

*ONLINE PERSONALISED
NUTRITION ADVICE*



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DEDICATION

I dedicate this work to the Brazilian tax payers who supported me financially.

DECLARATION

I confirm that this is my own work and the use of all material from other sources has been properly and fully acknowledged.

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ABSTRACT

The Internet has considerable potential to improve health-related food choice at low-cost. In order to provide online personalised nutrition advice, a valid and user-friendly method for recording dietary intake is key. Yet, the author's review of popular nutrition-related mobile apps revealed that none of these apps were capable of providing personalised diet advice

This work presents a web app (eNutri), which is able to assess dietary intake using a validated food frequency questionnaire (FFQ) and provide personalised food-based diet advice. The initial version of this app presented the food items in a list and its usability was evaluated in Kuwait. In response to user feedback, the design was modified to present a single food item at a time. This app was deployed in an online study to assess usability with 324 participants in the UK, using different devices. The median System Usability Scale (SUS) score (n=322) was 77.5 (IQR 15.0) out of 100, illustrating high acceptance by users.

Potential users were consulted during the design process, but assessing whether nutrition professionals (n=32) agree with the automated advice and collecting their insights were important in maximising the success and wider utility of this app. The mean scores for the appropriateness, relevance and suitability of the eNutri diet messages by nutritional professionals were 3.5, 3.3 and 3.3 respectively (maximum 5).

Its effectiveness was evaluated during a 12-week online randomly controlled parallel blinded dietary intervention (n=210) (EatWellUK study) in which personalised dietary advice was compared with general population recommendation (control). A significant improvement in the modified Alternative Healthy Eating Index (m-AHEI) score, against which the participants' diets were compared, of 3.06 (CI 95% 0.91 to 5.21, p=0.005), was reported following personalised compared to population advice.

This work indicates the benefit of personalised dietary advice delivered online to motivate dietary change. The eNutri app's design and source code were made publicly available under a permissive open source license, so that other researchers and organizations can benefit from this work.

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LIST OF ABBREVIATIONS AND ACRONYMS

24HDR: 24-hour dietary recall

AHEI: Alternative healthy eating index

API: Application program interface

App: Application

BCT: Behaviour change techniques

BMI: Body mass index

CC: Calorie Counter, by CalorieCount.com

CDN: Content Delivery Network

CNPq: National Council of Technological and Scientific Development (Brazil)

DA: Diet Assistant - Weight Loss, by Alportela Labs

DE: Domain expert

DDI: Dasman Diabetes Institute

DNS: Domain Name Server

DP: Diet Point, by DietPoint Ltd.

EatWellUK: Eat Well UK(study)

EatWellQ8: Eat Well Kuwait (study)

EPIC: European Prospective Investigation into Cancer Study

EWL: Effective Weight Loss, by naveeninfotech

FFQ: Food frequency questionnaire

Food4me: Food for me project

FS: Calorie Counter FatSecret, by FatSecret.

GP: General practitioner

GPS: Global positioning system

HEI: Healthy Eating Index

HTTPS: Hypertext Transfer Protocol Secure

iOS: (originally) iPhone operating system

JSON: JavaScript Object Notation

LI: Lose it!, by FitNow Inc.

LS: Lifesum - The Health Movement, by Lifesum.

LW: Lose weight without dieting, by Harmonic Soft.

m-AHEI: Modified alternative healthy eating index

MDC: My Diet Coach, by Inspired Apps.

MDD: My Diet Diary, by MedHelp Inc.

MPF: My Fitness Pal, by MyFitnessPal Inc.

NC: Noom Coach - Weight Loss Plan, by Noom Inc.

NCD: Non-communicable diseases

NP: Nutrition professional

OS: Operating system

PA: Physical activity

PN: Personalised nutrition

RCT: Randomized controlled trial

RNI: Reference nutrient intake

SPA: Single Page Application

SUS: System Usability Scale

SwB: Science Without Borders

UREC: University of Reading Research Ethics Committee

URL: Uniform resource locator

WFR: weighed food record

WW: Weight watchers

1 INTRODUCTION

1.1 Motivation

Non-communicable diseases such as diabetes and cardiovascular diseases account for almost two thirds of deaths globally. The general recommendations for addressing this epidemic are related to lifestyle changes, mainly encouraging healthy diets, physical activity (PA) and the reduction of tobacco use and alcohol consumption [1]. It is also estimated that 3 million people in the UK are malnourished or at risk of malnutrition, and of those, a third are over the age of 65 and 93% live in the community [2]. The majority of face-to-face nutritional consultation in public services is available to the population with some diagnosed condition such as diabetes and obesity. Preventive initiatives for the healthy population are focused on public guidelines only, such as the 5-a-day campaign, which aims to encourage the minimum consumption of 5 portions of fruit or vegetable per day in the UK [3].

Challenges with encouraging healthy diets include gathering accurate information about dietary intake and delivering interventions that can influence behaviour. Accurately assessing dietary intake can be challenging because people often misreport what they are eating or change their habitual dietary intake when undergoing measurement [4]. A nutrition consultation cycle can be simplified as comprising three main steps: assessment, decision-making and provision of advice. Typically, a person's dietary intake is assessed and then used as an input for decision-making, in order to provide feedback to the person. In developing an online system for personalized nutrition, all three steps are important to address. Regarding the assessment stage, a valid method for online dietary intake recording is key.

Internet technologies offer considerable potential for addressing these challenges, however, they need to fulfil a number of requisites in order to foster a wider uptake:

reproducibility, scalability, security and usability. The latter is especially important for groups that are not very familiar with technology, such as older adults.

There are indications that personalised recommendations are more effective than general population-based recommendations (based on diet, rather than phenotype or genotype) in nutrition interventions aimed at modifying health-related behaviour change [5]. Besides the dietary guidelines and information on dietary intake, it is important that interventions take into account information such as phenotype, health conditions, dietary restrictions, habits and routines for the elaboration of the intervention and feedback. This is of particular interest given recent proposals of digital health personalised interventions. This project will investigate an effective way of providing automated personalised online dietary recommendations in order to increase diet quality of the population.

1.2 Background

1.2.1 Nutrition assessment methods

Valid dietary intake recording is key for nutritional intervention. The methods used for collecting food intake data can be classified in a number of ways. Based on the time of the collection, the retrospective methods, such as the 24-hour food recall, require memory for recollection of foods eaten. In contrast, the prospective methods require diet reporting as food is consumed, acting as food diaries. In nutrition research, prospective dietary assessment is usually between 4 and 7 days. It is also possible to classify the methods as quantitative or weighed daily consumption, or food frequencies. The retrospective methods focus on recording the detailed food consumption as accurately as possible usually using weighed scales, typically for a couple of days. The latter assesses typical consumption patterns over longer periods [6] [7]. The prospective methods tend to be less convenient for the users since they require days of dietary intake recording (e.g. 4-day food diary) and may result in high dropout rates or change in usual intake in nutrition interventions or when used in diet apps.

An important and long-established retrospective nutrition assessment method is the Food Frequency Questionnaire (FFQ). It has been used in epidemiological studies for decades. For example, the European Prospective Investigation into Cancer and Nutrition (EPIC) study, one of the largest cohort studies in the world with more than half a million participants recruited across 10 European countries, used an FFQ in the UK

named EPIC-Norfolk FFQ [8]. This FFQ was adapted for used in the Food4me project [9], the largest study on personalised nutrition up to the time of this writing (n=1540). For FFQs, participants are asked to indicate frequencies and portion sizes for foods that they have consumed during a period of time (e.g. over the last month). This assessment method has some accuracy limitations (e.g. calorie estimation), but, relative to some other methods such as 4-day food diaries, FFQ may be more appropriate for initial dietary assessments aiming at personalized nutrition; FFQs are able to capture habitual dietary intake patterns, can be completed in a relatively short time by participants, and lend themselves to automated data processing [9]. Another important aspect to be considered is the reactivity, which is the influence of the assessment awareness on dietary choices [6][7][10]. This effect does not occur in retrospective methods, if they are applied without notice.

To ensure the accuracy in assessing dietary intake, nutrition assessment methods need to be validated against reliable and independent methods. For example, the online Food4me FFQ [11] was validated against a 4-day weighed food record (WFR) in the UK. Besides the validity, the reproducibility was also measured by asking the participants to repeat the FFQ within a short period of time (e.g. 4 weeks apart). The results of the validity and reproducibility of the online Food4me FFQ were published in 2014 [12] [13].

These nutrition assessment methods can be self-administered by the participant or led by an interviewer during the administration. After the dietary intake recording, researchers and nutrition professionals use some tools to evaluate the diet quality of an individual.

1.2.2 Diet quality scores

Most public nutrition campaigns aim to enlighten the population based on qualitative or simplified quantitative methods, such as the Eatwell guide in the UK [14]. In a similar way, food pyramid guides have been used to indicate how to define a balanced diet, presenting the proportion of the food groups (e.g. fruits and vegetables) [15]. These tools are important but mainly designed to offer a visualization of a balanced diet only, making the computational analysis less precise and robust.

On the other hand, based on the results of the dietary intake assessment and using more quantitative approaches, it is possible to calculate the energy, the nutrient content of the collected data and compare this with the nutritional guidelines [16]–[18]. Food composition tables can contain more than a hundred nutrients per food item and this

analysis can be complex and difficult to summarize into useful dietary advice [19]. With this in mind, some indexes of diet quality have been developed over the last decades. Some of them focus on local guidelines and others on specific target groups or diseases. A comprehensive report containing existing indexes of diet quality was published in 2005 [20].

The United States Department of Agriculture (USDA) developed the Healthy Eating Index (HEI) and its most recent version of which was published in 2010 [21]. In some cases, specific indexes have been created to address particular diseases, such as the Alternative Healthy Eating Index (AHEI) that predicts the risk of chronic diseases [22], which is the main nutritional public health issue to be targeted by the system proposed in this project.

The AHEI has eleven components. Six of them contain positive food groups (i.e. encouraged consumption), such as fruits, vegetables and whole grains. For these components, the scores increase (maximum score is 10) until a certain limit (i.e. criteria for maximum score). For example, if an individual consumes five or more servings of fruit per day, the score for this component will be 10. In the same manner, a proportional score of 5 will be resulted if the consumption is 2.5 servings per day. The other five components contain food items whose consumption are discouraged, such as sugar, sodium and trans-fat. The more a person consumes foods from these components, the lower their score. They have similar calculations, but with negative slopes. Each individual component varies from 0 to 10, resulting in an overall maximum score of 110 since all the components have the same weight [22], [23]. The calculations are very clear and quantitative, and this index can be used to evaluate dietary intake data derived from different assessment methods (e.g. 24-hour recall or FFQ).

1.2.3 Online personalised nutrition

Tailoring plays an important role in health interventions [24], [25] and there is an interest from the population in receiving personalised nutrition advice [26], [27]. Some studies are investigating how to personalise nutritional guidance for more effective behaviour change [28]. The levels of personalization may vary from changes in the communication to more intrusive methods, which may require genetic information collection, for example.

The Food4Me study was designed to measure the efficacy of different levels of personalised nutrition: based on diet intake alone; diet and phenotypic biomarkers; and

diet, phenotype and genotype. Results demonstrated that personalisation food based dietary advice based on dietary intake is more effective than generic advice, although no further benefit resulted from the additional of phenotypic or genetic advice in this study [5][29]. Although the Food4Me study gave personalised dietary advice it did not account for specific groups such as vegetarians, vegans or individuals with allergies or intolerances. The advice was based on a decision tree executed manually by the researchers during the study to create the report to be sent via e-mail. This decision tree was subsequently automated [30]. Details of the decision tree have not been published. Part of this thesis is based on the findings presented in various papers from the Food4me study [2][4][5] and it intends to expand the knowledge in this specific field.

The lack of transparency in reporting nutrition interventions makes the reproducibility and comparison between studies more challenging and the improvements in this field slower. This difficulty was reported in 2017 by Warner et al. in a systematic review of telehealth-delivered dietary intervention trials [31]. There are also studies investigating the personalization of recipes [32] and nutrition decisions [33], aiming to increase the acceptability of recommendations to the user. This thesis is limited to analyse alternatives of personalised nutrition that are applicable to online interventions without offline actions, such as genetic information collection.

1.3 Problem statement

The primary challenge of this research is to design an online system that can automatically provide personalized nutrition advice that will be effective in changing dietary behaviour favourably. Besides factoring in an individual's dietary intake relative to general recommended dietary guidelines, it is important that the intervention takes into account personal information (e.g. phenotype and dietary intake information) in defining advice.

This project proposes to increase the acceptability, effectiveness and adoption of online nutrition services. The basic requirements of the proposed system, showed in the following subsections, were defined as aiming to promote a wider uptake of digital nutrition assessment and personalised advice via the Internet.

1.3.1 Reproducibility and scalability

The motivations for using the Internet for encouraging healthier diets are global. With this in mind, the system deployment should be inexpensive and suitable for many

populations, including low income communities. One implication of this requirement is that the proposed solution must not depend on any significant financial investment to be deployed by other institutions or organizations and be built with commercially available technologies that can be replicable in other countries and scenarios.

In order to be used in public health campaigns or in similar large-scale initiatives, the solution should be scalable. In other words, it should be able to be used in population interventions with many participants using it simultaneously. Taking into account that this digital health solution collects personal data, information security is mandatory.

1.3.2 User acceptability and usability

Sections of the targeted population may not be familiar with technology (e.g. older adults), so the proposed system should be easy to use and take into account specific requirements also for these individuals, aiming to increase its user acceptance [34]. Another challenge is to develop an application that is designed to run effectively on mobile devices (smartphones and tablets) as they represent the most common devices used to access the Internet [35].

Feedback (i.e. nutrition advice) is an integral component of the nutrition improvement process. The system should be able to encourage and support users to have healthier nutrition habits. In order to do that effectively, it is important to evaluate the understanding by the potential users of the artefacts used during the nutrition advice (e.g. online report).

1.3.3 Validity and effectiveness of the treatment

The system will be designed to record “how much” a person has had to eat and drink, with some precision. Detailed food composition databases (containing energy and nutrient content of foods) will be used to enable analyses of the dietary intake and subsequently the diet quality of an individual to be determined [19].

The final aim of this proposed system is to change the users’ dietary behaviours and habits. There are several studies applying behaviour change techniques in order to encourage healthier habits. A taxonomy of techniques has been defined to enable investigators to standardise the naming and conventions and also to compare results [36], [37]. The translation of these psychological principles in artefacts (e.g. components of an application) is not trivial. Due to this complexity, there is literature available to properly design solutions for behaviour change [38]. There are also some

studies aiming to model and simulate human behaviour, so that systems can become more effective when encouraging behaviour changes [39].

Taking these points into account, the system should aim to offer a validated offering from the nutritional sciences perspective (i.e. real improvement in the diet quality) and be able to encourage this positive behaviour change via the Internet. The validity of the system can be based on existing reliable publications from the nutrition field (e.g. widely referenced by the scientific community) and should be checked against explicit knowledge from diet experts (i.e. nutritionists and dietitians). The effectiveness of the treatment can then be measured with robust controlled nutrition intervention studies, for example via a Randomized Control Trial (RCT).

1.4 Scope Definition

There are many opportunities for using technologies to improve nutrition assessment and advice. Due to these extensive possibilities, it was necessary to limit the scope of this project, considering its requirements and challenges. Although this PhD is applied to nutrition, its field of investigation is Computer Science. With this in mind, both the nutrition assessment and advice will rely on existing and validated methods in the nutrition field. For example, an assessment method, which had been previously validated in the UK (i.e. a representation of people's dietary intake with a certain level of accuracy) was used. In a similar way, the tool for measuring the quality of the diet (e.g. diet score) must be accepted by the scientific community in order to make the treatment effect measurement reliable.

From a technological perspective, the nutrition assessment stage (i.e. dietary intake recording) will only consider technologies which were validated in the field. In other words, an acceptable level of accuracy needs to be guaranteed in order to provide valid advice based on that. Emerging technologies not yet validated in this field, such as image recognition, were not considered in this project, especially if they did not meet the basic requirements mentioned in the previous section.

In order to increase the reproducibility of this system, it was limited to popular technologies and programming languages, so that it could be improved by other researchers and developers who would potentially have access to its open source code. Furthermore, it was not considered if it took advantage of any bespoke device or specific hardware and the use of public cloud services was a key aim of the project. Ideally, it was independent of software requirement or plugin installation.

Although, potentially, almost any person in the world could use this type of system, to encourage participants with no prior experience with the Internet would have made the usability evaluation much more complex and uncertain. Therefore, this project did not aim to encourage people to engage in the digital world specifically, but it targeted a wide audience with some level of familiarity with the Internet. This scope limitation also facilitated the recruitment which was conducted mainly online, which did not exclude participants due to lack of IT literacy, but did not target this specific group.

Nutrition advice via the Internet is still at an early stage. For that reason, it was considered important to limit the target population, so that people with very specific requirements (e.g. pregnant) did not receive advice that may have conflicted with the recommendations they might be receiving from health professionals or even cause some undesired consequences (e.g. recommending inappropriate foods for individuals with serious food allergies). Since this project also evaluated the effectiveness of the nutrition advice, it did not accept participants receiving face-to-face nutritional consultations, to avoid conflicting messages and potential bias. The more these systems evolve, the wider these eligibility criteria can become.

The overall aim of this project was to design, develop and evaluate an online system able to assess dietary intake and propose valid food-based personalised nutrition advice for adults (18+). The system was envisaged to be a web-based service, built with commercially available technologies, scalable, replicable, inexpensive, secure and independent of any bespoke device. This project proposed to answer a number of novel research questions detailed below.

1.5 Research Questions

The primary research questions were divided into three groups: system design, usability and nutrition advice. The first group explores features, reproducibility and scalability, having security as a mandatory requirement. The second group investigates inclusivity and usability aspects and the latter one evaluates the validity and effectiveness of the nutrition intervention. The main research questions presented below will be answered in chapters 3 to 7.

1. How to design and develop a nutrition application, which is inexpensive, replicable, secure, scalable and ready to be used on mobile devices?
2. How usable and acceptable is this application for the general adult population?
 - a. What difficulties do users encounter when using this application?

- b. How can its usability be improved?
 - c. How long is the completion time? How can this be reduced?
 - d. How usable is this application across different devices (laptops/desktops, tablets/smartphones)?
3. How can a nutrition decision engine, which is able to propose valid and effective online personalised nutrition advice be designed and developed?
 - a. How is it evaluated by nutrition professionals in the UK?
 - b. How is it evaluated by representative users in the UK?
 - c. How effective is it in encouraging healthier diet habits?

Chapter 3 described analyses of commercial popular nutrition-related apps to complement the literature review presented in Chapter 2. These analyses were important to answer the research question 1, together with the chapters 4 and 5 that presented two different versions of the designed app and their usability metrics, in order to answer question 2. Chapter 6 describes an experiment using nutrition professionals which evaluated the latest version of the app (question 3a). This version was used in the final randomised controlled dietary intervention study, which aimed to evaluate the acceptability of the nutrition advice by representative users (question 3b) and its effectiveness (question 3c).

1.6 Collaborations

Due to the interdisciplinary nature of this PhD, it benefited from collaborations with other students, researchers and projects. The applied nature of this project created an opportunity to work together with specialists in human nutrition, making the final solution more valid.

The two main collaborations were with Balqees Al Awadhi, PhD student in Human Nutrition (also under the supervision of Professor Julie Lovegrove) and with Dr Rosalind Fallaize, a research fellow in Human Nutrition at the University of Reading.

Balqees is a dietitian evaluating the effectiveness of web-based versus face-to-face personalised nutrition in Kuwait (EatWellQ8 study) during her PhD in Human Nutrition. She used the first version of the eNutri app developed during my PhD for validating an FFQ in Kuwait. In parallel with her validation study, I collected usability metrics from users (Chapter 4). She was responsible for recruiting volunteers in Kuwait. She also worked with Dr Fallaize to define the diet messages used during the EatWellUK study (Chapter 7), although she was not directly involved in that study.

Dr Fallaize was responsible for the recruitment and initial data analysis of the experiment with nutrition professionals. We worked together on the draft of Chapter 6. I took responsibility for the software design and development for the solutions presented in this thesis. Details of the collaborations are presented at the beginning of each study chapter (3 to 7). Each was written as a journal article and the publication status (i.e. published, accepted, submitted or drafted) of each is presented at the beginning of these chapters, together with the ordered list of authors.

1.7 Thesis outline

Chapter 2 details a review of the literature on digital nutrition assessment and presents some emerging technologies used in this field. It also describes how some algorithms have been used for meal planning and identifies some underexplored areas like artificial intelligence and fuzzy logic. After that, a feature assessment of popular diet apps is presented in Chapter 3, which was used to check the novelty of this thesis together with the literature review.

Chapter 4 and 5 focus primarily on the design, development and usability metrics of a graphical food frequency assessment system (eNutri) developed during this PhD. Two different versions of this app were used for measuring the differences in the usability metrics when the food items were presented either in a table-style (Chapter 4) or serialised (Chapter 5).

After addressing some challenges in the usability of the app, Chapter 6 presents an evaluation of the eNutri app by nutrition professionals. Chapter 7 contains the results of an RCT for measuring the effectiveness of the personalised nutrition advice provided by eNutri. Besides the content prepared for the journal articles, each study chapter includes an extra discussion at the end, showing the progress of the knowledge developed during this thesis. Chapter 8 presents a general discussion, main conclusions and suggestions for future work.

2 LITERATURE REVIEW

This chapter presents digital methods used for recording and analysing dietary intake and how they can be used as input for tailoring nutrition advice. Since the literature on systems for tailoring online nutrition advice is very limited, this chapter also contains algorithms used in the nutrition field but with slightly different aims, such as for meal and menu planning. The aim of this chapter is not to present a review of nutrition assessment and advice in general (i.e. traditional methods not using technology), but to focus on the technologies that are being applied in this field.

2.1 Technologies for recording dietary intake

Nutrition assessment methods are traditionally paper-based, their administration and analysis are time consuming and more expensive than digital methods [40]. Besides the fast and easy processing of data input, computerized methods brought the advantage of immediate results. The interest for digitalizing the recording of dietary intake is not recent. An overview of computerized dietary assessment programs published in 2005 presented 29 programs designed to be used by health professionals or in research [41]. They used one or two of these nutrition assessment methods: food record (n=13), diet history (n=8), FFQ (n=5) and 24HDR (n=5).

Prospective nutrition assessment methods (e.g. estimated food diary), usually offer a feature to search for the food items in a database. Although more convenient for the user than inserting the information manually from paper, these repetitive searches are still time consuming. Besides the fact that a single food diary may contain more than twenty food items, the recording of dietary intake using these methods still have to log the quantity (e.g. 2 bananas) and the weight. Depending on the food item, the weight may be derived from typical household portions, for example a teaspoon of sugar. However, some items present greater challenges for weight estimation. The end user (i.e. citizen/patient) normally does not know the weight of a banana and the textual units

(e.g. small, medium, large) may not be enough to accurately assess portion weight without food images. Furthermore, in order to increase the successful response rate during the food searches, the system designers may want to increase the size of the food database, so that a more specific search may be found (e.g. specific beer brand), but this may decrease the quality of the food composition database supporting the nutrient analysis (i.e. incomplete or less reliable nutrient data for these added items, especially branded foods). This is due to the fact that typical food composition tables do not contain all the food items available in a specific country, but only generic versions (e.g. soft drink) of popular items (e.g. Coke) [19].

These systems started to gain popularity in the Internet age and are now very popular not only among nutrition professionals [42] but also among the general population [6]. Due to this burden of data input and in an attempt to make these systems more acceptable, some emerging technologies have been considered to replace the textual search, mainly using image recognition and natural language processing. There are some open challenges in terms of accuracy of these technologies in this field, and the next subsections will show some systems using traditional technologies (food selection and search) and also how new technologies can bring improvement, increasing the convenience of dietary intake recording.

2.1.1 Established technologies

The principal retrospective nutrition assessment methods are the food frequency questionnaire (FFQ) and the 24-hour recall [43]. The FFQs are based on a food list, created from popular food items in a specific region, and typically contain around 100 items [44]. The first online versions presented simple tables with food names in the rows and frequencies in the columns [11], very similar to the paper-based versions [45].

Some paper-based FFQs present images for the participants to select the portion sizes. This same strategy was replicated in the digital domain during the development of the Graphical Food Frequency System [46]. FFQs have some accuracy limitations (e.g. calorie estimation) but are more appropriate for initial dietary assessment aiming at personalised nutrition, because it is able to capture longer-term patterns in the diet.

The presentation of many frequency options and a few images to the users is challenging in small screen devices, such as smartphones. The completion process is very repetitive, which may decrease the user satisfaction with the system. Another usability aspect to be investigated is the presentation of the frequency options, since

they are not necessarily using the same units (e.g. 2 per month, 3 per week, 1 a day), making the decision-making process more difficult. The online Food4Me FFQ presented three food images together with seven radio buttons for the user to select the portion size (i.e. very small, small, small/medium, medium, medium/large, large, very large) [9]. Both the small radio buttons and the number of options presented simultaneously on the screen are not appropriate for smartphones. On top of that, their web design was not responsive (i.e. adaptive to the size of the device screen). These points represent a research gap to be explored during this thesis.

One well-known project using 24-hour recall is the ASA24 [47], which is an automated self-administered system, developed by the American National Cancer Institute (NCI). Three British projects also used the 24-hour recall method: Oxford WebQ [48], Intake24 [49] and MyFood24 [50] [51]. This method is able to capture how a dietary intake is divided among the meals but does not contain much information about food patterns and frequencies over a longer time period. A 24-hour recall system can be adapted to work as a food diary, collecting dietary intake prospectively. For instance, MyFood24 is able to work retrospectively or prospectively.

During the WebQ evaluation, the participants (n=116) took a median time of 12.5 minutes (IQR 10.8-16.3 minutes), in contrast with the administered-led interviews which took 30 minutes to administer and another 30 minutes to code. Instead of offering the feature for searching food items, similarly to food diaries, the WebQ presents a list of food items (e.g. sliced bread), with predefined amounts (e.g. slice) and asks the participant to select the quantity (None, ½, 1, 2, 3, 4, 5 or 6+), followed by some extra questions related to that specific food item (e.g. flour type white or brown) [48].

Nutrition assessment methods can be combined during the dietary intake recording, in order to increase the nutrient accuracy and also collect different aspect of the information needed (e.g. time of the meals and consumption patterns). A recent publication (2017) shows a new web-based tool (Foodbook24) which combines a 24-hour recall, a FFQ and a supplementary questionnaire [52]. To improve the food and drink search, tags were applied in 484 out of the 751 items, so that brand names and misspellings could be linked to a similar food item. With these searchable tags, a specific food item may return in the search even if its name were not inserted correctly. For instance, the tag “Coca-Cola” can be attached to Coke, making both terms indexed in the search.

Popular nutrition-related mobile applications are using a nutrition assessment strategy based on food diaries [6]. The aim to collect detailed information about food consumption sounds promising, but it also demands time and discipline from users [43]. In order to simplify this process, some investigators have proposed alternatives such as the POND (Pattern-oriented nutrition diary), which is a Food Index-Based Nutrition Diary [53]. This study explored some alternatives to the food lookup (text search), using for example the “+1 button” for items previously inserted (i.e. common items).

Inclusivity is another important aspect to be considered in public nutrition strategies. The NANA (Novel Assessment of Nutrition and Ageing) project included older adults in the design of a system specific for this population. The existing version of this system was successfully tested with older adults and validated from a nutritional perspective. It is a native off-line application which requires cameras and does not provide feedback or advice to the users [54] [55] [56].

These studies showed some alternatives to established digital methods that still face many usability challenges. Most of the published studies in this field concentrate on the nutritional validity (accuracy against a gold standard method), but there is a lack of studies exploring how to increase the user acceptance of these digital methods. The amount of effort required to use these tools in relation to the perceived benefit from the user (self-monitoring or personalised nutrition advice) is one of the trade-offs that motivate this current work.

2.1.2 Emerging technologies

The need for technological innovation in dietary assessment has been reported in academic publications [43]. The main challenges are usually around the increase of accuracy and user acceptance in the same solution. One possible way to make progress in this trade-off is to propose more pervasive technologies, so that the user acceptability can increase, decreasing the burden for users. A comprehensive review of digital methods was published in 2013 and may serve as a reference for listing the main emerging technologies applied in this field during the last few years [57].

Food image recognition is probably the most promising technology for bringing convenience to dietary recording in a very scalable way since smartphones with cameras have become very popular. Some studies are focused on food recognition [58] [59] and Google has recently announced a research project named Im2calories in this area [60]. These experiments train the systems based on limited menus, from restaurants

or schools, and try to expand their applicability to new contexts, but they still have unsatisfactory accuracy. To design and develop a system that could recognize foods and estimate their weights in any context, including home-made meals, is still an open challenge.

Some of the difficulties in food recognition are related to hidden foods on the plates as well as depth and volume estimation. Some projects have been using laser beams to overcome this difficulty [57], although the use of extra hardware makes the scalability of these solutions less promising. Similar scalability challenges happen with solutions proposing to use wearables for automatic dietary monitoring [61]. Although the current project acknowledges the relevance of this strategy, the use of extra hardware conflicts with the basic requirements of this project, presented in the previous chapter.

Natural Language Processing (NLP) has also been applied to this field [62][63][64], but still without significant results as a stand-alone input method nor without evidence from experiments with end users recording food diaries, for example. This technology may be combined with image recognition in order to increase its accuracy. For instance, a smartphone user could take a food image and record the name of the food items in the meal, perhaps with some estimation of portion sizes. As mentioned in the previous chapter, new assessment methods have to be validated against independent methods (e.g. weighed food records). No validation study using NLP was found in the literature.

Another proposal for addressing the lack of trained professionals for dietary assessment utilized crowdsourcing of untrained workers to estimate calories and macronutrients of photographs [65]. This strategy could increase the scalability of nutrition assessment solutions, but probably not enough to support free or low-cost applications to the final users, due to the number of manual transactions.

The Journal of Biomedical and Health Informatics issued a special edition focused on nutrition informatics in 2016. Some innovative approaches using glucose sensor data [66] or food image recognition [67] were published. The first approach is for use in artificial pancreas for people with type 1 diabetes. It detects the consumption of a meal and estimates its carbohydrate content to determine the appropriate dose of insulin bolus. The study on food recognition presents a new dataset for the evaluation of food recognition algorithms and confirms the current challenges with applying image recognition in this field.

2.2 Technologies for nutrition assessment

After the recording stage, the dietary intake information is usually aggregated and analysed. In order to do that, each food item listed in the first stage needs to be matched with a corresponding item in a food composition dataset. With this mapping, it is possible to calculate the energy and nutrient consumption of a specific diet. Aggregation (e.g. average consumption per day) is an important step in this analysis, taking into account that most of the dietary reference values (DRV) report the recommendation of nutrients per day. This analytical and structured process opened opportunities for digitalization, in order to reduce costs and facilitate the data processing [8].

This type of nutrition information analysis is very common in epidemiological studies. The EPIC study team developed and published an offline tool, named FETA, for converting FFQ data into nutrient and food group values [45]. A similar PC software, named Diet*Cal, was developed by the National Cancer Institute (United States) for analysing outputs of their FFQ (Diet History Questionnaire II) [68]. The ASA24 tool, used for 24HDR, does not offer a feature for analysing the output, but it is able to export an output file to be analysed offline using statistical packages [47]. There are several systems available for both nutrition professionals and researchers. The following subsections will present some of the most important ones.

2.2.1 Professional nutrition software

Professional dietary analysis software, such as Nutritics [69] and DietPlan [70], has been used for many years. Their main features are nutritional and recipe analysis. For instance, a nutrition professional can enter a food diary and the software generates the nutrient report. Some of these packages provide meal planning tools, based on existing food composition tables, such as the McCance and Widdowson's composition of foods integrated dataset [19]. They differ from the system proposed in this project not only because of the target user population (their end user is the health professional) but because they are not focused on nutrition advice as this is expected to be provided by the nutrition professional.

2.2.2 Self-monitoring diet apps

As of September 2011, there were 5430 apps available in the health and fitness category at the Apple App Store. Among the paid apps, 651 were related to healthy eating [71]. Another review of health apps confirmed the popularity of diet apps, which was the

second most common category, followed by the fitness apps, focused on self-monitoring [72]. There is a predominance of diet apps focused on weight loss, although their incorporation of behaviour change techniques (BCT) were not found to be satisfactory (average of 6.3 (SD 3.7) out of 26 BCTs) in a review of these apps in the Australian app stores [73].

User engagement with self-monitoring diet apps, especially those using food diaries is an open challenge. A retrospective analysis was conducted on the sample of 189,770 people who had downloaded a specific free mobile app, called “The Eatery”, which aimed to promote healthy eating through photographic dietary self-monitoring. Users who had taken at least 10 pictures and used the app for at least one week were classified as “Actives”. Results from this study showed that only 2.58% of the users became “Actives”, whereas more than two-thirds of the users did not take any valid pictures [74]. This exemplifies the challenge of engaging users with diet apps, especially those using prospective nutrition assessment methods, which require many minutes per day for recording the dietary intake.

A study conducted with 570 dietitians in Australia, New Zealand and in the UK investigated the use of health apps in dietetic practice. 62% of these professionals used diet apps somehow in their practice, especially for tracking the dietary intake of their patients (60%).

2.3 Technologies for nutrition recommendation

After collecting information about dietary intake, a system would need to have a set of rules (e.g. knowledge base) to create the recommendation decision engine. One of the main challenges in this field is how to train these systems without clinical nutrition databases available. This might be the main reason for the scarcity of tools for nutrition recommendation. Because of this, the following subsections will present a diversity of tools applied in the nutrition field, not only directly to online personalised nutrition advice.

2.3.1 Menu and meal planning

The use of computational methods for supporting nutritional planning is not recent. The need of meeting the nutritional requirements via a vast number of possible combinations of foods opens an opportunity for the use of computers. Mixed Integer Linear Programming (MILP) was proposed as a possible solution for this in 1993, based on the

Simplex algorithm, considering nutrients and prices [75]. Besides meeting the nutritional guidelines, it is imperative to recommend meals that individuals will like. This challenge would be much simpler if it were only about finding some possible random combination of food items in order to meet the energy nutrient requirements.

This challenge was presented by Buisson et al. in 2003 [76] and further elaborated in a paper presenting the Nutri-Educ software in 2008 [77]. Based on the nutrition literature, they were aware that a valid solution could not propose a well-balanced diet very different from the user current diet. Improvements would need to be applicable gradually, in order to have a good user acceptance. With this in mind, they stated that the current meal is linked to similar meals via addition, deletion or portion modifications. Their solution was to consider this state space as a graph, in which nodes were possible meals and vertices between nodes the acceptable transformations. The search consists of finding an acceptable meal, meeting the nutritional recommendations, as close as possible to the initial meal [77].

Artificial Intelligence (AI) algorithms, such as Case-Based Reasoning (CBR), have also been proposed for planning menus [78]–[80]. Some of these systems were designed to be used by dietitians [78], [79] who predefined the menus to be selected via CBR based on some variables such as age, sex. Khan et al proposed to use ripple-down rules (RDR) to create the knowledge base (KB) through a direct system interaction while the domain experts is accomplishing their tasks of constructing a diet for a given client [79].

The decision-making process used in nutritional consultations in order to propose changes to the clients' diet is more complex, taking into account that nutritionists have to consider the usual diet habits, define the most relevant changes to propose, considering the clients' preferences. On the other hand, user preference is not necessarily the final target in nutrition recommender systems, considering that it could be very unhealthy. That is one of the limitations of approaches used to create recommender systems based on recipes collected from the Internet and their reviews [81].

The usual nutritional recommendation provided by nutrition professionals take into account some very important variables, such as age, sex, dietary restrictions and lifestyle. Some specific groups (e.g. older adults, vegans) need to receive very tailored advice. Technology-based systems in this area also need to have similar levels of personalisation. An example of such a system is described in the paper "Nutrition for

Elder Care: a nutritional semantic recommender system for the elderly", whose recommendation take into account participant's preferences [82]. This recent paper, published in April 2016, describes the system design and the ontology supporting the recommender system. The system takes into account demographic data (e.g. gender), physical properties (e.g. weight and height), nutritional state (e.g. malnourished) and also some responses from a FFQ without portion sizes. The aim of their system is to recommend variations of pre-defined diet plans, instead of modifications in the current diet.

These approaches are very useful when there are pre-defined meals and diets (e.g. hospitals), but it can propose diets that are very different from the current diet, making the goal harder to achieve by users. These techniques applied to tailor daily menus are not directly applicable to create personalised nutrition advice, similarly to nutritional consultations. The next subsection will present dietary modelling tools, which are closer to the final aim of this thesis.

2.3.2 Dietary modelling tools

For modeling well-balanced diets, the target is generally to balance the food groups (fruits, vegetables, etc.) and nutrients distribution. A recent study used nonlinear constraint optimization techniques to design a tool for standardizing the background diet of participants during a dietary RCT [83]. A constraint is a function resulting in a Boolean output, which is true if the combination of all values is allowed and false otherwise. An objective function results in a set of solutions that are optimal with respect to the objectives, during the constraint optimization process. The users of this tool (likely dietitians) enter the macronutrients (fat, carbohydrate and protein) and food groups serving targets (e.g. 5 servings of vegetables) and some participant details (height, weight, age and sex) so that the tool can calculate the estimated energy requirement (EER). After this step, using a reference food composition database and also pooled baseline food intake data from completed trials before intervention, the tool solves the optimization problem and returns to the user with target servings per food group to meet the trial requirements suited to each participant. This solution is possible because the macronutrients energy densities are constant (e.g. fat contains 9 kcal per gram), then the tool needs to minimize the difference (i.e. Euclidean distance) between the target and calculated macronutrient values, varying the possible servings per food group [83].

In the previous subsections, the approaches used by most of the systems for checking the outputs against the references are discrete. For instance, if the reference nutrient intake (RNI) for vitamin D in the UK is 10 micrograms and an individual is consuming 9.9 micrograms, a system could indicate, based on a specific rule, that this specific target was not met, using a binary evaluation. But the decision-making process for this type of evaluation is not discrete when done by domain experts (e.g. dietitians). Human intuition would evaluate this hypothetical scenario as something similar to “almost meeting the recommendation” or “very close to the recommendation”, but this rationale is not captured using Boolean logic. This fact motivated some researchers to investigate the possibility of doing this analysis using fuzzy logic [84][85][86][87][77] and some studies are presented in the next subsection.

2.3.3 Fuzzy logic for nutritional analysis

Lee et al proposed an "Adaptive Personalized Diet Linguistic Recommendation Mechanism Based on Type-2 Fuzzy Sets and Genetic Fuzzy Markup Language" [84] in 2015. Taking into account nutritional guidelines (e.g. recommended percentage of calories from fat in a diet) and knowledge from domain expert, it was possible, for instance, to model the fuzziness of PCF (percentage of calories from fat). When combining opinions from different DE, it was possible to model how those words (low, medium and high) were perceived differently by each expert.

Using the percentage of macronutrients (fat, carbohydrates and protein), the calorie ratio and food group balance, obtained from the food pyramid, it was possible to compute the diet health level (i.e. very low, low, etc.) from the domain expert and the Fuzzy system, as well as their matching. For the whole diet sample (n=160) the matching accuracy was 55% before training, but after learning, using genetic algorithms (GA), it increased to around 75%. This important study only evaluated one variable (diet health level), but this approach could be expanded to more complex systems as long as evaluation from domain expert could be collected also for other aspects of the diet, including nutrients.

One important aspect of the Fuzzy Logic approach is that real-life nutrition recommendations are more based on words (linguistic variables) than numbers. It seems more sensible to compute with words (CWW) than numbers in order to construct a mathematical solution for the nutrition decision-making process [88]. That is the main motivation for fuzzy logic in this context.

Regarding evolutionary algorithms, an article published in 2014 [89] confirms the small influence of this field on nutrition recommendation systems and indicates how promising this application could be.

2.4 Technologies used in remotely delivered nutrition interventions

There are a variety of systems for diet self-monitoring and for use by nutrition professionals to create tailored feedback, however the use of technology in nutrition interventions is limited. This can be confirmed from the results presented in a systematic review and meta-analysis of remotely delivered interventions using self-monitoring or tailored feedback to change dietary behaviour, published in 2018 [90]. This review considered any type of remote method, including printed material, text messages, CD-ROM and phone calls. Its objective was to analyse if remotely delivered standalone (i.e. no human contact) interventions were effective in changing eating behaviours [90].

This systematic review identified 26 studies (containing 21,262 participants), between 1990 and 2017. Taking into account the relevance of healthy diets in addressing the health challenges presented in the first chapter of this thesis, this number of studies is not high, especially considering a high risk of bias in most of these studies were reported [90]. In other words, there is a need for more evidence in this field. Out of these 26 interventions, 11 used some type of computer technology for delivering the feedback. Their technological platforms are shown in Table 2.1.

Table 2.1 - Technologies and general information of remotely delivered nutrition interventions ^[1]

First author	Year	Country	n	Months	System
Alexander	2010	USA	2513	12	Web application
Atienza	2008	USA	36	2	PDA
Campbell	1998	USA	526	3	Software
Huang	2006	Australia	497	5	Online shopping
Mummah	2016	USA	17	3	Native app
Poddar	2010	USA	294	5	Internet course
Springvloet	2015	Netherlands	1349	9	Web application
Tapper	2014	UK	100	6	Web application
Turnin	1992	France	105	12	Minitel
Turnin	2001	France	557	12	Minitel
Celis-Morales	2017	7 European countries	1607	6	Web application

^[1]Source: Adapted from [90]. Considering only interventions using computer technology and classifying these systems.

Two interventions used a French online service (Minitel) which is no longer available. Another outdated technology, a personal digital assistant (PDA), was used in 2008 [90]. The study conducted by Campbell et al. did not have human contact during the nutritional feedback but used an installed software in the offices where the study was conducted [91]. These technologies are very different to the modern web applications in terms of design and development.

Huang et al investigated the influence of dietary advice during online grocery shopping. This fully automated solution recommended specific switches from selected products higher in saturated fat to alternate similar products lower in saturated fat [92]. Although interesting, the experimental design and aim was very different from the project presented in this thesis because it was focused on online shopping.

The trial reported by Mummah et al in 2016 was a pilot (n=17) with iPhone users to encourage vegetable consumption in overweight adults. They have developed a fully automated theory-driven app (Vegethon) enabling self-monitoring of vegetable consumption, goal setting, feedback, and social comparison [93]. Subsequent analysis in the literature showed that a larger study (n=135) was conducted after the pilot. They used two nutrition assessment methods (FFQ and 24HDR) and the results reported show a significantly greater daily vegetable consumption in the intervention versus control condition (2.0 servings for FFQ; and 1.0 serving for 24HDR). The methodology and outcomes were reported in detail [94], but without details of the Vegethon app. It was

published in the Apple app store but not made publicly available to other software developers (i.e. open source), making the analysis and comparison more difficult.

In the study conducted by Alexander et al in 2010, three participant groups were used with the following materials: an untailed control website; a tailored website; or the tailored website plus motivational interviewing counselling delivered via e-mail [95]. This RCT was conducted between 2005 and 2006 and the details of the web application were not provided, but there is a publication with the results of a focus group conducted prior to the RCT, in order to collect some features preferred for a web-based educational intervention [96]. The FFQ used in this RCT contained only two items (fruit and vegetable) and the rationale for tailoring the advice was not detailed.

The intervention conducted in the Netherlands by Springvloed et al used a 66-item online questionnaire FFQ to assess the intake of fruit, vegetables, high-energy snacks, and saturated fat. Each of these had a specific module in the website, so that participants could read about these food items, check availability and prices in their supermarket, before setting a personal goal and make action plans. Besides the traditional individual cognitive elements (knowledge, awareness, attitude, self-efficacy) used in health interventions, this study tailored the goal setting using additional variables such as self-regulation processes and environmental-level factors (e.g. perception of availability and prices of healthy food products in supermarkets). The treatment effects provided another set of evidence of the better efficacy of tailored advice in comparison to generalized population advice [97]. This study may reinforce the importance of using validated behaviour change techniques in health interventions, taking into account that the rationale of the advice was elementary (recommendations) and the users were asked to set their personal targets.

Tapper et al measured the treatment effect of a healthy eating program on consumption of fruit and vegetables, saturated fat, and added sugar, via a 6-month RCT. The website homepage was presented using a screenshot, but without further details from a technological perspective [98].

At the bottom of Table 2.1, the study conducted by Celis-Morales et al is the Food4Me project [5], which has been used as the main reference of personalised nutrition intervention throughout this thesis. It targeted to improve seven outcomes (fruit, vegetables, whole grains, oily fish, red meat, salt and total fat), using an online FFQ for nutrition assessment. It was the broadest study in terms of targeting improvements in many food groups simultaneously.

Other aspects that Table 2.1 highlights are that there were only five interventions using either web or native apps, and also the small number (n=6) of interventions conducted in the last 10 years. The analysis of the technologies and methods used in these interventions highlights that there are novel contributions to be made in terms of improving the user acceptance and effectiveness of similar digital nutrition tools. Research studies can contribute significantly to progress this field, especially if they openly report their methods, material and evidence data. The next five chapters present some studies conducted during this project that aimed to make contributions to the online nutrition field.

3 POPULAR NUTRITION-RELATED MOBILE APPS: A FEATURE ASSESSMENT

This chapter presents a review of commercial nutrition-related app in order to complement the academic literature review presented in the previous chapter.

The author was responsible for the experimental design, data collection, data analysis, and writing of this chapter.

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Abstract

Background: A key challenge in human nutrition is the assessment of usual food intake. This is of particular interest given recent proposals of eHealth personalized interventions. The adoption of mobile phones has created an opportunity for assessing and improving nutrient intake as they can be used for digitalizing dietary assessments and providing feedback. In the last few years, hundreds of nutrition-related mobile apps have been launched and installed by millions of users.

Objective: This study aims to analyse the main features of the most popular nutrition apps and to compare their strategies and technologies for dietary assessment and user feedback.

Methods: Apps were selected from the two largest online stores of the most popular mobile operating systems—the Google Play Store for Android and the iTunes App Store for iOS—based on popularity as measured by the number of installs and reviews. The keywords used in the search were as follows: calorie(s), diet, diet tracker, dietician, dietitian, eating, fit, fitness, food, food diary, food tracker, health, lose weight, nutrition, nutritionist, weight, weight loss, weight management, weight watcher, and ww calculator. The inclusion criteria were as follows: English language, minimum number of installs (1 million for Google Play Store) or reviews (7500 for iTunes App Store), relation to nutrition (i.e., diet monitoring or recommendation), and independence from any device (e.g., wearable) or subscription.

Results: A total of 13 apps were classified as popular for inclusion in the analysis. Nine apps offered prospective recording of food intake using a food diary feature. Food selection was available via text search or barcode scanner technologies. Portion size selection was only textual (i.e., without images or icons). All nine of these apps were also capable of collecting physical activity (PA) information using self-report, the global positioning system (GPS), or wearable integrations. Their outputs focused predominantly on energy balance between dietary intake and PA. None of these nine apps offered features directly related to diet plans and motivational coaching. In contrast, the remaining four of the 13 apps focused on these opportunities, but without food diaries. One app—FatSecret—also had an innovative feature for connecting users with health professionals, and another—S Health—provided a nutrient balance score.

Conclusions: The high number of installs indicates that there is a clear interest and opportunity for diet monitoring and recommendation using mobile apps. All the apps

collecting dietary intake used the same nutrition assessment method (i.e., food diary record) and technologies for data input (i.e., text search and barcode scanner). Emerging technologies, such as image recognition, natural language processing, and artificial intelligence, were not identified. None of the apps had a decision engine capable of providing personalized diet advice.

3.1 Introduction

Non-communicable diseases such as diabetes and cardiovascular diseases account for almost two thirds of deaths globally. The general recommendations for addressing this epidemic are related to lifestyle changes, mainly encouraging healthy diets, physical activity (PA) and the reduction of tobacco use and alcohol consumption [1].

Valid dietary intake recording is key for nutritional intervention. The methods used for collecting food intake data can be classified in a number of ways. Based on the time of the collection, the retrospective methods, such as the 24-hour food recall and the food frequency questionnaire (FFQ), require memory for recollection of foods eaten, whereas the prospective methods require diet reporting as the consumption occurs, acting as food diaries. In clinical nutrition, prospective methods are usually applied between 4 to 7 days. It is also possible to classify the methods as quantitative daily consumption or food frequencies. The first group focuses on recording the detailed food consumption as accurately as possible, typically for a couple of days. The latter assesses typical consumption patterns over longer periods [2]. These methods have been delivered traditionally using a paper-and-pen format, but there is a burden associated with this system for both the patients and health professionals. The digitalization of food diaries saves time and resources and is preferred by patients [3].

With the proliferation of smartphones and tablets, there has been a rise in the number of software applications (i.e. “apps”) aimed at improving nutrition and physical fitness. The simple digitalization of input data is important and useful, but these devices have built-in capabilities that can increase the accuracy of data collection and decrease the time burden of the process and possible biases [4]. The most common example is the use of GPS for measuring PA [5]. Cameras can be used for image recognition in order to recognize foods and estimate portion sizes [6] [7]. In relation to the use of technology to encourage behaviour changes, there are studies and available diet apps that combine health behaviour theories and persuasive technology [8]. This topic is particularly important because one of the main goals of nutrition intervention is to modify unhealthy habits.

Due to the large number of nutrition-related apps, it is difficult to understand what these apps are offering and how the apps compare with each other. This study aims to review the main features and technologies used by popular nutrition-related apps available in the online market and to analyse their use of emerging technologies in the field of

online nutrition assessment and intervention. This review will be beneficial for industry, academia and health professionals who are interested in taking advantage of the benefits of technology in nutrition assessment and intervention.

3.2 Methods

During the publication of a mobile app, a developer specifies in which stores (usually divided by countries) the app will be available. They also specify what device requirements (e.g. versions of the operating system, smartphone or tablet) are necessary in order to install the app. Searching for apps from a specific device in a particular country can alter the apps that appear available to the user. In order to mitigate this, the initial search was conducted on a desktop PC not logged into any particular user account but located in the UK. Searches were conducted in November 2015.

For the Play Store, the initial search was executed using a Google Chrome browser in an Incognito window (private mode) logged off from the Google Account using the following keywords: calorie(s), diet, diet tracker, dietician, dietitian, eating, fit, fitness, food, food diary, food tracker, health, lose weight, nutrition, nutritionist, weight, weight loss, weight management, weight watcher, ww calculator. An initial list of popular apps, ordered by number of installs and reviews, was created. For the App Store, the initial search was performed via iTunes, software provided by Apple, logged off from any user account. The apps were ordered by number of reviews, because the App store does not list the number of installs. The user rating was used as an exclusion criterion. The rating range is between 0 and 5 and represents the user satisfaction with the app. Apps were excluded if ratings were below 3, in order to avoid considering apps that were downloaded by many users but may not be in use (e.g. because they were not working properly or did not deliver what was advertised in the store). Apps which only monitored weight or PA, such as Google Fit, or that only provided recipes were also not considered. After the creation of an initial list of apps, user accounts linked with a UK address and credit card were used to install the apps and verify the apps against the inclusion criteria.

Once the apps were installed, their features were reviewed from both nutritional and technological perspectives. From the nutritional perspective, features in the following categories were considered: dietary intake, phenotype, physical activity and others (see Tables 3 and 4). The technological perspective analysed what technologies were being used in order to compare with emerging technologies in the field of human nutrition

assessment and intervention. The functionalities were analysed in two main groups: input and output features. Features that required data from the user (e.g. weight, height) were considered as input features, whilst the results shown to the user were termed output features.

3.3 Results

3.3.1 App selection

In Play Store, it is not possible to sort the results by number of installs. It has an internal algorithm that classifies the relevance of the apps and presents them in a list. For this reason, it was necessary to open the first 20 results by keyword to get the number of installs in order to mitigate the risk of missing an app with a high number of installs. The app list created in this process was ordered by number of installs and a total of 21 apps with greater than 500,000 installs was identified (Table 3.1). To further reduce the number of apps for inclusion (for practical reasons and readability of results), apps with less than 1 million installs were excluded.

Table 3.1 - Popular (> 500k installs) nutrition-related apps available in the UK Play Store

App name ^a	Abbreviation	Installs (Range)	Reviews	Rating (0-5)
S Health - Fitness Diet Tracker	SH	100-500m	33,619	3.7
Calorie Counter - MyFitnessPal	MFP	10-50m	1,140,897	4.6
Calorie Counter by FatSecret	FS	10-50m	178,438	4.3
Noom Coach: Weight Loss Plan	NC	10-50m	161,237	4.3
My Diet Coach - Weight Loss^b	MDC	5-10m	102,318	4.3
Lose it!, by FitNow Inc.	LI	5-10m	45,391	4.4
Weight Watchers Mobile^d	WW	1-5m	66,897	3.9
Lose weight without dieting	LW	1-5m	56,617	4.6
Lifesum - The Health Movement	LS	1-5m	46,856	4.2
Diet Point - Weight Loss, D Point^c	DP	1-5m	28,906	4.2
My Diet Diary Calorie Counter	MDD	1-5m	17,711	4.1
Effective Weight Loss Guide^c	EWL	1-5m	16,156	4.1
Diet Assistant - Weight Loss^c	DA	1-5m	10,722	3.9
Calorie Counter, by CalorieCount	CC	1-5m	7,529	4.0
MyNetDiary Cal. Counter PRO^c	-	500k-1m	10,405	4.4
Weight Watchers Mobile UK^c	-	500k-1m	9,896	3.7
Calorie Counter & Diet Tracker^c	-	500k-1m	9,306	4.3
WWDiary by Canofsleep^c	-	500k-1m	8,564	4.6
Calorie, Carb & Fat Counter^c	-	500k-1m	7,923	4.3
Diet Plan - Weight loss 7 days^c	-	500k-1m	5,013	3.8
Calculator & Tracker for WWPP^c	-	500k-1m	1,898	3.8

^a Results from November 2015.

^b MDC provides some diet recommendations in the free version. The food diary is available only in the “Pro” version, which was not considered one of the most popular apps in this study.

^c DP, EWL and DA are not food diaries, but they provide diet recommendations via diet plans.

^d later excluded due to subscription

^e later excluded due to minimum threshold

All of the apps were in the "health & fitness" category of the store. No app was excluded by the rating criterion (i.e. rating <3). However, although WW is free to download, a subscription (£12.95 monthly for the online plan) was required to join the online program [9] and thus it was excluded from subsequent analysis.

The same search keywords were used in App store (Table 3.2).

Table 3.2 - Nutrition-related apps available in the UK App Store, ordered by number of reviews

App name	Abbreviation	Reviews	Rating (0-5) ^a
Calorie Counter & Diet Tracker by MyFitnessPal	MFP	108,072	4+
Calorie/KJ Counter and F. Diary by MyNetDiary	-	6,484	3.5
Calorie/KJ Counter PRO by MyNetDiary	-	3818	4+
Lifesum - healthier living, better eating	-	2,952	3.5
Tap and Track - Calorie Counter	-	2317	3.5
Easy Weight loss tips, by Michael Quach^b	-	2286	2.5
Calorie Counter and Diet Tracker by Calorie Count	-	1716	4
Calorie Counter+ by Nutratch	-	1501	4+
Argus - Calorie Counter and activity tracker	-	1291	4
Calorie Counter by FatSecret	-	1048	3.5

^a Results from November 2015

^b Not included in the analysis due to rating less than 3

One app did not meet the rating criterion (Easy Weight loss tips, by Michael Quach, rating 2.5), hence was excluded. The most reviewed app (MFP with 108,072 reviews) had around seventeen times more reviews than the second most reviewed app (6,484 reviews). As the latter had fewer reviews than the least popular of the apps included from the Play Store (CC with 7529 reviews), only MFP was considered suitable for inclusion in the study. However, since MFP had already been included from the Play Store list and because an initial assessment of both the Play Store and App store versions of the app did not reveal any notable differences, only the Play Store version was used in subsequent analysis.

3.3.2 Input features

Input features were analysed for four categories of recording: dietary intake, phenotype, PA, and others (e.g. personal reminders) (Table 3.3 and Table 3.4).

Table 3.3 - Nutrition-related app input features for dietary intake and phenotype

Feature / App	SH	MPF	FS	NC	LI	LW	LS	MDD	CC	MDC	DP	EWL ^b	DA ^c
Dietary Intake													
Text Search	✓	✓	✓	✓	✓	✓	✓	✓	✓	-	-	-	-
Barcode scanner		✓	✓	✓	✓		✓	✓	✓	-	-	-	-
Serving size	✓	✓	✓	✓	✓	✓	✓	✓	✓	-	-	-	-
Food by meal	✓	✓	✓	✓	✓	✓	✓	✓	✓	-	-	-	-
Favourite foods	✓	✓	✓	✓	✓	✓	✓	✓	✓	-	-	-	-
Create meal or recipe		✓			✓		✓			-	-	-	-
Add kcal/kilojoule			✓		✓		✓			-	-	-	-
Water consumption	✓	✓				✓	✓	✓	✓	✓	✓	-	-
Water settings	✓						✓						
Macronutrients settings							✓			-	-	-	-
Save photo						✓			✓				
Phenotype													
Current Weight	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Height	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓
Gender	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Age / date of birth	✓	✓	✓		✓	✓	✓	✓	✓		✓	✓	✓
Waist circumference		✓				✓							
Hips circumference		✓				✓							
Neck circumference		✓				✓							
Target weight		✓	✓	✓	✓	✓	✓		✓	✓			✓
Target date ^d				✓	✓		✓						
Body type									✓				

^a SH: S Health; MPF: MyFitnessPal; FS: FatSecret; NC: Noom Coach; LI: Lose it!.

LW: Lose Weight Without Dieting; LS: Lifesum; MDD: My Diet Diary; CC: Calorie Count; MDC: My Diet Coach; DP: Diet Point; EWL: Effective Weight Loss; DA: Diet Assistant;

^b Weight and height for BMI calculation. Age and gender for calorie calculation.

^c Weight and height for BMI calculation. Age and gender for profile.

^d Target date in "Lose it!" is set indirectly via the plan to lose fractions of kg per week;

"-" Features assessed only in apps providing food diaries.

MDC, DP, EWL and DA were not evaluated for some criteria because they are not food diaries; rather they propose diet recommendations using different approaches. Food items could be selected by 'text search' in all food diaries (n=9) or via 'barcode scanner'

in seven of them. 'Serving sizes' could be selected using units (e.g. grams) or household portion sizes (e.g. teaspoon) according to the food item. Daily meals were fixed (e.g. breakfast, lunch, dinner and snacks) and the food input was divided by meal ('food by meal') in all food diaries (n=9). Only three apps (MFP, LI, LS) provided a feature for the users to create and save personal meals or recipes by combining existing food items in the apps. FS, LI and LS also had a feature for adding calories ('quick add kcal' or 'add kjoule'), without entering a food name. LW and CC had a feature for taking a picture of the meal, which can be used to remind the user about the food items for later entry. This feature is useful when the user does not have time to log the items during or just after the meal.

The most common phenotype inputs were current weight, height, gender and age (Table 3.3). Circumferences (waist, hips and neck) were found in two apps (MFP and LW) and entered optionally after the initial registration. In some apps, the user could also enter a target weight (n=9) and the target date (n=3) expected to reach this personal goal. When setting the target weight, NC limited the weight loss to a maximum of 1 kg per week. CC was the only app that asked the user to input their body type (small, medium or large).

For reporting PA (Table 3.4), users could input the activity name and the duration in minutes (feature 'Type of PA'). As most of smartphones have GPS hardware, they are able to perform location tracking. Accelerometers are also used for detecting the number of steps taken by the user ('Pedometer'). Instead of performing movement tracking natively in the app (feature 'native GPS'), some apps (n=5) receive location information from other apps ('third-party GPS integration') or integrate with wearable devices (n=5) such as Fitbit, which measure distance using its internal hardware and software [10]. These wearable devices are acquired by the user separately and can be used independently of these nutrition-related apps. The 'average activity level' refers to the self-report level of activity of the user (low, moderate or high).

Table 3.4 - Features for physical activity and other input features

Feature / App ^a	SH	MPF	FS	NC	LI	LW	LS	MDD	CC	MDC	DP	EWL	DA
Physical Activity													
Type of PA ^b	✓	✓	✓	✓	✓	✓	✓	✓	✓				
Native GPS	✓			✓									
Third-party GPS integration ^c		✓	✓	✓	✓		✓						
Integration with wearables ^d	✓	✓		✓	✓		✓						
Pedometer	✓			✓									
Average activity level	✓	✓	✓			✓		✓	✓				✓
Exercise Goal	✓	✓		✓						✓			
Other features													
Community forums		✓	✓		✓			✓	✓	✓	✓		✓
Personal reminders	✓	✓		✓	✓	✓	✓			✓	✓		
Challenges	✓								✓	✓			
Health conditions								✓					
Daily Notes	✓								✓				

^a SH: S Health; MPF: MyFitnessPal; FS: FatSecret; NC: Noom Coach; LI: Lose it!.

LW: Lose Weight Without Dieting; LS: Lifesum; MDD: My Diet Diary; CC: Calorie Count; MDC: My Diet Coach; DP: Diet Point; EWL: Effective Weight Loss; DA: Diet Assistant;

^b MDD does not calculate the energy by type of activity, but ask the user to enter the amount of calories spent in the PA.

^c MPF integrates with other apps provided by the same company. FS integrates with Google Fit.

^d MND and LS provide wearable integration only after upgrade to paid version.

Eight of the apps had internal forums, similar to blogs, where users post questions, recipes and can share information (Table 3.4). Some apps offered the possibility of creating 'personal reminders', which could be used, for example, to remind users of snacks during the day. Some apps proposed diet challenges to users. For example, MDC users could log when they "fill half of the plate with vegetables".

MDD was the only software that required information about 'health conditions', including a specific mandatory input field about diabetes. Two apps offered the possibility of saving 'daily notes'. SH had data input features for caffeine tracking, blood glucose and blood pressure.

3.3.3 Output features

Output features refer to the data and results presented by the app to the users. In terms of nutrition assessment and diet recommendation, food diaries had similar features in terms of feedback on calories and macronutrients (protein, fat and carbohydrate) (Table 3.5).

Table 3.5 – Nutrition-related apps output features

Feature / App ^a	SH	MFP	FS	NC	LI	LW	LS	MDD	CC	MDC	DP	EWL	DA
Nutrition assessment													
Calculated energy (kcal)	✓	✓	✓	✓	✓	✓	✓	✓	✓	-	✓	✓	-
Macronutrients distribution (%)	✓	✓	✓		✓	✓	✓	✓	✓	-	-	-	-
Micronutrients intake (thresholds)	✓	✓	✓		✓				✓	-	-	-	-
Nutrition Facts	✓	✓	✓	✓	✓		✓	✓	✓	-	-	-	-
Calories by meal	✓	✓	✓	✓	✓	✓	✓	✓	✓	-	-	-	-
Recommended water consumption	✓					✓	✓			✓	✓		
Max calories to reach a target weight		✓	✓	✓	✓	✓	✓	✓	✓		✓		
Calories of the new recipe		✓	✓		✓		✓			-	-	-	-
Diet Plan						✓					✓	✓	✓
Shopping List											✓		
PA and phenotype													
Energy by type of PA ^a	✓	✓	✓	✓	✓	✓	✓		✓				
Weight progress	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓		✓
Circumferences monitoring		✓				✓							
Body Mass Index	✓					✓					✓	✓	✓
Other output features													
Forums or blogs		✓	✓		✓			✓	✓		✓		✓
Social media sharing		✓		✓		✓			✓	✓	✓		
Private social media		✓	✓		✓				✓				
Sharing with professionals			✓										
Healthy habits / rewards	✓									✓			

^a SH: S Health; MFP: MyFitnessPal; FS: FatSecret; NC: Noom Coach; LI: Lose it!;

LW: Lose Weight Without Dieting; LS: Lifesum; MDD: My Diet Diary; CC: Calorie Count; MDC: My Diet Coach; DP: Diet Point; EWL: Effective Weight Loss; DA: Diet Assistant;

^b MDD does not calculate since it asks for the amount of calories instead of type of PA and duration;

"-" Features assessed only in apps providing food diaries.

Five apps provided information on micronutrient intake. MFP and SH provided tables with the daily micronutrient intake (e.g. sodium, potassium, vitamin C and iron) and the consumption "goal" and "left". MFP provided some educational tips just after the food entry. For example: "this food is high in protein" and "this food has 1168 mg of sodium,

your goal for today is to stay below 2300 mg". Similar tips from other apps were more general and not based on the last food entry. Recommendations for water consumption (e.g. "8 cups per day") were given in five apps. After the selection of a food item, the user could examine the 'nutrition facts' of the item in a way similar to the tables used in industrialized foods (n=8). LW offered a meal suggestion combining some food items that meet the suggested number of calories for the meal.

The apps that monitored dietary intake did not provide diet plans. In contrast, diet plans were the focus of DP, EW and DA. These apps suggested diet plans, divided by meals during the day. DP also suggested a related shopping list to the users. MDC followed a distinct approach providing generic diet recommendations via challenges and tips. Some examples of these general tips are: "drink a flavored coffee (up to two cups a day)", "reduce your carbs consumption", "restrain yourself, eat an apple instead" and "eat a low fat yogurt".

In terms of nutritional assessment, SH had an interesting feature named nutrient balance score. During the day, it showed this score (0-100) based on the nutritional value of the recorded daily food intake. It was not clear if this was calculated from the macronutrient distribution only or micronutrients and other possible variables. Similarly, CC has a grade (e.g. A-, D+ and F) for the nutritional analysis and highlights with colours (green, yellow and red) if the nutrients are within the recommended threshold.

The apps also had output features related to PA and phenotype (Table 3.5). Weight progress, shown in graphs, was found in all the apps. Five apps presented the BMI calculation. 'Forums and blogs' were found in 7 apps and used frequently for sharing recipes and tips about weight loss and diets. Most of the possibilities for 'social media sharing' (e.g. Facebook) were related to weight loss achievements. MFP allowed users to connect with their Facebook friends who were also using MFP, after requesting their permission.

In addition, this review identified the existence of private social media, defined as having a feature for "following" other users, adding them "as a buddy" or supporting them. This feature was considered the distinction between forums/blogs and private social media. FS provided an innovative feature for sharing the results with nutritionists and other health professionals, so that they could follow the monitoring online. NC and FS had a feature for exporting recorded data in a comma separated value (CSV) format.

They did not export GPS data, but the results could be used for general data analysis or experiments.

As mentioned, MDC is not a food diary. It has a clear motivational focus using virtual rewards, via the Healthy Habits (HH) points, which can be obtained by drinking more water, eating vegetables or parking the car far away.

3.4 Discussion

3.4.1 Nutrition assessment

The most popular dietary intake apps available in November 2015 used prospective nutrition assessments. The focus of the food diaries was on the balance between the food intake and energy expenditure with personalized recommendation of diet plans not featuring in these apps. The four generic diet plans were based on a number of inputs required from the user (weight, height, gender and age), without subsequent dietary intake assessment. The feature for saving favourite foods and meals is an effective time saving feature, mainly for those who consume the same food items frequently. Three apps allowed the user to set a date for reaching a target weight, but only NC limited the weight loss rate.

There is a general focus on weight loss and calorie counting, with the majority of apps containing either 'calorie' or 'weight' in the title. It is important to note that nutrition assessment should not be related only to weight loss to target obesity, although this might be one of the main motivations for using nutrition-related apps. Ideal weights are not suggested to the users but are sometimes required as inputs. The target date for reaching a specific weight is also entered by the user. However, if used without professional recommendation, this may mislead the users to begin unhealthy diets or trigger an eating disorder [11] [12]. Although integration of food diaries and some types of PA monitoring have been successful, personalized nutrition advice is limited. The innovative feature of sharing results with health professionals might be a possible strategy for achieving part of this goal.

A quantitative approach is the usual strategy used by apps to balance the energy content of diets with energy expenditure. Data from the diet diary is used as the estimated energy intake and the basal metabolic rate and the energy expended through physical activities as the energy expenditure. However, this method does not take into account the quality of foods consumed. For instance, the distribution of food groups, as

recommended by some public health organizations, is not considered [13]. The score feature proposed by SH to assess the nutritional quality of the dietary intake might be an alternative to address this need. The textual feedback provided by MFP related to micronutrients and food grade mentioned in the CC nutrition fact might help users to gain some knowledge related to nutrients. The portion sizes are selected based only on text. Although the serving sizes can be useful in this situation, the apps do not present photos or icons for assisting the user to choose the most accurate portion size. Personalized advice based on health conditions or specific groups, such as vegetarians and vegans, was not available in the apps assessed.

All the apps collecting dietary intake used the same nutrition assessment method (i.e. food diary record). Although, there are alternative methods that are less time consuming such as the 24-hour recall [14] and FFQ [15] [16], which also have been validated in web-based formats.

3.4.2 Technologies

Within the apps offering food diaries, aspects of PA monitoring were available via the use of GPS or wearables. These features allow users to monitor their outdoor activities (e.g. walking and running) and the use of application programming interfaces (API) plays an important role in these integrations because they are created to facilitate the communication with other external applications. In general, the wearable devices collect data and save them in their own systems and allow third-party applications, such as the nutrition related apps, to import that data via APIs. In addition, indoor activities can be logged by selecting the type of activity and duration. Using the same strategy, LS and MFP provided the possibility to import weight measurements from Withings body scales (Withings, Inc., Massachusetts, USA), which can measure weight, BMI and heart rate and send this information via Wi-Fi to the Internet. [17].

Emerging technologies such as image recognition and natural language processing are not present in the most popular nutrition apps. The combination of these technologies could simplify the food and portion selection processes. Image recognition seems to be promising for recognizing food items and estimating their portion sizes [18] and natural language processing could be used to transcribe spoken dietary records [19]. In academia, some studies using apps take advantage of specific hardware, such as laser beams attached to smartphones [18], in order to increase the accuracy of the portion size estimation.

There is room for improvement in terms of connecting users and health professionals, in that the process of making diet recommendations could include more input from trained professionals. An automated system that proposes personalized nutrition advice was proposed and developed by the food4me study, based on a decision tree created by nutritionists and dietitians [20]. A diet information system that connects dietitians and the public was proposed by Ravana et al. in order to take advantage of artificial intelligence for proposing diet planning to the public [21]. In this context, artificial intelligence is used in an attempt to solve the diet planning challenge, so that the system can learn from past experiences (similar scenarios). In theory, the combination of big data analytics and artificial intelligence would create a decision engine able to propose personalized online intervention [22] [23] [24]. A similar challenge is under investigation by IBM, in a project named cognitive cooking, using these technologies to propose recipes to users [25]. These technologies have not featured in the apps assessed. This specific analysis could be a topic for future work in both academia and industry.

3.4.3 Limitations

We acknowledge that since Play Store and App store have different app ranking systems and market share, using the lowest number of reviews for the included Play Store apps as a threshold for including apps from the App Store may not reflect the number of downloads from the App Store. It is difficult to directly compare app popularity between the two stores, as the number of downloads from the App store is not publicly available. As Play Store does not provide the exact number of installs, it is possible that some apps in the range "500k-1m" could have approached 1 million installs. The criteria used to select the apps were based on the number of installs and reviews. Using these variables alone, it was not possible to identify the frequency and duration of use of these apps. This information would be valuable to measure the real engagement of the users and if they are accepting the burden of text searching and barcode scanning for a prolonged period. It would also be interesting to assess the percentage of users that upgraded to the premium versions of the apps. Since it is not possible to measure the upgrades, the premium versions were not considered popular and their extra functionalities were not included in this review. A similar limitation occurred with the WW app, which requires subscription [9]. Since the functionalities of these apps change rapidly, it is recommended that a similar assessment be conducted in the future. Although it is likely that these apps are also available and popular in other English speaking countries, such as USA and Canada, these results are limited to a UK

perspective. A review of popular apps in different countries and languages could reveal other important features and interesting cultural differences.

3.4.4 Comparison with Prior Work

Chen et al. have recently published research assessing the most popular smartphone apps for weight loss used in Australia [26]. They have developed a method for quantifying the quality of the apps and also assess the utilization of behaviour changes techniques (BCT). However, given that a different methodology for defining the most popular apps was used in the present study and that the apps published in the online stores are distinct by country, only 6 out of the 13 apps assessed in our study were alike. Some investigators have also conducted analyses of commercial nutrition-related apps in terms of content and health behaviour theories [8][27][28]. The current research complements and extends this prior work by providing a detailed analysis of the features offered by individual apps and also by analysing what emerging technologies have been applied by them.

3.5 Conclusions

Thirteen apps that had at least 1 million installs were identified. Nine of the apps collected dietary intake, all using the same assessment method (food diary record). Food selection was accomplished via text search and barcode scanning. Portion size selection was conducted by selecting text, and not by images or icons. Image recognition, natural language processing and artificial intelligence did not feature in the apps. There is significant opportunity for improvement in terms of personalized nutrition, which could include individualized feedback, diet plans or nutrition education.

3.6 Abbreviations

App: Application

API: Application program interface

BCT: Behaviour change techniques

BMI: Body mass index

CC: Calorie Counter, by CalorieCount.com

DA: Diet Assistant - Weight Loss, by Alportela Labs

DP: Diet Point, by DietPoint Ltd.

EWL: Effective Weight Loss, by naveeninfotech

FFQ: Food frequency questionnaire

FS: Calorie Counter FatSecret, by FatSecret.

GP: General practitioner

GPS: Global positioning system

iOS: (originally) iPhone operating system

LI: Lose it!, by FitNow Inc.

LS: Lifesum - The Health Movement, by Lifesum.

LW: Lose weight without dieting, by Harmonic Soft.

MDC: My Diet Coach, by Inspired Apps.

MDD: My Diet Diary, by MedHelp Inc.

MPF: My Fitness Pal, by MyFitnessPal Inc.

NC: Noom Coach - Weight Loss Plan, by Noom Inc.

OS: Operating system

PA: Physical activity

WW: Weight watchers

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3.8 Chapter discussion

This project started without a pre-defined nutrition assessment method to be used during the dietary intake recording. The existence of commercial food diaries in the app stores was known, but the total prevalence of this method in the most popular apps was not expected. This might be an indication that due to small number of usability and intervention studies in this field [90], the developers have probably inspired their solutions on existing apps, repeating the same assessment method (food diary). It is also possible that food diaries are preferred by app developers because they may have revenue from advertisement (i.e. paid click). Food diaries require prolonged periods with interaction with the app, in comparison with retrospective methods.

The creation of a database with product barcode information requires time and effort. It is likely that most of the apps have this feature due to the fact that there are barcode databases openly available, such as the Open Food Facts [99]. At the time of this writing, it contains 541,411 items registered via a collaborative effort. On the other hand, since nutrition facts contained in the product labels only presents the main or legally required information, the food composition database of these apps may not contain reliable information for micronutrients.

4 THE ENUTRI APP: DESIGN, DEVELOPMENT AND USABILITY METRICS

After the Literature Review (Chapter 2) and the analysis of the popular nutrition-related apps (Chapter 3), the decision to use an FFQ as the nutrition assessment methods was taken. Although it would be possible to create an online service for personalised nutrition advice using food diaries, this alternative could be very risky due to participant dropout. In order to provide nutrition advice, the decision engine would need to consider food diaries for a couple of days (baseline), in order to detect a dietary pattern and do the calculations, and then repeat this process after a few months, in order to measure the treatment effectiveness. This approach could be perceived as too burdensome from the participants. A similar decision was taken by the Food4Me project, which developed and validated an online FFQ during their study on personalised nutrition. The fact that they provided permission to use their food list and images also contributed to this decision.

I was responsible for the software development, data analysis, and writing of this chapter.

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Abstract

Background: Food frequency questionnaires (FFQs) are well established in the nutrition field, but there remain important questions around how to develop online tools in a way that can facilitate wider uptake. Also, FFQ user acceptance and evaluation have not been investigated extensively.

Objective: This paper presents a Web-based graphical food frequency assessment system that addresses challenges of reproducibility, scalability, mobile friendliness, security, and usability and also presents the utilization metrics and user feedback from a deployment study.

Methods: The application design employs a single-page application Web architecture with back-end services (database, authentication, and authorization) provided by Google Firebase's free plan. Its design and responsiveness take advantage of the Bootstrap framework. The FFQ was deployed in Kuwait as part of the EatWellQ8 study during 2016. The EatWellQ8 FFQ contains 146 food items (including drinks). Participants were recruited in Kuwait without financial incentive. Completion time was based on browser timestamps and usability was measured using the System Usability Scale (SUS), scoring between 0 and 100. Products with a SUS higher than 70 are considered to be good.

Results: A total of 235 participants created accounts in the system, and 163 completed the FFQ. Of those 163 participants, 142 reported their gender (93 female, 49 male) and 144 reported their date of birth (mean age of 35 years, range from 18-65 years). The mean completion time for all FFQs (n=163), excluding periods of interruption, was 14.2 minutes (95% CI 13.3-15.1 minutes). Female participants (n=93) completed in 14.1 minutes (95% CI 12.9-15.3 minutes) and male participants (n=49) completed in 14.3 minutes (95% CI 12.6-15.9 minutes). Participants using laptops or desktops (n=69) completed the FFQ in an average of 13.9 minutes (95% CI 12.6-15.1 minutes) and participants using smartphones or tablets (n=91) completed in an average of 14.5 minutes (95% CI 13.2-15.8 minutes). The median SUS score (n=141) was 75.0 (interquartile range [IQR] 12.5), and 84% of the participants who completed the SUS classified the system either "good" (n=50) or "excellent" (n=69). Considering only participants using smartphones or tablets (n=80), the median score was 72.5 (IQR 12.5), slightly below the SUS median for desktops and laptops (n=58), which was 75.0 (IQR

12.5). No significant differences were found between genders or age groups (below and above the median) for the SUS or completion time.

Conclusions: Considering all the requirements, the deployment used professional cloud computing at no cost, and the resulting system had good user acceptance. The results for smartphones/tablets were comparable with desktops/laptops. This work has potential to promote wider uptake of online tools that can assess dietary intake at scale.

4.1 Introduction

Food frequency questionnaires (FFQ) are a commonly-used tool for dietary assessment, and paper-based FFQs have been used for decades in the field of human nutrition [1-2]. A FFQ consists of a list of food and drink items, and for each item, an individual indicates their typical consumption frequency and portion size, based on their dietary intake for a given reference period (e.g. the past month). The list of foods is based on the most frequent foods in the region and typically has around 100 items. Consumption frequencies are normally indicated using categories described in text (e.g. 1 per day). Portion sizes can be indicated by selecting text-based categories (e.g. small, medium, or large) or by selecting the closest match from a selection of portion-size photographs of actual foods [3]. There have been studies published on the validity of FFQs in different countries, in both paper-based and digital versions [4-13]. FFQs are frequently used in epidemiological (i.e. population) studies as they are inexpensive to process, can be self-administered and relatively quick for participants to complete [14-15]. However, they are also prone to reporting bias; the consumption of healthy foods has been overestimated using this method [8-9].

FFQs have been traditionally delivered using a pen-and-paper format, but there is a burden associated with this format for study participants, health professionals and investigators. The digitalization of nutrition assessment methods has excellent potential to save time and resources, is preferred by participants [18], and is more suitable for large-scale studies. There exist other online dietary assessment methods such as the 24-hour recall [19-21], which claim better accuracy than FFQs. However, the motivations for investigating online FFQs include that they are easier to replicate technically than these other methods, which often require a much larger food database and more complex technologies such as text search functionality, and may also be more suitable for certain applications including online personalized nutrition interventions [22]. Although some web-based FFQs have been developed in recent years, they have not been widely used in this format as yet, and there are few published results in terms of user acceptability of online FFQs.

In order to facilitate the dissemination of online FFQs, it is important that the scientific and public health communities have open and free access, not only to the final results of validation studies, but also to the design, architecture, development and deployment of scalable, replicable and secure tools. Furthermore, interdisciplinary collaboration and shared understanding between the health and technical communities is important for

furthering research in this field, and as such, it is appropriate that studies also report their work from the perspectives of multiple disciplines. Therefore, this paper presents both the technical design of a web-based graphical food frequency assessment system alongside results from user testing, with an aim of making a contribution to the wider uptake of digital FFQs.

The online FFQ described in this paper was designed and developed for the Eat Well Kuwait project (EatWellQ8, www.eatwellq8.org), which aims ultimately to investigate whether web-based personalized nutrition (PN) (based on dietary intake and anthropometrics) is as effective as face-to-face communication of PN in Kuwait. The project is a collaboration between the University of Reading and the Dasman Diabetes Institute in Kuwait City [23]. The first stage of this project focused on the design and development of the web-based FFQ, and a validation study is currently under way to compare the online FFQ with the current paper version of a Kuwaiti FFQ and a 4-day weighed food record (WFR).

4.1.1 Objectives

This paper aims to make a contribution to the wider uptake of digital FFQs by describing the rationale, design, implementation, administration and user feedback of a web-based graphical food frequency assessment system. Online FFQs, as yet, are not being widely used, and this is due, in part, to a variety of technical challenges. This section summarizes some of the technical considerations relevant to facilitating wide deployment of online FFQs.

4.1.1.1 Reproducibility

With a view to decreasing completion time and thereby increasing user acceptability, the list of food items in an FFQ normally includes only the most common foods in a region, divided into food groups (fruits, vegetables, etc.). As these food lists and their related portion size images vary by location, it is useful to have either a customizable central system or an easily replicable system to help ensure that locally-applicable FFQs for different regions can be created easily. Ideally, this system should be inexpensive, in order to mitigate financial constraints that could block deployment. Furthermore, any need for technological expertise in customization and administration could hinder reproducibility and so it is important to design these aspects with ease-of-use in mind.

4.1.1.2 Scalability

One of the drivers for developing online dietary assessment methods is the potential to support population-level studies. When operating at this large scale, there is a potential to see high peaks in the system traffic, which are not easily handled. This is an important requirement to be considered in the system architecture.

4.1.1.3 Mobile friendly

The need to consider deployment on mobile devices and tablets is more and more relevant, considering an increase in the market share of smartphones and tablets as compared with desktops and laptops [24]. The delivery of a FFQ via tablets and smartphones presents particular challenges. For example, due to screen size constraints, it is difficult to present all the portion sizes (usually between 3 and 7 images) on the screen simultaneously. The layout and interaction design has the potential to influence participants' responses and/or increase the task completion time, and hence requires careful consideration.

4.1.1.4 Security

Population studies often store sensitive data, since they usually collect medical information together with personal details. In this scenario, it is important to provide authentication and authorization features and protect the database from unauthorized access and also communicate with the database using a secure protocol.

4.1.1.5 Usability

Empirical data on system usability is important for enabling evidence-based decisions in the design and improvement of further systems. The system should build in the ability to collect metrics such as completion time and usability surveys.

4.2 Methods

4.2.1 Technical Design

The design of the EatWellQ8 FFQ considered the main requirements described in the previous section and assessed and compared these with the main advantages and disadvantages of the currently most-used web architectures and technologies.

The requirements showed that the system was not intense computationally, pointing to the possibility of using a modern web architecture named Single Page Application (SPA) [25]. In this paradigm, all the necessary code (HTML, CSS and JavaScript) is

retrieved in a single load, and the updates in the view are managed by the code running in the browser. The JavaScript framework for creating SPA proposed by Google is called AngularJS, which is entirely client-side (i.e. browser only) [26].

A SPA architecture creates the possibility of using static hosting for delivering the code and media files (e.g. food images in this project), which is much cheaper than dynamic hosting (i.e. servers) and removes any need for server maintenance.

Besides the static hosting, there were three basic requirements that needed to be fulfilled: user authentication, user authorization and a secure database. Analysing several major cloud-computing providers (i.e. Amazon Web Services, Google, IBM and Microsoft), it was clear that the typical web application architecture could be delivered by any of them. One particular service that stood out during this comparison was Google Firebase for its particular focus in providing the most essential features for developing web and mobile applications in a very affordable way, which has attracted more than 400,000 developers worldwide. Its main features are a real-time database, user authentication and static hosting [27].

4.2.1.1 Reproducibility

Since data collection and retention have different policies around the world, a customizable central system may face some practical difficulties for implementation. This was one of the main reasons for choosing to create an easily replicable system, utilizing cloud-computing services, which are accessible worldwide.

Data is stored in a JavaScript Object Notation (JSON) document in the Firebase database. In order to facilitate the food list modification by non-technical administrators, the original food table was created as a Microsoft Excel spreadsheet. The cells were then concatenated (using Excel's concatenate function) into CSV (Comma Separated Values) text, which was then converted to JSON (using an online converter such as convertcsv.com). The JSON was then imported to Firebase. The following object shows a food item structured in JSON, illustrating its human-readable format:

```
"foods" : [ { "arabic" : "Broccoli in arabic", "english" : "Broccoli", "id" : 0 }, .... ]
```

4.2.1.2 Scalability

Using a SPA approach, combined with a Firebase database, all the processing is transferred to the client (browser), which can easily handle simple interactions and

functions for rendering the pages. The *Firebase Spark Plan (Free)* can support 100 simultaneous connections with the database (this increases to unlimited simultaneous connections with the *Flame Plan* which, at the time of writing, costs USD 25/month), using a secure HTTPS protocol, and deliver the pages and images via its global Content Delivery Network (CDN) [27].

4.2.1.3 Mobile Friendly

In order to design a web application that can be used readily on mobile devices, the design was based on Bootstrap, a highly popular responsive web framework. It is open source and has built up a big developer community since its launch in 2011 [28].

The Bootstrap functionalities that played important roles in our implementation were the responsive navigation bar and the modal component; the former creates an adjustable navigation bar that converts into a “hamburger” icon on small devices, and the latter displays a pop-up window on top of a current page and this was used to be able to display food portion images using the entire screen.

4.2.1.4 Security

Firebase provides a complete authentication feature. Among the possible authentication providers (Facebook, Google account, etc.), the e-mail and password combination was enough for this project, although the others could also be provided as alternatives. Firebase enables the use of AngularJS combined with its product via the AngularFire library. It provides a three-way-binding between the HTML, the JavaScript and the database. This means that any modification in one of these parts can be propagated to the other two. For example, a modification of one value in the database triggers an update in the website. This feature becomes even more powerful when different systems are connected to the same real-time database, enabling users to switch between a website and a mobile app, for example, with their data synchronised between the two. Best practices in terms of authentication and page routing are provided by Firebase in the AngularFire Seed, a small open source project that contains the implementation of the basic features (login, password reset, data binding, etc.) that was used in this project. Besides the authentication feature, Firebase provides Security Rules for defining authorization. Every time a user authenticates, an internal variable (*auth*) is populated with user information (e.g. user unique id). Using a simple JavaScript-like syntax, authorization was defined in order to prevent unexpected access. The following rules

exemplify how to block access (read / write) to new objects and only allow authenticated users to access their own FFQ results:

```
{"rules": {".read": false, ".write": false,  
"ffq": {"$user": {".read": "auth.uid === $user", ".write": "auth.uid === $user" }}
```

Another important security aspect is communication between the browser and the database. Firebase uses HTTPS (Hypertext Transfer Protocol Secure), which requires encryption in the communication between the browser and Firebase. If a custom domain is desired for the deployment (e.g. <https://eatwellq8.org>), it will be necessary to configure the Domain Name Server (DNS) according to the records provided by Firebase.

4.2.2 EatWellQ8 FFQ

The EatWellQ8 FFQ contains 146 food items (including drinks), adapted from the European Prospective Investigation into Cancer Study (EPIC) [29] and Food4Me FFQs [4] to reflect a Kuwaiti diet. The food names were shown in both English and Arabic. For each item, users indicate consumption frequency during the last month by selecting from one of eight options: "never or less than 1 per month", "1-3 per month", "2-4 per week", "5-6 per week", "1 per day", "2-3 per day", "4-6 per day", and ">6 per day" [4]. Due to the number of options, the selection was implemented via a select element (drop-down list), which is expanded on mobile devices. In order to speed up the completion time, the default choice was set to the first option ("never or less than 1 per month"), so that participants could simply skip an item if they did not consume that specific food item (Figure 4.1).

Food name	Select Frequency	Portion Size
Broccoli, green leafy vegetables القرنبيط	1-3 per month	Size B
Cabbage ملفوف	1-3 per month	Size A
Carrot جزر	<input checked="" type="checkbox"/> never or less than 1 per month <input type="checkbox"/> 1-3 per month <input type="checkbox"/> 1 per week <input type="checkbox"/> 2-4 per week <input type="checkbox"/> 5-6 per week <input type="checkbox"/> 1 per day <input type="checkbox"/> 2-3 per day <input type="checkbox"/> 4-6 per day <input type="checkbox"/> 6 per day	
Cauliflower زهرة		
Beetroot شمندر		
Cucumber خيار	never or less than 1 per month	
Garlic ثوم	never or less than 1 per month	

Figure 4.1 - Food items and frequency presented by the system

Users indicated portion size by selecting from one of three photographs of actual food portion sizes (Figure 4.2). Other studies have investigated various options to enable users to specify food portion sizes from photographs, including selecting from one of eight portion size photographs [30] and a combination of having three portion size photographs to select from combined with four radio buttons to indicate portion sizes that were bigger/smaller than those depicted in the photos [31]. For the current system, the decision to present three portion size photos was based partly on prior (unpublished from the FFQ described in [31]) user data indicating that photos are far more frequently selected than radio button options that did not have an associated photograph, and an aim of presenting all the photos to users in an efficient manner even on small screen sizes. Portion size photographs are sometimes labelled using descriptive labels of the portion sizes, for example small, medium or large. In our study, the photographs are presented without any labels, to avoid potentially biasing the users in their choices. Each time a user selects a food frequency, the appropriate portion images are automatically presented to the user, and this is implemented in a popup window using the modal component described earlier. After the portion size has been selected, the users' selections are presented as "Size A", "Size B", or "Size C" (see Figure 4.1).

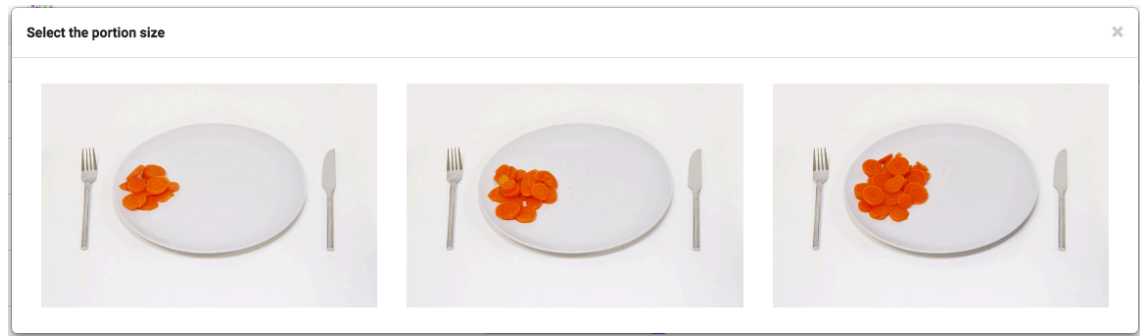


Figure 4.2 - Portion Sizes presented by the system

Although participants are encouraged to complete the FFQ in one sitting/session, it is important to offer the possibility to save the FFQ, in case the user is interrupted or loses their Internet connection temporarily. Hence, each food selection is saved individually (after the portion size selection) and the user has the option to retrieve the FFQ of a particular day when returning to the system. A timestamp (format yyyy-mm-dd) is saved together with each FFQ entry in the database, after formatting the JavaScript Date Object, in order to check the existence of an entry for that specific day.

4.2.3 Usability Metrics

To enable collection of data on system usability and use, the system included a usability survey and also logged usage data. The usability survey was presented after completion of the FFQ. A modified version of the System Usability Scale (SUS) [32], originally defined by Brooke [33], was used to assess the user acceptance of the online FFQ. The SUS consists of 10 questions alternating between positive and negative statements, with five possible responses from "strongly disagree" to "strongly agree". The statements relate to a range of aspects of system use, such as complexity, ease-of-use, and learnability. Each participant's responses are then scored, providing an overall SUS score between 0-100. After this stage, the overall usability of the system is evaluated via a general question "Overall, I would rate the user-friendliness of this system as:" with the following options: "Worst Imaginable", "Awful", "Poor", "Fair", "Good", "Excellent", and "Best Imaginable". An additional question ("Have you found difficulties in some part of the system?") was also presented. In the case of a positive answer, a textual description of the difficulties was requested.

Collecting usage data involved storing browser information and logging user's interactions with the system. Details of the browser were collected via the JavaScript Navigator Object. This object is not intrusive, is supported by all major browsers and contains information such as browser name, platform, version and language.

In terms of logging user interactions, the system logged timestamps on actions completed during the completion of the FFQ (e.g. opening and closing of the portion size selection screen), using the JavaScript Date Object, which contains the time in milliseconds since the beginning of the year 1970 [34]. The timestamps were analysed for the total time spent completing the FFQ, calculated based on the first and last click interaction with the FFQ. As the system allowed users to stop partway through the FFQ and to return to it within the same day, in order to measure only the periods in which the volunteers were actively engaged in using the system, time intervals greater than 60 seconds without any click interactions were considered interruptions (i.e. period of inactivity) and subtracted from the total completion time.

The EatWellQ8 web-based FFQ was deployed in January 2016 as part of a validation study comparing the online FFQ against a pre-existing paper version of a Kuwaiti FFQ and a 4-day WFR. The study was subject to ethical review according to the procedures specified by the University of Reading Research Ethics Committee (UREC 15/50) and by the Diabetes Institute's International Scientific Advisory Board and Ethics Review Committee (RA-2015-018), and was given favourable ethical opinions for conduct.

Because the usability study was being performed in parallel with the EatWellQ8 validation study, participant recruitment and eligibility criteria were set by the requirements of the wider study. Participants were recruited in Kuwait as part of the EatWellQ8 study, without financial incentive. Recruitment was conducted via the Internet, posters, and social media or word-of-mouth, mainly from the higher education institutions in Kuwait, during 2016. Volunteers were requested to create an online account on the study website and to complete a screening questionnaire to determine their eligibility to participate in the study. Participants with chronic diseases (e.g. diabetes), food allergies or food intolerances, or not within the age range (18-65) were not eligible to participate in the study.

4.3 Results

235 participants created an account in the system, of which 163 completed the FFQ. Of those 163 participants, 142 reported their gender (93 female, 49 male) and 144 reported their date of birth (mean age of 35 years, range from 18 to 65).

Regarding the devices used to complete the FFQ, 69 participants used a laptop/desktop computer, 87 used a smartphone, 4 used a tablet and 3 devices/browsers did not return

correctly their JavaScript Navigator Object and hence the device information is not available.

The mean completion time for all FFQs (n=163), excluding periods of interruption, was 14.2 minutes (95% CI [13.3mins, 15.1mins]). Female participants (n=93) completed in 14.1 minutes (95% CI [12.9min, 15.3mins]) and male participants (n=49) completed in 14.3 minutes (95% CI [12.6mins, 15.9mins]) (Figure 4.3). Participants using laptops or desktops (n=69) completed the FFQ in an average of 13.9 minutes (95% CI [12.6mins, 15.1mins]) and participants using smartphones or tablets (n=91) completed in an average of 14.5 minutes (95% CI [13.2mins, 15.8mins]) (Figure 4.1). Out of the 163 FFQs, 71 were completed without any interruptions, that is, there was no gap of more than 60 seconds without any interaction. Considering the 146 food items, the volunteers spent, on average, 5.84 seconds per food item. As the system collects timestamps just before the portion image presentation (i.e. after the frequency selection) and when they are selected (i.e. click on the portion image), it was possible to calculate the mean time spent in the portion size selection (4.18s / food item) and by subtraction the rest of the time (1.66s / food item) was considered spent on the frequency selection component of the task. For items where the frequency was “Never,” no explicit selection was required.

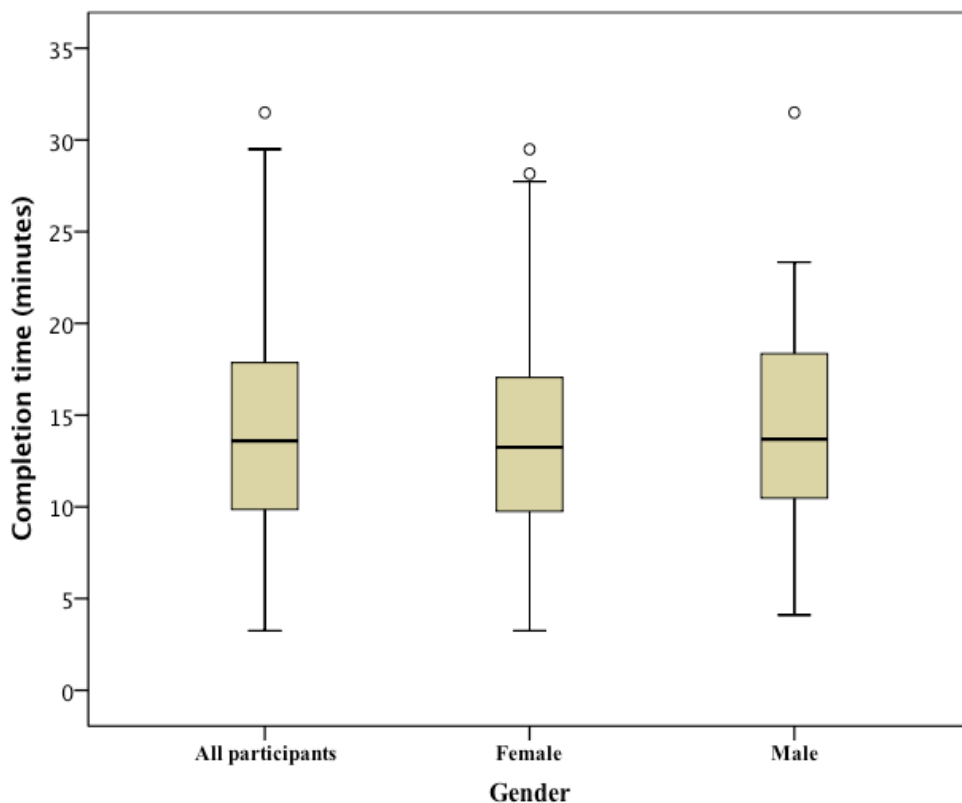


Figure 4.3 - FFQ completion time for all participants (n=163) and by gender (93 female, 49 male)

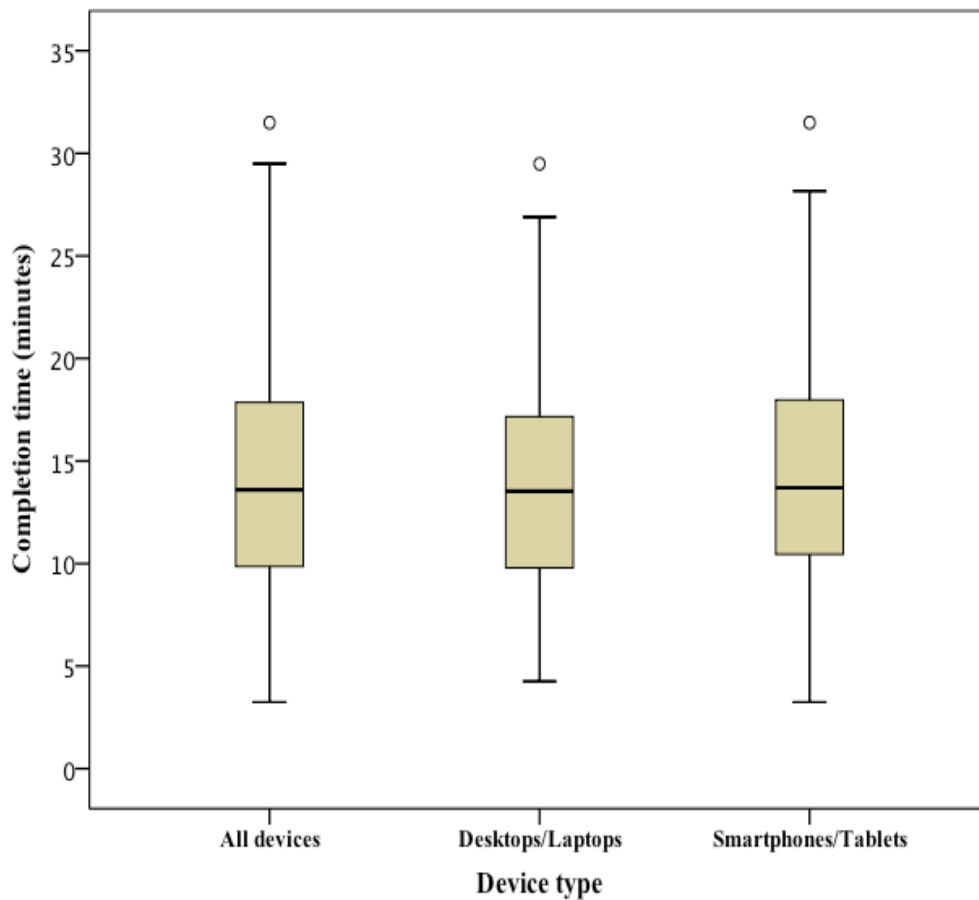


Figure 4.4 - FFQ completion time for all devices (n=163) and by device (69 laptops/desktops, 91 smartphones/tablets)

Regarding the portion size selection, we did not have the timestamp required to separate the time required for image loading from the time required by participants to decide on and select a photo, due to the fact that this information cannot be captured by the web application. However, informal testing with a good Internet connection showed that the pop-up is rendered with the three images (around 150 KB in total) in less than 1s.

For all participants, the usability survey was presented after completion of the FFQ. 141 elected to complete the usability survey, of which 125 reported their gender (80 female, 45 male) and 124 reported their date of birth (mean age of 36 years, range from 18 to 65). The median SUS score (n=141) was 75.0 (IQR 12.5) for all the participants, and of the 125 who reported their gender, 72.5 (IQR 12.5) for female (n=80) and 75 (IQR 11.25) for male (n=45) (Figure 4.5). Products with a SUS score higher than 70 are considered to be good [35-36]; this is discussed further in the Discussion. No significant differences were found between genders nor age groups (below and above the median)

for the neither SUS nor completion time. Considering only participants using smartphones or tablets (n=80) the median was 72.5 (IQR 12.5), slightly below the SUS median for desktops and laptops (n=58), which was 75.0 (IQR 12.5). Users' ratings on the overall user-friendliness of the system (based on the question "Overall, I would rate the user-friendliness of this system as") were predominantly "Good" and "Excellent" (Figure 4.6).

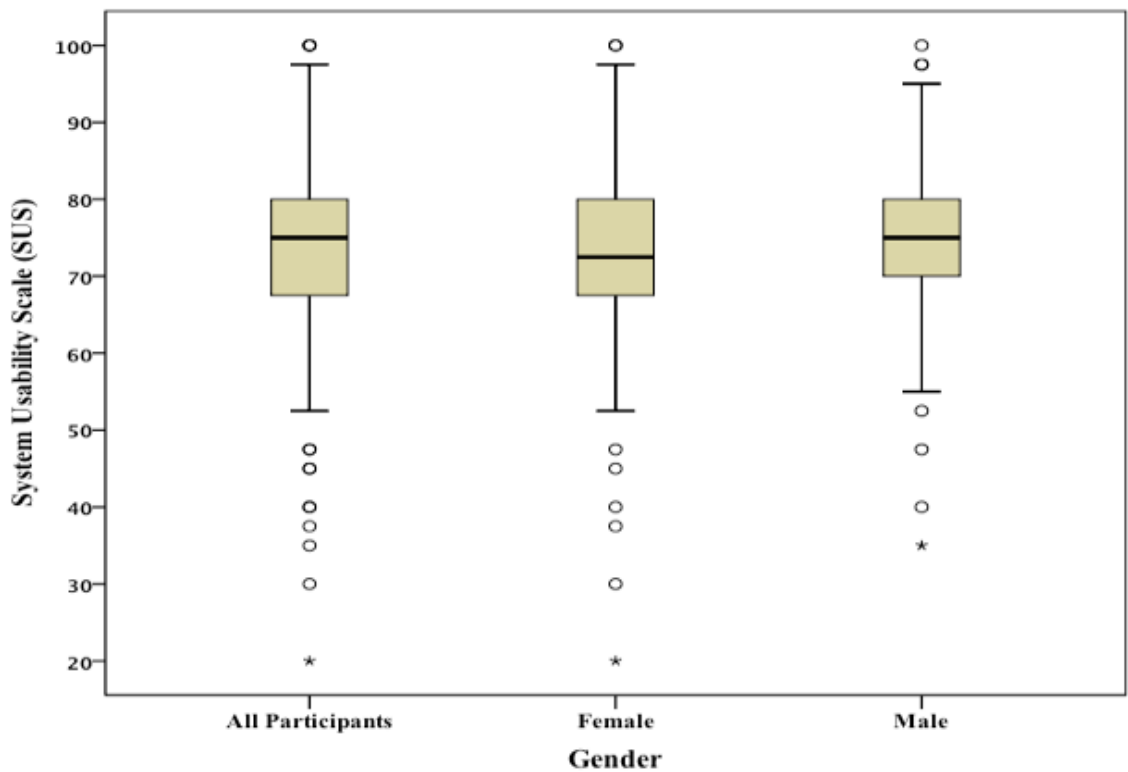


Figure 4.5 - System usability scale (SUS) of the food frequency assessment system by the study participants (n=141) and presented by female (n=80) and male (n=45) for those who reported gender (n=125)

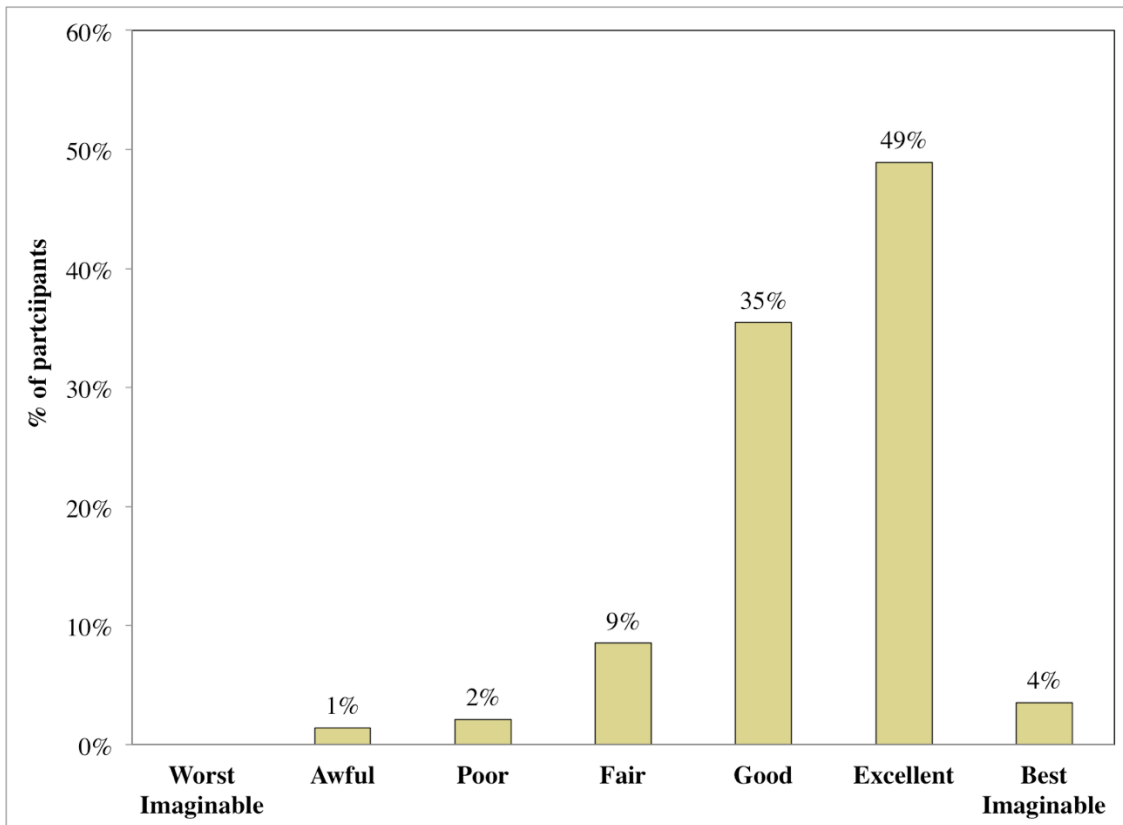


Figure 4.6 - Overall user evaluation of the of the food frequency assessment system by the study participants (n=141)

In the final question ("Have you found difficulties in some part of the system?"), 126 volunteers answered "no" and 15 answered "yes". Further examination of the participants who provided comments (n=13) showed that their responses were more related to the process (e.g. "too long and detailed", "repeated questions", "gets boring" and "time consuming") rather than fundamental problems with the system. Only three participants reported fundamental problems and they were related to the portion size pop-up in smartphones. Some selected comments related to the usability of the system were:

"The portion size pop-up aspect of the FFQ became a bit tedious. I think it might be slightly more user-friendly if the portion pictures are posted on the website rather than in pop-up form."

"The pictures were great, and really were on spot with the amounts difference."

"It was not clear for me when choosing the portion/size if there was more than a, b and c. By using mobile it was not easy at all to scroll down the size option"

4.4 Discussion

Participants gave the EatWellQ8 system a median SUS score of 75.0 (IQR 12.5). Kurtom and Bangor (2013) measured popular services and products and reported a SUS average of 70.14, including Microsoft Excel (54.4), Amazon (79.0) and ATM (80.5) [35-36]. Products with a SUS score higher than 70 are considered to be good [35]. When using this scale, it is useful to compare results within the same category. A very recent study published the SUS results of an online 24-hour recall system designed and developed during their project (myfood24) [37]. For an adult population, it resulted in a SUS median of 68 (IQR 40) for the beta version, and a SUS median of 80 (IQR 25) for the live version. No similar results have been published for online FFQs, but the SUS median from our current study indicates good design and user acceptability. We acknowledge potential for selection bias, which could not be quantified. This is further supported by participants' positive responses relating to the overall quality of the system (Figure 4.6). We observed similar completion times and SUS medians for completing the FFQ on smartphones/tablets when compared with laptops/desktops, which indicates a good responsive design.

Although retrospective dietary assessment methods such as the FFQ and 24-hour recall require less effort from users than prospective methods using similar technologies (e.g. web-based food diaries), completion times of around 14 minutes for completing the FFQ in full can still be a barrier if participants are not engaged with the study objectives. The challenge of engaging participants to complete data collection could potentially be addressed by providing personalized online feedback, acting as a reward to incentivise participants to complete the FFQ. A newer version of the EatWellQ8 system is currently under development, with the ability to provide personalized feedback, which may further improve user satisfaction and interest for investing this amount of time to complete the FFQ.

4.5 Conclusions

We have designed and deployed an online food-frequency questionnaire (FFQ) in a way that encourages reproducibility and is available to be used in other studies, using the same cloud services, for free. In this way, we hope to make a contribution to the wider uptake of digital FFQs and to make more widely-accessible their benefits in terms of time and resource savings and suitability to support large-scale studies.

The FFQ we have developed is a responsive website that has been tested on smartphones and tablets using two major mobile operating systems (i.e. iOS and Android). It addresses security requirements using features provided by Google Firebase, a cloud-based real-time database service. The user rating of this version from 141 participants was good (75 out of 100, using the System Usability Scale), and the completion time calculated from 163 FFQs (14.2 minutes) seems to be acceptable but with room for improvement. This paper is an important landmark in encouraging the research community to publish technical designs and usability information of online dietary assessment methods.

4.6 Acknowledgments

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4.7 Abbreviations

CDN: Content Delivery Network

CNPq: National Counsel of Technological and Scientific Development

DDI: Dasman Diabetes Institute

DNS: Domain Name Server

EatWellQ8: Eat Well Kuwait

EPIC: European Prospective Investigation into Cancer Study

FFQ: Food frequency questionnaire

HTTPS: Hypertext Transfer Protocol Secure

JSON: JavaScript Object Notation

SPA: Single Page Application

SUS: System Usability Scale

SwB: Science Without Borders

UREC: University of Reading Research Ethics Committee

WFR: weighed food record

4.8 References

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4.9 Chapter discussion

Most of the usability challenges are more complex in smartphones due to the size of the screen. As this proposed application does not use any specific internal hardware (e.g. GPS, accelerometer or camera), it was not necessary to develop a native application (i.e. iOS or Android) to meet the system requirements and collect usability data. However, this web application can be easily converted into a native app, because they take advantage of responsive JavaScript frameworks and there are commercial tools providing this conversion for running web apps as native apps for the major mobile operating systems [98].

To present the food items as a list in smartphones was very challenging. Although possible, it forced the font size reduction and required the users to scroll the page repetitively.

5 ENUTRI APP USING A SERIALIZED DESIGN: USABILITY STUDY

After the usability evaluation presenting the FFQ on a list, a newer version of the application was developed, presenting each food item individually on the screen. Although the web development library used in the first version (Bootstrap) is very popular and available since 2011 [100], it has no direct relation with the JavaScript framework used (Google AngularJS) [101]. In 2014, Google launched the first release (version 0) of a web development library, named Angular JS Material [102], which is based on their material design guidelines [103]. This library reached the first stable release (version 1) in October 2015, opening an opportunity for re-evaluation of the decision initially made for Bootstrap.

I was responsible for the experimental design, data collection, data analysis, and writing of this chapter.

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Abstract

Background: With widespread use of the internet, lifestyle and dietary data collection can now be facilitated using online questionnaires as opposed to paper versions. We have developed a graphical food frequency assessment app (eNutri), which is able to assess dietary intake using a validated food frequency questionnaire (FFQ) and provide personalised nutrition advice. FFQ user acceptance and evaluation have not been investigated extensively and only a few studies involving user acceptance of nutrition assessment and advice apps by older adults are published.

Methods: A formative study with 20 participants (including n=10 \geq 60 years) assessed the suitability of this app for adults and investigated improvements to its usability. The outcomes of this formative study were applied to the final version of the application, which was deployed in an online study (EatWellUK) with 324 participants (including n=53 \geq 60 years) in the UK, using different devices (smartphones, tablets and laptops/desktops). Completion times were based on browser timestamps and usability was measured using the System Usability Scale (SUS), scoring between 0 and 100. Products with a SUS score higher than 70 are considered to be good.

Results: In the EatWellUK study, SUS score median (n=322) was 77.5 (IQR 15.0). Out of the 322 SUS questionnaire completions, 321 device screen sizes were detected by the app. Grouped by device screen size, small (n=92), medium (n=38) and large (n=191) screens received median SUS scores of 77.5 (IQR 15.0), 75.0 (IQR 19.4) and 77.5 (IQR 16.25), respectively. The median SUS scores from younger (n=268) and older participants (n=53) were the same.

The FFQ contained 157 food items, and the mean completion time was 13.1 minutes (95% CI 12.6-13.7 minutes). Small, medium and large screen devices resulted in completion times of 11.7 minutes (95% CI 10.9-12.6 minutes), 14.4 minutes (95% CI 12.9-15.9 minutes) and 13.6 minutes (95% CI 12.8-14.3 minutes), respectively.

Conclusions: The overall median SUS score of 77.5 and overall mean completion time of 13.3 minutes indicate good overall usability, and equally, comparable SUS scores and completion times across small, medium and large screen sizes indicates good usability across devices. This work is a step toward the promotion of wider uptake of online apps that can provide online dietary intake assessment at-scale, with the aim of addressing pressing epidemiological challenges.

5.1 Introduction

Non-communicable diseases such as diabetes and cardiovascular diseases account for almost two thirds of deaths globally. The general recommendations for addressing this epidemic are related to lifestyle changes, mainly encouraging healthy diets, physical activity (PA) and the reduction of tobacco use and alcohol consumption [1]. It is also estimated that 3 million people in the UK are malnourished or at risk of malnutrition, and of those, a third are over the age of 65 and 93% live in the community [2].

Due to the widespread use of the internet, lifestyle and dietary data collection can now be facilitated by use of online questionnaires as opposed to paper versions due to the widespread use of the internet [3]. Food Frequency Questionnaires (FFQ), which are used for food and nutrient intake analysis, are an example of such a data collection method [4]. We have developed a graphical food frequency assessment app, which is able to assess dietary intake using a validated FFQ [5] and provide personalised nutrition advice. Users of this app record frequencies of food items consumed during the last month (e.g. "1/week" or "1/day") and select one of three portion size images for each specific food item [6].

This online app (named eNutri) aims to encourage healthier eating. In order to achieve this goal, it is essential that it has good user acceptability by the target adult population, including older groups. FFQ user acceptance and evaluation have not been investigated extensively and there are only a limited number of studies involving user acceptance of nutrition assessment tools by older adults [7,8]. Age-related changes in cognitive, perceptual and motor capabilities affect how older people interact with technology [9], and particularly for older adults, it is important to consider particular design principles, such as limiting the number of on-screen choices available to the user, using appropriate font size and avoiding hidden items [10].

Some studies using web-based graphical FFQs have reported data for user acceptance, using tailor made usability questionnaires (i.e. non-standard) [5,11-12]. These approaches for assessing usability and the lack of public access to the raw data greatly increases the challenge of employing users' feedback to improve similar tools. The interfaces of these web-based FFQs [13,14], were not designed to be used on smartphones (i.e. non-responsive web design). Furthermore, publications on these FFQs focus on the validity and reproducibility of the method from a nutritional perspective [13,15]. A recent publication presented a dietary assessment tool consisting of a 24-hour dietary recall (24HDR) and a FFQ which seems to be responsive, although it was not

explicitly stated that this tool could be used on smartphones (i.e. small screen devices) [16] and the source code was not available as open source. FFQ completion times by device types were reported for the first time in this article.

This study evaluated the suitability of this app for adults and investigated improvements with its usability. The description of the design decisions, their use in the app and related feedback from the study participants are important contributions to the research community interested in deploying online apps for nutrition assessment. These insights could also be applied in similar apps, especially in the digital health domain.

5.2 Materials and methods

5.2.1 eNutri application

Physical activity questionnaire

The physical activity level was assessed via the Baecke Questionnaire [17], which is a short questionnaire for the measurement of habitual physical activity. It has been validated and found to be repeatable [18] and it has been used in studies similar to this one [19].

5.2.2 Food frequency questionnaire

Our application was developed independently (i.e. original source code), however it employed the food list and related portion size images from an existing FFQ (Food4Me) that was previously validated in the UK [5]. The web design version used in the formative study was published in [6]. Each food item is presented individually on the screen, such that the user has only one navigation path through the FFQ. This design was also motivated by evidence showing that a linear style is preferred by older adults. [20].

5.2.3 Usability metrics

Just after completion of the FFQ, the app presented a System Usability Scale (SUS) [21] questionnaire. This standard usability metric contained 10-items that relate to a range of aspects of app use, such as complexity, ease-of-use, and learnability (e.g. "I thought the system was easy to use."), each with 5 response options from "Strongly disagree" to "Strongly agree". Products with a SUS score higher than 70 are considered to be good [22]. After the 10 items, the overall usability of the app was evaluated via a

general question "Overall, I would rate the user-friendliness of this system as:" with the following options: "Worst Imaginable", "Awful", "Poor", "Fair", "Good", "Excellent", and "Best Imaginable". The last usability question collected textual feedback via the question: "Have you had any difficulties with using the system?"

Timestamps on actions completed during the completion of the FFQ (i.e. clicks to move to the next food item) and browser details (e.g. device screen size) were automatically logged by the app, using the JavaScript Date Object [23] and the Navigator and Screen interfaces [24]. The timestamps were analysed for the total time spent completing the FFQ. The device screen sizes were classified as small (less than 480 pixels wide), medium (between 480 and 1240 pixels wide, inclusive) and large (more than 1240 pixels wide). In touchscreen devices, this application was used in the portrait position only, hence this classification can be interpreted broadly as handsets (smartphones), tablets, and laptops/desktops [25].

5.2.4 Formative study

5.2.4.1 Participants

The ultimate aim was that the eNutri app would be entirely self-administered by adults. To this end, it was important to assess whether target users were able to complete the user journey without assistance. In Human Computer Interaction studies, a small number of participants can effectively detect errors and highlight necessary improvements to a system [26].

In this formative study, adult participants (18+) were recruited from the Hugh Sinclair Unit of Human Nutrition (University of Reading) volunteers' database via e-mail, they were stratified into two groups based on age (18-59 and 60+ years). The recruitment and the study occurred between April and May 2017. Participants received a £5 shopping voucher for their participation.

5.2.4.2 Procedure

After a participant gave written informed consent, demographic characteristics (age, sex, height, weight, level of education) and familiarity with technology were assessed via a paper-based questionnaire at the beginning of the study. The level of familiarity of the participants with technology was assessed via four questions regarding the frequency of use of computer devices, device ownership, Internet use and main device used to access the Internet. In the first question, participants were asked to report how

often they use common computer devices. At the beginning of the experiment, it was explained that participants should try to complete the process without asking for help. Notes were taken regarding the point of stopping and related difficulties if the participant was unable to proceed. A researcher created an account in the app for the participant, using an iPad 4th generation (9.7-inch Retina display, 768 x 1024 pixels) running Google Chrome. The device was then handed to the participant for study commencement.

The app then asked participants to complete the Baecke Questionnaire for collecting basic physical activity information, the FFQ and the SUS questionnaire before proceeding to the semi-structured interview, which was designed to collect qualitative data relating to usability challenges with the app that could not be captured using the SUS or via the online forms. The first section of the interview focused on the FFQ (nutrition assessment) with questions regarding the participants' experience of using the app, what they liked and which aspects could be improved. The second section of the interview explored participants' understanding of the online report, which will be submitted for publication in another article.

A total of 20 participants (with n=10 \geq 60 years) were recruited. Their demographic characteristics and technology familiarity and the raw data collected are available in the Appendices (Tables from the formative study)

5.2.4.3 Results

All participants were able to complete the Baecke questionnaire without any difficulties, although four participants who were retired found the questions on work activities inappropriate. Five participants mentioned that either the division of sports and leisure categories were confusing or the examples [17] did not reflect the most common activities in the UK.

All participants were able to complete the FFQ without assistance from the researcher. None of the participants clicked on the main help button, which was visible at the top right of the screen [6]. Although it was not part of the original study protocol, during the interview, the researcher also asked 10 participants if they had noticed the progress indicator displayed in the FFQ screens [6]. Three declared that they had not noticed it during the FFQ completion.

During the semi-structured interview, 16 participants mentioned the main advantage of the app was its "easy-to-use" aspect, using this specific term (n=12) or related terms

such as “simple” (n=2), “intuitive” (n=1) or “friendly” (n=1). The other 4 participants mentioned that they “enjoyed it”, found the app “quite interesting” and “well setup” (Supplementary Table 10.8).

Six participants did not report any areas for improvement of the app. Eleven participants mentioned that the frequency selection could be improved, of which 5 stated that the order of the options [6] was not intuitive or made the decision-making process more demanding. Suggestions such as decreasing the distance between the columns or replacing the “/” with “per” and “>” with “more than” were also mentioned. Five participants stated that the portion size images could also be improved, because some of portion size options were very similar to each other or not presented as they were expecting (e.g. presenting different portions of bread as varying bread slice sizes instead of increasing numbers of slices of the same size; displaying beer bottles instead of pints).

The mean SUS score for the whole group (n=20) was 76.9 (IQR 13.1), for the older group (n=10) was 72.8 (IQR 10.6) and for the younger (n=10) was 81.0 (IQR 13.8) (Supplementary Figure 10.1). All participants completed the FFQ without interruption. The mean completion time (n=20) was 22.9 minutes (95% CI 19.7-26.1 minutes), with a range from 10.5 to 39.0 minutes. The mean for the younger group was 19.4 minutes (95% CI 16.2-22.6 minutes) and for the older group was 26.4 minutes (95% CI 21.2-31.5 minutes) (Supplementary Figure 10.2). The FFQ contained 157 food items, and the mean time per food item was 8.7 seconds.

The main suggestions and related improvements applied to the online FFQ were:

Move automatically to the next food item after selecting “Never” or the portion size, without requirement to click the forward arrow;

Reorder the buttons for selecting frequency of consumption to better facilitate selection (grouped by month, week and day). The layout was modified so that it would adapt to the device screen size (i.e. present the buttons in two-columns for small screens and in four-columns for medium and large screens). This modification can be seen by comparing the previous version of the eNutri app [6] and Figure 5.1;

The frequency “Never” was modified to “Not in the last month” to clarify that, in completing the questionnaire, participants should only report what they consumed in the last month, rather than estimating their average consumption of that item over a year.

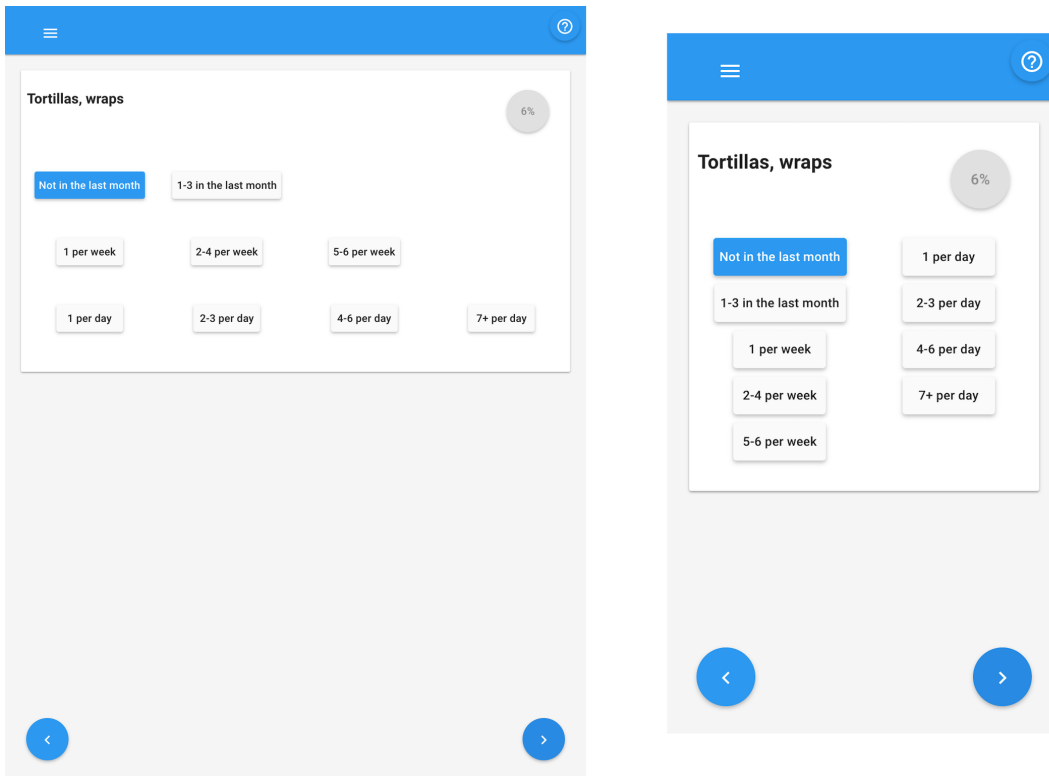


Figure 5.1 - Food frequency options reordered and presented in medium and small screens

These modifications were applied before the start of the EatWellUK study, which took advantage of the suggestions provided by the participants in the formative study.

5.2.5 EatWellUK study

5.2.5.1 Participants

Participants resident in the UK were recruited via e-mail, social media and online advertisements, between August and November 2017. This study recruited a generally “healthy” adult population, that is, adults of all ages who had no diagnosed health conditions. The following pre-requisites were applied during recruitment and screening: Adults without a diagnosed disease condition (e.g. diabetes, heart disease); not pregnant nor lactating; no food allergy nor intolerance; not on a specific diet (e.g. vegan); not receiving face-to-face nutritional services (e.g. from a nutritionist or dietitian) and able to speak English fluently. The participants would not receive money for their participation.

5.2.5.2 Procedure

During the EatWellUK study, potential participants were requested to go directly to the study website, create an account, give consent and confirm their eligibility criteria. Similar to the formative study, they were also asked to complete the Baecke, FFQ and

SUS questionnaires. Participants were encouraged to complete the FFQ in one session, but informed that if they had to leave the computer, responses would be saved and valid for 24 hours. As the browsers' timestamps were absolute values [23], intervals greater than 60 seconds between food items were considered breaks and replaced with an estimated completion time per food item (i.e. 10 seconds).

The formative and EatWellUK studies were subject to ethical review according to the procedures specified by the University of Reading and conformed with the Declaration of Helsinki. The School of Chemistry, Food and Pharmacy Research Ethics Committee approved these studies (Ref No. 04/17 and 13/17, respectively). The EatWellUK study was registered in the ClinicalTrials.gov (NCT03250858).

5.3 Results

5.3.1 Participants

A total of 439 participants created an account on the study website and 365 were accepted after screening. Of the 365 enrolled onto the study, 324 completed the baseline FFQ. The demographic characteristics of these 324 participants are shown in Table 5.1.

Table 5.1. Demographic characteristics of the participants (n=324) who completed the EatWellUK baseline FFQ

Characteristics	Total	%
Sex		
Female	258	79.6
Male	66	20.4
Level of Education		
Less than secondary	1	0.3
Secondary	43	13.3
College	39	12.0
Bachelor	115	35.5
Postgraduate	126	38.9
Age group		
Younger (<60)	271	83.6
Older (>=60)	53	16.4
Age (years)		
Mean	42.16	
Range	18-85	
BMI (kg/m²)		
Mean	25.1	
Range	16.5-60.8	

5.3.2 Usability metrics

Two participants completed the FFQ but did not complete the SUS questionnaire. The median SUS score (n=322) was 77.5 (IQR 15.0). Out of the 322 SUS questionnaire completions, 321 device screen sizes were detected by the app. Divided by device screen size, small (n=92), medium (n=38) and large (n=191) screens received median SUS scores of 77.5 (IQR 15.0), 75.0 (IQR 19.4) and 77.5 (IQR 16.25), respectively. The median SUS scores from younger (n=268) and older (n=53) participants were the same at 77.5 (IQR 15.0) (Figure 5.2). The aim here was not to compare for statistical differences between age groups nor screen size, only to gain further insight about how the data are distributed in order to know if there were any particular difficulties experienced by subsets of the sample. The results suggest comparable performance across age groups and screen sizes.

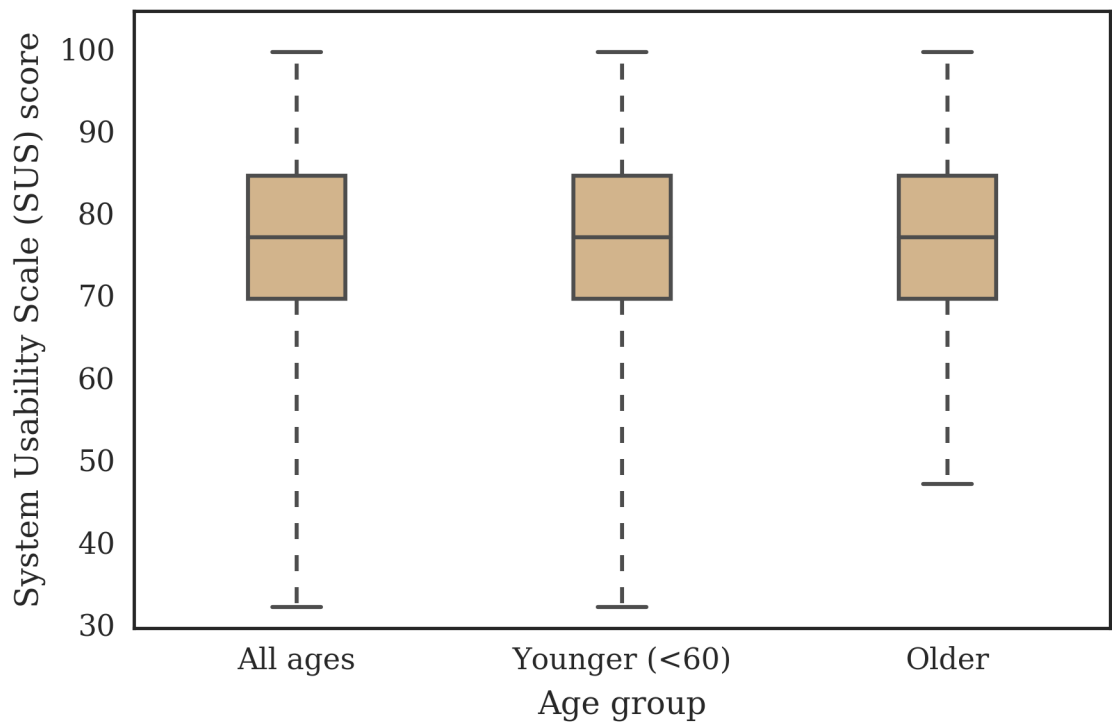
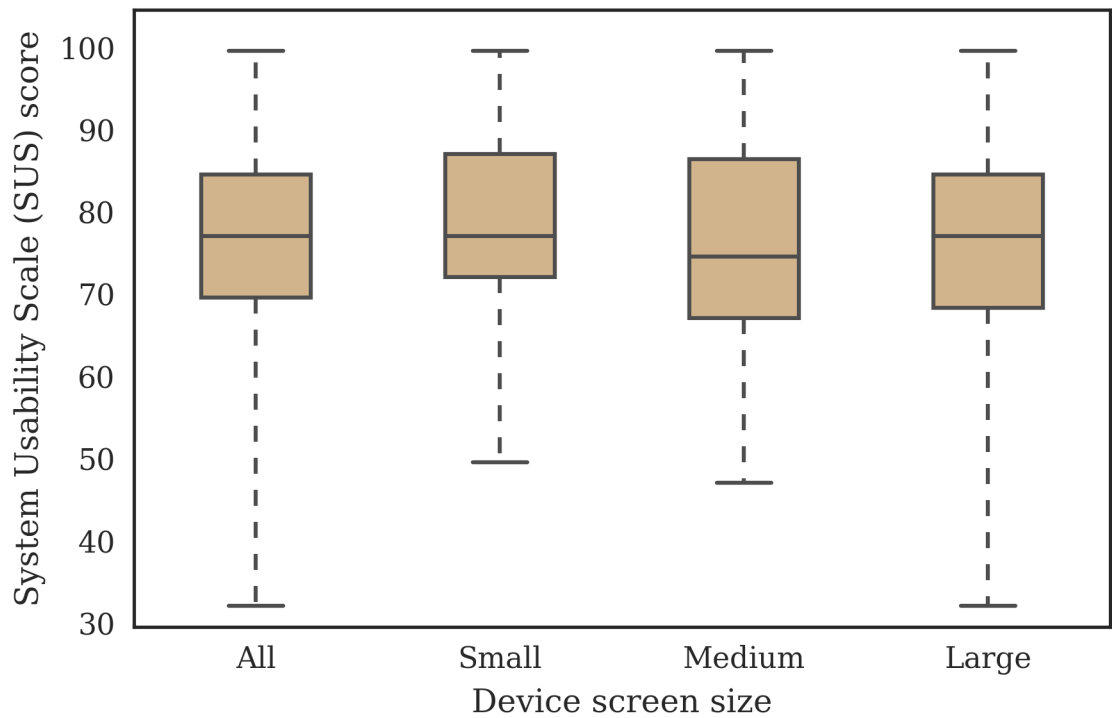


Figure 5.2 - System Usability Scale (SUS) score for participants (n=322) who completed the EatWellUK study presented by small (n=92), medium (n=38) and large (n=191) device screen sizes and by younger (n=268 <60 years) and older (n=53) adults

The device screen sizes were classified as small (less than 480 pixels), medium (between 480 and 1240 pixels, inclusive) and large (more than 1240 pixels)

The overall perceived quality of the app was reported as either “good” or “excellent” for 81% of the 322 participants (Table 5.2).

Table 5.2. Overall perceived quality of the eNutri app by participants (n=322) of the EatWellUK study presented by small (n=92), medium (n=38) and large (n=191) device screen sizes

	All devices	Small screen	Medium screen	Large screen
Perceived quality	%	%	%	%
Best Imaginable	4.7	8.7	7.9	2.1
Excellent	39.4	45.7	13.2	41.4
Good	41.6	38.0	60.5	39.8
Fair	13.0	7.6	18.4	14.7
Poor	0.9	0.0	0.0	1.6
Awful	0.3	0.0	0.0	0.5
Worst Imaginable	0.0	0.0	0.0	0.0

The mean FFQ completion time was 13.1 minutes (95% CI 12.6-13.7 minutes); for small, medium and large screen devices was 11.7 minutes (95% CI 10.9-12.6 minutes), 14.4 minutes (95% CI 12.9-15.9 minutes) and 13.6 minutes (95% CI 12.8-14.3 minutes), respectively. The younger adults (n=271) completed the FFQ in 12.6 minutes (95% CI 12.1-13.2 minutes) and the older adults (n=53) in 15.8 minutes (95% CI 14.3-17.3 minutes) (Figure 5.3). The aim was not to statistically compare the groups but to gain further insight into how completion times were distributed across groups, and the results suggest comparable completion times across age groups and screen sizes.

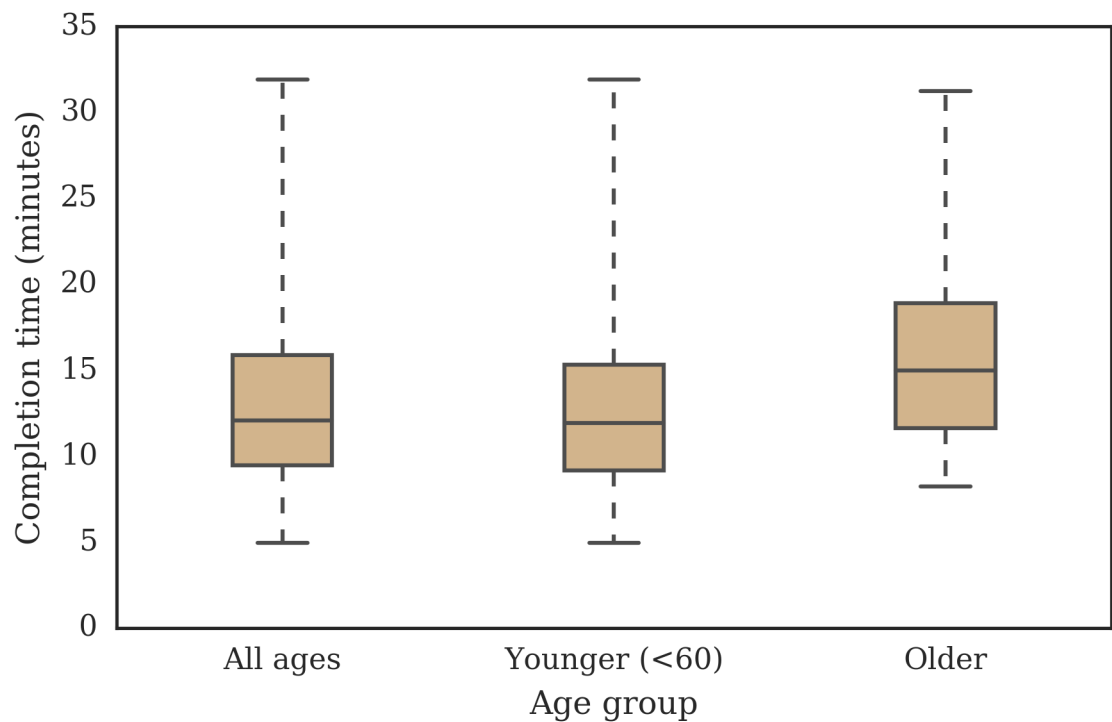
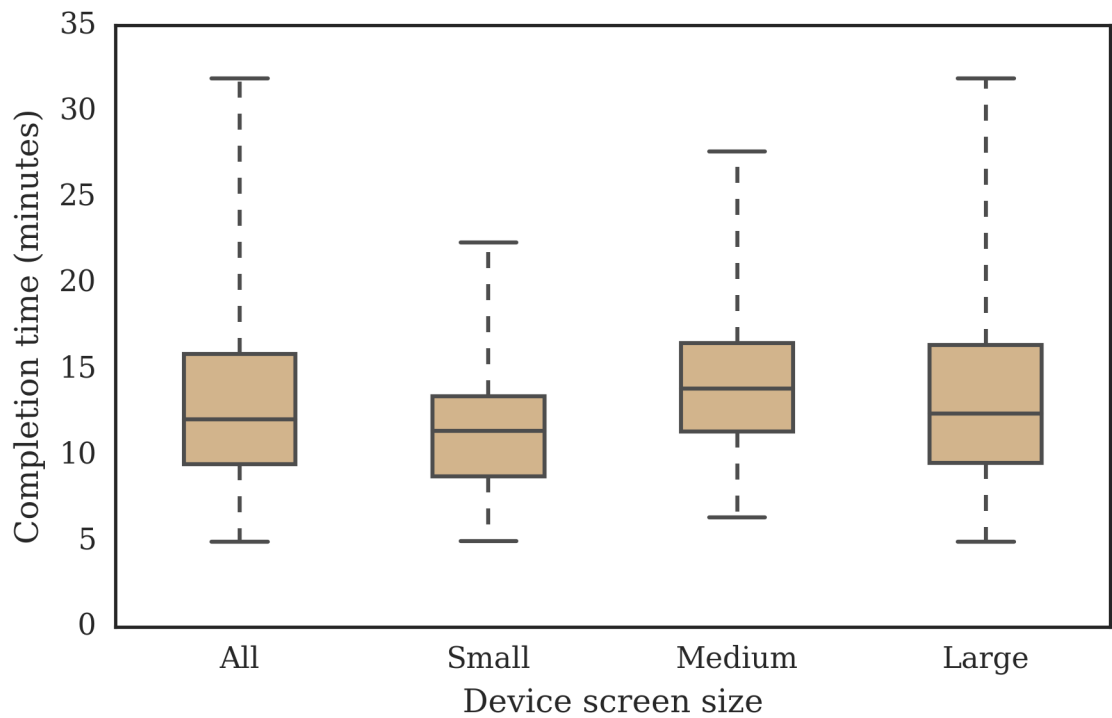


Figure 5.3 - FFQ completion time for participants (n=324) during the EatWellUK study presented by small (n=92), medium (n=38) and large (n=191) device screen sizes and by younger (n=271 <60 years) and older (n=53) adults

The device screen sizes were classified as small (less than 480 pixels), medium (between 480 and 1240 pixels, inclusive) and large (more than 1240 pixels).

In the final question (“Have you had any difficulties with using the system?”), 45 participants (n=322) answered “yes”. Further examination of the comments revealed that 10 were blank or included clarification that they had not experienced any problems. Six participants mentioned that the Baecke questionnaire was not suitable for retired participants and another six commented on the portion size images. Nine comments suggested issues with browser compatibility or Internet connection.

5.4 Discussion

This study presents the design of a graphical FFQ providing online personalised nutrition advice. The usability and user acceptance are presented initially in a beta version of the application, which was used in a formative study in order to validate its suitability for younger and older adults. Insights from the formative study were detailed and applied to the new version of the application, which was used in the EatWellUK study including 324 participants.

The completion of all the questionnaires without assistance and a good overall SUS score of 76.9 were important in confirming the suitability of this application for an online study including older adults. The mean completion time of 22.9 minutes (IQR 6.6) suggested that some improvements might be necessary in order to facilitate participants’ completion of the questionnaires. Key points for improvement highlighted by the formative study included an opportunity to have the app automatically moving to the next food item after a portion size had been selected and reordering of the food frequency options to make it easier for users. These two options impact the FFQ completion time, by reducing the number of clicks per food item and the decision-making time. Especially for very repetitive tasks, such as the FFQ, such modifications can impact drastically the completion time. The reduction from 8.70 to 5.02 seconds per food items in the completion rate indicated that these changes were effective.

The modification of the frequency “Never” to “Not in the last month” was an example of how simple and important modifications can emerge from formative studies. Kurtom and Bangor measured popular services and products and reported a SUS average of 70.14. SUS scores of popular applications, such as Microsoft Excel (56.5), GPS (70.8), and an automated teller machine (82.3) can be used as references [27]. This version of the application presented the food items individually on the page and received a median SUS score of 77.5 (IQR 15.0), which is slightly higher than our previous version of the application (75.0 (IQR 12.5)), which presented all the food items as one large list on the

screen [28]. The myfood24 project reported their SUS results of an online 24HDR system and for an adult population, it resulted in a median of 68 (IQR 40) for the beta version, and a median of 80 (IQR 25) for the final version [29]. No similar results have been published for online FFQs, especially presenting the data by device type.

This new completion rate (i.e. 5.02 s/item) was faster than the previous one using a food list (5.84s/item) [28]. An online FFQ deployed in Spain reported a completion time of 15 minutes for 84 food items [14]. This represents 10.34 seconds per food item, which is more than double the completion rate for eNutri app, although it is not clear if their completion time measure only the FFQ completion.

Although the results from these separate studies are not directly comparable because they were conducted in two different contexts and populations, these results do give an indication that the new design has improved the eNutri app, and that the design features offered a good level of usability and user acceptance. Considering there are one to two decisions per food item, this completion rate seems to indicate a good flow in the process. Further drastic reductions in this completion time are likely to be challenging, suggesting that other alternatives should be explored if the completion time is still not acceptable for a specific use. An alternative could be to reorder and reduce the food list dynamically, based on the participant's previous responses, via recommender systems techniques.

One of the challenges of designing online graphical FFQs is the ability to deploy the application on different devices, especially with the limited space on smartphone screens. This was one of the main motivations for examining the data by device screen sizes. The comparison of the SUS scores (Figure 5.2) and completion times (Figure 5.3) by screen size indicate the suitability of this web application for any device. This FFQ presented three portion size images per food item, making it possible to present them on-screen simultaneously, even on small screen devices. A need to increase the number of portion size images would demand a change in the design and potentially impact the completion time if additional clicks were added to the process. Other web-based online FFQs may not be suitable for smartphones due to the amount of information on-screen and would require a new responsive design [4,12,15].

The number of older adults (n=53) was smaller than younger adults (n=271), however the results of the SUS score and completion time for the older group indicated good suitability of this application for this population. The authors of this paper are not aware

of a similar online nutrition assessment usability study including this number of older adults.

5.5 Conclusions

These data confirm a validated design for dietary assessment and includes usability results that can be used as references for comparison with future applications in this field. The raw data of the study (Appendix Supplementary tables from the EatWellUK study) and the eNutri source code [30] were made publicly available. This work has potential contribution to promote wider uptake of online apps that can provide personalised nutrition advice at-scale, with potentially important implications for addressing pressing epidemiological challenges. General insights can also be applied in applications used in similar domains, especially in digital health.

5.6 Acknowledgments

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5.7 References

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5.8 Chapter discussion

To increase the acceptability by the older adult population, some design principles were included in the app such as: reduction of the user choices on the screen, appropriate font size, reduction of hidden items, help button always visible, individual help links for some items and user journey serialization.

In comparison with the Bootstrap library, and taking into account that this web application used AngularJS, this new version using AngularJS Material was easier to implement and more appropriate due to the direct relation with the JavaScript framework.

6 EVALUATION OF THE eNUTRI APP BY USERS AND NUTRITION PROFESSIONALS

Chapter 5 presented the results of the online FFQ used by eNutri, without their evaluation of the nutrition report, which is presented in this chapter, via a formative face-to-face study with representative users. A good user acceptance from users does not mean a valid nutrition advice tool. This chapter presents the results a study with nutrition professionals evaluating the eNutri app.

Dr Fallaize and the author were responsible for the recruitment, screening and primary data analysis (nutrition professional and formative study, respectively). They were also responsible for the preparation of the data input (scenarios), creation of the online forms and writing of this chapter. The author was responsible for the data analysis verification and software development.

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Abstract

Nutrition apps have great potential to improve food choice. A mobile web app capable of delivering automated personalised food-based nutrition advice (eNutri) was developed. A formative face-to-face study with representative users (n=20) was conducted to evaluate the understanding of the nutrition report and to inform important changes to the app. After implementing the suggested improvements, the nutrition professionals (NP) study validated the advice provided by the app against professional Registered Dietitians (RD) (n=16) and Registered Nutritionists (RN) (n=16) standards. Their recommendations were used to improve the app decision engine. Each NP received two pre-defined scenarios, comprising dietary intake analysis of FFQ data and individual characteristics. To assess the eNutri advice for each scenario NP were asked to use their professional judgment to consider the advice; provide the three most relevant nutrition recommendations and rate their level of agreement via 5-star scales. NPs were also asked to comment on the eNutri recommendations, scores generated and overall impression. Generally, the app was well received, with mean scores for the appropriateness, relevance and suitability of the eNutri diet messages of 3.5, 3.3 and 3.3 respectively. These studies also aim to help address the need for greater transparency and reproducibility in remotely delivered interventions.

6.1 Introduction

Nutrition apps have significant potential to improve health-related food choice. However, our recent review of popular nutrition-related mobile apps revealed that none of the reviewed apps had a decision engine capable of providing personalised dietary advice [1]. Despite this, a recent three country study (Australia, New Zealand and the UK) showed that nutrition apps were used by the majority of the respondent dietitians (62%, n=570), as information sources (74%) or for patient self-monitoring (60%) [2]. These data illustrate the high and increasing use of nutrition-related apps by both the public and dietetic professionals. There is a lack of evidence on whether users of nutrition apps are able to understand them (including design, data visualisation, messages) and whether nutrition professionals (NP) agree with the information and advice provided by them.

Two recent systematic reviews found that since 1981 around 30 dietary interventions had been delivered remotely [3-4] using different methods including websites (n=4) and apps (n=1) [4]. The materials used in these interventions (e.g. printed reports, e-mails, videos, list of SMS messages, decision trees) were rarely described clearly as reported by Warner et al who stated that out of the 37 eligible trials in their review, 39% reported the intervention material and only 20% described where to find copies of them [3]. To corroborate with this indication of incomplete reporting, Teasdale et al showed that only five studies, out of a total of 26, did not contain high risk of bias, according to the Cochrane tool. They also reported that the majority of the interventions involved face-to-face interactions before the remote stage [4]. These facts show that the popularity of diet apps is greater than the scientific evidence to support their reliability and effectiveness.

The pan-European Food4Me randomized controlled dietary intervention study investigated whether personalised food-based nutrition advice (based on diet, phenotype or genotype) delivered remotely, motivated participants to make healthy food choices compared with general public health dietary recommendations [5]. Results from this study suggest that online personalised nutrition advice, based on dietary intake (assessed using a validated Food Frequency Questionnaire (FFQ) [6-7] with photographs), was more effective in improving adherence to dietary advice than standard population guidance [8]. The decision tree for tailoring the diet

recommendation in the Food4me project is not available in the public domain and validation by independent nutrition professionals, outside of the research team, was not conducted.

We have developed a mobile web app capable of delivering automated personalised food-based nutrition advice (eNutri), the source code for which is publicly available [9][10]. Dietary assessment is via the validated Food4Me FFQ [6] with an updated user interface that has been designed for increased usability and the capability to be accessed across multiple commonly-used devices, including tablets and smartphone [11]. A unique feature of the eNutri app is that the dietary advice is derived from adherence to an 11-item modified US Alternative Healthy Eating Index, which we refer to as the m-AHEI. The AHEI was selected for its strong inverse association with CVD [12-13] and markers of adiposity [14], positive association with markers of dietary intake and physical activity and suitability towards Northern-EU countries [14].

During the design process for the advice system, a formative face-to-face study with potential users (n=20) was conducted to evaluate the understanding of the nutrition report and to inform important changes to the app. However, the app had yet to be validated against professional recommendations (usual care). Assessing whether Registered Dietitians (RD) and Registered Nutritionists (RN) agree with the automated nutrition advice (e.g. its appropriateness, relevance and impact) is important in maximising the success and wider utility of this app. The aim of the present study was to conduct a dietary feedback survey validating the advice provided by the eNutri app against professional RD (n=16) and RN (n=16) standards and to collect usual professional recommendations to improve the app decision engine with these insights. These studies also aim to help address the need for greater transparency and reproducibility in remotely delivered interventions.

6.2 Materials and Methods

Ethical approvals for the formative and NP studies were granted by the Research Ethics Committee of the School of Chemistry, Food and Pharmacy at the University of Reading, UK (Ref No. 04/17 and 11/17, respectively).

6.2.1 eNutri app

The study relates to the eNutri app [9], in which participants complete an online FFQ and a report with personalised food-based dietary recommendations is automatically generated and presented on the screen. The report comprises an introductory message (e.g. “Hi John, this is your personalised report. The following messages present the most important diet changes recommended for you.”), followed by messages highlighting three dietary changes that the participant is recommended to consider. The messages for the participant are automatically selected by the eNutri app based on the three m-AHEI components with the lowest scores [11].

The report also shows the participant’s m-AHEI score, referred to in the report with a more user-friendly name of “Healthy Eating Score”, presented as a percentage and a coloured bar (Figure 6.1). The colour of the bar denotes how close the user complied with the AHEI, with red representing a score in the lowest third, yellow in the middle third, and green in the highest third. Intakes were scored as a percentage of the target as recommended by the m-AHEI. The participant’s score on each of the 11 m-AHEI components are also shown, presenting first their scores for ‘recommended foods’ (vegetables, fruits, whole grains, dairy products, nuts & legumes, healthy fats, oily fish) followed by their scores for ‘foods to limit’ (sugars, red and processed meat, salt and alcohol). The bars for the ‘Recommended Foods’ used the same traffic light system as the overall “Healthy Eating Score” score. Although the ‘Foods to Limit’ had the same style of bars, the colours were inverted (e.g. red colour if the score exceeded two-thirds of the recommended maximum intake).

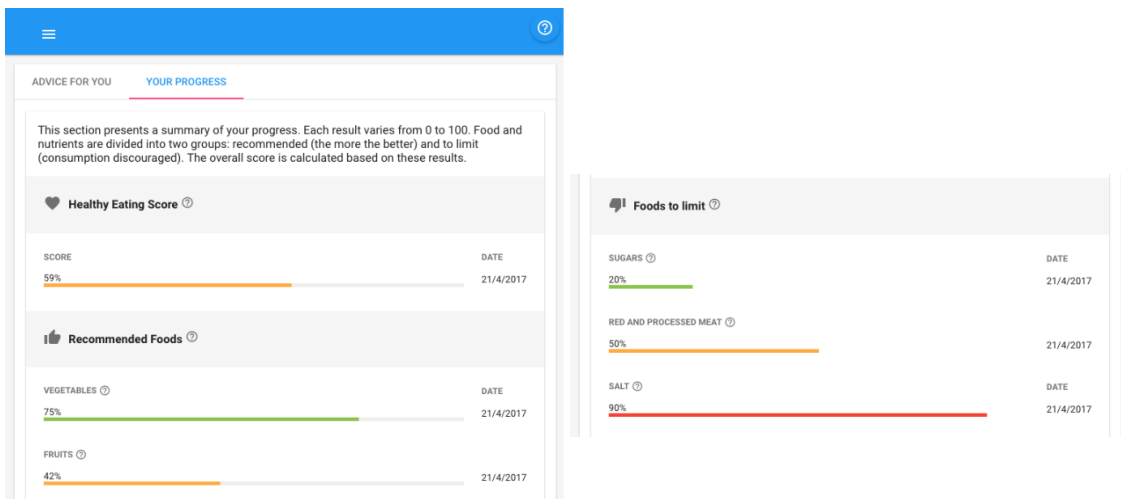


Figure 6.1 - eNutri presenting the ‘Healthy Eating Score’, ‘Recommended foods’ and ‘Foods to limit’

A user could see a weight range bar and recommendations based on their body mass index (BMI). The report did not present the BMI explicitly, but used the healthy BMI range (18.5-25kg/m²) to calculate the healthy weight range for the user’s height, and this range was presented in green. An arrow on the bar indicated the user’s current weight [11]. The physical activity levels are defined based on the Baecke Questionnaire [15], which is a questionnaire of habitual physical activity. It has been validated and found to be repeatable [16] (Figure 6.2).

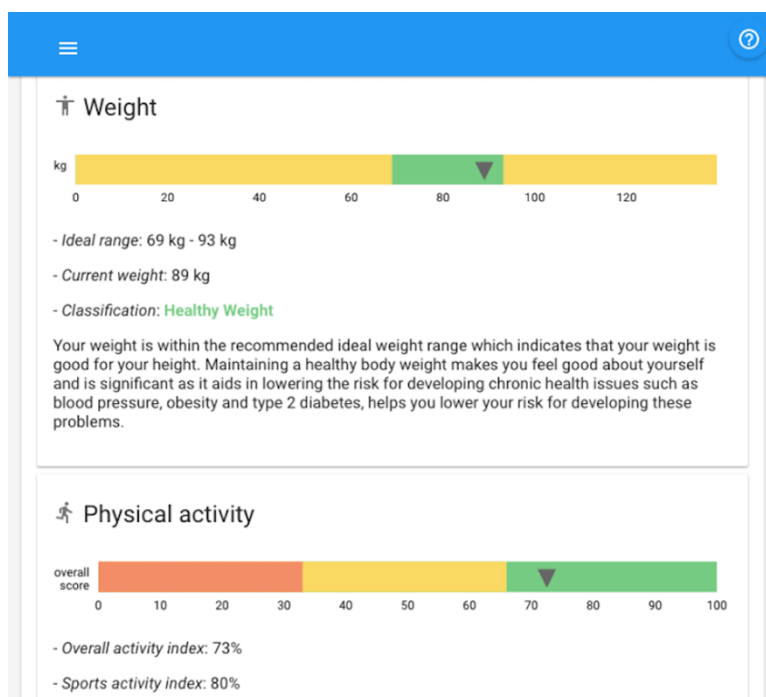


Figure 6.2 - eNutri presenting the weight and physical activity ranges

6.2.2 Formative study

Before the evaluation of the eNutri app by nutrition professionals, a formative study with 20 participants, without nutrition expertise, was conducted to evaluate the initial version of the app, which is described previously [11]. The participants' characteristics of the formative study have been described by Franco and colleagues in a publication that presented the evaluation of the FFQ [9], but not the evaluation of the nutrition report. Here, we report the latter which was evaluated via a semi-structured face-to-face interview. The interview included questions regarding participants' understanding of the content and terms used in the diet messages, and also the visual representation of the status bars [11]. The interviews also explored questions related to the perceived effectiveness of the report and ideas for potential improvements and new features for the system. An interview protocol, available as supporting information in the appendices (Protocol for the formative study interview), was used by the researcher. Positive comments, negative comments and suggestions were grouped and counted. The results of this formative study are summarized in the following paragraphs.

The most frequently displayed components (according to the participants' FFQ results) were "nuts and legumes" (27%), "red and processed meat" (27%) and "salt" (15%). The

20 participants indicated that they understood all the content and terms used in the advice messages. Two participants clicked on the small superscript help icons (Figure 6.1). Only 1 participant clicked on the “Your Progress” tab (Figure 6.1), which was the second option on the menu tab. For the remaining 19 participants, the researcher had to clarify that there was a second tab.

The 2 and 3-colour progress bars used for weight and physical activity [11] received very satisfactory responses, confirming participants’ understanding of these visual representations. One participant stated clearly that “I am thinking as a traffic light system”. Regarding the single colour status bars used for the food-based scores (Figure 6.1), the participants provided very good explanations for the traffic light representation for both categories (e.g. red colour in ‘Recommended Foods’ means to eat more and in ‘Foods to Limit’ means to decrease consumption). When asked, they were also able to compare the components (e.g. the ‘Vegetables intake’ is better than the ‘Fruits intake’ in Figure 6.1) for both categories, although they were not sure of the meaning when the score was 100% (i.e. full bar). One participant stated: “I understand the message, but I am not sure about the percent of what”. For the ‘Recommended Foods’, responses including “the higher, the better”, “I am eating 75% of what I should” were given, but some clarified that they were not sure if they should be eating exactly 100% and not more than that. For the ‘Foods to Limit’, the responses were much less satisfactory compared with responses for the ‘Recommended Foods’, in the context of what the bars were designed to represent, and it seemed that understanding of the messages were based on the traffic light colours only. In other words, the status bar was not increasing the user’s understanding.

Based on this formative study, a number of improvements were applied to the eNutri report based on the ‘main suggestions’ of the non-professional group. These are summarised below:

- a. The two tabs (“Advice for you” and “Your progress”) of the report (Figure 1) were merged into a single tab and the progress report was placed below the advice messages;
- b. Clarification of which individual food items contributed the most to the recommended foods or foods to limit (e.g. which items were the top contributors to “red and processed meat”) (Figure 6.3);

- c. Explanatory subheadings of the two component groups were included in parenthesis: Recommended Foods (The higher the better) and Foods to Limit (The lower the better).
- d. Each main message block (Figure 6.3) was revised to a standard format: the first paragraph focused on the current status of the specific component; the second provided advice (i.e. “call to action”) and the final paragraph described the health benefit potentially obtained from that specific behaviour change.

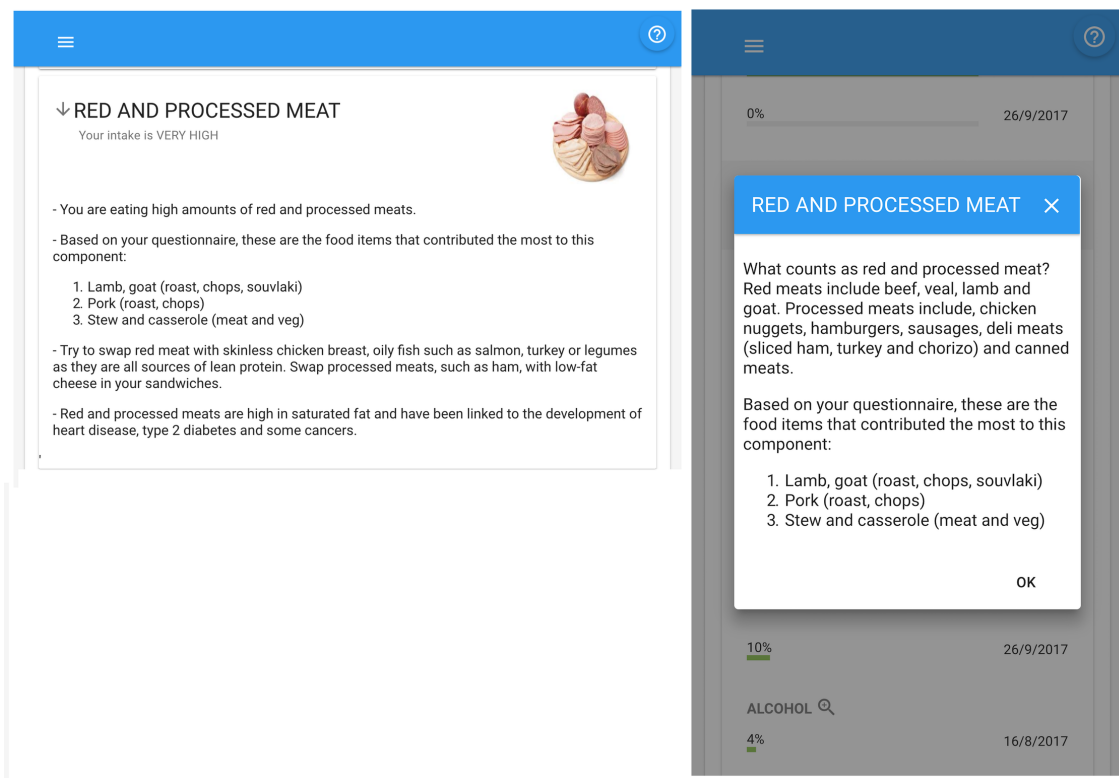


Figure 6.3 - Advice on the biggest contributors to a component as main advice and component details

These modifications were applied before the start of the NP study, which took advantage of the suggestions provided by the participants of the formative study.

6.2.3 Study Design

NP (n=32) were recruited via professional associations, the British Dietetic Association (BDA) and Association for Nutritionists (AfN) and invited to complete an online survey evaluating the eNutri app, via JotForm (jotform.com, San Francisco, CA). Following online screening and consent, each participant was sent two pre-defined scenarios, comprising dietary intake analysis of FFQ data (portion, frequency and weight per food

item, and energy and nutrient intake per day) and individual characteristics (age, gender, weight, height and BMI). The scenarios were designed to mimic outputs from Nutritics Professional Analysis Software (Nutritics Limited, Dublin, Ireland) (Supplementary Figure 10.3) and included the Dietary Reference Values (DRVs) provided by the Committee on Medical Aspects of Food and Nutrition Policy (COMA) and the Scientific Advisory Committee for Nutrition (SACN) in the UK (year 2015) [17]. NPs were asked to consider these scenarios using their professional judgment and provide the three most relevant nutrition recommendations, via JotForm (Q1). Participants were asked to provide responses via audio recording or free-text boxes.

Following this stage, NPs were asked to access the nutrition advice (i.e. not including the weight and physical activity blocks shown in Figure 6.2) generated by eNutri for each scenario (via a password-protected link) and rate their level of agreement, considering its appropriateness, relevance and suitability, via 5-star scales. NPs were also asked to comment (via audio or free-text) on the eNutri recommendations (Q2), scores generated (Q3) and overall impression (Q4), according to each scenario presented. Finally, participants were asked to provide any final comments or feedback on the eNutri app, irrespective of the individual scenarios evaluated.

6.2.4 Scenarios

Four NP (2 RD and 2 RN) evaluated each scenario (FFQ completed by an individual). With this approach, each scenario received 4 unique recommendations and evaluations. The scenarios were designed to represent a diversity of diets and individuals. The diet variable defined was the m-AHEI and different individuals were selected also based on gender, age and BMI. These four variables at two levels each (m-AHEI: <40 or >60, sex: M or F, age: <40 or >40 and BMI: Ideal or Overweight) were used to generate 16 distinct combinations as shown in Table 6.1. The FFQ scenarios (n=16) were drawn from a pool of FFQ responses from actual users, and so have good ecological validity. In total, 64 analyses were undertaken (16 scenarios x 4 analyses per scenario).

Table 6.1 - Characteristics of subjects presented to Nutrition Professionals according to scenario

Scenario	Gender	Age	BMI	m-AHEI
1	M	<40	Ideal	<40
2	M	<40	Ideal	>60
3	M	<40	Overweight	<40
4	M	<40	Overweight	>60
5	M	>40	Ideal	<40
6	M	>40	Ideal	>60
7	M	>40	Overweight	<40
8	M	>40	Overweight	>60
9	F	<40	Ideal	<40
10	F	<40	Ideal	>60
11	F	<40	Overweight	<40
12	F	<40	Overweight	>60
13	F	>40	Ideal	<40
14	F	>40	Ideal	>60
15	F	>40	Overweight	<40
16	F	>40	Overweight	>60

¹ Male, M; female, F; ideal, BMI 18.5-24.9 kg/m²; overweight, BMI >25kg/m²; modified alternate healthy eating index, m-AHEI.

The characteristics presented in Table 6.1 and their associated FFQs were entered into the app database in order to simulate the nutrition reports for the scenarios. The NPs were able to browse the reports online and their screenshots are presented in the appendices (Supplementary Figure 10.4).

6.2.5 Participants

Participants were RD and RN with more than 2 years' experience of providing individual dietary advice. RDs were recruited via the 'Freelance/Private Practice Dietitian's' Facebook Group, which had 945 members at the time of the recruitment post. A total of 28 RD responded to the request for volunteers within 12 hours of the post, after which the researcher [RF] advised the group that the recruitment target had been met. RD eligibility was verified according to participants' Health and Care Professions Council (HCPC) registration number (<http://www.hcpc-uk.co.uk>).

RN were recruited from the Association for Nutrition (AfN) website (www.associationfornutrition.org) via the 'search the register' function. Individuals registered as a Nutritionist on the AfN voluntary register who declared that they 'accepted clients' were contacted (n=85). The study was also advertised on the

researcher's Twitter account and re-tweeted by the AfN. In total, 21 RN responded to the email and 2 to the tweet. For both RD and RN, the first 16 participants who responded were included in the study.

6.2.6 Data Analysis

6.2.6.1 Quantitative Analysis

Subject characteristics (age and years since graduation) were presented as means \pm standard deviations according to type of nutrition profession and compared using an independent samples t-test.

6.2.6.2 Qualitative Analysis

Targets for diet change recommended by the professionals were collated by scenario and compared with the changes targeted by the eNutri app. Free-text comments were analysed using an inductive thematic approach [18], similar to that described by Cunningham & Wells [19]. Responses were analysed according to question and thus, divided into four data sets (Q1, NP nutritional suggestions; Q2, NP comments on eNutri ratings; Q3, NP evaluation of eNutri scores; Q4, overall impression and final comments). NP suggestions (data set 1) were analysed to identify themes in relation to provision of nutritional advice via the following steps: familiarization, coding, identification of subthemes and overarching themes, and interpretation. All data analyses were conducted by the primary author (RF) and independently verified by the second author (RZF).

Following familiarization, responses for data sets Q2-Q4 were broadly categorized into (1) positive (e.g. beneficial aspects), (2) neutral and (3) negative comments (e.g. aspects to improve upon) prior to further analysis. Comments were then coded, and themes/subthemes identified. Codes with similar content and meaning, for example 'personal preference', 'cooking abilities', 'adverse reactions' and 'body composition' were amalgamated into a single theme: 'consideration of wider context'. Whereby topics/ generated themes resulted in both positive and negative feedback (e.g. aspects of the app praised by some NP, and criticised by others), this was identified and included in the results. NP responses to Q1-Q4 could contribute to multiple themes. Quotes are presented according to anonymised identification codes.

6.3 Results

6.3.1 Participant Characteristics

Participant characteristics according to profession (RD, n=16; RN, n=16) are shown in Table 6.2. 90% of NPs were female. The mean age was 37 years (SD 10) and reported years since graduation was 10.9 (SD 8.2). No significant differences were observed between the professions.

Table 6.2 - Participant characteristics according to profession (RD, n=16; RN, n=16)

	All (n=32)	RD (n=16)	RN (n=16)	P Value ²
Gender (M/F)	3/29	1/15	2/14	n/a
Age (years) ³	37 ± 10	36 ± 10	39 ± 9	0.346
Years since graduation ⁴	10.8 ± 8.1	8.4 ± 6.5	14.2 ± 8.9	0.077

¹ Data are means ± standard deviation. Registered Dietitian, RD; Registered Nutritionist, RN

² Data analysed using independent samples t-test

³ Data not provided by n=1 RD and n=3 RN

⁴ Data not provided by n=2 RN

6.3.2 Professional Recommendations

The option to provide recommendations via audio recording was not used by any NP. The primary nutritional targets (n=3) listed by NPs following evaluation of the scenarios are shown in Table 6.3; a total of twelve targets are listed per scenario (4 NP x 3 recommendations). The targets selected included nutrients (e.g. fibre), food items (e.g. red meat), eating occasions (e.g. breakfast) or ‘ratios’ of different nutrients/composition of macronutrients in the diet (e.g. ratio of saturated to unsaturated fats). Targets were not set on five occasions (scenarios 8, 14 and 16), whereby the NPs described needing further information in order to ascribe a recommendation. For scenario 2, one NP stated that the individual’s diet was “ok”/required no improvement. A range of recommendations was selected by NPs, with the greatest similarities (frequency > 3) observed for energy, macronutrient targets (e.g. saturated fatty acids (SFA), fibre, alcohol) and fruit. Less agreement was observed for micronutrients (e.g. phosphorus, iron, vitamin A, selenium), which were selected less frequently by NP.

Table 6.3 - Professional nutrition recommendations according to scenarios (n=12 responses per scenario; 3 recommendations x 4 NP)¹

Scenario	Nutrition targets selected by nutrition professionals
1	SFA (n=3), fibre (n=4)*, sugar (n=2), salt (n=2), vitamin D (n=1)*
2	None (n=3), salt (n=2), energy (n=1), fibre (n=1)*, SFA (n=1), macronutrient ratio (n=1), vitamin D (n=1)*, fruit (n=1)*, sugar (n=1),
3	Alcohol (n=4), sodium (n=2), energy (n=1), fibre (n=1)*, fat composition (n=1), SFA (n=1), snack foods (n=1), vegetables (n=1)*
4	Fruit (n=3)*, sugar (n=2), fibre (n=2)*, low-fat dairy (n=1)*, vegetables (n=1)*, SFA (n=1), protein (n=1)*, coffee (n=1)
5	Carbohydrate composition (n=3), SFA (n=2), salt (n=2), red meat (n=1), protein (n=1), pizza (n=1), vitamin D (n=1)*, Brazil nuts (n=1)*
6	Total fat (n=2), oily fish (n=2)*, long chain omega-3 fatty acids (n=1)*, MUFA (n=1)*, vitamin A (n=1)*, starchy carbohydrate (n=2)*, fruit (n=1)*, fruit (n=1), phosphorus (n=1)
7	Energy (n=3), SFA (n=2), sugar (n=2), salt (n=2), vitamin D (n=2)*, alcohol (n=1)
8	Sugar (n=3), SFA (n=2), vitamin A (n=2)*, salt (n=1), fruit (n=1), vitamin D (n=1)*, breakfast (n=1), n/a (n=1)
9	Energy (n=2)*, fibre (n=2)*, fat composition (n=1), MUFA (n=1)*, iodine (n=1)*, vitamin A (n=1)*, calcium (n=1)*, iron (n=1)*, fish (n=1)*, sugar (n=1)
10	Vitamin D (n=3)*, iron (n=3)*, protein (n=2), fat (n=1), sugar (n=1), fluid (n=1)*, starchy carbohydrate (n=1)*
11	Fibre (n=2)*, SFA (n=2), refined carbohydrate (n=1), carbohydrate (n=1), sugar (n=1), salt (n=1), protein (n=1), selenium (n=1)*, red/processed meat (n=1), fruit (n=1)*
12	Energy (n=2), total fat (n=1), fat composition (n=1), fruit (n=1)*, omega-3 fatty acids (n=1)*, protein (n=1), carbohydrate (n=1)*, complex carbohydrate (n=1)*, folate (n=1)*, vitamin D (n=1)*, breakfast (n=1)
13	Alcohol (n=4), total fat (n=2), saturated fat (n=1), salt (n=2), fibre (n=2)*, takeaway (n=1)
14	Vitamin D (n=3)*, carbohydrate composition (n=2), fruit juice (n=2), fruit (n=1), dairy (n=1)*, SFA (n=1), salt (n=1), n/a (n=1)
15	Oily fish (n=2)*, SFA (n=1), fibre (n=1)*, sugar (n=1), high calorie snacks (n=1)*, fried food (n=1), fruit (n=1)*, vegetables (n=1)*, salt (n=1), iron (n=1)*, simple carbohydrates (n=1)
16	Vitamin D (n=2), energy (n=1), SFA (n=1), sugar (n=1), carbohydrate (n=1), vitamin A (n=1)*, selenium (n=1)*, fruit (n=1)*, n/a (n=3)

* Indicates advice to increase target; n/a, nutrient or food target not identified (e.g. NP stated more information required)

In the majority of cases a nutrient was the first target mentioned by the NP, although this was frequently followed up with food-based advice; for example: “Increase intake of dietary fibre by increasing whole grain food instead of white bread, non-wholegrain cereals” (RN16) and “reduce sugars: reducing intake of sweet biscuits, chocolate, rich cakes, buns, muffins, pastries (...)” (RD04). In some cases, NPs also mentioned the reason and associated health benefits of implementing the suggested changes; for example: “It is important that you start your day with a nutrient rich breakfast as this will not only help to keep your energy levels steady, but it will also support cognitive function helping to keep you focused and alert throughout the morning” (RN05) and “Reducing his intake of alcohol could help to reduce his weight” (RD03). Some NP also listed likely improvements to other nutrients, in addition to that targeted, for example: “try to include 2 portions of oily fish per week (...) This would also boost vitamin D and iron intake” (RD15). Alternatively, some described the consequences of current intake/habit: “Deficiency of vitamin A can cause fatigue, increase risk of infection, poor vision and dryness of the eyes, skin and hair” (RN06).

Nutrition recommendations were typically framed according to “increase”/”choose”/”consume more” or “reduce”/”decrease”/”limit”/”stop”/”cut down”, and less frequently as substitutions or food-swaps; for example: “Swap jams/marmalade/chocolate and nut spreads for low-fat cheese spreads” (RN10) and “(...) reducing intake of biscuits, chocolate and fizzy drinks. In place of these try fruit and natural yoghurt for puddings (...)” (RD02).

Overall, the detail provided by the NPs for each recommendation varied (range 12 – 176 words), with the greatest quantity of text provided for a “calorie deficit” recommendation; in this case, the NP described the weight loss target, energy requirements and deficit, and a list of food based swaps and portion size recommendations to facilitate a calorie reduction (e.g. “grill fish rather than fry”) (RN10). NPs referred to individuals’ characteristics, and particularly BMI for overweight cases, where relevant; recommendations to reduce energy were also more frequent in scenarios with overweight individuals (3-4, 7-8, 11-12, 15-16) (see Table 6.1). Females of childbearing age (“females of birthing age”, “(...) she may be wishing to conceive”) were also highlighted in relation to recommendations to increase iodine and iron (scenario 9), folate (scenario 12) and reduce protein by “(...) reducing number

of oily fish portions per week (no more than 2 per week recommended” (scenario 10, RN10).

Vitamin D was targeted by at least one NP in the majority of scenarios; follow-up recommendations included the consumption of vitamin D rich food/fortified products: “Increase intake of vitamin D foods e.g. dairy produce, oily fish, eggs, fortified products” (RD16) or supplementation during the autumn/winter months; for example “Depending on time spent outside in the summer, take a vitamin D supplement to ensure (...) intake averages out to 10ug/day” (RN07).

6.3.3 Evaluation of the eNutri Feedback

The diet targets automatically selected by the eNutri app and the professional evaluation of the advice generated, according to each scenario, are shown in Table 6.4. The mean scores for the appropriateness, relevance and suitability of the eNutri diet messages were 3.5, 3.3 and 3.3 respectively (maximum score, 5). Two scenarios (1 and 3) scored > 4 on all three aspects and the lowest mean scores (2.5) were observed for scenarios 15 and 16, which were both overweight females, aged > 40 years.

Table 6.4 - Professional evaluation of eNutri automated personalized nutrition advice according to scenarios (n=4 responses per scenario) ¹

N	eNutri targets			Appropriateness	Relevance	Suitability
	1	2	3			
1	Red meat	Oily fish	Fruit	4.0 ± 1.2	4.0 ± 1.2	4.0 ± 1.2
2	Legume	Salt	Healthy fat	3.5 ± 1.1	3.5 ± 1.1	3.3 ± 1.1
3	Alcohol	Red meat	Oily fish	4.8 ± 0.4	4.0 ± 1.0	4.0 ± 1.0
4	Red meat	Fruit	Legume	3.8 ± 0.4	4.3 ± 0.4	3.5 ± 0.5
5	Red meat	Legume	Whole grain	4.3 ± 0.4	3.8 ± 0.8	4.0 ± 0.7
6	Dairy	Whole grain	Oily fish	3.3 ± 0.8	2.8 ± 1.1	2.8 ± 1.1
7	Whole grain	Red meat	Oily fish	3.8 ± 0.4	3.5 ± 0.9	4.0 ± 1.2
8	Legume	Red meat	Whole grain	3.0 ± 1.2	3.0 ± 1.2	3.0 ± 1.2
9	Whole grain	Legume	Sugar	3.3 ± 0.4	2.8 ± 1.1	3.3 ± 0.4
10	Legume	Sugar	Healthy fats	4.0 ± 0.7	4.0 ± 0.7	3.8 ± 1.3
11	Sugar	Red meat	Legume	3.8 ± 0.8	3.0 ± 1.4	3.0 ± 1.4
12	Healthy fat	Fruit	Dairy	3.3 ± 1.3	3.3 ± 0.8	3.0 ± 1.0
13	Alcohol	Whole grain	Legume	3.5 ± 0.5	3.5 ± 1.1	3.3 ± 0.8
14	Whole grain	Healthy fat	Sugar	3.5 ± 0.9	3.0 ± 0.7	3.5 ± 0.9
15	Whole grain	Legume	Oily fish	2.5 ± 1.5	2.5 ± 1.5	2.5 ± 1.5
16	Legume	Healthy fat	Sugar	2.5 ± 0.5	2.5 ± 0.5	2.5 ± 0.5
Average	-	-	-	3.5 ± 1.0	3.3 ± 1.2	3.3 ± 1.2

¹ Male, M; female, F; ideal, BMI 18.5-24.9 kg/m²; overweight, BMI >25kg/m²; modified alternate healthy eating index, m-AHEI

6.3.3.1 Recommendations

The NPs comments regarding the eNutri recommendations predominantly related to whether the NP agreed with the three food components selected by the eNutri app. Positive quotes included: “All advice given was very appropriate” (RD16), “I definitely agree with the recommendations provided and would say they are more suitable than the ones I have provided! Great practical advice provided in the report” (RD15) and “Good advice relevant to diet” (RN03). However, considering the differences between the NP and eNutri recommendations (see Tables 6.3 and 6.4), preferential targets were frequently mentioned: “Give good information regarding the topics, although I feel some of the areas chosen by the software were not the most important aspect to change

in terms of the clients diet” (RN08). Particular components perceived to be important and omitted from the eNutri app advice included saturated fat, vitamin D and micronutrients. NP also queried the prioritisation of components such as whole grain when dietary fibre was adequate; and dairy when calcium and protein were sufficient.

Themes largely mapped to those identified in the analysis of NP recommendations, including message framing, client context (e.g. allergies) and reason for implementing suggested recommendation. There were contradictory opinions regarding the quantity of information presented to the individual: “recommendations are fine on but worrying that it is limited to 3?” (RN16) versus “It felt too overwhelming (...)” (RN04). NPs commented that client context, including allergies, intolerances, religious beliefs and food preferences, should be considered further to increase the ‘personalisation’ of the recommendations. For example, it was noted that in certain scenarios, individuals reported 0g of red meat, fish and dairy intake, yet advice included the consumption of more oily fish; thus, it was highlighted by a NP the “Need to discuss alternatives to oily fish for vegetarians or none [sic] fish eaters” (RD14). A NP also commented that: “It is not a tool that would help a professional especially if they were looking to help with health issues as it does not look at the individual - it is based on general dietary advice but what happens if that person has an allergy [...]” (RN02).

The inclusion of descriptions relating to the benefit of implementing a dietary change were perceived as positive: “I liked that the advice included the reasoning for the recommendations, and it was great that it mentioned preventing the non-communicable diseases”, although it was suggested that more relevant conditions could be mentioned according to the case: “The participant was a 25 year old male, who may not yet be concerned about Heart Disease etc. It may have been more appropriate to also mention about other benefits of the recommended foods, such as increasing satiety.” (RN04). Message framing was also praised: “(...) the positive reinforcement preceding the recommendation is an excellent way to introduce this change.” (RD12).

6.3.3.2 Scores

Quotes relating to NP appraisal of the eNutri scoring system are summarised in Table 6.5. In general, NP described ‘agreement’ with the scoring system (i.e. components and scales) and scores in the context of the scenarios’ nutritional analysis, for example: “Appears to reflect the individuals food choices” (RN05), “I felt the scores were all

accurate and suitable for this lady” (RD16) and “the healthy eating score is reasonable” (RN09). Although, a few NP stated “The healthy eating score is very low; it should be higher” (RN09) and “82% seems a bit low given that the diet is pretty good” (RN07). Perceived benefits of the scoring system included the presentation of the data according to the traffic light system and focusing the client to an area of diet that needs improving. However, concerns were raised regarding the benefit of a scoring approach: “I’m not convinced about the scoring system. It could appeal to those with competitive edge, but many of my clients would not be interested (...)” (RN04), including whether it would be understood: “Scores are useful but may be confusing to someone without a nutritional background” (RD16) or useful: “most people know if their diet is not healthy – the difficulty is how to change (...) scoring them could just be another indicator that they are not capable of getting their life in order” (RN02). It was also noted that a predominance of ‘red’/‘negative’ scores might be demotivating.

Within the comments relating to scores, NP also highlighted particular components that needed refinement; for example the combination of red and processed meat in the context of achieving sufficient iron intake was raised: “(it’s) risky to be advising intakes (of red and processed meat) should be ‘as low as possible’ when female, and clients intakes are low” (RN15). The absence of a component on total and saturated fat was also raised and a NP commented that feedback “Should consider fruit CHO sugars in the sugar recommendation or provide comment” (RD14).

In general, opinions on the scoring system differed, as demonstrated in Table 6.5, however a consistent theme was the desire for greater understanding of the scoring system in terms of an absolute amount (e.g. users intake marked as 2 portions/160g of vegetables), as opposed to percentage of an unknown maximum.

Table 6.5 - Quotes identifying positive and negative aspects of the eNutri automated personalized nutrition app scoring system identified by nutrition professionals

Positive aspects eNutri scoring	Negative aspects eNutri scoring
“I like the colour codes of red, amber and green” (RD16)	“I found the scores to be unclear and therefore unhelpful” (RD11)
“I like that you can click on the + button for additional information” (RN16)	“It could appear very disheartening to be red” (RD03)
“The visual scale would probably help to focus a client” (RD03)	“(…) it is hard to interpret these. 100% of what?” (RN11)
“Good scale, makes it easy to see where needs improvements” (RN03)	“Too many negative scores less likely to bring about change” (RD14)
“The scores are very clear and give excellent guidance for changes to be made” (RN14)	“I think having red and processed meat in the same category is a bit misleading (…) these should be separated” (RD05)
“Good scoring to highlight areas of change” (RD07)	“The scores are very harsh????” (RD08)
“Little room for misinterpretation by the person who would be looking at this information” (RD09)	“It felt too overwhelming (…) I think that was due to the higher the better/ lower the better system” (RN04)
“Appears to reflect the individuals food choices” (RN05)	“Dislike healthy eating score because dietary intake is personal and cannot follow gov guidelines for all” (RD14)
“Good way to rate the diet” (RD07)	

6.3.3.3 Overall Impressions and Suggestions

Positive aspects and areas for improvement to the eNutri app identified by NP are summarised in Table 6.6. Positive comments were generally shorter in length compared with negative comments/ recommended improvements. NP were positive about the ‘food-based’ approach used in the eNutri app: “(…) It was useful that individual food groups were recommended, rather than macronutrients as this may appeal to individuals who are less educated in nutrition” (RN04); although, several NPs commented on the need for specific advice on vitamin D intake and supplementation. One NP also perceived a lack of information about saturated fat as “a big gap” (RD10). The consideration of ‘foods to add’ in addition to ‘foods to limit/cut out’ was also considered positive, as was the framing of foods that should be eaten less frequently (i.e. foods to limit): “(…) I also like the fact that it describes food to “limit” rather than totally avoid which is a healthier message to spread” (RN04).

Table 6.6 - Positive aspects and areas for improvement to the eNutri automated personalized nutrition advice identified by nutrition professionals

Positive aspects eNutri	Suggested improvements
Focus on food items vs. nutrients	Greater focus on energy balance for overweight individuals
Clear presentation	Inclusion of advice on vitamin D supplementation
User friendly	Consideration of wider context (e.g. ethnicity, lifestyle issues)
Easy to read messages	Information on how to achieve ‘100%’ for a component
Positive reinforcement of good habits	Include information on food quality and nutrient density
Visual presentation and use of traffic light system	Include a message on the overall diet/m-AHEI score
Considered foods to add in addition to those to remove	Describe the maximum values for each component (e.g. 5 portions of vegetables)
Practical recommendations	Visual representation of data (e.g. pie/bar chart)
Focus on aspects of diet*	Display/ indicate how scores will change if diet advice followed
Use of ‘food swaps’	Provide links to recipes
	Sources of additional information (e.g. NHS website)
	Inclusion of a print function

Feedback relating to the visual presentation of the data (e.g. key messages, scores, use of traffic light system) was largely positive, for example: “the use of a scoring system is a helpful motivating measure for participants to make recommended changes” (RD12), “quite impressed with the report generated” (RD13), “Good to provide swap ideas” (RD01) and “really practical recommendations highlighting several important changes which could be made” (RD03). However, contrary opinions were also noted in relation to specific scenarios and, when comparing reports, a NP commented: “I am less happy with these recommendations. They are very difficult to put into practice” (RN11). In addition, NP raised concerns with the intake of certain foods, such as nuts and low-fat dairy products, being described in terms of ‘the more the better’.

Of particular note was feedback relating to overweight participants, and NP who reviewed these scenarios commented on the need for a greater focus on energy balance, nutrient density, motivation and weight loss: “Does not consider the need to lose weight and have a healthy BMI” (RD01); “too basic and general for someone who clearly needs nutritional help – they are overweight so the chances are they know diets inside out already” (RN02); “I don’t think the advice was correct for this patient as it did not take into account the fact she was overweight” (RD05). In relation to this, NP suggested that messages should include content on energy reduction and portion sizes.

Overall, NP considered that the system and associated advice was 'basic', provided "Good advice for general healthy eating feedback" (RD07) and was "(...) ok for someone who just wants to see where his diet needs improving (...)" (RN02). However, the advice was also described as: "too basic and generalised" (RN02) and that the advice "could be more personalised e.g. inclusion of (fibre-containing) nuts/oats in the participants' smoothies which would be in line with their existing intake and thereby making it more meaningful and easier to incorporate" (RD12) and "still far from a personalised advice that takes into consideration the preferences, adverse reactions to foods, body composition, etc." (RN09). Whilst it was acknowledged that an app might not be capable of providing the same 'level' of personalisation as a NP, several areas for improvement were noted, including: relating advice to a user's actual intake, providing links to recipes, ability for the user to interact with recommendations (e.g. select those they feel most able to implement) and including a message on the overall diet.

NP also commented on the need to consider the wider 'context of the client' and lack of 'big picture' when providing dietary advice, for example: "Need to understand background such as cholesterol and blood pressure" (RN02), "consideration of body composition" (RN09), "consideration of personal preferences/ cooking abilities" (RD11), noting that the system "does not take into context wider health and lifestyle issues" (RN15). A suggested improvement was that wider health issues be considered within the app: "I think it would be good to get an indicator of levels of activity and lifestyle choices e.g. smoking as you have mentioned alcohol but also I think as HCP we should also be encouraging healthier lifestyles in regards to alcohol, smoking and exercise" (RD09).

Specific improvements relating to the scores were mentioned, as there was some confusion regarding the percentage system; NP suggested that the absolute amount corresponding to the maximum score be provided for each component (e.g. a score of 100% for vegetables equals 3 portions per day) and that potential improvements in scores (i.e. if changes were made) might be visually presented to the user to enhance motivation. Contradictory comments were made in relation to the framing of diet messages, which some NP commented were 'slightly judgemental'/'harsh' and others described as 'quite positive', for example "The inclusion of positive reinforcement with words such as 'Good Job' also lends a personal, positive touch" (RD12).

6.4 Discussion

The interest in diet apps from both the public [1] and NP [2] reinforces the importance of studies that evaluate the suitability of dietary advice that is delivered by the apps. The participants of the formative and the NP studies confirmed that the diet messages (texts) were clear and highlighted the benefit of using a traffic light system in the data visualisation. They reported good understanding of the diet messages, which was in a large part due to the clear food-based recommendations, instead of advice that focused on nutrients, which is difficult to translate to dietary changes. Furthermore, practical advice on food swapping was given that facilitated easy application of the personalised advice to everyday food choice. The evaluation of appropriateness, relevance and suitability of the eNutri advice by the NP indicate a good acceptance by this group.

The NP provided recommendations regarding inclusion of advice on dietary energy in 10 out of the 64 recommendations. The eNutri app does not provide recommendations about energy intake explicitly, but does consider dietary energy in the calculation of two m-AHEI components (Free Sugars and PUFA). Two of the 11 AHEI components take sex into account in the score calculation [12]. Age and BMI are not usually embedded within indexes of overall diet quality [20] and the fact that eNutri was not tailoring the diet advice to encourage weight loss for the overweight participants was emphasized by some NP. In comparison, popular nutrition-related apps focus particularly on calorie counting to assist weight loss or maintenance [1]. Specific advice relating to weight loss or gain, where appropriate, could be considered for inclusion in future versions of the eNutri app, which may further personalise the advice to motivate dietary changes with an ideal body weight as a target.

The scenarios created from representative users of this app scored around 50 out of 100 in the m-AHEI (i.e. displayed in an amber colour and a bar extending to the middle of the scale), which supports data from other studies using similar indexes [8], [12], however this may endorse the concern raised by the NP that this diet score may be “harsh” and discouraging. There were some useful suggestions received from the participants on the formative and NP studies which could be incorporated into the eNutri and/or similar personalised nutrition apps. Among these are the availability of recipes that include the specific foods that have been advised, incorporation of data related to energy balance for overweight or underweight users, links to additional

sources of information (e.g. on health and wellbeing) and the consideration of other factors such as ethnicity and lifestyle issues that can inform further personalisation.

Comments on the lack of vitamin D advice were given in 25% of the analyses (Table 6.3). This may have been motivated by the recent attention on vitamin D, particularly with the new SACN recommendations of a daily intake of 10µg of vitamin D for all adults [21] and recognition of the low vitamin D status in European populations [22]. It was therefore suggested that personalised diet advice should consider vitamin D in these populations. To enable this, the dietary intake assessment method (e.g. FFQ) could be adapted to better capture vitamin D intake by collecting information on vitamin supplementation, which could be used to facilitate personalised vitamin D advice.

There was a diversity of feedback targets (i.e. average of 8 different targets, range between 5 and 9 targets per scenario). This diversity of targets creates a challenge for developing a system for generating automated recommendations. In other words, it would require a substantial quantity of scenarios and NP feedback to train the decision engine based on this information. Despite some limitations of using diet scores as the foundation of the decision engine, without taking BMI and age into account, this approach provided a more quantitative tailoring of the online diet advice, supported by scientific evidence related to the diet score selected. There is a need to design and evaluate dietary recommendation decision engines, which can combine the existing diet scores with other variables that affect directly the tailored diet advice, such as sex, age, BMI, lifestyle. This decision-making process is fuzzy (i.e. not simply yes or no, but similar to a percentage for each target) and some investigators are evaluating how to use fuzzy logic to evaluate diets and nutritional risks [23-24].

There are an almost infinite number of factors that can be used to increase the level of diet personalisation, however it is important to evaluate the efficacy of these online recommendations. In order to make more progress in this field, reproducible studies, particularly randomised control trials, openly describing the decision engine for tailoring the personalised advice and evaluation of their effects on dietary change, are essential. Although the role and importance of face-to-face consultations in public health nutrition will continue, validated and effective diet apps can be part of the solution for effective dietary advice for disease prevention for the general population. The eNutri app aims to contribute to bridging this gap and for this reason the decision

engine has been made publicly available, to enable other researchers and organizations to conduct similar studies and contribute to its improvement [10].

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6.7 Chapter discussion

From a technological perspective, some insights presented by the NP were easy to implement, for example to revise some diet messages or to split the “Red and processed meat”. In contrast, some suggestions would require a knowledge base (nutrition advice based on input data), which is not available.

One alternative for addressing the lack of initial data to train the system is to capture intelligence from national nutrition surveys, which provide detailed dietary intake (e.g. food diaries) and socio-demographic (e.g. gender and age) data. It opens a possibility for detecting correlations, such as the most consumed fruits by a specific age range and gender, or for assessing which food substitutions are more likely to be acceptable.

Population surveys, such as the National Diet and Nutrition Survey (NDNS) in the UK [104], can provide insightful information for tailoring nutrition recommendations. The NDNS covers a representative sample of around 1,000 British residents per year. This type of survey offers potential for analyzing eating behaviours, using for example Topic

Models [105]. Factor Analysis has potential to support the identification of food groups that correlate with each other and Cluster Analysis can identify clusters of individuals with similar dietary patterns [106].

Differently from FFQs, which use a limited food list, the nutrition surveys contain complete food diaries linked with extensive food composition tables (i.e. thousands of items). This type of dataset contains information that would not be captured even after intensive use of the system based only on the FFQ.

7 EFFECTIVENESS OF THE eNUTRI APP: EATWELLUK RANDOMISED CONTROL TRIAL

This chapter presents the main study of this project, aiming to evaluate the effectiveness of the eNutri app. The software version used in this chapter is the same used in Chapter 5 and 6.

The author was responsible for the software development, study management, data analysis and writing of this chapter. Dr Fallaize was responsible for the participants screening.

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Abstract

Background: The Internet has considerable potential to improve health-related food choice at low-cost. A mobile web app capable of delivering automated PN advice (eNutri), immediately after completion of an online FFQ, was developed and made available publicly via an open-source license. Its dietary advice was derived according to adherence to an 11-item modified Alternative Healthy Eating Index (m-AHEI).

Objective: The aim of this study was to investigate the effectiveness of this online PN advice tool, based on an individual's dietary intake and sex, in increasing diet quality compared with population dietary advice delivered online.

Methods: The EatWellUK study was a randomised, controlled, blinded, dietary intervention, which was delivered online. It compared the effect of automated personalised food-based dietary advice compared with population dietary advice (control) delivered online, on change in diet quality (assessed by m-AHEI) and specific foods and nutrients intake.

Results: The treatment effect observed (n=210) in the overall m-AHEI score was 3.06 (CI 95% 0.91 to 5.21), which reached statistical significance (p=0.005). Only one individual component (free sugars) had a statistically significant (p=0.032) improvement of 6.76 (CI 95% 0.58 to 12.95) during the intervention period.

Conclusions: Results show that the design and protocol followed by this study motivated change to a healthier diet. The use of eNutri app could contribute to improved diet quality.

7.1 Introduction

Non-communicable diseases (NCD) account for almost two thirds of deaths globally. The main recommendations for addressing this issue are related to lifestyle changes, such as the encouragement of healthier diets, physical activity (PA) and the reduction of tobacco use and alcohol consumption [1]. The current public health strategies to address this challenge are not personalised to individuals. The “5 a day” campaign to encourage the consumption of 5 portions of fruits or vegetables a day [2] and the Eatwell Guide [3] are examples of dietary guidance within the UK. The “5-a-day” campaign was associated with modest increases, particularly in fruit consumption, immediately after its launch [4], however these were not maintained and currently only a quarter of the UK population meet the recommendations of the “5 a day” campaign [5]. These and other data have motivated investigations into the efficacy of personalised nutrition (PN) on behaviour change [6].

The Internet has considerable potential to improve health-related food choice at low-cost, via apps for example. However, a recent review revealed that none of the popular nutrition-related mobile apps reviewed had a decision engine capable of providing personalised diet advice [7]. Evidence from the Food4Me study indicated that online PN advice, based on dietary intake (assessed using a validated Food Frequency Questionnaire (FFQ) with photographs [8]), was more effective in improving adherence to dietary advice than standard population guidance [9]. Their decision tree for tailoring the advice was executed manually by the researchers and automated after the completion of the Randomised Control Trial (RCT) [10], but this automated decision tree is not publicly available. The authors of the current article are not aware of any similar online PN RCT delivered automatically [11].

In order to help address this need, a mobile web app capable of delivering automated PN advice (eNutri) was developed and its effectiveness was evaluated during an online RCT, where personalised advice was delivered automatically by the app, immediately after completion of an online FFQ. Its dietary advice was derived according to adherence to an 11-item modified Alternative Healthy Eating Index (m-AHEI). The Alternative Healthy Eating Index (AHEI) was selected for its strong association with cardiovascular disease (CVD) and health [12][13]. The aim of this RCT was to investigate the effectiveness of this online PN advice tool, based on an individual’s

dietary intake and sex, in increasing diet quality compared with population dietary advice delivered online. This study tested the hypothesis that personalised dietary advice is more effective at motivating beneficial dietary change than general dietary public health guidance.

7.2 Methods

The EatWellUK study was a randomised, controlled, blinded, dietary intervention, which was delivered online. It compared the effect of automated personalised food-based dietary advice compared with population dietary advice (control) delivered online, on change in diet quality (assessed by m-AHEI) and specific foods and nutrients intake. The study was subject to ethical review according to the procedures specified by the University of Reading (School of Chemistry, Food and Pharmacy Research Ethics Committee) and was given a favourable ethical opinion for conduct (Ref No. 13/17) and conformed with the Declaration of Helsinki. It was registered at ClinicalTrials.gov (NCT03250858).

7.2.1 Participants

Participants were recruited from the Hugh Sinclair Unit of Human Nutrition's volunteer database (University of Reading), University mailing lists, social media (Facebook and Twitter), a university press release, online advertisements and word of mouth. Interested parties received information with links to the Consent Form and Participant Information Sheet hosted on the study website (eatwelluk.org), where these documents were available for reading and downloading. The online account creation, using e-mail and password, and the consent agreement were completed directly in the study website. It was made clear that participation was voluntary and that they were free to withdraw at any time without giving reason and without detriment. Participants were informed that they would need to complete online questionnaires at baseline, week 6 and week 12. There was no payment associated with participation, but all participants who completed the first set of questionnaires received an e-mail regarding a prize draw (4 prizes of £50 Amazon Vouchers were available) subject to the completion of the final questionnaire, which was included to improve participant retention. All contact with participants was via the website or e-mail.

Only subjects aged 18 years and older were included in the study. Screening was semi-automated in the web app where a minimal set of exclusion criteria were applied automatically (not living in the UK, pregnant, lactating, receiving face-to-face nutrition services, lactose intolerance, food allergies or diabetes). Other indications of potential exclusion were analysed by the researchers manually (self-report of health conditions, metabolic disorders, illness, medication and specific dietary requirements).

At the end of the screening form, participants were asked to report how they heard about the study, selecting from the following options: e-mail, Facebook, Instagram, Twitter, word-of-mouth or other. E-mails and social media links were created with customized URLs so that the application could also track the click source automatically [14], [15]. The participants were randomised automatically by the app using a random function [16] which ran in the browser. It generated a random number between 0 and 1. Depending on the value (lower or upper half of the interval) the participant was allocated to one of the two groups: PN or control.

7.2.2 Study protocol

The eNutri app had multiple functions [17]. It asked participants to complete a graphical FFQ [18] which was based on a previously validated FFQ [8], calculated the components of the m-AHEI [12], derived PN advice based on the m-AHEI score, and presented food-based dietary recommendations, together with a progress report. It also calculated and presented the ideal weight range of the participants, based on the Body Mass Index (BMI), and provided feedback on their PA level, based on the Baecke questionnaire [19]. In the version deployed in this study, the inputs to the decision engine generating the nutrition feedback were limited to a participant's diet data and sex. The EatWellUK RCT included the following groups:

- Control group: web-based delivery of non-personalised dietary and PA advice based on the UK general healthy eating guidelines.
- Personalised group: web-based delivery of personalised food-based dietary, PA and weight management advice based on the individual's dietary intake, anthropometrics and PA levels (assessed by the Baecke questionnaire [19]).

Participants were asked to complete the online FFQ, the Baecke PA questionnaire [19] and provide their self-reported weight at baseline and weeks 6 and 12 during the

intervention, and they received general (control group) or personalised (personalised group) advice at baseline and week 6. All participants received personalised recommendations at week 12 (upon completion of the study).

Although participants were encouraged to complete the FFQ in one session, it was important to offer the possibility to save the FFQ, in case of interruption or temporary Internet disconnection. Hence, each food selection was saved individually (after the portion size selection), and the participants could return to the last saved food item when they logged into the system again. Incomplete FFQs expired after 24 hours.

The interval between FFQs was also managed by the app. The second FFQ was made available only after 41 days (one day before the completion of 6 weeks) and the third (and final) FFQ after 77 days (11 weeks). If the participant logged into the system during the intervening intervals, a message was shown indicating the date when their next FFQ would be available. Textbox 7.1 summarizes the EatWellUK study procedure.

Textbox 7.1 - EatWellUK study procedure

1. Online recruitment, providing the participant information sheet and consent form.
2. Account creation via the eatwelluk.org website.
3. Online consent form agreement.
4. Semi-automated screening.
 - a. Manual screening for textual analysis (descriptions).
5. Participant's characteristics (gender, age, height, level of education).
6. Group allocation (randomization).
7. Weight, PA questionnaire and FFQ.
8. System usability scale (SUS) questionnaire.
9. Presentation of online advice.
10. Online advice evaluation.

Steps 1 to 9 were completed once at baseline (week 0) (~20 minutes in total) [18]. The first completion of step 7 served as baseline data. Steps 7 and 9 were presented again in week 6 and week 12. Optional step 10 was presented only at the end of the study.

7.2.3 Outcome measures

Changes from baseline in dietary intake at 6 and 12 weeks were assessed via a FFQ [18]. The AHEI [12] was used as the foundation for the measuring the quality of the diet and to quantify the dietary intake changes. Some modifications were applied to the original AHEI to adapt it to the UK dietary guidelines and to improve its use as the decision engine for the nutrition recommendation (i.e. not only the dietary intake assessment). The modified version of the index was named m-AHEI, which is described in Table 7.1. The maximum component score was changed from 10 to 100, in order to facilitate the data visualization and progress monitoring to the participant. The report design was presented in [20]. All of the 11 individual components were weighted equally, and the overall score ranged from 0 to 100.

Table 7.1 - Modified Alternative Healthy Eating Index (m-AHEI) components and score criteria

Component	Criteria for minimum score (0)	Criteria for maximum score (100)
Vegetables, servings/d	0	≥5
Fruits, servings/d	0	≥4
Whole grains, g/d		
Women	0	≥75
Men	0	≥90
Dairy products^a, servings/d	0	≥3
Nuts and legumes^c, servings/d	0	≥1
PUFA^d, % of total energy	≤2	≥10
Long-chain (n-3) fats (EPA + DHA), mg	0	≥250
Free sugars^e, % of total energy	≥15	0
Red and processed meat, servings/d	≥1.5	≤0.03
Sodium^f, mg/d	Highest decile	Lowest decile
Alcohol^g, drinks/d		
Women	≥2.5	≤1.5
Men	≥3.5	≤2

^a The original AHEI was defined by Chiuve et al in [12]. Modifications for this intervention are indicated in the table with superscripts. Components have also been reordered, such that the components for which consumption is to be encouraged appear together at the top of the table.

^b This component was not part of the original AHEI

^c Vegetable protein was not included in the calculation of the m-AHEI score

^d Presented to participants as “Healthy fats”

^e Presented to participants as “Oily fish”

^f Component was modified to “Free sugars” and presented as “Sugars”

^g Presented to participants as “Salt”. Highest and lowest deciles based on the Food4me study

^h Score for non-drinkers was modified from the original AHEI where non-drinkers received a score of 2.5 out of 10

The original “sugar-sweetened beverages and fruit juice (serving/d)” was modified to “Free sugars (% of total energy)” to meet the recent recommendations in the UK [21][22]. Regarding the “alcohol” component, in the original AHEI non-drinkers received a score of 2.5 out of 10. This component was modified because this score could encourage non-drinkers to have moderated alcohol consumption. This type of recommendation was considered inappropriate, especially due to challenges related to alcoholism [23]. The “dairy products” component was not present in the original AHEI but introduced to meet European guidelines such as the Netherland’s recommendations: “take a few portions of dairy produce daily, including milk or yogurt” [24] and French “consume foods that are rich in calcium (mainly dairy products...) [25]. The original

“Trans Fat” component was excluded after simulations with data from a prior study, which indicated limitations in the FFQ food list to estimate this component accurately (i.e. participants could receive a good score on this component due to a lack of food items in the food list with a significant proportion of trans fatty acids in their composition).

The effectiveness of the decision engine was captured in terms of users’ actual diet change, using the m-AHEI as a primary outcome measure. Three diet messages were presented based on the three lowest m-AHEI component scores following each FFQ, following a protocol published previously [18][20].

Secondary outcome measures were weight and PA level. Changes from baseline were measured for self-reported weight (kg) at 6 and 12 weeks. Only two questionnaires per participants were considered in the outcome analysis, based on the date closest to the target date (12 weeks). Weight variation was combined with height (constant for adults) and reported as BMI variation (kg/m^2). A healthy BMI ranges from 18.5 to 25.0 kg/m^2 , hence an ideal weight for a participant was presented as the midpoint at 21.75 kg/m^2 . This approach was used to tailor the textual messages and visual representations in the app (i.e. coloured bars on the scale to represent the ideal weight range) [18].

As participants could be advised to either gain or lose weight, an analysis of the change in BMI without taking into account the direction of the change (i.e. increase/decrease) would not capture the effectiveness of the recommendation (i.e. opposite variations across participants would cancel one another). Thus, in the study, the absolute difference from the current BMI to the ideal BMI was analysed to see if the personalised advice decreased this difference significantly, in comparison to the control group.

Regarding PA levels, change was measured from baseline in self-reported PA (Baecke questionnaire) at 6 and 12 weeks. After each use of the app, all participants in the personalised group received their overall PA scores, followed by the three categories scores (sports, leisure and work), as defined by Baecke et al [19]. Messages related to the sports and leisure categories were provided, according to the participant’s score in each category. As it was deemed unlikely for participants to have much control over the nature of their activities at work, no personalised message regarding the work category was provided [18]. Participants in the personalised group were able to see a progress

report after each diet questionnaire. Participants in the control group were only able to see this report at the end of the study.

7.2.4 Online report evaluation

After completion of the study, the personalised online report was evaluated via nine questions regarding the users' perceived system effectiveness [26] and perceptions on its design. The first six questions were Likert items. The final three questions offered the possibility to write comments. The questionnaire is presented at the end of the results section, together with participants' responses.

7.2.5 Statistical analysis

For an individual m-AHEI component (e.g. fruits), a smaller treatment effect is expected if the participant in the personalised group did not receive advice for changing that specific component. Furthermore, the subgroup of participants with lower scores in the control group for a specific component have greater room to improve their score for that component than the group as a whole. In order to consider these points in the analysis, besides the treatment effect calculation for the two whole groups, it was also calculated for the participants in the personalised group who received personalised messages for a specific component in comparison with the matched participants in the control group [27].

This RCT was powered based on the outcomes of a similar study [9], expecting an increase of 6.5% (mean=49.58, SD=9.51; Alpha=0.05; Power=0.8) in the m-AHEI. With these variables, the recruitment target 330 participants considering a 20% dropout rate.

7.3 Results

7.3.1 Participants

A total of 438 participants created accounts in the web application. Table 7.2 presents which recruitment sources were reported by the participants and also the results of the URL automatic tracking.

Table 7.2. Recruitment sources reported by the participants and automatically detected by the app

Recruitment Source	Self-report	Automatic URL track
e-mail	164 (37.4%)	199 (45.4%)
Facebook	59 (13.5%)	26 (5.9%)
Twitter	43 (9.8%)	11 (2.5%)
Instagram	0 (0.0%)	0 (0.0%)
Word-of-mouth	63 (14.4%)	0 (0.0%)
Other	72 (16.4%)	34 (7.8%)
Not available	37 (8.4%)	168 (38.4%)
Total	438 (100%)	438 (100%)

Out of the 438 accounts, 393 participants completed the screening questionnaire. Of these, 29 participants were excluded due to country of residence (n=6), medication (n=8) or dietary requirements such as lactose intolerance (n=10) or food allergy (n=7). Excluding the 29 participants who were not eligible to participate, 364 participants were randomized automatically by the app, but 39 participants did not complete the baseline questionnaire (Figure 7.1).

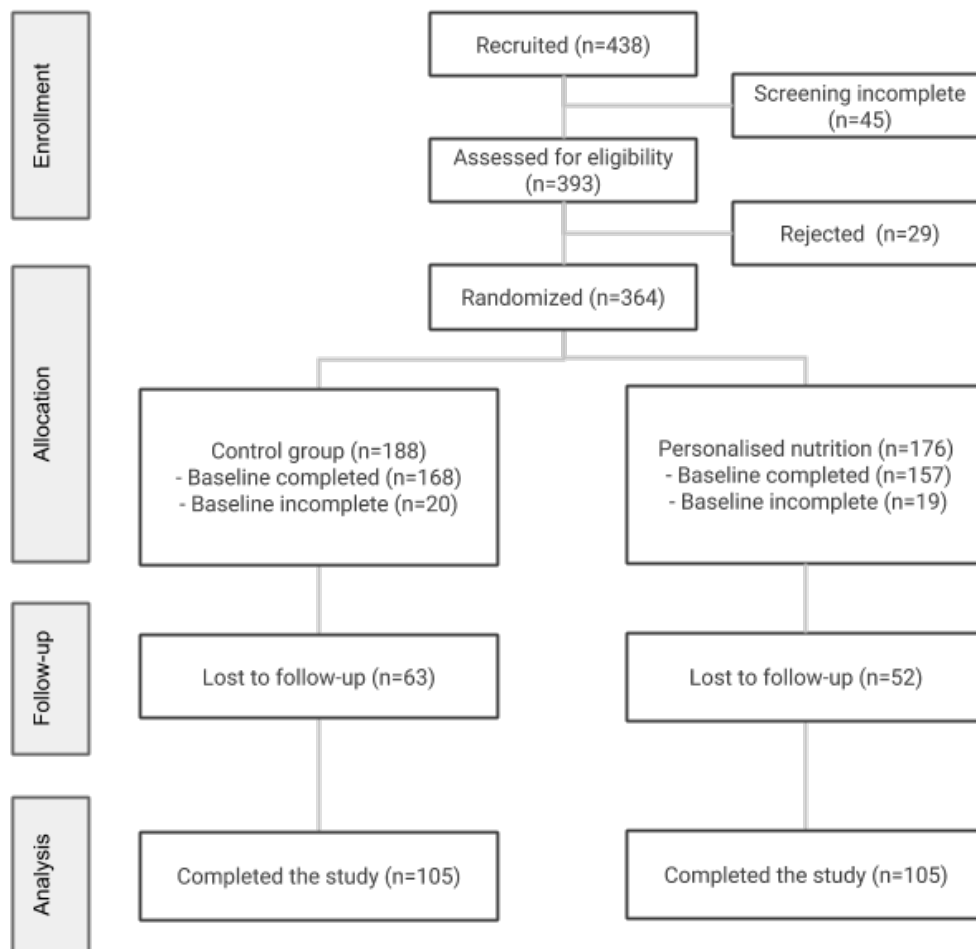


Figure 7.1. CONSORT flow diagram for the EatWellUK study

Out of the 325 participants who completed the baseline FFQ, 210 completed at least one additional FFQ and these were considered in the RCT. 114 participants from the control (n=54) and PN group (n=60) also completed their third FFQ. At the end of the study, the participants were presented with an optional questionnaire to provide feedback on the report. Of the 123 feedback forms received, 58 were from the control group and 63 from the PN group. These feedback responses were combined since all of the participants were able to see the same report at the end of the study and no significant differences were found between the groups. The characteristics of the participants included in the analysis are presented in Table 7.3.

Table 7.3 - Characteristics of the EatWellUK study participants

Characteristics	Total	Control	PN
Total, n (%)	210 (100%)	105 (50%)	105 (50%)
Sex			
Female, n (%)	169 (80.5)	88 (41.9)	81 (38.6)
Male n (%)	41 (19.5)	17 (8.1)	24 (11.4)
Level of Education			
Less than secondary	0 (0.0)	0 (0.0)	0 (0.0)
Secondary	25 (11.9)	16 (7.6)	9 (4.3)
College	24 (11.4)	12 (5.7)	12 (5.7)
Bachelor	70 (33.3)	28 (13.3)	42 (20.0)
Postgraduate	91 (43.3)	49 (23.3)	42 (20.0)
Age (years)			
Mean	43.0	42.4	43.6
Range	18-85	20-82	18-85

7.4 Diet and physical activity questionnaires

The baseline results of the first set of questionnaires are presented in Table 7.4.

Table 7.4 - Unadjusted baselines of the control (n=105) and personalised group (n=105) presented as means (SD) for m-AHEI scores, Baecke scores and BMI.

Variables	Unadjusted	
	Control (n=105)	Baseline PN (n=105)
m-AHEI overall score	58.25 (12.28)	55.95 (11.73)
Vegetables	67.12 (26.97)	58.80 (29.03)
Fruits	64.52 (31.67)	59.97 (34.86)
Whole grains	40.81 (34.72)	34.76 (33.19)
Dairy products	86.26 (29.21)	94.35 (18.79)
Nuts and Legumes	45.95 (37.98)	26.55 (33.79)
Free sugars	44.7 (27.52)	49.81 (27.34)
Red and processed meat	29.82 (37.58)	25.87 (36.51)
Healthy fats	53.46 (18.01)	50.15 (16.50)
Oily fish	60.87 (42.97)	69.82 (37.88)
Salt	55.91 (35.75)	57.31 (31.67)
Alcohol	91.50 (25.57)	88.69 (28.16)
PA (Baecke) overall score	53.25 (10.19)	51.37 (9.83)
Leisure score	59.67 (13.23)	59.05 (13.3)
Sports score	54.67 (21.34)	49.67 (19.09)
Work score	45.46 (11.49)	45.61 (10.94)
Absolute BMI (kg/m²)	24.64 (5.05)	24.52 (4.93)
Distance to ideal BMI (kg/m²)	3.84 (4.37)	3.77 (4.21)

7.4.1 Primary outcomes evaluation

Considering the protocol for selecting the second FFQ (i.e. the one closest to the 12-week), the trial resulted in an average interval between FFQs of 10.8 weeks. The analysis by group confirmed that the intervals were equivalent across the control (10.7 weeks) and PN groups (10.8 weeks). The outcomes for the second FFQ were adjusted with the corresponding baseline means as a covariate in order to measure the treatment effect [27]. The results for the m-AHEI scores are presented in Table 7.5.

Table 7.5 - Effects of the 12-week intervention on the m-AHEI components, considering all of the participants in the control (n=105) and PN groups (n=105)^a

Variables	Adjusted Mean		Adjusted Δ		Treatment Effect	p
	Control (n=105)	PN (n=105)	Δ Control (n=105)	Δ PN (n=105)	Δ PN- Δ Control (95% CI)	
Overall m-AHEI score	56.85	59.91	-0.25	2.81	3.06 (0.91 to 5.21)	0.005
Vegetables	58.31	55.85	-4.65	-7.11	-2.45 (-8.29 to 3.39)	0.409
Fruits	56.44	58.76	-5.81	-3.48	2.33 (-3.76 to 8.41)	0.452
Whole grains	33.54	32.63	-4.25	-5.16	-0.91 (-7.72 to 5.89)	0.792
Dairy products	89.81	91.56	-0.49	1.25	1.74 (-4.17 to 7.66)	0.562
Nuts and Legumes	40.92	45.97	4.66	9.72	5.05 (-4.35 to 14.45)	0.290
Free sugars	45.78	52.54	-1.48	5.28	6.76 (0.58 to 12.95)	0.032
Red and processed meat	30.35	35.58	2.51	7.74	5.22 (-0.77 to 11.22)	0.087
Healthy fats	52.73	51.12	0.92	-0.68	-1.60 (-5.80 to 2.59)	0.452
Oily fish	62.86	68.6	-2.48	3.25	5.74 (-2.99 to 14.47)	0.197
Salt	64.64	69.79	8.02	13.18	5.15 (-2.10 to 12.40)	0.163
Alcohol	93.08	92.92	2.99	2.83	-0.16 (-5.57 to 5.24)	0.953

^a Data presented as adjusted means with the baseline values as covariate [27].

The treatment effect observed in the overall m-AHEI score was 3.06 (CI 95% 0.91 to 5.21), which reached statistical significance (p=0.005). Only one individual component (free sugars) had a statistically significant (p=0.032) improvement of 6.76 (CI 95% 0.58 to 12.95) during the intervention period.

All of the participants in the personalised group (n=105) received feedback regarding their m-AHEI overall score and were able to see the progress report with all of the individual m-AHEI scores, however, the focus of the advice was on just 3 personalised diet messages [18]. In other words, the outcomes for individual m-AHEI components presented in Table 7.5 did not take into account whether a specific participant received a personalised message for that component, but showed how the individual m-AHEI components were affected by the intervention on the whole.

The decision to present three personalised messages per report [28] directly affects the analysis of the outcomes of the personalisation. The higher the number of diet messages presented, the higher the percentage of participants in the personalised group who will receive personalised messages for each component. The same rationale is valid for matched participants in the control group who would have received those messages if

they had been randomised to the personalised group, as presented in Table 7.6. The distribution presented in the final column of Table 7.6 gives an indication of the individual components coverage applying this specific decision engine for PN in the UK adult population.

Table 7.6 - Messages presented to the personalised group (total n=105) and matched participants in the control group (total n=105) when only messages for the top 3 components in need of change are presented ^a

m-AHEI Component	Matched Control		PN messages		Total messages	
	n	%	n	%	n	%
Red and processed meat	64	10.2	69	11.0	133	21.1
Nuts and Legumes	49	7.8	77	12.2	126	20.0
Whole grains	49	7.8	54	8.6	103	16.3
Salt	33	5.2	26	4.1	59	9.4
Free sugars	32	5.1	20	3.2	52	8.3
Oily fish	33	5.2	18	2.9	51	8.1
Fruits	17	2.7	15	2.4	32	5.1
Healthy fats	14	2.2	10	1.6	24	3.8
Vegetables	8	1.3	13	2.1	21	3.3
Alcohol	7	1.1	9	1.4	16	2.5
Dairy products	9	1.4	4	0.6	13	2.1
Total	315	50	315	50	630	100

^a Components are ordered by the number of total number of messages that were (personalised group) or would have been (control group) presented to participants. Since each participant received 3 messages, the total of messages is 315 for each group (n=105)

The treatment effect on participants in the personalised group who received personalised messages for a specific component was also calculated in comparison with the matched participants in the control group, as shown in Table 7.7.

Table 7.7 - Changes in the m-AHEI components from baseline to week 12 for participants in the personalised group who received individual component messages and the matched participants in the control group ^a

m-AHEI Component	Matched Control			Personalised Nutrition			Treatment effect	
	n	Mean	Δ	n	Mean	Δ	ΔPN-ΔControl (95% CI)	P
Vegetables	8	38.75	9.85	13	33.00	4.09	-5.75 (-29.03 to 17.52)	0.610
Fruits	17	25.35	2.57	15	28.47	5.69	3.11 (-9.53 to 15.75)	0.618
Whole grains	49	19.89	6.46	54	22.77	9.34	2.89 (-5.07 to 10.84)	0.473
Dairy products	9	35.18	15.11	4	67.59	47.51	32.40 (-19.23 to 84.03)	0.192
Nuts and Legumes	49	34.17	19.18	77	39.40	24.42	5.23 (-7.31 to 17.78)	0.411
Free sugars	32	23.27	6.79	20	39.67	23.19	16.40 (1.46 to 31.35)	0.032
Red and processed meat	64	13.09	9.22	69	18.26	14.39	5.17 (-2.73 to 13.06)	0.198
Healthy fats	14	50.07	7.57	10	52.40	9.90	2.32 (-10.66 to 15.30)	0.714
Oily fish	33	25.92	18.48	18	37.38	29.94	11.46 (-8.95 to 31.87)	0.264
Salt	33	46.54	28.88	26	58.85	41.19	12.31 (-5.09 to 29.70)	0.162
Alcohol	7	45.37	35.99	9	62.71	53.34	17.34 (-35.06 to 69.74)	0.487

^a Data presented as adjusted means with the baseline values as covariate [27].

7.4.2 Secondary outcomes evaluation

As all of the participants received advice on weight and PA, analysis of matched participants was not required for the secondary outcomes evaluation. Absolute BMI was not affected by the treatment, with both groups reporting a -0.12 kg/m^2 reduction after 12 weeks (Table 7.8). The mean distances to the ideal BMI decreased (i.e. BMI improvement) less in the control group (-0.06 kg/m^2) than in the personalised group (-0.18 kg/m^2), but this improvement (-0.07 kg/m^2) was not statistically significant ($p=0.488$). Some participants in the control ($n=13$) and personalised group ($n=21$) reported the same weight at week 12 and baseline. The overall Baecke score improved by 0.37 (CI 95% -1.12 to 1.87) but this effect was not significant ($p=0.624$).

Table 7.8 - Changes in BMI and PA level (Baecke) score from baseline to week 12 for participants in the control (n=105) and personalised group (n=105). Values presented as adjusted means

	Adjusted Mean		Adjusted Δ		Treatment Effect	p
	Control (n=105)	PN (n=105)	Δ Control (n=105)	Δ PN (n=105)	Δ PN- Δ Control (95% CI)	
BMI (kg/m²)^a						
Absolute BMI	24.65	24.66	-0.12	-0.12	-0.00 (-0.20 to 0.21)	0.964
Ideal BMI distance	3.79	3.72	-0.06	-0.13	-0.07 (-0.27 to 0.13)	0.488
PA (Baecke) score^b						
Overall score	52.79	53.16	0.39	0.76	0.37 (-1.12 to 1.87)	0.624
Leisure score	57.28	58.70	-2.12	-0.70	1.42 (-0.87 to 3.71)	0.222
Sports score	55.08	53.17	2.68	0.76	-1.92 (-5.02 to 1.18)	0.224
Work score	46.20	47.62	0.66	2.09	1.43 (-0.16 to 3.01)	0.077

^a Presented as simple variations and absolute distance to the ideal BMI (21.75 kg/m²)

^b Values are reported on a scale between 0 and 100

7.4.3 Online report evaluation

The analysis of the 15 comments provided in the first qualitative question (Table 7.9) showed that 9 were related to the stages before the diet advice itself (i.e. assessment). Minor issues related to the FFQ (n=3), Baecke questionnaire (n=3) and difficulties finding the link to the online report (n=3) were mentioned. One participant asked to see the scientific evidence for the recommendations (i.e. details of the m-AHEI score calculations) and 5 participants disagreed somehow with the personalised advice provided, mainly due to the dairy products and meat recommendations (n=4).

Table 7.9 - Qualitative user feedback for the open questions related to the personalised report

Question	Yes n (%)	No n (%)
1. Was there anything in the report that you found particularly difficult to understand?	15 (12.2)	108 (87.8)
2. Do you need additional information to help you make changes to your diet at this moment?	6 (4.9)	117 (95.1)
3. Do you have any further comments regarding the feedback you received?	14 (11.4)	109 (88.6)

For the second question (Table 7.9), five out of the six comments were confirmations of the need for dietary change (e.g. “Diet reflects difficult time in personal life - need to change that”, “more time to prepare meals” and “late night eating”) and one participant

requested more scientific explanation of the advice (“If you want me to follow advice I would like to understand the basis”). Out of the 14 comments received in response to the third question (Table 7.9), three were related to the FFQ. Five comments were about the limitations of the PA feedback (e.g. “I do not think the report is a reflection on my sporting activity”, “I am a successful amateur athlete in good health. I am interested to hear some of the reasoning behind the recommendations you have made for me”). The other six questions were about the diet recommendations and the majority (n=4) mentioned their partial disagreement with some of the diet advice (e.g. “I do not agree with the advice to increase dairy foods. This is a very narrow view of the full picture”, “I have too much salt and meat but I don't think I do”, “It did not reflect I cook from scratch rather than buy ready-made meals”).

The results of the questions related to the quality of the design (first two questions) and the perceived effectiveness of the recommendations [26] are shown in Table 7.10 using a Likert scale.

Table 7.10 - User evaluation of the online report in a likert scale

Question	Strongly Disagree n (%)	Disagree n (%)	Neutral n (%)	Agree n (%)	Strongly Agree n (%)
I find the feedback report attractive to read	2 (1.63)	7 (5.69)	45 (36.59)	61 (49.59)	8 (6.5)
Overall, I understood the feedback report	2 (1.63)	2 (1.63)	15 (12.2)	84 (68.29)	20 (16.26)
After reading the report, I know how to change my diet to make it healthier	2 (1.63)	9 (7.32)	29 (23.58)	73 (59.35)	10 (8.13)
The report showed useful advice	2 (1.63)	10 (8.13)	32 (26.02)	69 (56.1)	10 (8.13)
The report reflected my diet intake	1 (0.81)	19 (15.45)	33 (26.83)	62 (50.41)	8 (6.5)
I found the application useless	29 (23.58)	56 (45.53)	27 (21.95)	10 (8.13)	1 (0.81)

7.5 Discussion

7.5.1 Principal Results

This RCT was designed to primarily test whether personalised food-based dietary online advice, using the m-AHEI as the foundation of the decision engine, was more effective than generalised population advice at motivating beneficial dietary change. The significant treatment effect (3.06 points in the m-AHEI scale), as shown in Table 7.5,

represented an increase of 5.36% in the mean m-AHEI baseline (57.10) (Table 7.4). This result confirmed the hypothesis that the eNutri app is an effective online tool for PN advice, at least in the UK.

Only one m-AHEI component (“Free sugars”) reached significance in the treatment effect (Table 7.6), but apart from “Vegetables” all the other components had positive effects, indicating that the personalisation could potentially have reached significance with more participants. This study was powered to primarily measure the treatment effect in all the participants (i.e. not the individual components). The fact that individual m-AHEI scores started from different baselines (Table 7.4) and are presented to the participants with different probabilities (Table 7.6) makes it more difficult to reach statistical significance. For example, some m-AHEI components (e.g. “Dairy Products” and “Alcohol”) started with mean baseline values close to the best possible score and were presented to small numbers of participants. This does not mean that these components should be removed from the m-AHEI, but in order to test the significance of the personalisation of these diet messages, a much larger RCT would be necessary, which is viable over the Internet.

The decrease in the distance to the ideal BMI by 0.07 kg/m² (Table 7.8) in 12 weeks does not indicate that similar interventions may be effective for weight loss and control.

The results of the PA questionnaire (Table 7.8) also did not indicate that this type of personalisation may be effective. It may confirm that more robust and personalised PA trackers, such as GPS or pedometers, may be necessary for delivering effective interventions.

Results presented in Table 7.10 showed that the participants understood the report and were confident about the next changes in their diets. The first two questions in Table 10 indicated good acceptance of the content and design of the report but also showed that its understanding was better than its attractiveness. Further improvements in its design may be necessary. The last four questions in Table 7.10 showed a good perceived effectiveness of the report by the majority of the participants.

7.5.2 Limitations

The power calculation for this study was based on the expected increase in the overall m-AHEI score. Other studies with more participants, taking into account the baseline

values (Table 7.4) and distribution of messages (Table 7.6) may be necessary if the individual m-AHEI components are to be analysed. For this reason, where advice on a particular component was delivered to only relatively few participants, the effect of the advice on the component should be read cautiously considering the large confidence intervals described.

Although the design of the diet messages had followed the same structure [18], some messages were presented to only a few participants (Table 7.6), then the understanding of the report (second question in Table 7.10) should not be generalized to all the textual diet messages.

The fact that weight was self-reported online may have impacted on the results, especially as some participants may not have had weighing scale at home or were not able to weigh themselves for the subsequent app visits (i.e. participants may have re-entered the original value without taking a new measurement). This may justify why 24 participants reported no change in weight, increasing the difficulty to reach statistical significance for the BMI changes.

7.5.3 Comparison with Prior Work

A recent systematic review presented 26 remotely delivered dietary interventions using self-monitoring or tailored feedback. A total of 51 dietary outcomes were analysed in the 23 interventions considered in the meta-analysis, resulting on an average of 2.2 dietary outcomes per intervention. The most popular were fruits, vegetables and fat and only three interventions target more than four dietary outcomes. This review also considered interventions delivered over the phone or offline media (e.g. printed reports, CD-ROM). Only seven interventions used modern online methods, such as websites or apps. The aim of this literature review was to analyse the effectiveness of these interventions, and the authors concluded that they showed a significant, but small positive effect on dietary change which was at risk of bias, [11]. The differences in the dietary outcomes make the comparisons more difficult, especially because the changes in some dietary outcomes may affect other components not measured during the intervention (e.g. the increase of fruits and vegetables may decrease nuts and legumes), due to the dynamic aspect of diets.

Prior to the EatWellUK study, the most closely-related and comprehensive study was the Food4Me study [29], in which 1269 participants completed a 6-month PN study. The researchers also reported no significant effect of personalised advice on BMI (-0.24 kg/m²) relative to a control group. It is difficult to compare the effectiveness on BMI since the authors did not report the distance to the ideal BMI, as proposed by the current research. The Food4me study used the Healthy Eating Index (HEI) [30], which was the basis for the AHEI [12], as a secondary outcome measure of the quality of the diet. Their treatment effect on the overall HEI was 1.27 (95% CI 0.30 to 2.25, p=0.010), suggesting an improvement in diet quality following PN advice. Participants randomized to receive PN were reported to consume less red meat, salt, saturated fat and energy and also increased their folate intake [9]. Although statistically significant, their increase in the HEI was also relatively small, confirming the challenge to encourage healthier diets and the need of similar studies.

7.6 Conclusions

This work presented the treatment effects of a 12-week online RCT with 210 participants, which is likely to be the second largest online dietary intervention in the UK and the only one delivered automatically [11]. It aimed to measure the effectiveness of a novel online PN advice tool (eNutri), using a modified version of the AHEI as the foundation of the decision engine to deliver online personalised food-based dietary advice. Results show that the design and protocol followed by this study motivated change to a healthier diet. The use of eNutri app could contribute to improved diet quality. Findings from this study, including the online report evaluation, are important to inform improvements in eNutri or similar apps. The design principles and algorithms can be used and improved by other researchers and institutions interested in online PN advice, especially because the eNutri web app was made publicly available under a permissive open-source license [31]. This work represents an important landmark in the field of automatically delivered online dietary interventions.

7.7 Abbreviations

AHEI: Alternative healthy eating index

BMI: Body mass index

CNPq: National Council of Technological and Scientific Development (Brazil)

FFQ: Food frequency questionnaire

Food4me: Food for me project

m-AHEI: Modified alternative healthy eating index

NCD: Non-communicable diseases

PA: Physical activity

PN: Personalised nutrition

RCT: Randomized controlled trial

URL: Uniform resource locator

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7.9 Chapter discussion

Although the latest version of the eNutri app can be very useful and potentially contribute to healthier dietary habits, its decision engine is elementary computationally and deterministic (i.e. if two individuals have the same dietary intake information, they will receive the same advice, even if they have different preferences). In addition, its decision engine does not take into account important data sources, such as population data, historical data or individual’s preferences. In other words, the current feedback is driven purely by the diet data and sex, and the question of how best to balance nutritional healthiness against users’ preferences in a way that maximizes the likelihood of the user adopting healthier choices remains an open research challenge

8 GENERAL DISCUSSION AND CONCLUSIONS

This project proposed to increase the acceptability, effectiveness and adoption of online nutrition services. It investigated an effective way of providing automated personalized online dietary recommendations in order to increase the diet quality of the population. The overall aim of this project was to design, develop and evaluate an online system able to assess dietary intake and propose valid food-based personalised nutrition advice for adults (18+). In the following subsections, the research questions presented in subsection 1.5 are revisited, and the overall contributions of this work, its general limitations and suggestions for future work are presented.

8.1 Research questions

In order to address the main motivations of this work, it was deemed important that the solution be built with commercially-available technologies, scalable, replicable, inexpensive, secure and independent of any bespoke device. The research question behind these requirements (research question 1) was not how to find the best solution to meet these requirements (i.e. to compare different solutions), but how to meet them in an effective way. In other words, there are many possible solutions that could have been proposed.

The solution presented in Chapter 4 was to develop a web application using a single page application (SPA) architecture. The only service in the back-end was Google Firebase, which is offered by one of the most popular public cloud providers currently and available for other customers worldwide. Using a SPA architecture, the processing occurs mainly in the browsers, making this solution scalable. It also facilitates the

reproducibility, because it does not require any server-side installation or maintenance. Google Firebase allows up to 100 simultaneous connections in their free plan, and with 25 US dollars per month, this limit is increased to 100 thousand [107], meeting the low-cost requirement. Regarding security, Google Firebase is compliant with the main global standards and security certifications, including the recent 2018 General Data Protection Regulation (GDPR) from the European Union [108] [109]. From a software perspective, the security rules, detailed in Chapter 4, met the authentication and authorization requirements needed for processing and storing personal data.

Regarding the research question 2, this work addressed a number of important challenges in usability of assessing dietary intake assessment online and proposed a set of tools and development principles for collecting usability metrics. The eNutri app collected timestamps (research question 2.c) and device details directly from the web browser, and presented and calculated the results of the System Usability Scale (SUS) [110] automatically. This type of data can offer insight into how people are using the app (research question 2.a). Similar strategies should to be applied in research studies in this field, so that researchers and developers can test and compare different application designs (research question 2.b).

Two front-end designs were investigated for the online FFQ. The first presented the food items in a list and the second presented only one food item at a time (research question 2.b). Both versions resulted in similar completion times and user acceptance but there is evidence from the literature that a serialized design is more appropriate from a usability perspective, especially if the solution is aimed at including older adults [34]. Based on these results, the serialized FFQ design would appear to be the more appropriate one of these two options.

Potential users were consulted during the design process via a formative study (research question 3.b), and the advice system was subsequently (Chapter 6) validated against professional recommendations (usual care). Assessing whether nutrition professionals (NP) agree with the automated feedback (research question 3.a) was important for informing us on how to improve the success and wider utility of this app. These professionals also highlighted that other important variables, especially weight, should be directly incorporated into the nutrition advice. The eNutri app had a specific section

to report the personalised healthy weight range, but the BMI was not considered for tailoring the nutrition advice.

Regarding the decision engine used for this personalisation, the main decision taken during this PhD was to use the m-AHEI as the foundation for tailoring the personalised advice. Indexes of overall quality of diets have previously been used for diet assessment only, not for generating online advice. This was somewhat a risky decision, as there was no prior literature as to whether this strategy would generate a significant treatment effect, but the results of the RCT presented in Chapter 7 confirmed that the eNutri app was an effective app (research question 3.c) for providing personalised food-based nutrition advice and changing dietary intake at scale.

8.2 Contributions

The first study on popular nutrition-related apps (Chapter 3) was important to gain background from the nutrition domain and also to contribute to the literature on digital nutrition from a different perspective (i.e. commercial apps), since most of the reviews and publications only reported solutions developed in academia. The results of this study confirmed the popularity of these apps, which is an indication of the interest from the population in these types of applications. The study highlighted that the commercial apps are using a single nutrition assessment method (food diary) and providing very limited nutrition advice, hence confirming the novelty and importance of the current work.

This work presented detailed usability metrics of online FFQs (Chapters 4 and 5), which contributed to increasing the user acceptance of this important nutrition assessment method. Both versions of the app were used by participants across different devices, including smartphones, and this represents a contribution towards the modernization of the FFQs' web design, considering the responsiveness as a mandatory requirement.

Based on a recent systematic review [90], an analysis of the systems used to remotely deliver nutrition interventions confirmed that there is no other publicly available decision engine that provides valid online personalised nutrition advice automatically. This publication also showed that all of these interventions were conducted in high-income countries, reinforcing the need for a reproducible and inexpensive solution for online personalised nutrition advice. The eNutri design and source code were made

publicly available under a permissive open source license, so that other researchers and organizations can benefit from this work.

8.3 General limitations

The analysis of the most popular nutrition-related apps (Chapter 3) is not exhaustive and may have not listed important features used by non-popular commercial apps.

The majority of the studies were conducted online and rely on information self-reported by the participants. The fact that the recruitment to these studies used University of Reading's mailing lists may have influenced the characteristics of the participants, mainly increasing the level of education in comparison with the UK general population.

Although the participants were offered the option to report difficulties and provide feedback at the end of the online studies, it is likely that some of them dropped out due to difficulties which were not captured by the online questionnaires. This is a general limitation of online studies. The reporting of difficulties and feedback via text fields may limit the amount of feedback provided by participants, due to the time required to type the text or limitations with entering text on touchscreen devices.

The participants of the studies presented in this work might represent a part of the population more inclined to accept online nutrition interventions, hence there are limitations with the generalization of the results to the UK population. This limitation is also applicable to the study with nutrition professionals.

8.4 Future work

The version of the decision engine used in the RCT derived the advice based on dietary intake (FFQ data) and sex information. In alignment with the behaviour change theory [111], the user should take more control of the diet changes. A possible solution is to evaluate the quality of a diet change using the AHEI itself, in order to identify multiple foods that can improve the AHEI score and to let the user choose from the multiple modifications. If the app also allows the users to rate the proposed modifications, that could act as further input to improve the recommendations. This type of approach seems to lend itself well to the use of node graphs, where the nodes represent the dietary intakes and vertices the possible changes [77]. Different from basic meal planning, it is

important to have different weights (i.e. change acceptability) for the vertices, similar to map routing with different traffic conditions.

It is particularly important that future versions of this app are able to consider participant's actual willingness to change their behaviour. For instance, one could want to improve nutrition and yet be unwilling to decrease alcohol consumption, so the cost of the path for reducing the alcohol component would need to be recognized as higher than an alternative method for increasing the diet quality index, such as including more fruit for example. In other words, the system would need to take into account participants' interactions and propose different paths for increasing their diet quality.

Another key challenge for future work is how to train the decision engine. In a typical recommender system, for example a medical diagnosis system, there is available data on the inputs (e.g. symptoms) and corresponding outputs (i.e. diagnosis/treatment). One of the main differences with a nutrition recommender system is that there is no existing openly-available dataset with people's case histories and the corresponding proposed diet modifications from nutrition professionals that could be used for training. Furthermore, differently from many common recommender systems (e.g. online shopping based on previous purchases), the food items that users like and consume the most are not necessarily the healthiest. In other words, the recommender system must consider factors other than users' preferences and prior consumption.

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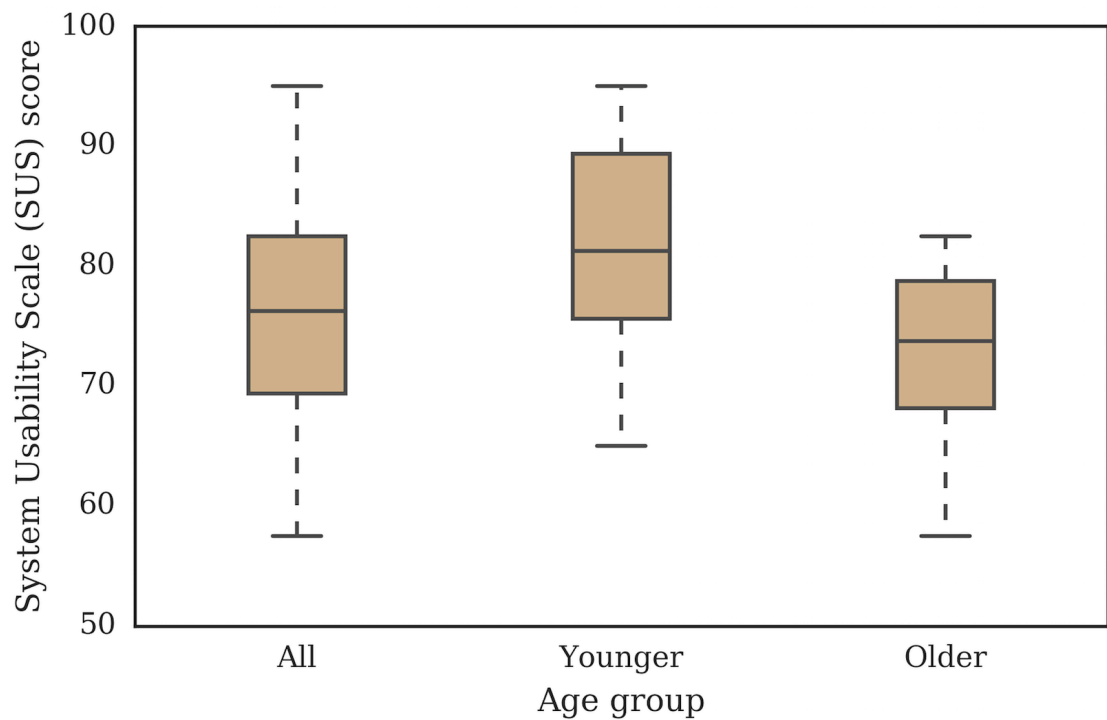
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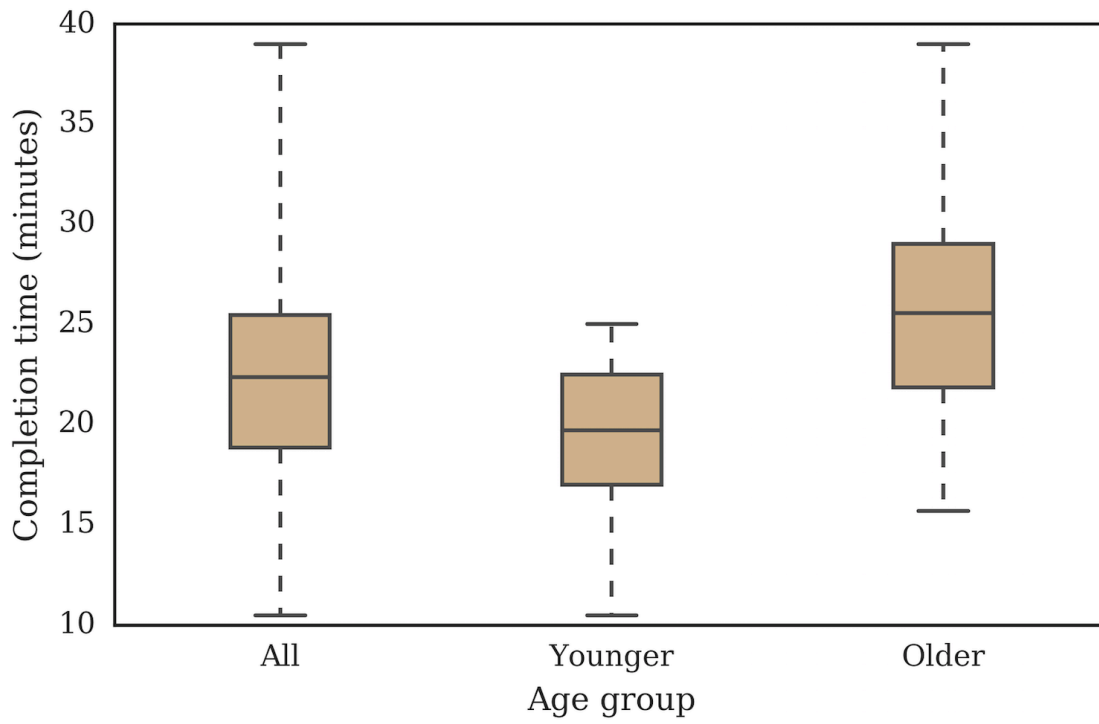
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10 APPENDICES

10.1 Figures from the formative study



Supplementary Figure 10.1 - System Usability Scale (SUS) score for younger (n=10 <60 years) and older (n=10) adults in the formative study



Supplementary Figure 10.2 - Completion time for younger (n=10 <60 years) and older (n=10) adults in the formative study

10.2 Tables from the formative study

Supplementary Table 10.1 - Demographic characteristics of the younger (n=10 <60 years) and older (n=10) participants of the formative study

Characteristics	Younger	Older	Total	%
Sex				
Female	6	6	12	60
Male	4	4	8	40
Level of Education				
Less than secondary	0	0	0	0
Secondary	3	2	5	25
College	3	0	3	15
Bachelor	4	2	6	30
Postgraduate	0	6	6	30
Age (years)				
Mean	38	65	51	
Range	18-59	60-77	18-77	
BMI (kg/m²)				
Mean	26.1	22.5	24.3	
Range	18.9-38.0	17.7-26.6	17.7-38.0	

Supplementary Table 10.2 - Overall perceived quality of the system by the younger (n=10 <60 years) and older (n=10) participants in the formative study

Perceived quality	Younger	Older	Total	%
Best Imaginable	1	0	1	5
Excellent	5	1	6	30
Good	4	7	11	55
Fair	0	2	2	10
Poor	0	0	0	0
Awful	0	0	0	0
Worst Imaginable	0	0	0	0

Supplementary Table 10.3 - Technology familiarity of the younger (n=10 <60 years) and older (n=10) participants (formative study)

Device type	Desktop		Laptop		Tablet		Smartphones	
Age group	Y	O	Y	O	Y	O	Y	O
Main device	2	4	3	1	1	4	4	1
Frequency of use								
Every day	6	6	7	2	4	4	10	5
Every 2-3 days	2	1	1	0	1	0	0	1
Once a week	2	0	0	1	0	2	0	0
Once a month	0	1	0	0	1	0	0	0
Rarely	0	0	0	2	3	0	0	1
Never	0	2	2	5	1	4	0	3
Period of ownership								
Never	3	2	2	6	1	5	0	3
Less than 1 year	1	0	0	1	1	1	1	1
1 year	0	0	1	0	2	0	1	0
2 years	0	0	0	1	2	2	0	4
3 years	0	0	0	1	1	1	0	0
4 years+	6	8	7	1	0	1	8	2

Y: Younger; O: Older

Supplementary Table 10.4 - Participants (n=20) characteristics data (formative study)

ID	Gender	Age	Group	Level of education	What main device do you use to access the Internet?
1	female	61	Older	College	Smartphone
2	female	18	Younger	Secondary	Smartphone
3	female	66	Older	Bachelor	Desktop
4	female	59	Younger	Secondary	Desktop
5	male	54	Younger	Bachelor	Tablet
6	male	60	Older	Secondary	Desktop
7	male	69	Older	Secondary	Desktop
8	female	71	Older	Secondary	Tablet
9	male	60	Older	Bachelor	Tablet
10	female	61	Older	Bachelor	Tablet
11	female	66	Older	Bachelor	Desktop
12	male	77	Older	College	Tablet
13	female	26	Younger	Postgraduate	Smartphone
14	female	61	Older	College	Laptop
15	male	49	Younger	Bachelor	Smartphone
16	female	45	Younger	Postgraduate	Laptop
17	male	27	Younger	Postgraduate	Laptop
18	female	30	Younger	Postgraduate	Smartphone
19	male	30	Younger	Postgraduate	Laptop
20	female	39	Younger	Postgraduate	Desktop

Supplementary Table 10.5 - Participants (n=20) characteristics data (formative study)

ID	How often do you use a (desktop)?	How often do you use a (laptop)?	How often do you use a (tablet)?	How often do you use a (smartphone)?	How long do you own a (desktop)	How long do you own a (laptop)	How long do you own a (tablet)	How long do you own a (smartphone)
1	Never	Everyday	Never	Everyday	N/A	>4 years	N/A	2 years
2	Everyday	Everyday	Every 2-3 days	Everyday	N/A	1 year	1 year	1 year
3	Everyday	Once a week	Never	Everyday	>4 years	2 years	N/A	>4 years
4	Once a week	Never	Everyday	Everyday	>4 years	N/A	1 year	<1 year
5	Every 2-3 days	Never	Everyday	Everyday	N/A	N/A	3 years	>4 years
6	Everyday	Never	Once a week	Everyday	>4 years	N/A	>4 years	>4 years
7	Everyday	Never	Once a week	Never	>4 years	N/A	2 years	N/A
8	Once a month	Never	Everyday	Never	>4 years	N/A	2 years	N/A
9	Everyday	Rarely	Everyday	Everyday	>4 years	N/A	3 years	2 years
10	Every 2-3 days	Rarely	Everyday	Never	>4 years	N/A	<1 year	N/A
11	Everyday	Never	Never	Rarely	>4 years	N/A	N/A	2 years
12	Never	Never	Everyday	Every 2-3 days	N/A	<1 year	N/A	<1 year
13	Everyday	Every 2-3 days	Rarely	Everyday	>4 years	>4 years	N/A	>4 years
14	Everyday	Everyday	Never	Everyday	>4 years	3 years	N/A	2 years
15	Every 2-3 days	Everyday	Once a month	Everyday	<1 year	>4 years	2 years	>4 years
16	Once a week	Everyday	Never	Everyday	N/A	>4 years	>4 years	>4 years
17	Everyday	Everyday	Everyday	Everyday	>4 years	>4 years	2 years	>4 years
18	Everyday	Everyday	Everyday	Everyday	>4 years	>4 years	>4 years	>4 years
19	Everyday	Everyday	Rarely	Everyday	>4 years	>4 years	<1 year	>4 years
20	Everyday	Everyday	Rarely	Everyday	>4 years	>4 years	>4 years	>4 years

Supplementary Table 10.6 - System Usability Scale (SUS) data (formative study)

ID	Group	SUS	Overall ID	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10
1	Older	80.0	Good	4	2	5	1	4	2	4	2	4	2
2	Younger	87.5	Excellent	4	2	5	1	4	2	4	1	5	1
3	Older	72.5	Good	3	2	4	2	4	2	4	2	4	2
4	Younger	65.0	Good	3	3	3	2	4	3	4	2	4	2
5	Younger	75.0	Good	4	2	4	1	4	2	4	2	3	2
6	Older	67.5	Fair	3	3	4	1	4	3	4	2	3	2
7	Older	67.5	Good	3	3	4	2	4	2	4	2	4	3
8	Older	82.5	Good	4	2	4	1	4	2	4	1	4	1
9	Older	70.0	Good	3	2	4	1	3	3	4	3	4	1
10	Older	80.0	Good	3	1	4	1	4	2	4	2	4	1
11	Older	75.0	Good	3	2	4	1	4	2	4	2	3	1
12	Older	75.0	Excellent	4	2	4	2	4	2	4	2	4	2
13	Younger	90.0	Excellent	4	2	5	1	4	2	5	1	5	1
14	Older	57.5	Fair	3	3	2	1	3	2	4	3	2	2
15	Younger	95.0	Best Imaginable	4	1	5	1	4	1	5	1	5	1
16	Younger	80.0	Excellent	3	2	4	1	4	1	4	1	4	2
17	Younger	82.5	Excellent	4	2	3	1	4	2	5	1	4	1
18	Younger	90.0	Good	5	1	4	1	4	1	4	2	5	1
19	Younger	67.5	Good	4	3	4	3	4	3	4	2	4	2
20	Younger	77.5	Excellent	2	4	4	1	5	1	4	1	4	1

Supplementary Table 10.7 - FFQ completion timestamps during the formative study (n=20)

ID	Date	0	1	2
1	20/04/2017	1492679673265	1492679681414	1492679684787
2	20/04/2017	1492682344786	1492682347770	1492682349820
3	20/04/2017	1492687089611	1492687112767	1492687117096
4	20/04/2017	1492700801761	1492701177452	1492701177812
5	21/04/2017	1492780267185	1492780278105	1492780291501
6	21/04/2017	1492784280172	1492784325923	1492784343755
7	21/04/2017	1492788119078	1492788153081	1492788158053
8	21/04/2017	1492790047909	1492790107521	1492790118118
9	04/05/2017	1493907028838	1493907035351	1493907056920
10	04/05/2017	1493910020875	1493910025225	1493910027822
11	04/05/2017	1493914357262	1493914373900	1493914382567
12	11/05/2017	1494508279893	1494508304081	1494508318185
13	11/05/2017	1494511840012	1494511893609	1494511895497
14	11/05/2017	1494515084631	1494515099108	1494515110475
15	11/05/2017	1494519168651	1494519179787	1494519182806
16	18/05/2017	1495101321859	1495101331085	1495101342688
17	18/05/2017	1495098748340	1495098786744	1495098800944
18	18/05/2017	1495116727324	1495116736996	1495116748971
19	18/05/2017	1495120365298	1495120372689	1495120375174
20	25/05/2017	1495715648548	1495715679161	1495715689654

Supplementary Table 10.8 - Summary of the semi-structured interviews (formative study)

ID	Describe Experience	Advantages	Disadvantages
1	Confident Fine I don't how you can make it more interesting	Easy to use	Exercising section was the most confusing Because it's so simple, you cannot elaborate No place to inform Yoga or weights. It's not tailored to me.
2	You don't need to be taught how to use it	Easy to use Self-explanatory	No
3		Easy to use	More explanation to help during the process; Food list: not sure the next question will be
4		Easy to use Easy to answer No need to type People would be use to use even if they don't use tablets I didn't have to think much. Portion sizes very clear	Frequencies: jump between months/weeks/days Not sure what food item comes next
5	Limited number of choices	Easy to use Helps focusing your thinking. Quite of forcing it... which is good. Quite Clear Much easier than a food diary	Selecting the portion size wasn't obvious Order of the frequencies was confusing
6		Easy to use It's definitely beneficial	Difficult to estimate the frequency (seasonal) and portion size (e.g. bananas are pretty much the same)
7		Enjoyed it I liked it Plates: Fork and knife (reference)	I wasn't entirely sure about the frequencies. For me should be Once a day, Once a week, etc. Some of the foods I have so rarely;
8		Easy to understand. I knew exactly what to do	I couldn't be exactly accurate when selecting the frequencies and portions;
9		Possibility to return (previous item)	Order of the frequencies
10	I wasn't very confident coming in, but it was quite simple	Easy to use	I didn't find the portion sizes easy to understand (e.g. bread) It wasn't very pretty/colourful Frequencies weren't in a sensible order

11	It was my first time using a tablet	Easy to use Easy to go back	Frequency: I was reading it down. I was a bit uncertain.
12	No problem	Quite interesting Language was very good	Frequency: per day instead /day
13	Quite relaxed	Very user-friendly Flowed very well Straightforward	It was quite repetitive, but it wasn't too bad. I wasn't exhausted at the end...
14		Well setup	Frequencies: I had to concentrate a lot... it was my biggest stress.
15	It's very interesting. After a short period of time answering those questions and to come up with this report is beneficial.	Easy to use Go back and change	On the application I can't think anything to make it better
16		Easy to use Very intuitive Interface is friendly	None
17		Good Very intuitive very straightforward very intuitive	None
18	Not so long. Lots of thinking but necessary	Quite simple very clear	I liked everything
19		Simple to use	Portion sizes were close to each other; Frequencies: I think daily/weekly/monthly
20		User friendly Easy to navigate	None

10.3 Supplementary tables from the EatWellUK study

Supplementary Table 10.9 - Feedback summary and classification of the EatWellUK study FFQ

ID	Full Text	Classification
1	The blue button covered the lower left answer option so I had to guess what it was.	Usability
2	vocabulary	Text or Messages
3	I am retired so I the first questions about physical activity were irrelevant. however, your reply to my email made clear that I could simply refer to my normal daytime activity.	Baecke questionnaire for retired people
4		Blank
5	When on images of food you can't opt to go backwards	Return to previous food item
6	I don't understand what system this survey is describing, I have only answered a questionnaire so far, and have no experience of using the system (this second survey came up straight after the food survey)	Instructions
7	I didn't know what to do with the images at the first time	Portion size photos
8	I am retired, no section for that	Baecke questionnaire for retired people
9		Blank
10	Browser compatibility	Browser compatibility
11	No problem at all	No problem
12	Not so much the system but I didn't feel that it was possible to give completely accurate answers because of the way questions are asked and the available answers	Instructions
13	Sensitivity of the graphics to record choices when touched	Usability
14	Sometimes missed change in questions due to similar wording	FFQ
15	Questionnaire was frozen on first attempt	Internet connection
16	All very good any easy to use but would be great to have a 'back up' button if you make a mistake	Return to previous food item
17	Tried to access via a mobile phone but had problems progressing through the screening questionnaire. Grand now	Browser compatibility
18	You asked how much e.g. onion or carrot I had. Were you wanting a total (raw carrot, carrot cooked into a stew, carrot boiled as a side veg, or only boiled carrot. Your picture was of raw or boiled carrot; the onion picture looked like raw sliced onion which i never have, but I do eat onion cooked into e.g. stew. Some of your pics were of white stoff (banana, cauli) on a white	FFQ

plate - not very helpful.

19	couldn't really tell what the portion sizes meant, as it depends on plate sizes, and whether the foodstuffs were in a meal or not- some didn't look much different	Portion size photos
20	The portion sizes and foods shown weren't always relevant. The foods were group strangely on some questions.	Portion size photos
21		Blank
22	Initially, the first question about physical activity wasn't automatically clicking on to the next question when I clicked my answer. I contacted the team and the problem was resolved when she contacted the programmer.	Browser compatibility
23	Assume people work. I am retired	Baecke questionnaire for retired people
24	odd problem in explore had to try three times in chrome to get it to work	Browser compatibility
25	Sometimes the picture wouldn't load but I think it was my WiFi	Internet connection
26		Blank
27	Just that I couldn't tap on the pictures of food on my phone (nothing happened) so I had to switch to my laptop	Browser compatibility
28	the exercise questionnaire only related to work and so I filled it in wrongly. Some of the questions were difficult as you didn't know what would be asked later. Also I have been on holiday for a month so it is not reflective of my true diet.	Baecke questionnaire for retired people
29	Sorry meant no	No problem
30		Blank
31	The image sizes looked similar so hard to choose an option	Portion size photos
32	Pictures of portion sizes are indistinct. Sometimes confusing as to what is being asked in portion sizes and frequency eg I eat 3 prunes and 3 dried apricots a day for breakfast but not able to choose an option that matches this.	Portion size photos
33	Was not moving to the next page - had to refresh a few times to be able to do anything with the system.	Browser compatibility
34	portion size section didn't always properly, had to backtrack several times	Portion size photos
35		Blank
36	The portion size pictures did not appear on	Internet connection

	roughly 5/6 questions.	
37	my own fault, screen was on landscape, when i turned to potrait, all ok	No problem
38		Blank
39	I am retired, so difficult to answer about "working" activity!	Baecke questionnaire for retired people
40	Guys - add an option to 'where did you see this advertised' - online (unless I just missed this!!)	Suggestion
41	Going back didn't seem to work - I had to start again	Return to previous food item
42	Cd not find back button on early pages. No option for retired people (like me).	Baecke questionnaire for retired people
43	wanted to return to the start of the food section but couldn't see a return button on the page. needed to return as didn't read the intro before I moved on to the questions - so wasn't quite sure I was doing the right thing...	Instructions
44	Confusion over what is included in a particular food group, often clarified by the following question but then it is too late	Instructions
45	If I ate/drank something every day but only for a week it was difficult to judge	FFQ

10.4 Figures from the nutrition professionals study

Participant 1, 19-year-old male, 73kg, 1.83m, BMI 21.8kg/m²

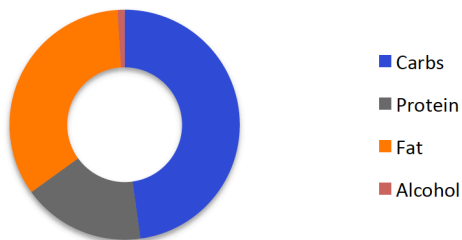
Analysis of Food Frequency Questionnaire, DRVs UK SACN 2015/COMA

Nutrient	Intake	Target	Limits
- ENERGY -			
Energy (Kcal)	2471	2196	
Energy (Kj)	10385	9188	
- MACRONUTRIENTS -			
Total fat (g)	96		<85
Saturated fat (g)	41.4		<26.8
Monounsaturated fat (g)	33.7	31.7	
Polyunsaturated fat (g)	16.9		>6.5 <24.4
Long-chain Omega-3 (g)	0.00		>0.49
Protein (g)	110	55	
Carbohydrate (g)	325	275	
Sugars (g)	118		N/A
Starch (g)	192		N/A
Dietary fibre (g)	20.0	30	
Alcohol (g)	3.6		<15.7

Supplementary Figure 10.3a - Example of input information for a specific scenario

- MINERALS & TRACE ELEMENTS -			
Sodium (mg)	3115	1600	>575 <2400
Potassium (mg)	3597	3500	>2000
Calcium (mg)	1437	1000	>480
Phosphorus (mg)	1779	775	
Magnesium (g)	372	300	>190
Iron (mg)	16.8	11.3	>6.1
Zinc (mg)	11.6	9.5	>5.5
Copper (mg)	1.3	1	
Manganese (mg)	3.3		>1.2
Selenium (µg)	55	70	>40
Iodine (µg)	159	140	>70
- VITAMINS -			
Vitamin A (µg)	432	700	>300
Vitamin D (µg)	3.4	10	
Vitamin E (mg)	9.4		>4
Thiamin (B ₁) (mg)	2.1	1.1	>0.23
Riboflavin (B ₂) (mg)	2.7	1.3	>0.8
Niacin (B ₃) (mg)	34.6	14.5	>9.7
Pantothenic acid (B ₅) (mg)	6.7	3-7	
Vitamin B ₆ (mg)	2.9	1.5	>0.91
Folate (mcg)	363	200	>100
Vitamin B ₁₂ (µg)	4.0	1.5	>1
Biotin (B ₇) (µg)	53	10-200	
Vitamin C (mg)	36	40	>10

	CARBOHYDRATE	PROTEIN	FAT	ALCOHOL
Intake	325	109.8	96.2	3.6
g/kg body-weight	4.5	1.5	1.3	0.0
Kilocal %	49	17.8	35.0	1.0



Supplementary Figure 10.3b - Example of input information for a specific scenario

Diet Log (grams per day)

Food	Intake	Food	Intake
Breakfast non-wholegrain cereals	25.7	Nuts and seeds	2.1
Breakfast cereals	42.9	Non-creamy soups	22.9
White bread	205	Creamy sauces	21.4
Potatoes - mashed, instant, roast	20.7	Dark sauces	9.1
Potatoes - boiled, jacket	32.4	Tomato sauces	16.0
Chips	20.6	Tomato ketchup	2.6
White rice	24.7	Jam/marmalade/honey	8.1
White pasta, noodles and other grains	114	Nut or chocolate spreads	23.6
Beef, venison	11.6	Coffee, milky, latte, cappuccino	725
Stew and casserole	123	Wine	26.4
Chicken or poultry, grilled, roast	68	Beer, lager, cider	23.6
Bacon	1.6	Bananas	16.6
Sliced cold meats	33.0	Carrots	9.9
Full fat milk	189	Cabbage	6.1
High fat cheeses	40.0	Fresh/frozen peas	5.1
Egg - boiled, scrambled, omelette	24.7	Green, broad or runner beans	7.1
Salad cream, mayonnaise	14.0	Parsnips, turnips, swedes	5.1
Butter	0.6	Onions	4.4
Other vegetable oils	2.1	Garlic	1.3
Flapjacks, muesli bars, oatmeal cookies	25.7	Green salad	15.0
Chocolate snack bars	25.3	Corn	3.6
Sugar	25.0	Baked beans	13.4

Supplementary Figure 10.3c - Example of input information for a specific scenario



Participant 1, 19 years old, male, BMI = 21.8

PROVIDE FEEDBACK

ADVICE

SELECT PARTICIPANT ID

Hi Participant 1,

This is your personalised report.

The following messages present the most important diet changes recommended for you.

↓ RED AND PROCESSED MEAT

Your intake is VERY HIGH

- You are eating high amounts of red and processed meats.
- Based on your questionnaire, these are the food items that contributed the most to this component:
 1. Sliced cold meats (ham, turkey)
 2. Stew and casserole (meat and veg)
 3. Beef, venison (roast, steak, mince)
 4. Bacon
- Try to swap red meat with skinless chicken breast, oily fish such as salmon, turkey or legumes as they are all sources of lean protein. Swap processed meats, such as ham, with low-fat cheese in your sandwiches.
- Red and processed meats are high in saturated fat and have been linked to the development of heart disease, type 2 diabetes and some cancers.

Supplementary Figure 10.4a - Output online report for a specific scenario

↑ OILY FISH

Your intake is VERY LOW

- The amount of oily fish in your diet is low.
- Try to include a portion of oily fish, such as a salmon or fresh tuna, the size of a deck of cards in your weekly diet (e.g. instead of red meat for dinner) to ensure that you are meeting the minimum requirements.

- Adding more sources of oily fish into your diet will help to maintain healthy blood fat levels and prevent heart disease.

↑ FRUITS

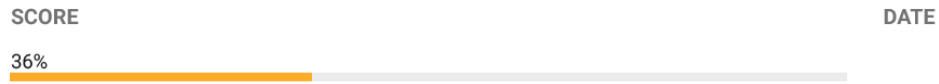
Your intake is VERY LOW

- You are not eating enough fruit.
- Add more fruits into your diet by having them as a snack (e.g. apples, pears, oranges, bananas, a handful of dried fruit) or with your meals, for example by having 3-4 dates with lunch or a cup of berries with breakfast.
- Diets that are high in vitamin-rich fruit may help improve your immune system, and may help to prevent the development of certain cancers and heart diseases.

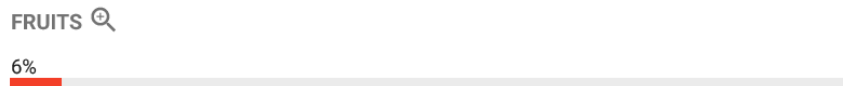
Supplementary Figure 10.4b - Output online report for a specific scenario

This section presents a summary of your progress. For each component, you receive a score between 0 and 100. Foods are divided into two groups: (1) recommended foods (the more the better, and (2) foods to limit (less is better). Your overall Healthy Eating Score is a combination of your scores from these two groups.

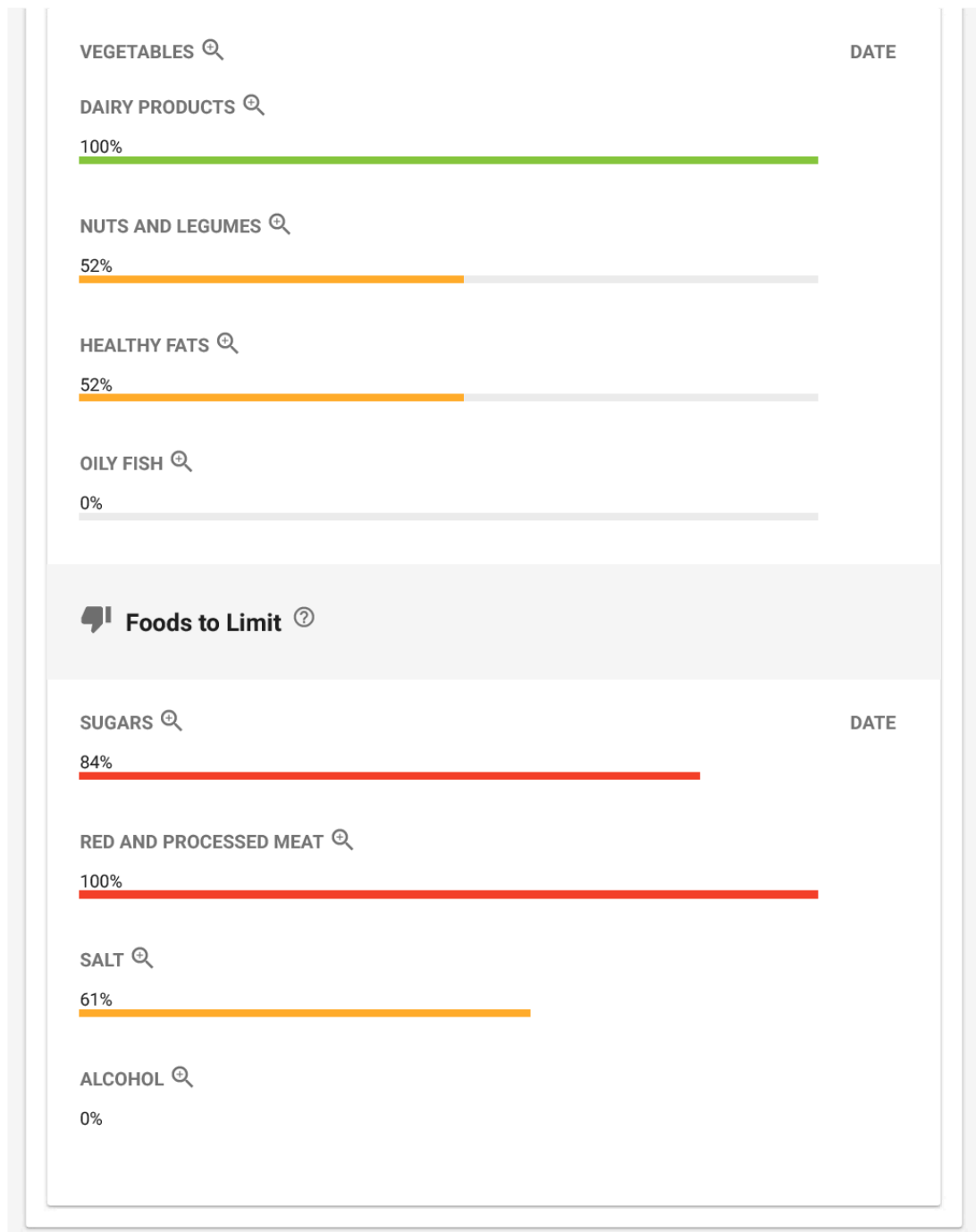
♥ Healthy Eating Score [?]



👍 Recommended Foods [?]



Supplementary Figure 10.4c - Output online report for a specific scenario



Supplementary Figure 10.4d - Output online report for a specific scenario

10.5 Protocol for the formative study interview

1. Take some time to look through the report and tell me your impressions of it.
 - a. Are there expressions or terms that you don't understand?
 - b. Do you have any questions about what the content means?
2. What type of food was you recommended to eat more of?
3. What type of food was you recommended to limit?
4. Does the report help you know how to change your diet to make it healthier?
5. Do you need additional to help you make changes to your diet at this moment?
6. Do you have any other comments regarding the feedback you received from the report?