data-umap
\(^3\)https://www.giallozafferano.it/
Fig. 2. The study’s interface for two first course meals. The recipe depicted on the left is our healthy-algorithm recommendation, the one on the right is generated by a popular algorithm. Depicted within the red box is a justification in a specific style, in this case a ‘Comparative’ User Skills justification; the box is missing in the ‘No Justification’ condition. Users were asked to choose one recipe or neither of them, and to provide reasons why they had chosen a recipe.

4.1.3 Participants. Participants were recruited at Amazon MTurk to complete a study in which they would receive three recipe pairs of food they could enjoy. Participants were required to be US-based and to have a hit rate of 98%, with a minimum of 500 approved hits. The typical completion time fell between 3 and 10 minutes, for which participants were reimbursed with 0.5 USD. In total, 503 participants (54.7% Male) completed our user study, among which 61.0% was between 20 and 39 years old. The majority of users was employed (73.6%; 14.9% was student) and had a weight loss goal (51.1%), while only 70 users (13.9%) had a weight gain goal.

4.1.4 Procedure. Users were first asked various questions that were used to model their profile. The features used are outlined in Table 1, and included questions about demographics, self-reported health and well-being, experience with home cooking, and dietary restrictions and preferences. After users submitted their responses, the profiler (cf. Figure 1) would generate three pairs of recommendations. One example of a such recommendation pair is presented in Figure 2, of which the left one based on the healthy food RS, and the one on the right was generated using a popularity-based algorithm. Three different pairs were presented sequentially to a user, presenting two first course meals, two second courses and, finally, two desserts. For each pair, users were asked to either choose the left-hand side or right-hand side recipe, or neither. Note that we did not inform the users about which recipe was the healthy recommendation, or if there was any for that matter. Users who had chosen one of the two recipes were asked, in turn, to indicate to what factors were underlying their decision, such as a recipe’s healthiness, taste, or ease of preparation.

Such participants are more likely to generate high-quality data and to meet attention checks.
4.1.5 Research Design. Whether justifications were presented underneath each recipe pair or not was subject to three between-subject conditions. Users were either presented no justification for the presented recipes (i.e., baseline), a justification style that focused on each recipe separately (i.e., ‘Single Justification’), or a justification style that compared the two recipes (i.e., ‘Comparative Justification’). The strategy in which a single or comparative justification was presented, was subject to eight within-subject conditions, which are outlined in Table 2. This way, one user could be presented three different single justifications (e.g., Popularity, Food Goals, and Health Risks), while another user would be presented three different comparative justifications (e.g., User Lifestyle, Food Features, Health Benefits), or no explanation for each recipe. Figure 2 shows an example of a ‘User Skills’ justification, depicted within the red box.

4.1.6 Measures. For our analyses, we considered the effect of different justification styles on the percentage of healthy recommendations chosen. We did so by comparing the ‘No Justification’ baseline either with any justification style, with ‘Single’ and ‘Comparative’ justifications separately, or across all different strategies outlined in Table 2. The effectiveness of different justification styles were contrasted against the no explanation baseline, across all dish types for all choices made (i.e., choosing the popular recommendation or choosing neither of the recipes). Different justification strategies were compared between the no explanation baseline and the comparative style, because we found that ‘Comparative’ was the most effective justification style.

Furthermore, we examined a user’s motivation for choosing any of the two presented recipes. Users were asked to indicate on 5-point scales to what extent a reason was applicable as to why they had chosen either recipe. Choice motivation items were related to ‘a match with the user’s preferences’, the recipe’s taste, healthy eating goals, weight-loss or gain goals, and ease to prepare.

We also inquired on a set of user characteristics, which was also used by the profiler to generate healthy recommendations, as described in Table 1. Besides obtaining information on demographics (i.e., gender, age, BMI) and food preferences, we asked users whether they had any eating goals (i.e., either weight-loss, weight-gain, or no goals), to rate the healthiness or their lifestyle and the importance of having that (5-point scales). Users were also asked to rate their frequency (5-point scale) of either making healthy food choices, looking at food’s nutritional values, using recipe websites, and engaging in home cooking. Moreover, with regard to well-being, we inquired on their current mood, level of sleep and level of physical activity (3-point scales), whether they reported to be stressed or depressed (‘yes’ or ‘no’). Finally, we inquired on users’ domain knowledge, asking them to indicate their self-reported cooking experience (5-point scale), as well as their time and cost constraints for cooking.

4.2 Results

We examined user choice behavior through three different analyses. First, we investigated whether presenting any explanation affected user preferences for healthy recommendations. Second, we examined preferences for different justification strategies. Third, we examined why users had either chosen healthy or popular recipes.

4.2.1 Single and Comparative Justifications. We investigated whether users were more likely to choose healthier recipes if any justification was presented. We used a one-way ANOVA to examine choices made across all meal types, which showed that the healthy recommendation was chosen more often if any justification was presented alongside it (47.4% of choices, $S.E. = 1.6\%$), compared to the ‘No Justification’ baseline ($M = 38.1\%, S.E. = 2\%$): $F(1, 1507) = 11.80, p < 0.001$. This suggested that justifications helped to steer user preferences towards the health-aware recommendation. To
Fig. 3. Percentages of choices per condition, per meal type. Depicted are choices for neither recipe (in blue), the Popular recipe (in red), and the Healthy recommendation across three different meal types. Conditions are the three different justification styles: No justification, single justifications, and comparative justifications. Meal types are First Course, Second Course, and Dessert.

6Performing a Repeated Measures ANOVA that included 'meal type' as a categorical variable did not affect the main effects of the explanation styles.

We also examined choices for different justification strategies across all conditions (both 'Single' and 'Comparative'), as well as for 'Single' Justifications only. Although nearly all effects pointed into a similar direction, fewer differences were significant; mostly for 'Single' Justifications. Since 'Comparative' justifications were shown to be the most effective in the previous subsection, we only reported the results for that style.
We examined the effectiveness across all meal types, as well as per type. Table 3 describes four different logistic regression analyses, which each predicted whether our health-aware recommendation was chosen (compared to a popularity-based choice or no recipe chosen). We found effects to be mixed across the different meal types, while the second course and dessert models had the highest pseudo $R^2$-values. However, all significant effects across all models were positive, indicating that the different justification strategies in the comparative condition increased the likelihood that the healthier recommendation was chosen, not the popularity-based option.

We first examined significant differences. The model across all meal types in Table 3 shows that three justification strategies effectively supported health-aware choices. A comparison of the food features of the two recipes (e.g., Recipe A contains less fat than Recipe B) was related to a higher likelihood of choosing the healthy recommendation compared to the no justification baseline: $\beta = .86, p < 0.001$ (also in the first course model), as did justification that compared the health risks of both recipes: $\beta = .98, p < 0.001$ (also in the second course and dessert models).

In a similar vein, comparing recipes in terms of their health benefits led users to choose the healthier dessert more often: $\beta = .84, p < 0.05$, but not for other meal types. Table 3 also shows that comparing recipes in terms of food goals increased the likelihood of choosing the healthy option for first courses: $\beta = .78, p < 0.05$, but not for second courses and dessert. In contrast, a somewhat counterintuitive effect was that a popularity justification strategy, which typically showed that the healthy recipe was less popular than the popularity-based recommendation, increased the likelihood of choosing the healthy recommendation: $\beta = .59, p < 0.05$ (also in the dessert model).

Table 3 also highlights which strategies did not affect preferences between the 'Comparative' and 'No Explanation' conditions. Providing comparative descriptions of the recipe contents (e.g., the ingredients) did not affect user preferences, nor did comparing whether the recipes match with the user’s lifestyle – for each meal type. Moreover, notable was that comparative justifications of food goals did not affect dessert choices, while emphasizing health risks and benefits did not influence choices for first course meals.

### 4.2.3 Choice Motivation

Beyond justification styles and strategies, we finally examined why users had chosen either recipe. To do so, we performed four logistic regression analyses to compare why users had either chosen the healthy or popular recommendation, ignoring cases where neither recipe was chosen. Table 4 outlines a model that includes a user’s choice motivation across all meal types, as well as three meal-specific models, where in each model positive effects indicated reasons why the healthy recommendation was chosen, while negative effects indicated why the popular

**Table 3.** Four logistic regression models, predicting choices for healthy-aware recommendations (against no choice or popularity-based choices) in the 'Comparative' justification condition, compared to the no explanation baseline. The first model examines choices across all meal types, the other models are meal-type specific. $*** p < 0.001$, $** p < 0.01$, $* p < 0.05$. 

<table>
<thead>
<tr>
<th>Justification Style</th>
<th>All Meal Types</th>
<th>First Course</th>
<th>Second Course</th>
<th>Dessert</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\beta$ (S.E.)</td>
<td>$\beta$ (S.E.)</td>
<td>$\beta$ (S.E.)</td>
<td>$\beta$ (S.E.)</td>
</tr>
<tr>
<td>Description</td>
<td>0.37 (0.24)</td>
<td>0.56 (0.43)</td>
<td>0.094 (0.40)</td>
<td>0.49 (0.40)</td>
</tr>
<tr>
<td>Popularity</td>
<td>0.59 (0.28)*</td>
<td>-0.30 (0.52)</td>
<td>0.92 (0.49)</td>
<td>1.14 (0.51)*</td>
</tr>
<tr>
<td>User Skills</td>
<td>0.58 (0.32)</td>
<td>0.48 (0.60)</td>
<td>0.62 (0.49)</td>
<td>0.50 (0.63)</td>
</tr>
<tr>
<td>Food Goals</td>
<td>0.44 (0.23)</td>
<td>0.78 (0.39)*</td>
<td>0.64 (0.44)</td>
<td>-0.058 (0.42)</td>
</tr>
<tr>
<td>User Lifestyle</td>
<td>0.67 (0.25)</td>
<td>0.55 (0.39)</td>
<td>-0.17 (0.43)</td>
<td>-0.23 (0.51)</td>
</tr>
<tr>
<td>Food Features</td>
<td>0.86 (0.24)***</td>
<td>1.11 (0.44)*</td>
<td>0.74 (0.41)</td>
<td>0.76 (0.42)</td>
</tr>
<tr>
<td>Health Risks</td>
<td>0.98 (0.26)**</td>
<td>0.39 (0.45)</td>
<td>1.51 (0.49)**</td>
<td>1.09 (0.44)*</td>
</tr>
<tr>
<td>Health Benefits</td>
<td>0.42 (0.27)</td>
<td>0.28 (0.48)</td>
<td>0.079 (0.16)</td>
<td>0.84 (0.43)*</td>
</tr>
<tr>
<td>Intercept</td>
<td>-0.48 (0.092)***</td>
<td>-0.48 (0.16)**</td>
<td>-0.30 (0.16)</td>
<td>-0.68 (0.16)***</td>
</tr>
<tr>
<td>Pseudo $R^2$</td>
<td>0.0199</td>
<td>0.0238</td>
<td>0.0361</td>
<td>0.0337</td>
</tr>
</tbody>
</table>
Whereas popular recipes are preferred by most users if no explanation is presented (our ‘baseline’), we have shown that when presenting both recommendations along with a comparative justification, what types of justifications are most effective to promote our health-aware recommendations, through a user study. 

\( \beta \) were also chosen more often because a match in food goals: 

The contribution of this paper is twofold. First, we present a recommendation approach that captures a user’s eating preferences. In contrast with most earlier work [14, 52], we do not focus on recipes that users liked in the past, but we consider a user’s general eating preferences, affect, self-reported skills, and domain knowledge. This has resulted in a recommendation pipeline that presents personalized, yet healthier recommendations. Second, we have presented an approach to generate natural language justifications for food recommendations. While the NLP pipeline is a contribution in its own respect, particularly in a food recommender system, we have also validated its effectiveness by showing what types of justifications are most effective to promote our health-aware recommendations, through a user study.

Whereas popular recipes are preferred by most users if no explanation is presented (our ‘baseline’), we have shown that most users prefer our health-aware recommendations over a challenging popularity-based recommendation baseline, when presenting both recommendations along with a comparative justification.

With regard to specific justification styles, we find that comparative approaches are more effective in promoting choices for health-aware recommendations than single justifications. This taps into research that people are much at making comparative judgments than combining two ‘singular’ observations [3], which is reflected by the effectiveness of our ‘Comparative’ justification style over the ‘Single’ style. The obtained evidence is convincing, since we have observed this effect across different meal types – even desserts, for which food choices tend to be more related to taste

<table>
<thead>
<tr>
<th>Choice Motivation</th>
<th>All Meal Types β (S.E.)</th>
<th>First Course β (S.E.)</th>
<th>Second Course β (S.E.)</th>
<th>Dessert β (S.E.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Matched User Preferences</td>
<td>.13 (.070)***</td>
<td>-.052 (.13)</td>
<td>.52 (.13)***</td>
<td>-.20 (.12)</td>
</tr>
<tr>
<td>Tastiness</td>
<td>-.47 (.072)***</td>
<td>-.54 (.14)***</td>
<td>-.58 (.13)***</td>
<td>-.22 (.11)</td>
</tr>
<tr>
<td>Healthiness</td>
<td>.41 (.063)***</td>
<td>.78 (.12)***</td>
<td>.13 (.11)</td>
<td>.47 (.12)***</td>
</tr>
<tr>
<td>Matched Food Goals</td>
<td>.064 (.062)</td>
<td>-.0031 (.11)</td>
<td>-.21 (.11)</td>
<td>-.13 (.12)</td>
</tr>
<tr>
<td>Easiness</td>
<td>-.080 (.054)</td>
<td>-.26 (.099)***</td>
<td>-.030 (.098)</td>
<td>-.047 (.096)</td>
</tr>
<tr>
<td>Intercept</td>
<td>.040 (.32)</td>
<td>.52 (.62)</td>
<td>-.52 (.55)</td>
<td>.62 (.56)</td>
</tr>
<tr>
<td>Pseudo R²</td>
<td>.0628</td>
<td>.134</td>
<td>.0671</td>
<td>.0545</td>
</tr>
</tbody>
</table>
instead of health [35]. Moreover, we have also examined the effectiveness of specific justification strategies, suggesting that presenting a comparison of each recipe’s features and health risks seems to cater towards a user’s healthy food preferences. The sophistication of these strategies may have contributed to their effectiveness, for they link and compare different aspects, namely user characteristics, recipe features, and food goals. Although the large number of comparisons for specific justification styles may have been prone to a higher false positive rate, the overall results point out that all explanation strategies either promote healthy food choices – even the popularity-based strategy – or have no net effect.

We have also examined what drives users to choose healthier recommendations, and whether this differs per meal type. For most meal types, we have found evidence that popularity-based choices are related to taste motivations, while choices for our health-aware recommendation are linked to health-related reasons. This confirms that our health-aware recommendation pipeline caters to users with healthy eating goals, which is promising for future applications that seek to support such users. Moreover, ‘because it fits my preferences’ is also found to be a reason to choose the healthy recommendation across all meal types, suggesting that our approach could generate both satisfactory and healthy food recommendations, which is rarely found in food RSs to date [52].

An interesting avenue of future research is to test whether the insights can be generalized in a practical application if more than two recipes in a recommendation list. Moreover, we will introduce justifications combining several user-focused aspects, such as food taste and goals, to assess whether these can persuade a user to choose the healthier recommendation. Moreover, we will investigate whether such natural language justifications can be personalized further, and whether this would increase their effectiveness. For example, presenting justification styles that address healthy eating goals make more sense if a user has indicated to have such a goal. While the current user study has done so by inquiring on the user’s preferences in the first screen, such questions would only need to be asked when a user’s profile is created, for instance on a recipe website.

Finally, we wish to emphasize that the study can serve as a blueprint for future studies on healthy food recommendation. We have shown that our algorithm successfully generates healthy recommendations, as users who chose them indicated to have health-related choice reasons. Moreover, we have also shown how such recommendations should be presented to support healthy food choices. Such a combination of a knowledge-aware algorithm and UI design should pave the way for even more sophisticated applications in food recommendation, as well as for applications in other behavioral recommendation domains. Moreover, future work should extend the number of inputs in the recommender framework, by taking into account a larger and more comprehensive set of algorithms and to evaluate them.

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REFERENCES


