PEC Innovation 6 (2025) 100372

Contents lists available at ScienceDirect

PEC Innovation

journal homepage: www.elsevier.com/locate/pecinn

Supporting healthier food choices through AI-tailored advice: A research agenda

Alain D. Starke[a,b,*], Jutta Dierkes[c], Gülen Arslan Lied[c,d], Gloria A.B. Kasangu[b], Christoph Trattner[b]

[a] Amsterdam School of Communication Research, University of Amsterdam, Nieuwe Achtergracht 166, 1018 WV Amsterdam, the Netherlands
[b] MediaFutures, Department of Information Science and Media Studies, University of Bergen, Norway
[c] Centre for Nutrition, Department of Clinical Medicine, University of Bergen, Norway
[d] Department of Medicine, Division of Gastroenterology, Haukeland University Hospital, Bergen, Norway

ARTICLE INFO

Keywords:
Artificial intelligence
Home cooking
Hypertension
Nutrition
Recommender systems
Tailoring

ABSTRACT

Objective: To develop a research agenda to investigate the effectiveness of AI-tailored advice to support healthier home cooking. It aims to support healthier food choice in the context of hypertension, allergies, and sustainable diets.

Methods: We describe an agenda that has been formed between 2019 and 2022, through multiple rejected grant applications to the Research Council of Norway. We focus on the case of tailored recipe advice for individuals, formulating research questions and methods for three topics: "Acceptance of Personalized Food Advice", "Algorithm and Interface AI: App Development", and "Nutrition Modeling & Clinical Trials". The overall methodology focuses on mitigating health issues among individuals with hypertension.

Conclusion: The design of AI to support healthier home cooking should tap into computational principles, as well as (psychological) theories of behavioral change. The effectiveness of an AI-driven home cooking app can be evaluated in a clinical trial akin to 'regular' dietary intervention studies.

Innovation: The development of a research agenda requires an integrated effort between scientists from different domains, during both the development and writeup of ideas. The proposed project is innovative, as most food technology and AI approaches have yet to be tested in proper trials on changes in eating habits.

1. Introduction

A healthier dietary intake can be achieved through frequent and enhanced home cooking. While there are food applications available for purchase that are designed to assist users in improving their home cooking, for example, by proposing suitable dishes, their health benefits are uncertain because of their short-term focus and often non-personalized approaches. Moreover, most food technology and artificial intelligence (AI) approaches have yet to be tested in proper trials on changes in eating habits.

This paper reports on grant applications submitted to the Research Council of Norway between 2019 and 2022, which were all rejected with good to excellent reviews. Hence, we consider this contribution to be a 'Brilliant Failure', as the ideas have been judged to be excellent, yet we have not been allowed to execute them. To promote our ideas, we present an outline of our submissions as an agenda for integrating research in AI and nutrition science. We describe the context of the problems that would be addressed, as well as the novel technology that would be developed. We outline the different tasks that should be planned, describing general protocols for the main randomized controlled trials (RCTs) or clinical trials, where AI is used to tailor nutritional advice.

Taken together, this paper serves as a small-scale research agenda for performing RCTs with AI-tailored advice. It is based on lessons learned from our 'Brilliant Failure', for we have found out that unifying two scientific disciplines is challenging, particularly when deciding what to emphasize in reporting ideas and outcomes. This is, for example, apparent when proposing the development of a personal health app.

* Corresponding author at: Amsterdam School of Communication Research, University of Amsterdam, Nieuwe Achtergracht 166, 1018 WV Amsterdam, the Netherlands.

E-mail addresses: a.d.starke@uva.nl (A.D. Starke), jutta.dierkes@uib.no (J. Dierkes), gulen.arslan@uib.no (G.A. Lied), gka013@uib.no (G.A.B. Kasangu), christoph.trattner@uib.no (C. Trattner).

https://doi.org/10.1016/j.pecinn.2025.100372
Received 22 December 2023; Received in revised form 22 December 2024; Accepted 8 January 2025
Available online 10 January 2025

Computer sciences have previously engaged in 'user modeling' to predict what an end user would like and need, but less commonly so in high-stake domains such as health. This can lead to the omission of key details related to end users, including public health outcomes and patient agency in our case. For example, digital interaction data in an app can be rather ambiguous: Is a longer interaction indicative of an intention to act or does it signal confusion? This paper presents a synthesis of two competing perspectives, formulating research questions and a methodology, for which a team with practitioners and scholars from multiple disciplines is recommended.

1.1. Societal context

Many of today's diseases (e.g., obesity, cancer, diabetes, cardiovascular) are related to one's lifestyle choices and dietary habits, the World Health Organization reports that approximately 80 % cases of cardiovascular diseases, stroke, metabolic syndrome, and type-2 diabetes mellitus could be prevented with healthier dietary practices [1]. Western countries see high levels of body mass index (in kg/m^2) that indicate that the average adult male is overweight. In particular, cardiovascular diseases and type-2 diabetes mellitus are related to hyperlipidemia after consuming a meal (i.e., postprandial plasma triglyceride response), which could be moderated through healthier dietary patterns (e.g., by increasing fiber intake) [2]. According to dietary intake data in Norway, the average consumption of saturated fat (SFA) amounts to 14 % of the total caloric intake, surpassing the recommended intake of maximum 10 %. Added sugar, which should not exceed 5–10 % of the total caloric intake, accounts for 7.5 % of the total caloric intake. In contrast, the dietary fiber intake requirements frequently fall below adequate levels.

Dietary patterns are influenced by numerous factors, such as cooking experience and food preferences, but also dietary constraints [3], including food allergies and intolerances. Although changes in dietary patterns have been examined in the context of recommendations provided by nutritionists, less is known about the potential of AI to support behavioral change. In particular, to what extent can personalized food advice for home cooked meals, presented in an application, affect consumer dietary patterns?

1.2. Problem

Around 50 % of today's food interactions are online [4]. Various types of food technologies are on the market [5], including food checkers (e.g., to check the calorie content of a food product), health integration applications (e.g., Yazio, LifeSum), food recipe websites (e.g., 'BBC Good Food', AllRecipes.com), and food diaries (e.g., MyFitnessPal). While clinical dietitians and nutritionists are able to personalize their food recommendations to a client, for example by creating 4-week meal plans repeatedly over 6 months, this approach is both time-consuming and expensive. Nonetheless, many food applications, although proficient in optimizing their algorithms to encourage short-term recipe selection (i.e., a few days) [5], often overlook the potential to leverage user data to recommend specific choices that align with long-term culinary goals and sustained dietary patterns [6]. A striking feature is that many applications either promote widely favored recipes (e.g., 'BBC Good Food') [3], or assume that dietary goals can be attained 'linearly' (e.g., at Yazio, where one can be suggested to lose a similar amount of weight each week) [15]. Such promotion of popular foods is problematic, for there seems to be a negative correlation between recipe popularity and healthiness [3], based on nutritional intake indicators such as the Food Standards Agency score [5].

These mechanisms reveal that such applications have a limited understanding of how behavioral change occurs [6,7]. For example, simple feedback (e.g., "you are too many calories today") and short-term goals (e.g., "lose 2kg in 4 weeks") largely overlook how new eating habits are gradually learned [6,8]. Instead, AI should not only incorporate one's current preferences and dietary constraints, but also consider one's dietary aims, identify any existing deficiencies, and formulate a plan to achieve one's dietary goals [10].

An improvement would be to personalize food interactions in a digital application. One AI-driven approach to do so is through recommender systems, a technology that outperforms non-personalized applications in terms of accurately predicting a person's *current* preferences [9]. Recommender algorithms typically use historical interaction, such as purchases of food products or ratings of recipes, to compute the similarity between recipes and users based on user interaction data, reinforcing a user's current preferences or behavior [10]. For example, if a user currently consumes many unhealthy food products (e.g., a high potato-based product intake), then current food algorithms match them with other users who share a similar preference for these unhealthy dietary options (e.g., potato chips) and impose their preferences upon the presented food advice [11]. However, if a user's food preferences change, current recommender systems often cannot support these changes beyond a simple algorithmic re-rank based on health [11].

Whether AI can drive behavioral change is understudied [8,10]. Food recommender research focuses on short-term food choices [9], maximizing the modeled predictive accuracy of a user's current or past preferences, without knowing whether this leads to long-term satisfactory suggestions [10,13,14]. In doing so, few studies have explored relevant psychological constructs that underlie one's evaluation of such an AI-driven application [13]. To date, one study has specifically examined how people change their diet over time using a German, non-personalized recipe website [15]. Individuals adopting vegetarian or vegan diets were observed engaging with replacements for their current diet, such as substituting beef hamburger patties with plant-based alternatives, before further changing their dietary habits. These intermediate recipes are touted as 'transition' recipes, which may not be part of a user's current or end preferences, but seem to play a pivotal role in supporting behavioral change, suggesting a gradual move towards new dietary habits.

We propose that theories of psychology and human-computer interaction can illuminate how to approach this problem. For example, Prochaska's transtheoretical model [16] shows that behavioral change can be split in six stages, discerning between the easy-to-achieve awareness and contemplation, and the more difficult action and maintenance. Similarly, Social Judgment Theory describes how an individual's attitude determines their individual's 'Latitude of Acceptance' for new viewpoints [19], which could be extended towards the acceptance of advice and suggestions for changes in one's diet. This has recently been operationalized through the psychometric Rasch model [17], which shows that for healthy eating, individuals require a trajectory of small behavioral steps. For example, one should first replace high-fat meal options with grain-based alternatives, before transitioning to different meal components [15].

1.3. Related work

To delve deeper into our arguments, we highlight a few bodies of literature from different scientific disciplines. We argue that an effective research agenda requires insights from multiple domains, including medicine, psychology, and computer science. For a successful application of these ideas, we also recommend to recruit a team with practitioners or scholars from these different domains. Throughout multiple iterations of formulating this research agenda, we have noticed that the expertise of domain experts is invaluable when translating findings from one discipline (e.g., computer science algorithms used in e-commerce) to another (e.g., nutrition), to design appropriate metrics. For example, model accuracy in a recommender system (see below) is arguably less important in the health domain.

1.3.1. Food recommender systems

To assist users in exploring alternative dietary options, automated meal plans have shown huge potential. Technologies capable of generating meal recommendations to users date back to 1986, including CHEF [18]. More recently, research on AI methods that customize food recommendations to individual preferences center on food recommender systems, presenting foods or recipes based on the needs and preferences of end users [9]. Food recommender systems apply techniques that better profile users and deconstruct recipes into several components [20], computing similarity between recipes based on their ingredients or names [20,21]. While food recommender systems commonly begin by suggesting food items similar to the ones a user has preferred in the past [20], most food recommendation technologies routinely prioritize current preferences, which can hinder attempts to encourage healthier dietary patterns [8]. This challenge is also amplified by the popularity of unhealthier recipe options [3]. In fact, only a limited number of randomized controlled trials (RCTs) have considered the healthiness of recipes [17], while none have considered food as a multi-objective recommendation problem or have studied how to help users to eat more sustainable food options (i.e., with a reduced carbon footprint).

Technological support for behavioral change has focused on changes in recommender algorithms (e.g., increasing the diversity of recommended items [22]) or interfaces (e.g., nudging users to submit longer search queries [23]). With regard to the former, today's (food) recommender systems typically generate recommendations using Collaborative Filtering (CF), based on user-user or item-item similarity measures within historical user data (e.g., ratings [9]). This implies that users with unhealthy dietary patterns may find it challenging to implement healthier dietary adjustments, as suggestions tend to be retrieved based on individuals' diets that are similar to one's current diet.

Since recommenders tend to expose users to a somewhat narrowing set of food items over time (e.g., filter bubbles) [10,12], we argue that 'behavioral change-aware' algorithms and interfaces need to be developed. Recently, a few initial attempts have surfaced. Schäfer and Willemsen [17] present a food recommender system based on a user's nutritional intake, in which they use the psychometric Rasch model to match the user's ability to eat healthily to the difficulty of different eating habits. Also work in other domains show that users require a trajectory of behavioral steps, setting intermediate goals to achieve long-term behavioral change [24,25].

1.3.2. Nudging and food labels

Besides changing what is recommended, literature on nudging points out it also matters *how* options are presented. The field of behavioral economics suggests using nudges, which are changes in the way choices are presented that can predictably influence individual preferences, without hiding or restricting any options [26]. A well-known example is the use of simple food labels, which affect consumer decision-making by highlighting a food's nutritional content. For example, by using a traffic light system for 'low' (green), 'medium' (orange), or 'high' (red) sugar content [27,28]. However, such labels might be too simplistic and confusing in the context of health. Moreover, review studies suggest that food decision-making is also influenced by other contextual factors, such as weight control, health, but also convenience and price [29].

1.3.3. Interaction methods & user modeling

One way to lower behavioral thresholds to encourage healthier dietary choices is to simplify interaction methods with recommender technology, and to model users properly. To date, a number of interaction methods have been proposed for food technology [30], which attempt to improve the user experience when eliciting their preferences and choices (e.g., what a user eats), as well as the relevant contextual data (e.g., why and when something is eaten). Although this is typically done through ratings and tags [9], new methods include spoken-dialogue systems, immersive environments, and other interfaces that are part of the 'multisensory human-food interaction' [30]. However, as not all traces of online food behavior represent a user's true preferences [5,9,10], robust methods of elicitation are required.

1.4. Research gaps

What stands out from current apps and studies on AI and recommender systems is a lack of psychological user modeling to account for behavioral change, a focus on the short-term, and the absence of clinical studies [10,17]. Moreover, many personalized food interventions suffer from a profound lack of AI-based methods, still relying on simple personalization techniques [31]. The current examples in food tech (e.g., applications) are too simplistic, for they do not consider how behavioral change can be supported over time. Although nutrition science has expertise in analyzing changes in key health indicators, it has yet to use AI to cultivate dietary adjustments.

The main knowledge need and gap is that AI needs to be developed, tested and validated that can support changes in food intake through tailored advice. We seek to do so by incorporating existing or novel psychological theories of food decision-making and behavioral change into recommender algorithms. We call this *psychology-aware AI*: algorithms and interfaces that can support its users to attain *and* sustain new behavioral goals; AI aimed towards future outcomes rather than present circumstances. Additionally, we require interfaces that present personalized home cooking advice to be aligned with user goals, effectively explaining why items are suitable for a user.

Finally, there is a distinct lack of longitudinal research on the effects of AI on behavioral change, including in the context of dietary patterns. To date, all AI-driven interventions, such as recommender studies on health [32], could only make assumptions about whether short-term choices translate to sustained long-term changes. This points out the most fundamental knowledge needed in this area: *Understanding the long-term dietary effects of AI-driven food choices*.

A main challenge to be addressed is to test the effects of AI-driven personalized home cooking advice in a longitudinal context. We propose that psychology-aware AI should be implemented in a *state-of-the-art Home Cooking App*, testing the effects on nutritional intake. In this paper, we describe how to do so in two 'clinical trials', which we have not been able to execute due to a lack of funding (i.e., our 'Brilliant Failure').

1.5. Research questions

For our research agenda, we have formulated research questions based on preceding research. Along with our proposed methodology, these are the main results of our 'Brilliant Failure'. The primary objective is the development and validation of such an app, which not only involves usability testing, but also a validation of its effectiveness to support changes in dietary intake in the long-term among users with different dietary goals and constraints. We specifically focus on three different types of dietary changes: People suffering from hypertension (disease based), people with allergies (constraint based), and people who have a specific dietary goal (intrinsically based).

Main RQ: How can AI, interfaces and algorithms alike, be developed to generate personalized advice that effectively supports different user groups to attain long-term health diet goals?

For a robust research agenda on AI-tailored advice for dietary change, this main question should be supplemented by sub-research questions that represent different areas of research and methodologies. We propose three different sub-questions that we have identified to be important to evaluate the effectiveness of AI-driven food advice to support behavioral change and health outcomes:

- *RQ1*: Which psychological factors can determine acceptance of personalized food advice, as well as subsequent behavioral change, and how can they be integrated into AI-driven approaches?
- *RQ2:* How can user preferences and nutritional needs be modeled in AI algorithms and how can these be embedded in a Home Cooking App interface to support behavioral change?

- *RQ3*: To what extent is a Home Cooking App that generates personalized food advice capable of supporting dietary changes, in the short term and long term, among users with specific health issues and dietary restrictions: Hypertension (cardiovascular disease), allergies, and intrinsic dietary goals (i.e., weight loss or sustainable eating)?

2. Proposed materials and methods

We describe our research agenda in more detail, highlighting the different areas of work. We discuss three sub-research questions that underlie the main RQ, which each can be executed by a team focused on either social sciences, computer science technology, or nutrition. Fig. 1 below depicts an overview of the different themes and how match the research questions. In short, the work on RQ1 should examine *user acceptance of AI-generated food advice and working on the conceptual development of psychology-aware AI*. The team for RQ2 should work on the *main development of a Home Cooking App*, training and implementing psychology-aware AI in algorithms and interfaces, and modeling users and foods (i.e., recipes). Work on RQ3 should seek to *test and validate whether the developed AI and app technology is capable of supporting dietary changes* among users with different dietary constraints. In our rejected grant applications, we proposed an overall project runtime of approximately 48 months.

2.1. Acceptance of personalized food advice (RQ1)

First, literature on psychological determinants of AI-generated advice acceptance should be reviewed (RQ1). This is invaluable for setting up a RCT with technology. For example, one might find that people who are experienced in home cooking are more likely to comply with advice that is framed in terms of health benefits rather than risks. The output should be a framework with factors that affect user acceptance of personalized advice, which can be used subsequently to develop a psychology-aware algorithm. This should address both how advice is presented, as well as *which* advice is shown, focusing on an individual's latitude of acceptance for new foods.

We expect that research on RQ1 can leverage psychological theories of behavioral change (e.g., Prochaska [16]), along with validated psychometric models (i.e., social judgment theory and Rasch model [17,19,25]). These should help to address the challenge of user preferences changing over time, leading up to a (healthy) eating goal. In line with [15,17], we assume that users will initially make incremental dietary changes, as this might be perceived as manageable, before transitioning towards habitual healthy eating. This should lead to two types of outputs. First, a framework for how advice should be presented to individuals to clearly communicate the possible nutritional benefits. Second, design guidelines for how to balance two important factors of

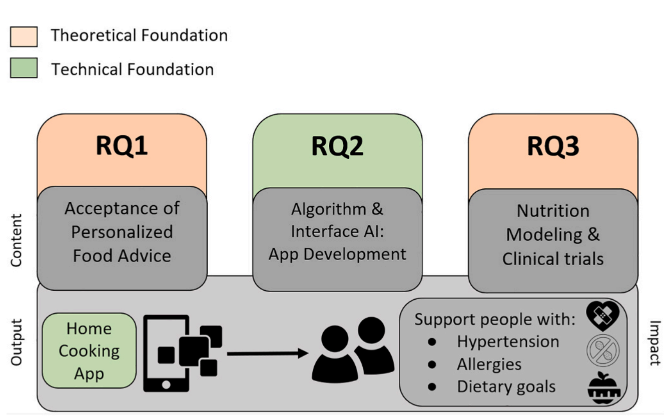

Fig. 1. General overview of the research agenda, in which an app is developed, validated and tested to address three different research questions.

determining what advice should be presented, considering individual preferences for food, as well as dietary or nutritional constraints for specific participant groups.

Integration of psychological theories in recommender algorithms is relatively new [24]. A good example is the use of the psychometric Rasch model to determine an individual's behavior-based attitude towards specific nutrients and eating goals more holistically, while assigning difficulty parameters to different foods. This way, probabilities for each individual as to how likely they are to engage with or consume specific nutrients or recipes can be inferred. According to the Rasch model, an item with a difficulty equal to an individual's attitude leads to a consumption probability of 50 %, deeming it somewhat feasible but also novel. This approach has been previously used in the energy conservation domain [24,25], as well as in food choice studies [17]. Whereas those studies used models with only two parameters, more complex models have been developed in Item Response Theory [24].

2.2. Algorithm & interface AI: app development (RQ2)

A second step is to implement the technological fundamentals (i.e., algorithms, interfaces) of a Home Cooking App. The effectiveness of this app should be assessed in clinical trials related to RQ3. First, however, novel kinds of food-psychology informed algorithms should be developed using deep neural networks (DNNs). These can be employed to present accurate and personalized food advice based on historical previous food interactions. The algorithm should build upon psychological insights obtained from RQ1, for example by being explainable and accounting for a user's dietary constraints. Subsequently, it should be trained (e.g., through a method called active learning), predominantly on user preferences data, along with dietary constraints.

For RQ2, a model based on a person's current preferences should initially be validated using offline simulation, a common method in computer science [20]. This involves training a model based on user-item data (e.g., ratings of recipes) that can predict which items (i.e., foods, recipes) a user may like, and validate that using a test set. This involves the method k-cross-validation, where different parts of the dataset are used in each step to train (e.g., 80 %) and test (e.g., 20 %) a model, after which the averages of estimated parameters can be used.

For datasets, we recommend to access large databases of online food recipes. For example, combined datasets of Allrecipes.com, Xiachufang.com, and Cookpad.com include interaction data for than 1.5 million recipes [4,11].

Technical work related to the app should also examine how an interface should be designed to effectively present personalized food advice. This analysis should be made in terms of interaction design, as well as in terms of how advice should be explained (e.g., nutritional content). In the context of a research project, teams working on the different research questions should work together to integrate food choice interface design principles. For example, this could be in the form of explicit and implicit food nudges such as food labels. Finally, before submitting the App for in-depth testing and validation to the Clinical Trials, research teams should perform a series of controlled lab studies to pre-test the App in terms of their functionality and short-term behavioral change capabilities. These can be grounded in a user-centric evaluation framework [13].

2.3. Nutrition modeling and clinical trials (RQ3)

RQ3 should be addressed if work on RQ1 and RQ2 has largely been completed. To test the short and long-term dietary effects of AI-tailored advice on different user groups, it should tap into the psychological insights obtained from work on RQ1, as well as use the developed technology (i.e., the Home Cooking App) related to RQ2. It is anticipated that AI-generated advice will lead to healthier food choices, which will, in the long-term, affect risk factors for non-communicable diseases like cardiovascular disease, hypertension, obesity, and diabetes.

To examine RQ3, we propose to first review literature on food labeling and nutrition in online or digital contexts. This supports the development of health labels, founded in both nutrition and environmental sciences. Thereafter, the effectiveness of the AI and App prototypes should be examined in two different longitudinal clinical trials, by comparing its effectiveness to support dietary changes in the short-term across different user groups (i.e., first trial), as well as by comparing the developed app to a relevant industry benchmark food app (i.e., second trial).

We present the design of our envisioned clinical trials here to show how our research agenda could be deployed. In the first trial, the dietary intake for hot meals (i.e., dinner) should be assessed among different, comparable participant groups. Fig. 2 shows this can be measured before and after users have received dietary advice in a controlled study; a control group should not receive personalized dietary advice. To examine the impact on participants' health, we propose to include three groups: People with hypertension, participants who suffer from allergies, and people with a goal to attain more sustainable eating habits. We define a sustainable diet in line with [33,34], examining the impact on a diet on health and the environment, even though additional parameters (e.g., economy) could studied. Health indicators of interest should be selected based on problem areas in a population. However, we recommend to include self-reported saturated fat intake (SFA), sugar intake, as well as dietary fiber intake, which is frequently reported as below recommended levels [35]. For environmental sustainability, we argue that Greenhouse Gas Equivalents Emission (GHGE) is a feasible option.

We further exemplify the proposed methodology using the hypertension participant group (see Fig. 2). The dietary advice is generated by the psychology-aware AI in the Home Cooking App. It should produce lists of hot meal recipes that aim to reduce harmful nutrition intake and boosting fiber intake, which reduces hypertension, while also communicating the rationale and specific health benefits behind each recipe recommendation. This should deem the recipes to be attainable and compelling at the same time. Increasing fiber intake is generally beneficial for mitigating cardiovascular diseases, but would also be beneficial to those who seek a sustainable diet.

The app should be used to keep dietary records over an 3-day period, before and at the end of the study period. 3-day dietary records are an established method to measure dietary intake with a moderate impact on effort and time use of the participants [36]. For groups with cardiovascular disease and hypertension, we anticipate that personalized home cooking advice can lead to an increase of dietary fiber of 4 g per day, while fiber intake is not expected to change in the control group. Assuming a standard deviation of 12 g and 90 % power, this would require a sample size of 100 participants (25 per intervention group and 25 in the control group).

A second clinical trial should thereafter focus on longer-term effects of the AI, monitoring a smaller participant group ($N = 30$) that suffers from cardiovascular diseases. The effectiveness of the developed app should be compared to an industry baseline. To this end, the participant group should be split in two, with one group using the Home Cooking App in a similar way as depicted in Fig. 2, but over a longer time period (three weeks rather than three days). The other group follows the same protocol, but should use an industry benchmark app, after which the nutritional intakes before and after the trial can be compared.

2.4. Interdisciplinarity

One of such a project's unique contributions and challenges is its interdisciplinary partnership, bringing together researcher partners with broadly different research credentials. This requires continuous communication, such as through weekly technical meetings, as well as through co-designed and co-tested experiments. Researchers that examine RQ1 would apply psychology and other social sciences, while 'RQ2 researchers' would apply expertise in computer & information science and 'RQ3 researchers' tap into insights from medicine, nutrition science and public health. Even though this could lead to 'the best of three worlds', we have also experienced challenges that could lead to 'failure'. For example, by developing an app that impacts in computer science fields due to the human-informed design and advanced AI, the human dimension might be simplified too much. As computer science methods have been naïve in translating human behavior to computation methods [24], planned randomized controlled trials should adhere to the design requirements of nutrition studies. This should be leading in the design of studies, where AI would simply determine the advice presented to users.

3. Discussion

The earliest version of the research agenda outlined in this paper was formulated in 2019. At the time, there was less focus on home cooking and a greater emphasis on the possibilities of AI to optimize predictive accuracy. Progressively, the project description has become more interdisciplinary, requiring expertise from various scientific disciplines. Although we feel this has made the research agenda far more interesting, the programs that would be able to fund such a proposal seem to have been reduced.

We consider this 'adjusted summary' of rejected grant proposals, which were submitted between 2019 and 2022 to the Research Council of Norway, the main product of our brilliant failure. At the moment, we remain hopeful that this research agenda can be executed by ourselves in the future, but we also encourage other researchers to step in. It would provide rich data to understand the processes of stages of change in diet and how AI-tailored advice can help. It can help to discover the patterns of changes in health behavior in a target population, thus positively influencing awareness of public health, behavioral changes and public health protection.

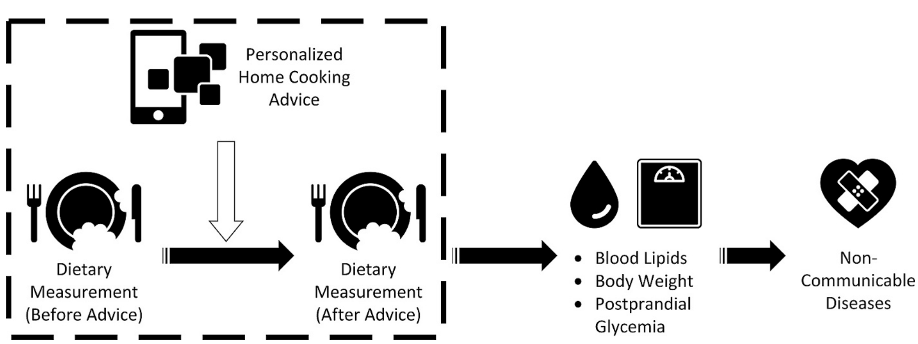

Fig. 2. Procedure of the first clinical trial, here mainly targeting participants with hypertension as an example. The clinical trial intervention addresses the area inside the dashed box.

3.1. Reflection

The research agenda presented in this paper has benefited from reviews received over the course of multiple years when submitting grant proposals. Quite often, feedback focused on monodisciplinary details, which highlighted aspects that had been overlooked by one part of the project team. For example, the team that wrote the proposal to develop the app (RQ2), initially took a top-down approach that focused on technological methods, rather than considering the possibilities of bottom-up methods that included potential users, such as co-creation. This has led us to reconsider the collaborative structure in the team. Our initial approach was to generate ideas and formulate end goals, after which we distributed the work between monodisciplinary ‘nutrition’ and ‘technical’ teams. Now, we better understand that methodologies for an AI tool in the context of food and health go beyond ‘standard’ computer science methods, and require collaboration from the start. Conversely, we can imagine that other reviewers could also scrutinize technologically-naïve approaches proposed by nutritionists.

Hence, what could still be improved is how to communicate our ideas across the borders of different scientific domains. Between grant applications, we noticed that expanding on the details in our area (e.g., computer science), would lead to confusion among reviewers in another area (e.g., nutrition science). A significant challenge is to effectively communicate one’s ideas in a manner that highlights both the scientific relevance and societal implications. For example, by emphasizing home cooking, the impact should be geared towards problems in one’s household context, which might also involve some group decision-making problems when it comes to AI advice acceptance. While enhancing specificity in one area may increase project feasibility, it might jeopardize the scientific foundations that support it, if other areas lack clarity.

3.2. Innovation

The work presented here is innovative due to its interdisciplinary nature. It taps into methods of computer science (i.e., recommender systems) that are typically used for other domains of personalization and tailoring, such as e-commerce and video streaming. These methods, however, have the potential to also steer user preferences and subsequent behavior when used in appropriate domains. We feel that a project as described here would be fruitful to move an interdisciplinary project forward, due to its novelty. We firmly believe that a more data-driven or automated future for public health should be designed in a collaborative effort, for innovation is most likely to be achieved by a multidisciplinary team.

4. Conclusion

We have presented a research agenda for the design and evaluation of a AI-driven nutrition application to present tailored home-cooking advice. Our ‘Brilliant Failure’ is the outcome of multiple rejected grant applications, submitted to the Research Council of Norway. We have learned that developing such an agenda requires an integrated effort between scientists from different domains, during both the development and writeup of ideas. The resulting agenda presents an innovative idea, being among the first to propose how an AI-driven technology can be evaluated using nutrition science methods.

CRediT authorship contribution statement

Alain D. Starke: Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Jutta Dierkes:** Writing – review & editing, Methodology. **Gülen Arslan Lied:** Writing – review & editing, Methodology. **Gloria A.B. Kasangu:** Writing – review & editing. **Christoph Trattner:** Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Alain Starke reports financial support was provided by Research Council of Norway. Christoph Trattner reports was provided by Research Council of Norway. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This work was supported by industry partners and the Research Council of Norway with funding to MediaFutures: Research Centre for Responsible Media Technology and Innovation, through the Centres for Research-based Innovation Scheme, project number 309339.

References

[1] W.H.O.R.O. for Europe. Adolescent Obesity and Related Behaviours: Trends and Inequalities in the WHO European Region, 2002–2014. World Health Organization. Regional Office for Europe; 2017. https://apps.who.int/iris/handle/10665/329417 [accessed May 20, 2020].
[2] McAuley MT, Mooney KM. Lipid metabolism and hormonal interactions: impact on cardiovascular disease and healthy aging. Exp Rev Endocrinol Metabol 2014;9(4):357–67. https://doi.org/10.1586/17446651.2014.921569.
[3] Trattner C, Elsweiler D. Investigating the healthiness of internet-sourced recipes: Implications for meal planning and recommender systems. In: Proceedings of the 26th International Conference on World Wide Web, Geneva, Switzerland; 2017. p. 489–98.
[4] Dove J. The best recipe apps for iOS and android, digital trends. https://www.digitaltrends.com/mobile/best-recipe-apps/; 2020.
[5] Trattner C, Elsweiler D. Estimating the healthiness of internet recipes: a cross-sectional study. Front Public Health 2017;5.
[6] Flaherty S-J, McCarthy M, Collins A, McAuliffe F. Can existing mobile apps support healthier food purchasing behaviour? Content analysis of nutrition content, behaviour change theory and user quality integration. Public Health Nutr 2018;21:288–98.
[7] O’Brien MC, McConnon A, Hollywood LE, Cuskelly GJ, Barnett J, Raats M, et al. Let’s talk about health: shoppers’ discourse regarding health while food shopping. Public Health Nutr 2015;18:1001–10. https://doi.org/10.1017/S1368980014001116.
[8] Hebden L, Cook A, van der Ploeg HP, Allman-Farinelli M. Development of smartphone applications for nutrition and physical activity behavior change. JMIR Res Protoc 2012;1:e9. https://doi.org/10.2196/resprot.2205.
[9] Elsweiler D, Hauptmann H, Trattner C. Food Recommender Systems. Recommender Systems Handbook. New York, NY: Springer US; 2012. p. 871–925.
[10] Ekstrand MD, Willemsen MC. Behaviorism is not enough: Better recommendations through listening to users. In: Proceedings of the 10th ACM Conference on Recommender Systems. New York, NY, USA: ACM; 2016. p. 221–4.
[11] Rokicki M, Trattner C, Herder E. The Impact of Recipe Features, Social Cues and Demographics on Estimating the Healthiness of Online Recipes. 2018.
[12] Konstan JA, Riedl J. Recommended for you. IEEE Spectrum 2012;49:54–61. https://doi.org/10.1109/MSPEC.2012.6309257.
[13] Knijnenburg BP, Willemsen MC. Evaluating recommender systems with user experiments. In: Recommender Systems Handbook. Springer; 2015. p. 309–52. https://doi.org/10.1007/978-1-4899-7637-6_9 [accessed March 30, 2017].
[14] Nguyen TT, Hui PM, Harper FM, Terveen L, Konstan JA. Exploring the filter bubble: The effect of using recommender systems on content diversity. In: Proceedings of the 23rd International Conference on WWW. New York, NY, USA: ACM; 2014. p. 677–86.
[15] Asano YM, Biermann G. Rising adoption and retention of meat-free diets in online recipe data. Nat Sustain 2019;2:621–7.
[16] Prochaska JO. Decision making in the Transtheoretical model of behavior change. Med Decis Making 2008;28:845–9.
[17] Schäfer H, Willemsen MC. Rasch-based tailored goals for nutrition assistance systems. In: Proceedings of the 24th International Conference on Intelligent User Interfaces - IUI ’19. Marina Del Rey, California: ACM Press; 2019. p. 18–29.
[18] Hammond KJ. CHEF: A Model of Case-Based Planning, AAAI-86 Proceedings. 1986. p. 267–71.
[19] O’keefe DJ. Persuasion: Theory and research. Sage Publications; 2015.
[20] Freyne J, Berkovsky S. Intelligent food planning: Personalized recipe recommendation. In: Proceedings of the 15th International Conference on Intelligent User Interfaces. New York, NY, USA: ACM; 2010. p. 321–4.
[21] Elsweiler D, Trattner C, Harvey M. Exploiting Food Choice Biases for Healthier Recipe Rec. SIGIR; 2017. p. 575–84.
[22] Jannach D, Lerche L, Kamehkhosh I, Jugovac M. What recommenders recommend: an analysis of recommendation biases and possible countermeasures. User Model User-Adap Inter 2015;25:427–91.

[23] Oinas-Kukkonen H, Harjumaa M. A systematic framework for designing and evaluating persuasive systems. In: Persuasive Technology. Berlin, Heidelberg: Springer; 2008. p. 164–76.

[24] Starke AD, Willemsen MC. Psychologically informed design of energy recommender systems: Are nudges still effective in tailored choice environments?. In: A human-centered perspective of intelligent personalized environments and systems. Cham: Springer Nature Switzerland; 2024. p. 221–59.

[25] Starke AD, Willemsen MC, Snijders CCP. Beyond "one-size-fits-all" platforms: applying Campbell's paradigm to test personalized energy advice in the Netherlands. Energy Res Soc Sci 2020;59:101311.

[26] Thaler RH, Sunstein CR. Nudge: Improving decisions about health, wealth, and happiness. Yale University Press; 2008.

[27] El Majjodi A, Starke AD, Trattner C. Nudging towards health? examining the merits of nutrition labels and personalization in a recipe recommender system. In: Proceedings of the 30th ACM Conference on User Modeling, Adaptation and Personalization; 2022. p. 48–56.

[28] Temple NJ. Front-of-package food labels: a narrative review. Appetite 2020;144: 104485.

[29] Scheibehenne B, Miesler L, Todd PM. Fast and frugal food choices. Appetite 2007; 49:578–89.

[30] Velasco C, Karunanayaka K, Nijholt A. Editorial: multisensory human-food interaction. Front Psychol 2018;9.

[31] Reinders MJ, Starke AD, Fischer AR, Verain MC, Doets EL, Van Loo EJ. Determinants of consumer acceptance and use of personalized dietary advice: a systematic review. Trends Food Sci Technol 2023;131:277–94.

[32] Schäfer H, et al. Towards health (aware) recommender systems. In: Proceedings of the 2017 International Conference on Digital Health; 2017. p. 157–61.

[33] Macdiarmid JI. Is a healthy diet an environmentally sustainable diet? Proc Nutrition Society 2013;72:13–20.

[34] Angelsen A, Starke AD, Trattner C. Healthiness and environmental impact of dinner recipes vary widely across developed countries. Nature Food 2023;4: 407–15.

[35] Lundblad Marie W, et al. Energy and nutrient intakes in relation to National Nutrition Recommendations in a Norwegian population-based sample: the Tromsø study 2015–16. Food Nutr Res 2019;63.

[36] Crawford PB, Obarzanek E, Morrison J, Sabry ZI. Comparative advantage of 3-day food records over 24-hour recall and 5-day food frequency validated by observation of 9-and 10-year-old girls. J Am Diet Assoc 1994;94(6):626–30.