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Determinants of consumer acceptance and use of personalized dietary advice: A systematic review

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ABSTRACT

Background: There has been growing attention towards personalizing dietary advice to the specific lifestyle, phenotypic and genotypic properties of consumers. Consumer acceptance and advice adherence is critical for the success of services offering personalized dietary advice. However, more insight is needed in the current body of knowledge on the determinants of consumer acceptance and use of personalized dietary advice.
Scope and approach: This literature review provides an overview of the current knowledge on consumer acceptance, use and effectiveness of personalized dietary advice based on the four information flow stages in personalized dietary advice: (1) information provision from consumer to formulate a personalized dietary advice, (2) personalized advice generation, (3) advice provision to the consumer, (4) advice acceptance and adherence.
Key Findings and Conclusions: Results show that the extent to which each step in the cycle is considered in the reviewed studies varies strongly, with most emphasis on the advice adherence, such as changes in dietary intake. In contrast, it is less clear how consumer data is used to generate a personalized dietary advice. Based on the studies in our review, we identify aspects that play a role in the consumer acceptance of personalized dietary advice and the best design practices for creating a successful personalized advice.

1. Introduction

Diet-related non-communicable diseases remain one of the major causes of illness, incapacitation, and death in high income countries (Huffman et al., 2010). Important causes of such diseases are one's diet and a lack of physical exercise (Branca et al., 2019). However, it has become increasingly clear that individuals differ in terms of health and subsequent dietary needs and that individuals show differential physiological responses to nutritional intake, making a personalized approach to initiate healthier dietary behavior an important way forward (Celis-Morales et al., 2015). However, giving personalized advice to a wide audience over a longer period of time is very labor intensive. This bottleneck can possibly be overcome by digitalizing the process of creating and giving personalized advice. The digitization of our society has made such data-driven personalized dietary advice increasingly feasible and implementable. Virtual health coaches on the internet are developed by commercial companies to compete with real-life dieticians and, as part of the Internet of Things (IoT) for health and nutrition (Boland et al., 2019), more and more dietary advice apps (e.g., FatSecret, Lifesum, MyFitnessPal) and hardware (e.g., Fitbit) are brought to the market. These technologies aim to help their users, among others, to select meals by providing feedback and advice based on general nutritional guidelines (e.g., recommended daily intake for fat or kcal), what a user likes to eat, or other personal information. For example, information-filtering technologies such as 'recommender systems' present personalized suggestions for food products or meals based on a person's past choices or preferences on a website (Freyne & Berkovsky, 2010; Starke, Trattner, Bakken, Johannessen, & Solberg, 2021).

However, most of these technologies are not yet personalized beyond allergies and daily intake levels, towards a broader range of a person's health needs or constraints (Musto et al., 2020; Tran et al., 2018). A future can be envisioned in which nutrition advice will be personalized based on more advanced health markers, along with personal preferences. Wearables and sensors can continuously measure personal health

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indicators (e.g., blood fat, glucose, blood pressure, etc.), physical activity, stress, sleep and food intake. Such personalization can benefit from the growing research attention towards personalizing nutrition advice to the specific lifestyle, phenotypic and genotypic properties of consumers. Much of this research has focused on finding genetic markers or other biological parameters relevant to personalizing one's diet (Gibney & Walsh, 2013; Reinders et al., 2020). For example, the potential of personalized dietary recommendations has been fueled by better insights into the relevance of genotypes in the nutrient and health research disciplines, such as the completion of the human genome project in the early 2000s (Collins et al., 2003). However, the actual knowledge needed to make personalized dietary advice a useful and accepted consumer tool (in the long-term) has been much scarcer and more scattered. It has indeed been recognized that more research is needed to provide better knowledge on how personalized dietary advice enables and motivates consumers to make lasting change to their diet (Mathers, 2019).

Consumer acceptance and advice adherence will, thus, be critical for the success of services providing personalized dietary advice. To further understand consumer acceptance, we need to first unravel what constitutes personalized dietary advice. The information flow in services or systems for personalized dietary advice typically consists of four consecutive stages forming a feedback loop (Berezowska et al., 2014), describing the relation between a service providing personalized dietary advice (e.g., a provider of a dietary advice app) and the user of that service. (1) An individual user first provides their information to a selected service in a format and through a service they prefer. (2) Then, this service processes this information to arrive at a personalized advice to maintain or adjust the current diet in a specific way, (3) which is then transmitted back to the user of the service. (4) In turn, the user receives the information and may or may not adjust their behavior accordingly. Subsequent changes in health status or dietary intake are then transmitted back to the service to check efficacy of the advice and create follow up advice (Fig. 1).

Although this loop includes all relevant stages, there is to date no overview on the current body of literature on how to optimize the different elements, nor the entire information flow with regard to supporting advice acceptance and adherence. Most technologies on the market (e.g., apps) typically do not consider the whole cycle and either focus on advice personalization (e.g., recommender systems) or on how advice should be framed based on personal information (cf., Musto et al., 2021). To provide much-needed knowledge on this topic, the current paper reviews the literature to present the current status quo across all four stages of the information flow: 1) What types of personal information were collected and what types were valuable as input? 2) How was the advice be prepared for use by the consumer? 3) How was the advice communicated to the consumer and how should it be communicated to maximize advice adherence? 4) What was the effect of the advice on the consumer, what behavioral changes did the consumer engage in once the advice has been received?

Based on the studies in our review, we identify aspects that play a role in the consumer acceptance of personalized dietary advice and what could be design practices for creating a successful personalized advice. In doing so, we show possible opportunities for personalized dietary advice.

2. Materials and methods

2.1. Selection criteria and search strategy

A series of steps were applied to ensure appropriate rigor and transparency in the review process (following Sargeant et al., 2006). Note that all authors of the manuscript were involved in at least one of the steps of the study selection process and were equally qualified to contribute.

First, we set the following three criteria through which we defined the query to identify studies in the scientific literature: (1) the study should involve some kind of personalization strategy (e.g., personalization, customization, tailoring) (2) the study should focus on dietary advice (e.g., diet, food, nutrition in combination with advice, guidance or consult), and (3) the study's outcome variable should be some kind of behavioral measure, either objectively measured or self-reported (e.g., choice, purchase, intention, acceptance, compliance, adherence). For each criterion, search terms consisting of several keywords were combined into a query. Two separate queries were specified in the syntax of two electronic databases (Web of Science and Scopus), to search in an article's topic, keywords, title, and abstract. Each query was limited to scientific articles written in English, published between 2000 and the time of the search (October 7, 2020). This latter was chosen to get an overview based on the latest and up-to-date scientific findings. The queries were tested and refined through several rounds of paper identification, and by running them in both electronic databases, until a manageable number of papers resulted, while simultaneously demonstrating face validity (i.e., important key papers in the area of interest were picked up by the search string used). See Appendix 1 for the query syntaxes used. The final search yielded 549 articles in Web of Science and 936 articles in Scopus. The retrieved articles were stored in Endnote, which resulted in 1,141 unique articles after removing duplicates.

2.2. Study selection

A protocol was developed to identify articles to be included in the review. First, articles were screened on title and abstract, based on a list with eligibility criteria for inclusion/exclusion. These criteria were evaluated in 'pilot runs', in which a subset of papers was randomly selected from the database and evaluated by each of the researchers involved in this task. Based on these pilot runs, the inclusion/exclusion criteria were refined and finalized, which led to a criteria list that was used for coding the abstracts and full papers (see Appendix 2). For example, one of the eligibility criteria was that studies should be focused on human nutrition and not on animal nutrition. If there was doubt whether to include a paper based on title and abstract, these papers were

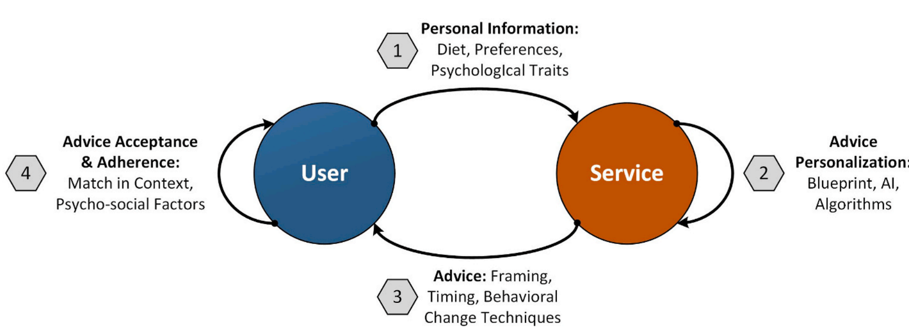

Fig. 1. Information flow in a service for personalized dietary advice.

included and taken to the next phase.

Five researchers were involved in screening titles and abstracts for inclusion/exclusion. Subsamples were created in such a way that each abstract was independently coded by two of the researchers. Disagreement between two coders on whether to include a paper or not was resolved through a discussion between them. This resulted in 154 articles (Fig. 2).

In the next phase, full-text articles were obtained for all remaining 154 articles after screening titles and abstracts. Special attention was paid to articles that already raised doubts during the abstract screening phase. Again, each paper was examined by two researchers. Three researchers were involved in coding full articles for inclusion/exclusion, according to a refined screening criteria list (see Appendix 3). Subsamples were created in such a way that a researcher had half of the articles in common with one researcher and the other half with another researcher. Disagreement on articles was resolved through a discussion between the two coders. Eventually 60 articles were retained for in-depth coding after screening the full-text articles.

2.3. In-depth coding and data synthesis

The key data from the 60 included articles were extracted and tabulated in a codebook, which was set up as a questionnaire in Qualtrics (see Appendix 4). The codebook was developed based on the research questions in close collaboration between two researchers. It was subsequently tested with seven papers (>10% of the total full-text sample) by these two researchers. Based on this pilot, disagreements in coding were resolved and necessary adjustments to the coding scheme were made. The coding of the seven pilot papers was then finalized, and the remaining papers were coded. The information extraction was conducted by three researchers.

Based on this final step of in-depth information coding, all 60 articles were coded. Three articles were deemed non-eligible, because of bad quality or non-representativeness. For example, one study reported a single-arm intervention that involved no personalization. Additionally, all non-empirical papers were excluded in this stage, such as systematic reviews, which resulted in the exclusion of another 11 articles. This left 46 papers remaining for data synthesis (see Fig. 2 for a flowchart of article exclusion). Due to the varied outcome measures and reporting of effect sizes, a meta-analysis was not appropriate, so a narrative synthesis was developed.

3. Results

3.1. Sample description

In total, 46 articles reporting a total of 47 studies were included in this review. Publication dates ranged from 2000 to 2020, with about two-thirds of the studies published after 2010 (see Table 1 for an overview of the main study characteristics). Most of the retained papers were from journals in the public health domain (n = 16), followed by papers in the domains of nutrition and dietetics (n = 12) and (health) psychology (n = 7). Table 2 reports the descriptive characteristics of the 46 articles in this review. In total, the studies were conducted in eight different countries. Striking is the high number of studies from The Netherlands, something that may be attributed to the fact that The Netherlands hosts several research groups that explicitly focus on the topic of personalized and tailored diet and health advice. Next to studies among the general public, studies involving disease-related (e.g., diabetes Type II) or demographically related target groups were most frequently reported. Most studies included multiple data collection waves, mostly two (i.e., a pretest-posttest design) or three waves (i.e., pretest - intermediate measurement - posttest). Similarly, most studies consisted of some kind of experimental design, with two or three experimental groups most reported (including a control group). Ten articles reported no comparison, often assessing different aspects related to personalized dietary advice. For example, Shoneye et al. (2020) presented a qualitative study in which the usability of a new digital weight management tool is examined.

3.2. Results on providing information to the service (stage 1)

Next, we describe the results of the literature review pertaining to the first of the four stages of the information flow process (see Table 3). Most information was obtained from the participants through self-reports (44 studies), mostly provided online (25 studies). Next to self-report, nine studies took physical measurements (blood samples, body weight, etc.). Harrington et al. (2019) was the only paper that also collected

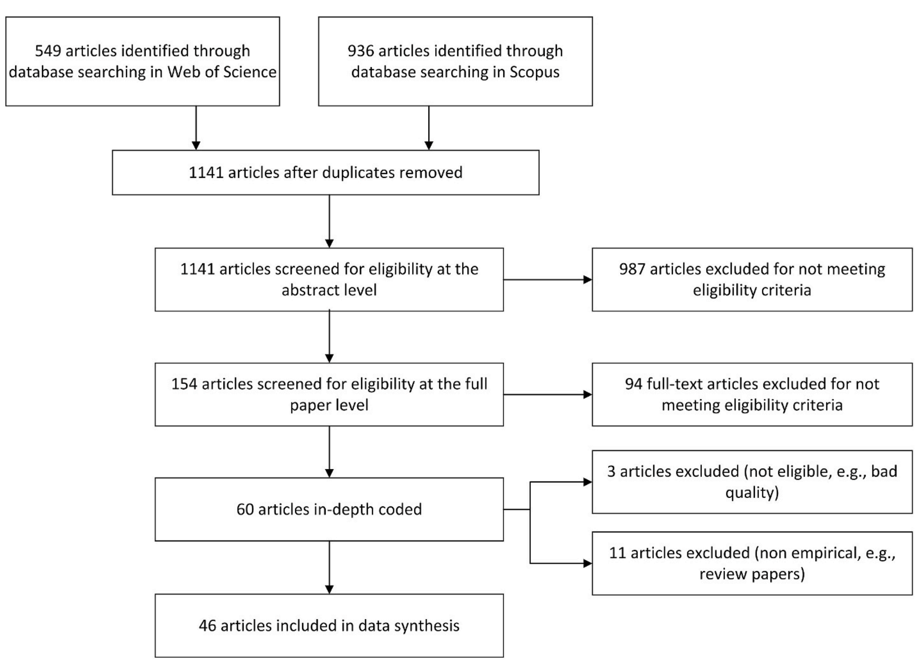

Fig. 2. Flow chart of the article selection for the literature review.

Table 1
Overview of included research articles. Sample Size denotes participants in the first wave of data collection and, if applicable and available, the last wave. *Note: Exp denotes whether the study involved a comparative study with personalized dietary advice and recorded advice adherence or acceptance (experimental design).*

Author	Year	Journal	Exp	Sample Size (1st; last wave)	Data Collected	Country of Data
Alexander et al.	2010	American Journal of Public Health	Yes	2513; 1788	2005–2006	United States of America
Allicock et al.	2010	Preventive Medicine	Yes	289; 195	2005–2006	United States of America
Anderson et al.	2001	Annals of Behavioral Medicine	Yes	296; 277	Unspecified	United States of America
Anderson et al.	2018	BMJ Open	Yes	78; 69	2015–2016	UK
Belot et al.	2020	European Economic Review	Yes	309	2016	UK
Berendsen et al.	2018	Nutrients	Yes	1141	2014	Unspecified
Berezowska et al.	2017	Psychology & Health	No	3453	2013	Unspecified
Berezowska et al.	2014	Public Health Genomics	No	124	Unspecified	Unspecified
Berezowska, Fischer & van Trijp[a]	2018	British Journal of Health Psychology	No	236, 242[a]	2015	Netherlands
Blalock et al. (2002)	2002	American Journal of Health Promotion	Yes	714; 547	Unspecified	United States of America
Block et al. (2008)	2008	Journal of Medical Internet Research	Yes	787; 549	2006	United States of America
Bouma et al.	2018	Patient Education and Counseling	Yes	204; 123	2011–2014	Netherlands
Campbell et al.	2004	Journal of Nutrition Education and Behavior	Yes	307	Unspecified	United States of America
Clark et al.	2004	British Journal of Health Psychology	Yes	166; 100	Unspecified	UK
De Vries et al.	2008	American Journal of Health Promotion	Yes	2827; 1331	Unspecified	Netherlands
Demark-Wahnefried et al.	2007	Journal of Clinical Oncology	Yes	543; 519	2002–2005	United States of America; Canada
Glanz et al.	2006	American Journal of Health Promotion	Yes	36; 33	Unspecified	United States of America
Hageman et al.	2014	International Journal of Behavioral Nutrition and Physical Activity	Yes	289; 272	2007–2010	United States of America
Harrington et al.	2019	JMIR Formative Research	Yes	496; 208	2014–2015	UK
Kegler et al.	2012	Progress in Community Health Partnerships	Yes	162; 90	Unspecified	United States of America
Khan et al.	2019	HealthRecSys (Conference Proceedings)	No	48	Unspecified	Unspecified
Kroeze et al.	2008	Journal of Nutrition Education and Behavior	Yes	442; 383	2003–2005	Netherlands
Mosca et al.	2008	Circ Cardiovasl outcomes	Yes	501	2005–2008	United States of America
Nielsen et al.	2014	Journal of Nutrigenetics and Nutrigenomics	Yes	149; 138	Unspecified	Canada
Oenema & Brug	2003	Preventive Medicine	Yes	298	Unspecified	Netherlands
Papadaki & Scott	2008	Patient Education and Counseling	Yes	72; 51	2003–2004	UK
Parekh et al.	2014	International Journal of Behavioral Nutrition and Physical Activity	Yes	4676; 3065	2008–2009	Australia
Parekh et al.	2012	International Journal of Behavioral Nutrition and Physical Activity	Yes	2306; 1711	2008	Australia
Rankin et al. (2018)	2018	Public Health Nutrition	No	9381	2013	Unspecified
Reinders et al.	2020	Plos One	No	1000	2016	Netherlands
Resnicow et al. (2008)	2008	Annals of Behavioral Medicine	Yes	504; 423	Unspecified	United States of America
Robb et al. (2010)	2010	Preventive Medicine	Yes	365; 234	2006–2008	UK
Ronteltap, van Trijp & Renes	2009	British Journal of Nutrition	No	438	2006–2007	Netherlands
Shoneye et al.	2020	JMIR Mhealth and Uhealth	No	56	2016	Australia
Siero et al.	2000	Health Education Research	Yes	230	Unspecified	Netherlands
Smeets et al.	2007	Annals of Behavioral Medicine	Yes	2827; 2160	Unspecified	Netherlands
Springvloet et al.	2016	Appetite	No	1349	2012–2013	Netherlands
Storm et al.	2016	Journal of Medical Internet Research	Yes	790; 121	2014–2015	Germany; Netherlands
Stubbins et al.	2018	JCO Clinical Cancer Informatics	No	33; 25	Unspecified	United States of America
Swobodaa et al.	2017	Patient Education and Counseling	Yes	54	2014–2015	United States of America
Torrado et al. (2015)	2015	Nutricion Hospitalaria	Yes	99	2012–2013	Spain
Vandelanotte et al.	2007	Annals of Behavioral Medicine	Yes	567+; 392	Unspecified	Belgium
Vandelanotte et al.	2008	Preventive Medicine	Yes	767; 567	Unspecified	Belgium
Walthouwer et al. (2015)	2015	Journal of Medical Internet Research	Yes	1419; 1015	2012–2013	Netherlands
Wipfli et al.	2019	Safety and Health at Work	Yes	134	2014	United States of America
Wright et al. (2011)	2011	International Journal of Behavioral Nutrition and Physical Activity	Yes	178	2002–2003	Australia

[a] This research article comprised two studies that were coded for the review.

observational data, namely food purchase data obtained from the supermarket loyalty card database.

In 38 studies, the type of data that was obtained from the participants was food or nutrition data, from which general food intake (n = 21), for instance measured by the Food Frequency Questionnaire, and fruit and vegetables intake (n = 19) were reported most frequently. Another substantial number of studies reported health data (n = 30), predominantly related to weight (BMI; n = 25). Nielsen et al. (2014) was the only study in our sample that obtained genetic data from participants. Notable was that none of the studies recorded any data on allergies or any other ingredient- or nutrient-related dietary constraints, even though this has become a more common feature in meal-planning apps (Grifantini, 2016).

Sixteen studies included lifestyle data, such as data on physical activity, general eating habits and dietary-related lifestyle (e.g., vegetarianism). Psychological data was also frequently recorded (n = 35), with self-efficacy (n = 21) and stages of change (n = 18) clearly being most popular amongst a plethora of different psychological variables recorded. On top of that, nearly all studies (n = 41) included demographics, with age, gender and education being the most frequently reported variables.

The majority of the studies collected information from the participants at baseline, as basis for personalized feedback and advice. Only a few studies collected participant's information merely as background information used to describe the sample or as variables in a hypothetical model. To give an example of the latter, Berezowska et al. (2017) did not collect data from participants to obtain a personalized advice since participants were presented with fictitious personalized nutrition services to reflect on. Instead, they measured two types of motivation to incorporate as predictors in a quasi-experimental design. In addition, in

Table 2
Sample characteristics of the 46 papers, reporting on 47 studies in 8 high-income countries.

Sample Characteristic	Specification	Number of studies
Target population[a]	Age-related	11
	Disease-related	13
	General public	13
	Non-representative sampling (convenience)	6
	Other Demographic-related targeting	12
	Other	2
Country[a]	Australia	4
	Belgium	2
	Canada	2
	Germany	1
	Netherlands	13
	Spain	1
	United Kingdom	6
	United States of America	15
	Unspecified	5
Type of data collected[a]	Behavioral data	38
	Opinion data	31
	Physiological data	9
	Other	3
Number of Data Collection Waves	0 Waves (i.e., No intervention)	2
	1 Wave (i.e., Single Measure)	6
	2 Waves (i.e., pretest-posttest)	19
	3 Waves (i.e., pretest-measure-posttest)	14
	4 Waves (i.e., pretest-2 measures-posttest)	6
Design: Number of Experimental Groups	0 (No intervention)	3
	1	6
	2	18
	3	11
	4	4
	6	4
	8	1
Design experimental interventions	Observations/none/all participants received same intervention (incl. repeated measures)	10
	Randomly-assigned experimental design	30
	Stratified experimental design	7
Design control groups	Benchmark to best practice (including non-tailored approaches)	20
	No comparison (of experimental groups or baseline)	10
	Placebo or non-intervention (negative control)	17

[a] Some studies were conducted in more than one target group or country or collected several types of data.

some studies it was unclear to what extent the collected information from participants was used as input for the tailored intervention (e.g., Demark-Wahnefried et al., 2007).

3.3. Results on processing data to generate advice (stage 2)

For the second stage in which data is processed and the advice is being prepared for use by the consumer, almost half of the studies (n = 19) either did not specify how that advice is accomplished (n = 14) or described how the generation of advice was achieved through a fictitious service (n = 5; see Table 3). Furthermore, another 21 studies used a type of blueprint or template with threshold values based on which some advice was derived. In four studies, the advice was generated manually. For example, in Bouma et al. (2018) the advice was generated by professional counsellors during special sessions. Only three studies used computer-based algorithms to generate the advice, although in all three instances, these were not self-learning algorithms, but rather off-the-shelf personalization technologies (e.g., recommender approaches in Khan et al., 2019) or a more constraint-based approach, in which dietary advice was based on health requirements (e.g., Kroeze et al., 2008). For example, in the study by Belot et al. (2020), participants were provided with personalized health information via an adapted version of a computer-based health assessment tool called ‘Your Disease Risk’ (YDR). Khan et al. (2019) involved a procedure to extract food features from recipes. They presented a set of so-called ‘recommender approaches’ for personalized advice, for which more advanced algorithms were more successful in terms of predictive accuracy and user preferences. Among these three studies, only Khan et al. (2019) provided sufficient details to reproduce the preference-based approach, while the other studies were less transparent.

Table 3
Overview of how information was transferred to the service, what types of data were collected as well as how the advice was personalized towards the consumer. *Data were either used by the service to personalize advice or as outcome variable in the study. Note that the category totals exceed the number of studies examined, because some studies had mixed methods or multiple measures.*

Category	Factors	Number of Studies
Method of data collection	Self-report, using the following means of communication:	44
		25
	- Online	8
	- Face to face self-report	6
	- Phone	12
	- Written	
	Observational	1
	Physical Measurements	9
Food (nutrition) data (n=38)	Fruits and vegetables	19
	General food intake (e.g., FFQ)	21
	Specific nutrients	10
	Other	5
Health (physiological) data (n=30)	Blood pressure, heart rate	3
	Blood samples (e.g., glucose)	3
	Cholesterol	3
	Genetics (DNA)	1
	Medical conditions/history	2
	Subjective health status	6
	Weight/BMI	25
Lifestyle data (n=16)	Dietary-related lifestyle (e.g., vegetarian, religion)	4
	Food choice motives	3
	Physical Activity	14
	Smoking	2
	Other	4
Psychological & behavioral data (n=35)*	Attitude	3
	Emotions & Depression	3
	Intention	3
	(Intrinsic) motivation	6
	Knowledge Level	4
	Perceived Barriers	6
	Perceived Intake	5
	Planning	2
	Regulatory focus (promotion/prevention)	4
	Self-efficacy	21
	Self-regulation	5
	Social Influence & Support	7
	Stages of change	18
	Other	4
Demographics (n=41)	Age	39
	Gender	36
	Education	34
	Employment	19
	Ethnicity	15
	Household size	6
	Homeownership	2
	Income	9
	Living Area/Region	3
	Marital Status	16
	Other	1
How was the content personalized?	Blueprint/Template	21
	Computer-based algorithms	3
	Manual	4
	Fictitious service	5
	Not specified/Not applicable	14

3.4. Results on communicating advice to users (stage 3)

Most studies provided information on the third stage (see Table 4), that is how the advice was communicated to the users of that advice. Our review showed that most studies involved services that provided both feedback and associated advice (n = 31). A small number of studies supplied *only* advice (n = 6) or provided *only* feedback on a participant's personal progress (n = 2). Eight studies did not involve an intervention where a nutrition service produced personalized feedback or advice. Instead, this would entail, for example, fictitious descriptions of services that provided personalized dietary advice (e.g., Berezowska et al., 2017), or qualitative studies in which the adoption intention of general personalized nutrition services or dietary self-assessment tools was examined (e.g., Swoboda et al., 2017). Among them, Glanz et al. (2006) conducted a pilot study with hand-held computers before smartphone-enabled apps were on the market, that enabled real-time recording and immediate, automated feedback. Their system allowed for easy data transmission for central monitoring of dietary compliance. Moreover, the system had an easily adaptable database and high potential for individual tailoring of feedback.

Most of the studies reported that the advice was communicated by a university or a research institute (n = 37), followed by a healthcare institute (including general practitioners; n = 7). The delivery methods of the advice varied between studies, with online services (websites and apps; n = 21) and advice on paper (n = 17) standing out. The format of the advice was written advice in most studies (n = 35), followed by spoken advice (e.g., through telephone or personal consults; n = 13) and advice in the form of graphics (n = 10). A substantial number of studies offered a personalized advice in a mixed or multi-modal format (n = 18), such as by combining graphics and written text or spoken and written text. In many studies, the advice was given in specially designed sessions, either online or in real-life. In addition, some studies also reported the location of where advice was provided. In 15 studies, this was in a home context, while in 11 studies advice was provided at a doctor or a dietician.

The importance to adapt the design format of the delivered advice to the context of the target group was stressed by the study of Wipfli et al. (2019), which reported an intervention conducted in a specific work environment, namely that of truck drivers. The success of the intervention was in part attributed to its delivery format, namely as a mobile intervention service. This made it easy to collect logs and to allow participants to monitor their progress, which could support behavioral change.

Finally, we analyzed the behavioral change techniques used in communicating the advice. In total, 40 studies used one or more techniques. Most studies (n = 28) used personal goal-setting as communication technique for the advice, whereas another 22 studies used feedback and monitoring in supporting the implementation of the personalized dietary advice. Other less frequently used techniques are: shaping knowledge (n = 12), providing information about consequences (n = 8), social support (n = 5), comparison of behavior (n = 5) and self-belief (n = 5). While some other behavioral change techniques barely appeared as communication strategies among the studies (e.g., reward and threat, associations), many studies used combinations of, or multiple techniques in the same study (see Table 4 for an overview of advice communication).

3.5. Results on adhering and accepting of advice (stage 4)

For the fourth stage, i.e., users' adherence to the personalized advice, several studies measured either consumers' attitudes/evaluation of the advice (n = 14), perceived benefits of the advice (n = 10) or intention to use the advice (n = 10). Most studies (n = 37) measured one or more changes in behavioral health status. In most cases (n = 33), changes in dietary intake were reported, followed by changes in weight (n = 11) and physical activity (n = 9), although the latter strictly spoken is

Table 4
Overview of how the advice is communicated to users in services for personalized dietary advice.

Category	Factors	Number of Studies
What information is provided to the consumer?	Feedback and advice	31
	Only advice	6
	Only feedback	2
	Not applicable	8
Who is the advice responsible?[a]	Commercial Party	2
	Healthcare/GP	7
	University/Research Institute	37
	Other	2
	Not specified/applicable	5
Who is giving the advice?	Government Institute	1
	Healthcare/GP	14
	University/Research Institute	26
	Not specified/applicable	6
How is the advice communicated/delivered?[a]	In person, face-to-face	11
	On paper	17
	Telephone contact	6
	Via email	6
	Website, app or other online service	21
Format of advice[a]	Graphics	10
	Spoken	13
	Video	4
	Written	35
	Unknown	1
Location of advice[b]	At a doctor/dietician/university/hospital/public location	11
	At home	15
	At work	3
	Undefined	16
Which Behavioral Change Techniques have been used?[a]	Comparison of behavior	5
	Comparison of outcomes	3
	Construal Level Theory	2
	Feedback and monitoring	22
	Goals and planning	28
	Information about consequences	8
	Regulation	3
	Repetition and substitution	4
	Self-belief	5
	Shaping knowledge	12
	Social support	5
	Other	4
	Not applicable	8
What was measured in terms of advice adherence?[a]	Attitude & evaluation	14
	Intention	10
	Observed Use	3
	Perceived Barriers	3
	Perceived Benefits	10
	Perceived Risks	4
	Self-reported Use	3
	Other	2
What was measured in terms of changes in health status?[a]	Blood Fat or Sugar	3
	Blood Pressure	3
	Dietary Intake	33
	Physical Activity	9
	Weight	11
What was measured in terms of changes in psycho-social states and factors?[c]	Attitude	5
	Health Expectations	2
	Intention	5
	Knowledge	5
	Perceived Risks & Barriers	4
	Self-efficacy	5
	Stages of Change	4
	Other	2

[a] Adds up to more than 47 studies, as several studies used more than one approach. Nonetheless, some categories still did not apply to specific studies, such as 'location of advice' for feedback-only studies.

[b] Adds up to less than 47 studies, as multiple studies did not provide advice, but e.g., only feedback.

[c] Adds up to less than 47 studies as not all studies reported such a change.

unrelated to personalized nutrition. Most studies showed positive behavioral effects of personalized advice. Examples include improved levels of dietary components like fat or fiber, or increased consumption of healthy foods like fruits and vegetables.

Some studies also recorded cognitive changes in psycho-social states and factors before and after the intervention. These comprised changes in (indicators related to) attitude, knowledge, intention, self-efficacy, stages of changes or perceived benefits and risks (for a detailed list, see Table 4).

In addition, we specifically examined which outcome variables were impacted by personalized dietary advice interventions for the 36 studies in this review that performed a comparative study. These outcome variables included physiological indicators, dietary intake (i.e., food and

Table 5
Selection of the most important outcome variables affected by providing personalized dietary advice (after the specified intervention time), either in a single-arm design or compared to a baseline.

Author	Physical activity	Weight loss	Blood Levels	Fruit & Veg	Food Intake	Kcal	(Sat) fat	Fiber	Other Nutrients	Self-efficacy	Other Eval. & Psycho-social
Alexander et al.				X							
Allicock et al.				X							
Anderson et al. (2018)	X	X	Pressure (X)				X				Satisfaction (X)
Anderson et al. (2001)				X			X	X		X	Outcome Expectations (X)
Belot et al.						X		X			Risk Belief (X)
Berendsen et al.				X	Healthier (X)		X	X			
Blalock et al. (2002)	0								Calcium (X)		Stage of Change (X)
Block et al. (2008)										X	Mental Health (X), Quality of Life (X), Stage of Change (X)
Bouma et al.	X			0							
Campbell et al.				0			0			X	Knowledge (X)
Clark et al.	X	X									
De Vries et al.	X			X			X				
Demark-Wahnefried et al.	X	X	Sugar (X)	X			X				Quality of Life (0)
Glanz et al.							X	0			
Hageman et al.		X	Pressure (X)	X			X				
Harrington et al.				0			0		Salt (0), Sugar (0)		Stage of Change (0)
Kegler et al.	0	0		0	Healthier Available (X)						
Kroeze et al.						X	X				
Mosca et al.	X	0	Sugar (X); Fat (0), Pressure (0)				0		Protein (0)		
Nielsen et al.											Favorable Perception (X)
Oenema & Brug											Intake Intention (X)
Papadaki & Scott			Fat (X)	X	Alcohol (X), Healthier (X), Legumes (X)						
Parekh et al. (2014)	0	0		X	Alcohol (X), Fish (X), Healthier (X)						
Parekh et al. (2012)	0	0		0	Fish (X)				Salt (X)		
Resnicow et al. (2008)				X							Intervention Satisfaction (0)
Robb et al. (2010)	0			X							
Siero et al.											Stage of Change (X)
Smeets et al.	0			X			X				
Storm et al.	X			X						X	
Swobodaa et al.					Healthier (X)					X	
Torrado et al. (2015)		X									
Vandelanotte et al. (2007)	X						X				
Vandelanotte et al. (2008)	X						X				
Walthouwer et al. (2015)	0	X				X					
Wipfli et al.	0	X		X							
Wright et al. (2011)				X			X				

Note: Included are physiological and psychological changes, and changes in dietary intake. 'X' indicates a significant change in the outcome variable, '0' indicates a null result. Names of food groups and nutrients indicate changes in intake. In some columns, the name of an outcome variable is specified with an associated significant change (X) or not (0).

nutrients), and psycho-social states and factors (see Table 5 for details). Although the personalized advice interventions led to statistically significant changes for the majority of examined outcome variables, such as fruit and vegetable consumption and fat intake, there were some mixed findings. Especially in relation to weight loss as outcome variables, several studies reported null results (Kegler et al., 2012; Mosca et al., 2008; Parekh et al., 2012, 2014).

A notable difference between studies is the number of recorded variables. Whereas some studies only examined a user's evaluative response to using a personalized advice service (Nielsen et al., 2014; Oenema & Brug, 2003), other studies recorded possible changes in a plethora of indicators, related to physiology, dietary intake and a participant's evaluation (e.g., Demark-Wahnefried et al., 2007).

4. Discussion

4.1. Discussion of findings pertaining to the four stages of the information flow process

In the current systematic literature review on the consumer acceptance of personalized dietary advice, we summarize the current status quo of research addressing the four central stages of the information flow process:

1. Information provision from a user to a personalized nutrition service
2. Personalized advice generation
3. Advice provision to users
4. Advice acceptance and adherence

The extent to which each step in the information flow cycle is highlighted in the reviewed studies varies strongly. Regarding the first stage, studies are clear on *what data is provided from a user to a service providing personalized dietary advice*. Most studies rely on self-reported data that is collected, most of the times in traditional surveys. This may prove to be problematic as self-reported measures possibly introduce false-positive findings due to social desirability or memory bias, as shown previously by Eyles and Mhurchu (2009) in a review. When relying on such self-reports, it is important to design short questionnaires when obtaining information from consumers. This is supported by findings of Demark-Wahnefried et al. (2007), who showed that intervention participants considered brief interim surveys that specifically assessed progress in selected behavioral domains more helpful than long, standardized surveys used. Technology-based methods may help to improve the data accuracy of self-reported dietary assessments (Brouwer-Brolsma et al., 2020; Lucassen et al., 2021).

Only a few studies have been found to depend on observational data. This may be due to the complexity of collecting such data. This could change rapidly, however, as ubiquitous smartphone technologies, sensing technologies (e.g., health trackers) and other information technologies (e.g., loyalty card data, retail online shopping platforms tracking your shopping card) increasingly offer many opportunities to collect observational data alongside the 'traditional' self-reported measures that were used in most of the studies reported in this review. In the future, these may even be triangulated with physiological data; this combination was hardly present in our sample.

Although the reviewed studies are clear on what data is collected from consumers, it is less clear *how such data is used to generate a personalized dietary advice*. Several studies focused on tailoring but not on personalization. Tailoring does not really represent personalized advice in terms of combining and weighting different personal characteristics, but involves the limited adaptation of advice according to some threshold levels. For example, in the study by Oenema and Brug (2003), feedback was given based on whether someone's computed fat score exceeded the average fat score of others of the same age and sex. But maybe more importantly, in a significant number of studies claiming to generate personalized advice, the personalization procedure is rather opaque. Therefore, it is hard to assess the quality of any claims based on the connection between personalization approaches and changes in, for example, nutrient intake, fiber or other outcomes. This applies less to the reviewed studies that rely on algorithmic approaches, although only Khan et al. (2019) mentioned the details.

Regarding the third stage, *communication of the advice to the user*, we observed that interventions incorporating behavioral change techniques showed to be effective ingredients to achieve changes in dietary intake (Berendsen et al., 2018). For example, personalized feedback and advice are more effective when taking an individual's stage of change (Siero et al., 2000; Vandelanotte et al., 2008), self-efficacy (Springvloet et al., 2016; Storm et al., 2016) and motivation (Berezowska et al., 2017) into account. Also, feedback and advice based on personal goals or specific (food-related) behaviors tend to be more effective than providing general information (Parekh et al., 2012). However, only a relatively limited set of behavioral change techniques are used in the studies covered in this review. Most studies used 'personal goal setting' and 'feedback and monitoring' as behavioral change techniques. These findings are in line with what is observed in a recent review by Ronteltap et al. (under review), who found that goal setting was the most frequently applied behavioral change technique in e-health interventions targeted at individuals with a lower socioeconomic position. Taken together, these findings imply that a relatively narrow scope of techniques was used in communicating personalized advice, from the broad range of available techniques (e.g., as specified by Michie et al., 2011). As other behavioral change techniques could add to the effectiveness of personalized dietary advice, we recommend future studies to incorporate a broader range of behavioral change techniques and look for potential synergies by combining different behavioral change techniques.

Finally, in relation to *advice acceptance and adherence*, we found a differential uptake of and adherence to the personalized advice, depending on a range of underlying factors. These factors included, for example, the fit between the advice and the communication towards the consumer and the behavioral change techniques that were used (see previous paragraph), but also the context where this communication takes place. The consumer's daily context determines whether the advice will be accepted and adhered to.

Furthermore, this review shows that it is hard to tease apart which aspects of the interventions were successful in triggering change. Several studies reported interventions where multiple elements were changed simultaneously. For example, one study reports the combined effect of phone support combined with a personalized nutrition advice (Allicock et al., 2010). Hence, we agree with the studies in our review, such as De Vries et al. (2008), that concluded that more research is needed to better understand the individual parameters that limit the differential effectiveness of personalizing nutrition and to identify those variables upon which it is most important to tailor or personalize. On top of that, we argue that more attention needs to be paid to long-term behavior change. In that respect, results in the reviewed studies were mixed. For example, whereas Campbell et al. (2004) observe positive effects of a tailored intervention on one's self-efficacy related to healthful eating, these positive effects dissipate after one or two months. This suggests that (continued) salience and attention may play a key role in changing behavior that is habitual in nature. Broekhuizen et al. (2012) suggested that repeated feedback moments throughout a prolonged intervention period may be needed to improve effects beyond the short term. On the other hand, Vandelanotte et al. (2007) showed that personalized computer-tailored feedback can maintain long-term effects, up to two years after the intervention, on both physical activity and fat intake.

The reviewed papers thus show initial evidence in all four stages of the information exchange between consumers and services providing personalized dietary advice as identified by Berezowska (2014), but substantial further knowledge is needed. Even though we found some mixed effects of personalized dietary advice interventions over a longer period, the need for further research may be even more important as it is not clear to what extent the positive results in many studies are simply due to study participation. Stated differently, the effects could be due to simply paying more attention to the intervention groups in which some form of personalization was implemented, as compared to the control groups that were used in the studies in our review; this effect would entail some kind of Hawthorne effect (Sedgwick & Greenwood, 2015). Several studies, on the other hand, have compared their approach against a relevant benchmark or a placebo suggesting there is at least some real effect.

In a similar vein, the study design may also play a role in the effectiveness of the studies. In that respect, Broekhuizen et al. (2012) state that it remains unclear whether the effect of tailored interventions is caused by tailoring as such or by the fact that the communication in tailored interventions is more likely to be carefully designed (e.g., based on behavioral theory), and hence it is the communication quality rather than the advice itself that makes the difference.

Given our mixed findings about success of services providing personalized dietary advice, we should keep in mind that the findings we could identify may in fact be more pronounced than justified, as publication bias may have played a role in suppressing null findings. Put differently, publication bias leaves interventions that are less effective often unpublished, but can also have resulted in an over-assessment of the efficacy of the used interventions as their failed application is not published either (Easterbrook et al., 1991).

4.2. Implications for consumer acceptance of personalized dietary advice

Based on the current review, combining the four stages of the information flow process, we can raise five aspects that play a role in the consumer acceptance and enduring adoption of personalized dietary advice.

First, services targeting efficacy beliefs and expected outcomes are more likely to be accepted. For example, feedback that compares daily intake allowances to relevant peer groups are evaluated more positively than general information (Oenema & Brug, 2003), just as goal-based feedback, combined with psychosocial tailoring (Papadaki & Scott, 2008). Acceptance can be enhanced by making benefits tangible (e.g., placing health effects as close in time as possible, Berezowska et al., 2018) and accounts for attributes that reduce privacy risk perception (e.g., trustworthy expert advice providers, Berezowska et al., 2014).

Second, the design of the service that provides the personalized dietary advice plays an important role. For example, Alexander et al. (2010) show that a service's website should be well-designed and appealing to retain participants. Being able to ask for real-time feedback, while having access to different health indicators, increases the likelihood that people adhere to health goals (Stubbins et al., 2018). Services that combine computer-based feedback and real-life contact with a dietitian or coach further positively affect the acceptance (Wipfli et al., 2019). On the other hand, poor service design might put off users of a service offering personalized dietary advice. Engagement with (only) remotely delivered digital behavior change interventions is low (Harrington et al., 2019), and the (perceived) effort that must be put in the service has a demotivating effect (Campbell et al., 2004) just as the perceived complexity of using the system providing the personalized dietary advice (Glanz et al., 2006).

Third, studies show that consumers differ in their receptiveness to personalized dietary advice. For example, considering a consumer's state of change, attitude towards engaging in healthy behavior, and self-efficacy can lead to a higher acceptance rate of tailored feedback and advice (Smeets et al., 2007). Consequently, personalized nutrition services should be tailored to the needs of specific consumer segments to enhance advice adherence.

Fourth, environmental factors play an important role for personalized advice adherence (Springvloet et al., 2016). In this respect, consumers report that their everyday routines or family commitments are barriers to dietary changes and uptake of personalized dietary advice (Anderson et al., 2018; Reinders et al., 2020). Targeting not only the recipient of the advice but also the meal preparer and/or food shopper as the primary change agent may be a more efficient approach for changing the home environment (Kegler et al., 2012). In this sense, personalized advice should also consider the role of meal moments in consumer acceptance (Reinders et al., 2020), as well as who is present along with the advice recipient when consuming a meal. For example, the importance of family support for advice uptake is also shown in a few of the reviewed studies (e.g., Hageman et al., 2014; Kegler et al., 2012).

Fifth, next to initial acceptance, continued use of personalized dietary advice and lasting change of habitual behaviors are important. In that respect, continued salience and attention may play a key role (Belot et al., 2020). Clark et al. (2004, page 375) emphasize the centrality of this kind of lasting acceptance by stating that: "Maintenance of behavior change should be conceptualized as a process in itself rather than merely as the last step in the behavior change process, with a shift in focus to include not only relapse prevention but also importantly, relapse management." Automatization of measurements also helps: measurement of outcomes (e.g., food purchasing behavior) using loyalty card data can lead to high retention rates (Harrington et al., 2019); real-time monitoring and feedback can increase the effectiveness of a personalized nutrition service (Stubbins et al., 2018).

4.3. Implications for technological implementation of personalized dietary advice

If we consider the technological implementation in the personalized advice generation stage, this review shows that a lot of ground still needs to be covered. Only a few studies have included some form of artificial intelligence to personalize their health-based interventions. Consequently, advice is often provided in a labor intensive, offline manner and most studies could only give advice on a few moments. To fulfill the potential of relevant, timely, and continuously updated nutrition advice, it is thus not only essential that an individual is monitored by health trackers and other services that collect information about a consumer, but also that this information is integrated, and feedback is communicated more often than we have found in the current sample of studies. Only three studies, of which two were conducted recently, have included algorithms to personalize their advice, of which none are self-learning (i.e., Belot et al., 2020; Khan et al., 2019; Kroeze et al., 2008). This seems to be a long way from the predictive modelling on individual responses to food and nutrient intake. However, given the rapid development of machine learning, this may change in the near future.

In terms of learning as a community, it is problematic that most studies in this review have provided few details on how the advice is personalized. In many of the interventions that involve a dietitian, the advice generation step remains a black box and is, assumedly, based on the experience level of a dietitian rather than evidence-based knowledge rules. The use of such tacit instead of explicit knowledge is, however, an important problem to those who aim to develop personalized interventions based on machine learning using health markers and food intake data (Shamanna et al., 2020). We posit that an important step towards capturing a dietician's knowledge in an algorithm is needed, in terms of how different categories and factors should be weighted when generating advice; noting that contact with a dietitian is often experienced as valuable in dietary interventions (Wipfli et al., 2019). Moreover, we also envision that it would be valuable to include communication techniques in the advice to a consumer. For example, personalized dietary advice that emphasizes certain aspects or frames information in a specific way that is more effective for a specific person than presenting the advice 'neutrally'. Consequently, the communication presentation may need adjustments based on the consumer characteristics (Ronteltap, van Trijp, & Renes, 2009). For example, Berezowska et al. (2017) suggests that personalized dietary recommendations take one's level of self-determination into account. For individuals with high levels of autonomous motivation, i.e., the decision to eat healthy is self-determined, the communication of the advice should focus on the benefits; while for individuals with high levels of controlled motivation, i.e., related to negative behaviors such as shame and quilt, risk-related issues should be emphasized. Design features like interface and graphics certainly also play a role here, as shown in other personalized advice domains (Starke, Willemsen, & Snijders, 2021). Future studies could pay more attention to these design aspects of the delivered personalized advice, also in relation to specific contexts and target groups.

4.4. Limitations and conclusion

As with all systematic reviews, the scope of the identified articles depends on the query used and the databases searched. We consulted broad electronic literature databases (Scopus and Web of Science), but that may still have resulted in missing specific niche outlets, particularly conferences, gray literature, and industrial reports which may report some recent developments. The latter may be a particular omission, as developments in personalized advice research are often also industry-based (Tran et al., 2018). In addition, by limiting ourselves to high income countries and, for practical reasons, literature in the English language we may have missed some relevant papers.

Nevertheless, we argue the gist of the findings is very similar across the identified papers and our main conclusions remain that for the further development of services offering personalized dietary advice:

(1) Each of the stages of the feedback loop needs to be further studied and effects of different simultaneous factors should be disentangled.
(2) The connection between the stages should be studied more frequently and these connections should be reported in a more transparent way, containing all details about the personalization process.
(3) The potential of data technology and machine learning should be better utilized in personalized dietary advice interventions. Feeding the tacit knowledge and blueprints used by current dietitians into such algorithms could speed up development of truly real-time, online, timely and relevant personalized nutrition services.

Declaration of competing interest

The authors report there are no competing interests to declare.

Data availability

No data was used for the research described in the article.

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Appendix 1. Search criteria and strings used in Web of Science and Scopus

Web of Science

Constructs	Search terms
Personalization	AB=((Personali* OR customi* OR tailor* OR segment*) NEAR (method* OR strategy OR procedure OR technique OR means OR process OR implement* OR practice))
Dietary advice	AB=(Diet* OR Nutrition OR Food OR meal) AND AB=(advice OR guidance OR consult* OR recommend* OR regimen OR strategy OR intervention)
Behavioral measure	AB=(choice OR motiv* OR purchase OR orientation OR selection OR intention) OR AB=(Acceptance OR compliance OR adherence OR follow-up OR follow up OR adoption OR uptake)

Scopus

Constructs	Search terms
Personalization	ABS(Personali* OR customi* OR tailor* OR segment*) W/15 (method* OR strategy OR procedure OR technique OR means OR process OR implement* OR practice)
Dietary advice	TITLE-ABS-KEY(Diet* OR Nutrition OR Food OR meal) AND (TITLE-ABS-KEY(advice OR guidance OR consult* OR recommend* OR regimen OR strategy OR intervention)
Behavioral measure	ABS(choice OR motiv* OR purchase OR orientation OR selection OR intention) OR ABS(Acceptance OR compliance OR adherence OR follow-up OR follow up OR adoption OR uptake)

LANGUAGE(English) AND PUBYEAR >2000 AND (ABS(Personali* OR customi* OR tailor* OR segment*) W/15 (method* OR strategy OR procedure OR technique OR means OR process OR implement* OR practice)) AND (TITLE-ABS-KEY(Diet* OR Nutrition OR Food OR meal)) AND (TITLE-ABS-KEY(advice OR guidance OR consult* OR recommend* OR regimen OR strategy OR intervention)) AND (ABS(choice OR motiv* OR purchase OR orientation OR selection OR intention OR Acceptance OR compliance OR adherence OR follow-up OR adoption OR uptake)).

Appendix 2. Eligibility criteria for article selection based on abstracts

Code	Explanation	Exclude if	Do not exclude if
(1) Duplicate	Article is a duplicate of an article encountered above	Scopus and Web of Science have different ways of dealing with special characters (ö etc.).	
(2) Lookup	Article does not provide an abstract	Editorials; retractions; comments; errata	

(continued on next page)

(*continued*)

Code	Explanation	Exclude if	Do not exclude if
			No exclusion – but end of coding at this stage as we have agreed not to judge on title alone
(3a) Scientific journal paper	Article is not a scientific paper	Article is conference paper Article is book chapter	
(3b) No English	Abstract/article is not in English	Abstract is not in English	
(4) No western study	Only studies conducted in western countries	Exclude papers with studies performed in: Non-western countries (see CBS list in Appendix and Indonesia + Japan) Low-income countries	Include papers when: - Western countries (not included in CBS list, with exception of Japan and Indonesia) - Specific regions/cities in western countries - Country is not provided in abstract
(5) No human study	Article does not focus on human subjects	Article focuses on animals or other non-human objects (i.e., materials, ingredients, companies, organisations)	
(6) Not about personalized nutrition or tailored communication about nutrition/food intake	Not about personalized nutrition or tailored communication about nutrition/food intake or related terminology	Exclude if: - The topic is clearly not about personalized nutrition or tailored communication on nutrition or related terminology - Aim of paper is to identify/describe consumer segments	Include if: - Test/identify food strategies/ advice to individual consumers - Test/identify food strategies/ advice to consumer segments/ communities
(7) No (normal) food	Articles does not focus on food or normal food	- Article does not focus on food - Article focuses on medical food, supplements, medicines, pharmaceuticals, etc.,	
(8) No appropriate research design	Abstract/article does not have appropriate research design	- Research design without empirical data (study protocols etc); case reports; etc.	- Review papers; meta-analyses; - Papers reporting follow-up of an intervention - Qualitative research (interviews, focus groups)
(9) No outcome measure(s) directly related to consumers	No outcome measure(s) related to consumer acceptance of personalized nutrition advice or dietary behaviour change	Exclude if: - Outcome measures/Acceptance is not on level of end user/final consumer, but on organisational/ intermediary level (i.e., by managers, staff, etc.)	
(10) Doubt	When still in doubt whether to include or exclude		
Include	Everything not excluded based on above		

Appendix 3. Eligibility criteria for article selection based on full papers

Code	Explanation	Exclude if	Do not exclude if
(1) Not retrievable	Article is not retrievable/recoverable (also not by library)		
(2) No English	Full paper not in English		
(3) No western study	Only studies conducted in western countries	Exclude papers with studies performed in: Non-western countries (see CBS list in Appendix and Indonesia + Japan) Low-income countries	Include papers when: - Western countries (not included in CBS list, with exception of Japan and Indonesia) - Specific regions/cities in western countries
(4) Insufficient method description	Method gives not enough information on how personalization was implemented	- Effect of personalization techniques on provided advice is not described	
(5) No appropriate research design	Article does not have appropriate research design	- Narrative reviews, opinion papers - Research design without empirical data (study protocols etc); case reports; etc. - No relevant generalizability (sample and research populations are not the same, non-biased research sample, e.g., pilot among fellow researchers or students) - No real exposure to personalized advice (or explanation of personalized advice), i.e., too explorative studies about the topic should be excluded	- Systematic review papers; meta-analyses -> keep separate, also for check if review contains relevant papers that are included in our review (snowballing decision has to be made after screening of full papers) - Papers reporting follow-up of an intervention - Qualitative research (interviews, focus groups) - Multicomponent interventions - Studies with no baseline/control, but where different interventions are compared
(6) Clinical populations	Target population in study is clinical population	- Hospitalized patients - Nursing homes - Cancer patients	- Chronic diet-induced diseases (e.g. diabetes type II) - Overweight and obesity - High risk groups (prevention) - Recovery
(7) No (normal) food	Article does not focus on normal food	- Article does not focus on food - Article focuses on medical food, supplements, medicines, pharmaceuticals, etc. - Multi-intervention studies that do not separate effects on diets from other effects	Discussion/results of multi-intervention studies explicitly refer to the effects on diet

(*continued on next page*)

(*continued*)

Code	Explanation	Exclude if	Do not exclude if
(8) No personalization at individual level	Personalization should be at a named subject level	- Families in general - community-based intervention - Groups bigger than 10 (so neighbourhoods and communities etc are excluded)	- Person X - Household X - Family X
(9) Consumer/user is no decision maker	The final user of the personalized advice is not the decision maker	- Parental decision making about children - Nurses deciding for patients - Dietists/practitioners deciding	
(10) No outcome measure(s) directly related to consumer acceptance/ behaviour	No outcome measure(s) related to consumer acceptance of personalized nutrition advice or dietary behaviour change	- Outcome measures/Acceptance is not on level of end user/final consumer, but on organisational/intermediary level (i.e., by managers, staff, etc.) - Exclude if consumer behaviour is indicator for dietists/practitioners acceptance	
(11) Doubt	When still in doubt whether to include or exclude		
Include	Everything not excluded based on above -> see report below		

Appendix 4. Systematic review codebook (Qualtrics questionnaire)

Start of Block: Starting block - definition at paper level.

Paper number

____

Author

____

Year of publication

____

Journal

____

How many distinct studies are reported within this paper (enter 0 for papers without empirical data collection)?

____

Exclude? The paper has been excluded from the data set after all (based on coding) please justify
◯ Paper is rejected (Justify) (1) ______________________________

End of Block: Starting block - definition at paper level.
Start of Block: Study 1 block.

First section - overall setup of study

Year(s) of data collection
◯ Year (4) ______________________________
◯ There was no additional empirical study (5)

Skip To: End of Block If FIRST SECTION - OVERALL SETUP OF STUDY Year(s) of data collection = There was no additional empirical study.

In which country was the study conducted?
▾ Multiple - fill in next question (0) … Iraq (81)
Only if multiple: name all countries of data collection across all studies separated by semicolon

____

Total sample across all conditions in the study (N). If multiple waves with different samples sizes due to dropout report sample sizes per wave separated by semicolon. Only if all waves have equal numbers report a single N

____

Target group of the study
◯ General public (1)
◯ Age related (2)
◯ Disease related (3)
◯ Demography related (incl ethnicity) (4)
◯ Culture related (5)
◯ Non representative sampling (convenience) (7)
◯ Other - specify (6) ______________________________
What kind of data was collected on the behaviour change after the personalized advice (more than 1 option possible)?
- Opinion data (attitudes, intentions etc) (1)
- Behavioural data (2)
  - Physiological data (3)

- Other please specify (4) ________________________________

How was the behaviour change data recorded (multiple options possible)?

- Self report (1)
- Observation (2)
- Physical measurement (body functioning) (3)
- Other please specify (4) ________________________________

How was the behaviour change data of consumers reported to the PN service?

◯ Fully online (1)
◯ Fully face to face (2)
◯ Mix of online and face to face (3)
◯ Other please specify (4) ________________________________

What was the design of study?

◯ Cross sectional (one-off) (1)
◯ Single intervention followed by single later measure (5)
◯ Longitudinal with pretest - report # waves, time between each wave separated with; example (3; 2 weeks; 3 months) (2) ________________________________
◯ Longitudinal without pretest - report waves as above. (3) ________________________________
◯ Other specify (4) ________________________________

Total duration of study from pretest or intervention until last reported measure

◯ in days (1) ________________________________
◯ in months (2) ________________________________
◯ in years (3) ________________________________
◯ Not reported in paper (5)

How was variation in independent variables managed in participant assignment?

◯ Observing/measuring personal traits (1)
◯ Random assignment to conditions (2)
◯ Biased (e.g. purposive) assignment to condition (3)
◯ Other specify (4) ________________________________

How many factors were manipulated (also count variables beyond treatment groups e.g. covariates?

____

List all factors (with levels) and covariates (with levels in brackets where relevant) separated with semicolon. Example: Intervention (placebo; information}; gender (male; female; other); age

____
____
____
____
____

What was the total number of experimental groups (if any) in the design (e.g. for a $2 \times 3 \times 2$ design this is 12)? Do not count covariates, if no IV's skip this question

____

List all outcome variables separated by semicolon

____
____
____
____
____

List all mediating (if any) variables separated by semicolon or leave blank

____
____
____
____
____

List all moderator (if any)variables separated by semicolon or leave blank

____
____
____
____
____

Second section: information flow from consumer to service

What information does the participant provide?

- General food intake (e.g. FFQ) (1)
- Fruits and vegetables consumption (2)
- Specific nutrients e.g. fat, protein, sugar (specify which) (3) ________________________________
- Other (4) ________________________________

What physiological and health data does the pp provide?
- •Weight/BMI (1)
- •Blood glucose (2)
- •Blood pressure, heart rate (3)
- •Gene related (DNA profile) (4)
- •Subjective health states (5)
- •Other (6) ________________________________

Demographics submitted by participant to system
- •Age (1)
- •Gender (2)
- •Education (3)
- •Income (4)
- •Household size (5)
- •Other (6) ________________________________

Are there any lifestyle data asked for?
- •Dietary related lifestyle (incl vegetarian/religion), if relevant specify (1) ________________________________
- •Food allergies (self report) (2)
- •Food preferences (3)
- •Eating habits (4)
- •Food choice motives/values (5)
- •Other (6) ________________________________

Which psychological or behavioural measures are recorded?
- •Self efficacy/perceived control (1)
- •Self regulation (Deci Ryan etc) (2)
- •Stages of Change (3)
- •(intrinsic) motivation (4)
- •Regulatory focus (promotion prevention/approach avoidance) (5)
- •Need for cognition (tolerance for ambiguity faith in intution etc) (6)
- •Internet literacy specific for health (7)
- •Other (8) ________________________________

General statement on data collecting from participants (paraphrased from paper).

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Third section: generating the advice

◯ Self learning algorithms, AI (1)
◯ Following blueprint, template, flow chart (2)
◯ Other (3) ________________________________

Who is the main responsible party for setting up maintaining and safeguarding the advice procedure?
- University/research institute (1)
- Health care professional (GP, dietician, municipal health service) (2)
- Governmental organisation (3)
- Employer (4)
- Health insurance company (5)
- Commerical provide (supermarket, app service) (6)
- Other (7) ________________________________

Fourth section: providing advice

What behavioural intervention technique (BCT taxonomy) was used?
- Goals and planning (1)
- Feedback and monitoring (2)
- social support (3)
- Information about consequences (health emotions) (4)
- Comparison of behaviour (5)
- Associations (6)
- Repetition and substitution (7)
- comparison of outcomes (8)
- rewards and threats (9)
- regulation (10)
- shaping knowledge (11)
- antecedent (12)
- identity (13)
- scheduled consequences (14)

- self belief (15)
- covert learning (16)
- Other/don't know to which it fits but reference is made (if no references skip question) (17) ________________________________

Type of information provided

◯ Only feedback (e.g. on personal progress) (1)
◯ Feedback and associated advice (2)
◯ Only advice (3)
◯ Other (4) ________________________________

Who is the main responsible party for providing the information?

◯ University/research institute (1)
◯ Health care professional (GP, dietician, municipal health service) (2)
◯ Governmental organisation (3)
◯ Employer (4)
◯ Health insurance company (5)
◯ Commercial provide (supermarket, app service) (6)
◯ Other (7) ________________________________

Through what channel is the advice transferred?

- Website, app or other online (1)
- In person face to face (2)
- Through email (3)
- By phone (4)
- By videocall (Skype etc) (5)
- Other (6) ________________________________

What format did the advice have (multiple options possible)?

- Written text (1)
- (info) graphics (2)
- Spoken text (3)
- Other (9) ________________________________

At what physical location does the consumer receive adive?

◯ At home (1)
◯ At work (2)
◯ Healthcare setting (doctor, hospital dietician, university lab) (3)
◯ Out of home (e.g. restaurant) (4)
◯ Unspecified or other (if other specify) (5) ________________________________

Frequency of advice

◯ every ….. days (1) ________________________________
◯ every ….. weeks (use fraction for e.g. 0.5 week when report is twice a week) (2) ________________________________
◯ every …. months (3) ________________________________

General statement on advice communication to participants (paraphrased from paper).

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Final section: What does it report on advice adherence

What was reported on acceptance of the advice?

- Observed actual USE (1)
- Self reported USE (2)
- Intention to use (3)
- Attitude/evaluation/liking etc (4)
- Perceived benefits (e.g. assumed effectiveness, personalization benefit (5)
- Perceived risk (e.g. privacy risk) (6)
- Perceived barriers (not framed as risk - e.g. lack of opportunity, social pressure) (7)
- Trust (in service providers) (8)
- Other (9) ________________________________

Behavioural and health status changes

- Weight change (1)
- Non weight health indicators change (e.g blood pressure). Specify (2) ________________________________
- Change in dietary intake (3)
- Other (4) ________________________________

Which cognitive factors change?

- Change in attitude (1)
- Change in knowledge (2)
- Change in risk-benefit-barrier perceptions (3)

- Other (4) ________________________________

Other changes

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General statement on advice adherence by participants (paraphrased from paper).

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End of Block: Study 1 block.
Start of Block: Wrap up block.

The following questions are about the paper as a whole

Main (qualitative) conclusion from the paper on BEST PRACTICES TO DESIGN A PN SERVICE (PARAPHRASE FOR INCLUSION IN REPORT)

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Main (qualitative) conclusion from the paper on BEST PRACTICES ABOUT EFFICACY OF PN SERVICE (PARAPHRASE FOR INCLUSION IN REPORT)

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Main (qualitative) conclusion from the paper on BEST PRACTICES ABOUT CONSUMER ACEPTANCE OF PN SERVICE (PARAPHRASE FOR INCLUSION IN REPORT)

____

Anything relevant in the paper that you want to retain but does not fit elsewhere (PARAPHRASE FOR POSSIBLE INCLUSION IN REPORT)

____

Any reflection of the coder on the paper (WILL NOT BE INCLUDED IN REPORT BUT CAN BE USED IN INTERNAL DISCUSSION)

____

This paper is done.
Enter another paper? then click on THIS LINK
https://wur.az1.qualtrics.com/jfe/form/SV_e5aIbWhqYtkmMyq.
End of Block: Wrap up block.

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