A Literature Review on Food Recommendation Systems to Improve Online Consumer Decision-Making

by

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Abstract

Food recommendation systems (RSs) are software systems that make personalized recommendations form a large range of different options and thus provide a promising solution for information overload and unhealthy food decisions. In this BSc Thesis a literature review synthesized findings from three literature reviews and seventy-three articles on food RSs. An overview of the types and approaches of food RSs, current challenges and solutions, and future research on food RSs is provided. Furthermore, a link was made between the online consumer decision-making process and food RSs. It can be concluded that most articles on food RSs for individual users: focus on recipes, use hybrid approaches, are user preference RSs types, and mainly help consumers with evaluating alternatives in the consumer decision-making process.

Keywords: literature review, food recommendation systems, online consumer decision-making

Content

1. Introduction

In today's society most individuals use the internet to search for information, to communicate with their social network or to buy goods and services (Ergezer, 2016). Next to this, the amount of internet users worldwide is constantly increasing and is currently around 4.5 billion, of which 2.1 billion people buy goods and services online (Clement, 2019; Internet World Stats, 2019). In other words, e-commerce is growing as it provides benefits to companies and consumers. Some advantages for online consumers are that they can have access to it at any place and at any time; can purchase the same goods and services from several companies; and can save time, money, and effort (Anastasiadou, Lindh & Vasse, 2019; Chiu, Lo, Hsieh & Hwang, 2019). Nevertheless, it can also lead to information overload, meaning an abundance of information that makes it hard to separate useful from useless information (Häubl & Trifs, 2000; Pedersen, 2000). This results in a more complex and overwhelming decision-making process for the consumer (Häubl & Trifs, 2000; Pedersen, 2000).

Information overload is a serious problem as consumers can feel overwhelmed and either decide not to buy anything or do not take all options into account and make a suboptimal decision (Chugh & Bazerman, 2009; Ghasemaghaei, 2020). To solve this problem, online companies can use Recommendation Systems (RSs) (Häubl & Trifts, 2000). RS can be defined as a software system that makes personalized recommendations from a large range of different options by implicitly or explicitly eliciting the user's preference for a product, service, or seller (Li & Karahanna, 2015; Tran, Atas, Felfernig & Stettinger, 2018; Xiao & Benbasat, 2007). A few popular examples of RSs implementations are, Amazon's 'Customers who bought this item also bought' bar, Netflix's film recommendations, and Spotify's music recommendations that are all based on customers' search or viewing history (Li & Karahanna, 2015; Schäfer et al., 2017; Verruck & Nique, 2017). RSs benefit consumers as they reduce consumers' cognitive effort and search costs by making it faster and easier to compare alternatives and collect information (Häubl & Trifts, 2000; Pedersen, 2000). This can improve the consumer's decision quality and confidence in their decision (Häubl & Trifts, 2000). Next to this, RSs benefit companies, hence, it is not strange that more and more sectors use RSs, such as education, healthcare, e-commerce, and food (Nyati, Rawat, Gupta, Aggrawal & Arora, 2019; Xiao & Benbasat, 2007). With the constant development of web-based technologies, RSs have become more accurate in predicting customers' preferences. Therefore, these developments resulted in RSs that can recommend alternatives and complementary items, and RSs that can give recommendations even when online consumers are not familiar with the commodity (Yang, Song, Wu, Yang & Wang, 2020; Yang, Ou & Ziying, 2017).

Recently, RSs are also being developed for the online food sector as more consumers buy food or search for food related content online. With 'food' also food-related items are meant, such as meal planning, recipes, ingredients, coffee shops, restaurants, restaurant menus, and grocery shopping (Min, Jiang & Jain, 2019; Trattner & Elsweiler, 2017). "Food RSs recommend food based on the consumers' preferences, suggest healthy food choices, keep track of eating behaviour, understand health problems, and persuade the user to change their behaviour" (Tran et al., 2018, p. 502). There are different types of food RS, but the majority of researchers focus on healthy food RSs to prevent and overcome overweight and obesity, which is necessary as at least 39% of people who are 18 years and older are overweight and of whom 13% are obese (Nyati et al., 2019; WHO, 2020). However, food RSs are in their infancy and their accuracy, trustworthiness, and reliability need to be improved (Schäffer et al., 2017). This is why a huge amount of research has been done on this topic in the past decade. Only a few literature reviews were made to make a good overview of food RSs by Tran et al. (2018), Trattner & Elsweiler (2017), and Min et al. (2019). That is why another literature review is necessary as research on e-commerce is constantly and rapidly evolving (Fouskas, Pachni-Tsitiridou & Chatziharistou, 2020). Furthermore, these reviews predominantly focused on making a comprehensive summary of the current technical aspects of food RSs and up till now no existing literature review has classified food RSs according to the consumer decision-making process. However, getting a better understanding of this connection is important so that food RSs can better support consumers in different stages of their decision-making (Ghasemaghaei, 2020). In other words, it improves the performance of food RSs.

To fill these gaps, this paper tries to answer the following research question: *How have the recommendation systems for individual users been applied in the food sector?* The following sub-questions are defined to tackle this research question:

a) What types and approaches of recommendation systems have been applied in the food sector?
b) How can these food recommendation systems be classified based on the consumer decision-making process?
c) What are the current challenges and solutions for food recommendation systems?

The rest of this paper is structured as follows. Section 2 provides a theoretical framework on RSs and consumer decision-making. Section 3 describes the method used for the literature review. Section 4 presents the results. The last section discusses the implications and limitations of these findings and will give suggestions for further research.

2. Theoretical Framework

2.1 Recommendation Systems

2.1.1 General Introduction

Research on RSs began in the 1990s and gained more attention after the growth of e-commerce (Alyari & Navimipour, 2018). A variety of terms refer to RSs, such as interactive decision aid system (Li & Karahanna, 2015), "recommender systems, recommendation agents, shopping agents, shopping bots, and comparison-shopping agents" (Xiao & Benbasat, 2007, p. 1). The general process of RSs can be explained using Adomavicius and Tuzhilin's three-stage process model, which is depicted in Figure 1 (Li & Karahanna, 2015).

1. In the first stage the main aim is to understand the consumer.
    a. *Consumer information collection*: the RSs implicitly or explicitly collects consumer information (Li & Karahanna, 2015; Verruck & Nique, 2017). An example of an explicit method is using a questionnaire to elicit personality, past purchases or demographics, and an implicit method is using clickstream or social media information from the consumer or their friends. Although the explicit methods requires effort from the consumer, it results in more accurate recommendations and it did not lead to dissatisfaction compared to implicit methods. However, it is best to use both methods to increase the accuracy even more (Li & Karahanna, 2015). An important aspect to take into consideration is the knowledge of the consumer. If the consumer has little knowledge about the product, service, or vendor the RS must elicit consumer's needs and should show less recommendations (Ghasemaghaei, 2020). However, if the consumer is more familiar with the product, service, or vendor the RS should elicit the consumer's preferences of product attributes, such as price, brand, and reputation (Ghasemaghaei, 2020; Huang, 2016).
    b. *Building consumer profile*: a consumer profile can be built based on the selected consumer information. Online companies do not use all information since this is not optimal and realistic. According to Li & Karahanna (2015) social-network information is likely to be used more together with product attributes and consumer demographics in the future.

2. In the second stage the main aim is to identify and delivering recommendations.
    a. *Matchmaking approaches*: different matchmaking approaches can be used to identify the products or services that matches the consumer's profile. The information used to build the consumer profile determines which approach will be chosen (Li & Karahanna, 2015). In section 2.1.2 'Matchmaking Approaches of Recommendation Systems' different types of matchmaking approaches will be discussed in detail.
    b. *RS presentation*: the next step is the RS presentation or interface design of the recommendations. If the design is not adequate, consumers might not understand the recommendations or ignore them. Things that need to be taken into consideration are for example, the number of recommendations shown on one page (set size), the degree to which the recommendation matches the consumer's profile (sorting cue), recommendation instruction facilities, and whether or not to use an animated persona (avatar) (Li & Karahanna, 2015).

    Stage 1 and stage 2 determine the accuracy of the personalized recommendations.
3. In the third stage the impact of the RS on the consumers, companies, and market is measured. The recommendations are adjusted based on the feedback from the customer (Li & Karahanna, 2015). More information about this will be given in section 2.1.3 'Impact of Recommendation Systems on Consumers'. Only the impact on consumers will be further explained, since they are the main focus of this paper.

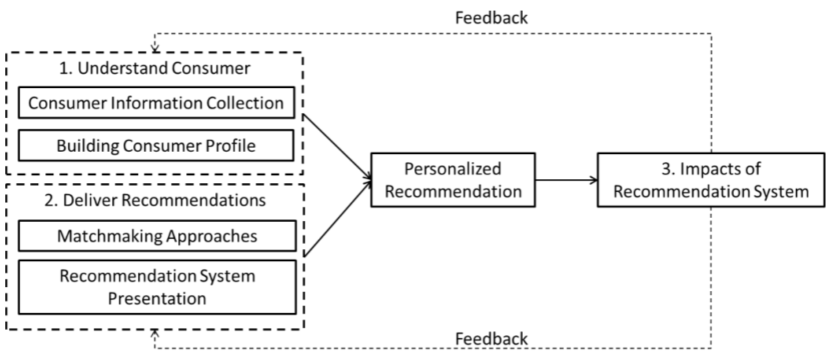

Figure 1 Three-stage process model of Adomavicius and Tuzhilin (Li & Karahanna, 2015, p. 77)

2.1.2 Matchmaking Approaches of Recommendation Systems

There are a variety of matchmaking approaches used to create recommendations for individual consumers. The following is an overview of the main approaches:

1. *The content-based approach* predicts the users' preferences by looking at e.g. their ratings of product or service attributes and purchase history (Alyari & Navimipour, 2018). The products or services that are similar to the high-rated items and purchase history are recommended.
2. *The collaborative filtering approach* predicts the users' preferences based on the preferences and ratings of like-minded people (Alyari & Navimipour, 2018; Huang, 2016; Qiu & Benbasat, 2010). A user has to rate implicitly or explicitly some items and based on this; the RS recommends items that like-minded people also liked (Tran et al. 2018). It is the most common RS type according to Alyari & Navimipour (2018).
3. *The knowledge-based approach* uses the information from the user and items, to match the items to the user's criteria. This approach explicitly elicits information from the user to build a user profile. On the one hand it is time-consuming as the user needs to interact with the RS. On the other hand, it provides an explanation to the user of why the item has been recommended (Alyari & Navimipour, 2018). One example of a knowledge-based approach is constraint-based, that tries to satisfy all constraints (e.g., user preferences) given to them (Tran et al., 2018). Another example is case-based, that keeps a memory of their successful past recommendations and is able to modify them or base their new recommendations on them (Hammond, 1986).
4. *The demographic approach* uses reviews, ratings, and preferences of other people with the same demographics as the user of the RS. For instance, people with the same age, gender, or occupation as the user (Alyari & Navimipour, 2018).
5. *The context-based approach* not only use consumer characteristics and item attributes, but also contextual information of the user, such as why someone is buying the commodity and for whom they are buying it (Wang, Lin & Yang, 2016).
6. *The social network-based approach* base the recommendations on data of the users' social networks, such as prior purchases of the users' Facebook friends (Li & Karahanna, 2015).
7. *The hybrid approach* combines the techniques of the other RS approaches to generate recommendations (Alyari & Navimipour, 2018; Huang, 2016). By doing this, they can use the advantages of each RS approach and can avoid their disadvantages (Alyari & Navimipour, 2018). "For instance, collaborative filtering methods have to face the new-item problem. Whereas content-based approaches can tackle this problem because the prediction for new items is usually based on available descriptions of these items" (Tran et al., 2018, p. 5).

2.1.3 Impact of Recommendation Systems on Consumers

RSs have an impact on the consumer's intentions and decision-making process (Li & Karahanna, 2015). The intention of using the RS depends on the consumer's perceived benefits, trust, and risk (Kim, Ferrin & Rao, 2008). If the perceived benefits are high, the perceived trust is high, and the perceived risk is low, consumers are more likely to use the RS (Kim et al., 2008). The benefits of RS were already discussed in the introduction. The perceived trust and risk are influenced by the relation between the consumer and the company; the company's reputation; and the site's security, privacy, and customer-service (Fouskas et al., 2020). Furthermore, consumers who never shopped online before perceived it as riskier than people who already have experience with online shopping (Huseynov & Yildirim, 2016). Trust can be enhanced, for example, by providing clear information and an easy navigation on the website (Darley, Blankson & Luethge, 2010). Moreover, consumers are more likely to use RSs in their decision-making process if they see the recommendations early on in the decision-making process, they perceive it is easy to use, the RS recommendations are similar to the consumer's own decision outcome, they heard others use it too, they think the recommendations are personalized and will satisfy their needs, and they perceive the recommendations as accurate (Huang, 2016; Li & Karahanna, 2015; Qiu & Benbasat, 2010; Verruck & Nique, 2017).

2.2 Online Consumer Decision-Making

2.2.1 General Introduction

As previously stated, consumer decision-making can be complex and difficult. That is why several models have been created to describe this process. One of the most widely used and accepted core theories is the Engle, Kollat, and Blackwell (EKB) model founded in 1968 (Ashman, Solomon & Wolny, 2015). This model explains the offline consumer decision-making process in five stages: problem recognition, searching for information, evaluation of alternatives, purchase, and post-purchase evaluation (Ashman et al., 2015). However, since the 1990s, more consumers purchased products and services online, which influenced their decision-making process (Ashman et al., 2015; Chiu et al., 2019). Although the process did not change much, the actions and decisions within each stage differed, resulting in online consumer decision-making process models (Maçik, 2016). In the next section, we further elaborate on this by explaining an online consumer decision-making process model. After that, the external factors that influence consumer decision-making and the shortcomings of the model will be discussed. This is required to achieve a better understanding of why RSs can assist consumers with their decisions, and in which stages they can influence this process.

2.2.2 Online Consumer Decision-Making Process Model

The models of Maçik (2016) and Darley et al. (2010) will be combined into one model to explain the consumer decision-making process. Both models use the five stages of the EKB model. In Figure 2 a visual overview of the model is given.

1. *Stage 1 – Problem recognition:* where the consumer recognizes an unfulfilled need or want (Ashman et al., 2015; Darely et al., 2010; Maçik, 2016).
2. *Stage 2 – Searching for information*: where the consumer uses internal sources such as their own memory and experiences, and external sources such as websites, (online) word-of-mouth, advertisements, promotional sales, sales persons and social media to identify criteria and priorities for the product or service and vendor (Ashman et al., 2015; Darley et al., 2010; Maçik, 2016; Mughal, Mehmood, Mohi-ud-deen, & Ahmad, 2014).
3. *Stage 3 – Evaluating alternatives*: where the consumer evaluates all alternatives based on selection criteria. In general, the consumer first compares the products or services based on their attributes, examples are functional features and brand image or emotions (subjective

factors) (Darley et al., 2010; Maçik, 2016). The consumer will do this just as long as the search costs are lower than the expected utility of collecting more information about one additional product or service (Pedersen, 2000). They eliminate some options and end up with a 'choice set' (Ashman et al., 2015). After that, the consumer chooses the purchase channel (online or offline), the purchase platform (e.g., auction, shop, website, mobile application), and the seller (Maçik, 2016).

4. *Stage 4 – Purchasing*: where the consumer chooses the delivery and payment method to purchase the product or service that meets the criteria (Ashman et al., 2015; Darley et al., 2010; Maçik, 2016). The Theory of Reasoned Action (TRA) of Ajzen and Fishbein can be used to explain that the purchase decision is influenced by the intentions of the consumer (Macovei, 2015). These intentions are affected by the belief that he or she is able to do the behaviour, and the positive or negative attitude towards that behaviour (Darley et al., 2010; Macovei, 2015). Moreover, as said before, intentions are also influenced by the perceived benefits, trust, and risk of buying the good or service online. This depends on the consumers perception of the online environment and characteristics of the individual (Kim et al., 2008).
5. *Stage 5 – Post-purchase evaluation*: where the consumer consumes the commodity and evaluates if he or she made the right decision based on their (dis)satisfaction and experiences (Ashman et al., 2015; Darley et al., 2010). Whether someone is satisfied or dissatisfied depends on his or her expectations beforehand and his or her perception of a product or service afterwards. If there is a difference it can lead to cognitive dissonance, which in this context means that the consumer is satisfied if the perception outperforms the expectations or dissatisfied if the opposite occurs (Zhu, Ko & Munkhbold, 2016). The last step in this stage is disinvestment, which means that the consumer resells, recycles, or throws away the product (Oke, Kamolshotiros, Popoola, Ajagbe & Olujobi, 2016). Consumption, cognitive dissonance, satisfaction or dissatisfaction, and disinvestment all influence the beliefs of the consumer about the product, service, or vendor (Darley et al., 2010).

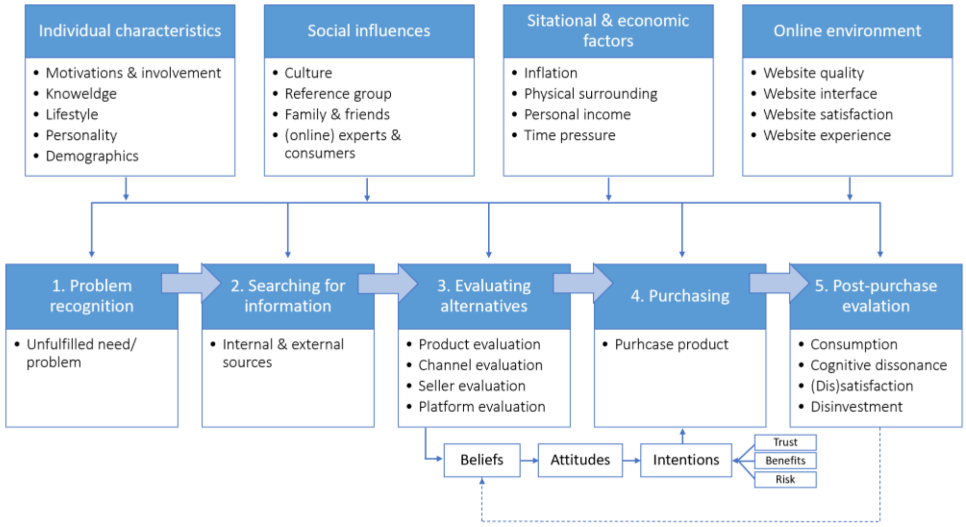

Figure 2 Online consumer decision-making model based on Maçik (2016) and Darley et al. (2010)

2.2.3 Influence of External Factors

According to Darley et al. (2010) and Maçik (2016) every stage is influenced by external factors, such as individual characteristics, social influences, situational and economic factors, and the online environment. Individual characteristics are, for example the motivation and involvement, knowledge, values, personality type, education level, lifestyle, and demographics of the person (Čavoški & Marković, 2015; Darley et al., 2010; Kim et al., 2008; Maçik, 2016; Malik & Purohit, 2020). Next to this, consumers are socially influenced by their own (sub-)culture, social class, reference group, family, friends, media, and the (online) advice of experts and other consumers when making a decision (Darley et al., 2010; Maçik, 2016; Malik & Purohit, 2020). For instance, people can read the opinion and experience of others in online reviews, blogs, or social media posts (Ashman et al., 2015). This can affect the reputation of the seller and product (Čavoški & Marković, 2015; Kim et al., 2008). The reason for this, is that these sources are seen as more credible and trustworthy by consumers, since the producer or seller of the commodity cannot control them (Maçik, 2016). This social influence not only helps consumers to choose for a certain product or service, but it can also elicit unrecognized needs or wants (Ashman et al. 2015; Maçik, 2016). Moreover, situational and economic factors affect the consumer decision-making, these factors usually cannot be controlled by marketers such as inflation, physical surrounding, personal income, and time pressure (Kalaiarasan, Govindan & Nasaratnam, 2018; Malik & Purohit, 2020; Mughal et al., 2014). Lastly, consumers are influenced by the online environment (Darley et al., 2010; Maçik, 2016). For instance, the website quality and design, quality of product or service information, privacy and security protection, and financial risk of the online transaction. This all influences the customer's satisfaction, evaluation, and experience with the website (Darley et al., 2010; Maçik, 2016).

2.2.4 Shortcomings of the Online Consumer Decision-Making Model

Although this model is already very extensive, it still has a few shortcomings. First of all, the model shows a linear process, while consumers often move back and forth between the stages (Wang et al., 2016). Next to this, the model assumes that the consumer mainly uses system 2 to maximize their decision, which is rational, slow, conscious, and costs energy and effort (Chugh & Bazerman, 2009). However, most consumers make suboptimal decisions to satisfy their decision (Simon, 1972). For example, if people are hungry, emotional, or stressed, they tend to eat more unhealthy food that in the end can lead to overweight or obesity (Elsweiler, Trattner & Harvey, 2017). They use system 1, which is intuitive, emotional, fast, automatic, and effortless (Chugh & Bazerman, 2009). The frequent use of System 1 can be explained by the bounded rationality theory of Simon (1972). According to the theory people can only process information up to a certain limit and they are not able to calculate the optimal choice since they often lack information and/ or time (Chugh & Bazerman, 2009; Simon, 1972). This is especially true for complex decision with a lot of alternatives (Häubl & Trifts, 2000). That is why people also use heuristics, which are rules of thumb to simplify their decision-making process. For example, the Lexicographic heuristic, where the consumer ascribes a value to all attributes of a product or service and determines which one is the most important, e.g. colour or price. After that, the consumer chooses the option with the highest value on that attribute (Bettman, Johnson & Payne, 1991). Lastly, since this is a general model for the online consumer decision-making process, food related characteristics are not included. However, these characteristics will be discussed in the 'Results' section.

3. Research Method

In this section, the method of this literature review is presented to answer the research question and sub-questions. A literature review was chosen as this is more feasible than a systematic literature review. The reason for this, is that food RSs research is a relatively new and multidisciplinary research area. For instance, it is covered by nutrition, sociology, consumer research, marketing, computer science, and food science research fields (Min et al., 2019; Xiao & Benbasat, 2007). This would have resulted in a variety of keywords that retrieve too many search results to conduct a systematic literature review. The following sections describe the steps taken to ensure that this literature review retrieved a comprehensive overview of relevant researches.

3.1 Designing the Review

The aim of this literature review is to answer the research question: *How have the recommendation systems for individual users been applied in the food sector?* With the following sub-questions:

a) What types and approaches of recommendation systems have been applied in the food sector?
b) How can these food recommendation systems be classified based on the consumer decision-making process?
c) What are the current challenges and solutions for food recommendation systems?

First, an umbrella review was done to summarize the literature reviews on food RSs, to answer sub-questions a and c. Next for sub-question b, the types of food RSs were categorized based on the online consumer decision-making model of Figure 2. For this, the original articles that were used as examples of food RSs in the tables and texts of the literature reviews were used as starting point. After that, more recent papers were added by searching for literature on this topic published in the last 5 years (see section 3.2).

For the literature reviews the inclusion criteria were:

1. The studies are about RSs in the food sector, as this study focuses on this sector.
2. The studies are literature reviews.
3. The studies are published in the last 5 years (2015-2020), since it is a new research field and research in the e-commerce is developing quickly (Fouskas et al., 2020).
4. The studies are written in English, as most articles are written in this language.

For the original articles and more recent papers the inclusion and exclusion criteria were:

1. Only studies on RSs in the food sector were included.
2. Literature reviews were excluded because the focus is on articles about a specific food RS.
3. Only studies on food RSs for individual users were included. Group decision-making food RSs are excluded as it would result in even more search results for this literature review.
4. Only articles written in English were included.

3.2 Searching for Literature

The literature search was conducted from May 25th 2020 – June 12th 2020. The databases Scopus, Web of Science, and Google Scholar were used. These databases were chosen, because they are accessible for more people than the WUR database and they all include studies from different scientific fields. This is an advantage as food RSs are researched in different disciplines. For the literature review, sources with the key words 'literature review', 'recommendation systems', and 'food' or synonyms in the title or abstract were added. Three literature reviews were found (Min et al., 2019; Tran et al., 2018; Trattner & Elsweiler, 2017).

For the original studies included from the literature reviews, only studies that were used as example within the text or in the tables were looked at, see Supplementary Materials. It was decided to include studies from all publication years, since the literature reviews used older studies in their whole research, meaning that it would have been impossible to refer to the literature reviews as they are based on studies older than 2015. Furthermore, it gives a better overview of the food RSs over the past few decades. The key words 'food', 'recommendation system' and 'consumer' or synonyms in the title or abstract were used. The synonyms used for RSs are derived from Xiao & Benbasat (2007) and Li & Karahanna (2015): 'recommendation agents, 'recommender systems', 'shopping agents', 'shopping bots', 'interactive decision aid systems', and 'comparison shopping agents'. The synonyms for 'food' are derived from Min et al. (2019) and Trattner & Elsweiler (2017): 'meal planning', 'recipes', 'ingredients', 'coffee shops', 'menus', and 'grocery shopping'. Lastly, consumers can be called 'users', so this was also included in the search term (Min et al., 2019; Tran et al., 2018; and Trattner & Elsweiler, 2017).

For the more recent studies, also the key words 'food', 'recommendation system' and 'consumer' or synonyms in the title or abstract were used. The only difference with the original studies from the literature review is that publications of the last 5 years (2015-2020) were included. Figure 3 provides an overview of all studies included.

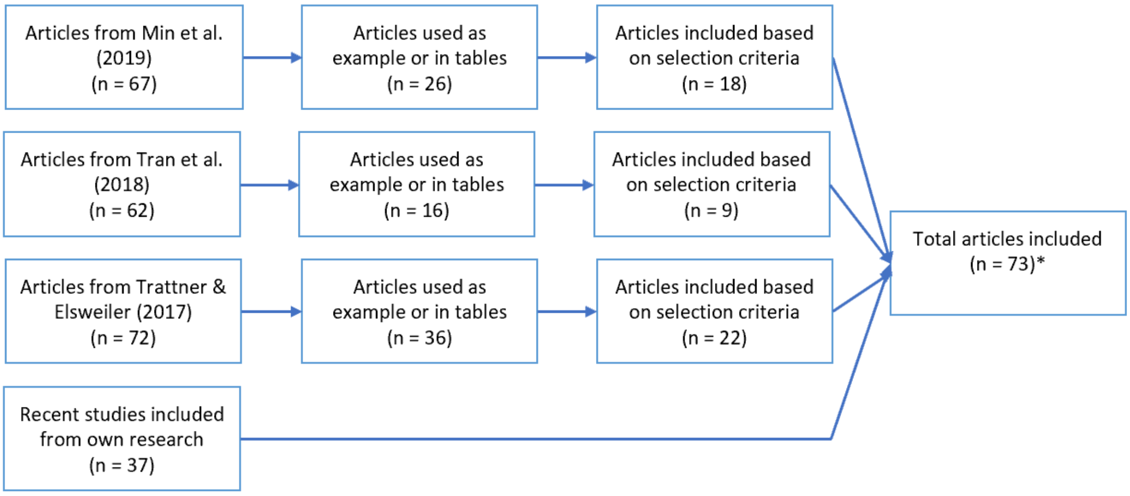

Figure 3 Overview of search for studies- add flowchart

**=* *13 articles were used by more than one literature review, so those are only counted once*

3.3 Synthesis

After collecting all articles their data was extracted. First, the texts of the literature reviews were merged to make an overview of the types of food RSs, the challenges and solutions, and future research suggestions. A colour code was used to make this process easier, see Supplementary Material. After that, a table was made with the descriptive information of the total amount of studies per: publication year, food type, RS approach, decision-making stage, RS type, and type of study (see Table 1) (Snyder, 2019). Lastly, a thematic analysis was done per article see Tables 2-4 (Transfield, Denyer & Smart, 2003). Those tables were divided per food RSs type and contained further details on: author, publication year, topic of the study, type of food, type of study, RS approach(es), and which decision-making stage it influences (see Figure 2). It was decided to separate the tables per food type, as this gives additional information about the kind of food RSs made in that specific research area. The data of the articles were compared to each other to identify themes and categories that can be useful to answer the sub-questions (Transfield et al., 2003).

4. Analysis & Results

In this chapter, the three literature reviews on food RSs by Min et al. (2019), Tran et al. (2018), and Trattner & Elsweiler (2017) are summarized. Min et al. (2019) is a literature review of 67 articles that proposes a framework for food RSs. Tran et al. (2018) is a literature review of 62 articles that gives a state-of-the art in food RSs that focuses on food types and approaches used. Trattner & Elsweiler (2017) is a literature review of 72 articles that focuses on technical aspects of food RSs, such as algorithms, evaluation methods, and resources or databases used for food RSs. All three literature reviews discuss the current challenges, current solutions, and future directions. After colour coding the articles (see Supplementary Material) they were merged together to easily identify the different topics of interest. First a general introduction of the development of food RSs is given. Thereafter, the types of food RSs, and the challenges and solutions of food RSs are discussed.

4.1 General Introduction of Food Recommendation Systems

Since the 1990s, food RSs were implemented to solve the problems of information overload of multimedia food content (e.g., food websites, videos and social media) and of inappropriate eating behaviour that can lead to chronical diseases (Min et al., 2019; Tran et al., 2018; Trattner & Elsweiler, 2017). One example of a food RSs is RecipeKey that “filters recipes based on the user’s favourite ingredients, allergies and item descriptions (e.g., meal type, cuisine, preparation time, etc.)” (Tran et al., 2018, p. 507). According to Tran et al. (2018) and Trattner & Elsweiler (2017) recommendations for food items or recipes are the main focus in this research field. Also, popular recommendation approaches are content-based, collaborative filtering, constraint-based, and hybrid approaches.

According to Min et al. (2019) and Trattner & Elsweiler (2017), food RSs differ in several ways from RSs in general. First of all, there are other factors that influence food preferences than user preferences of products or services. Secondly, more and different types of contextual real-time information is required. Thirdly, the user’s nutritional needs, weight goals, and health problems can be taken into consideration. More information on these three differences can be found in the next section. Fourthly, different domain knowledge and food databases are needed to recommend healthier food, such as nutritional, medical, and dietary knowledge. Lastly, food has unique characteristics, “such as cooking methods, ingredient combination effects, preparation time, nutritional breakdown, and nonrigid visual appearance” (Min et al., 2019, p. 3). In sum, food RSs thus base their recommendations on user information, nutrition and health resources, and recipe or food database(s). These information sources are important, as their quality directly affects the accuracy of the food RSs and indirectly affects user satisfaction. Next to the accuracy of the RSs, user satisfaction can be improved by providing a nutritional value table or explanations of why the food item is recommended. This will encourage users to comply to healthy eating behaviour (Min et al., 2019; Tran et al., 2018; Trattner & Elsweiler, 2017).

The user's preferences, contextual factors, and the user's nutritional and health situation mentioned above, can be used to build a user profile. The user's food preferences are elicited from the user explicitly (e.g. via a survey or food journal) or implicitly (e.g. online ratings, reviews or browsing history) (Min et al., 2019). Food preferences change over time, as it is influenced by many factors such as biological (e.g., allergy constraints and genes), psychological (e.g., attitudes and beliefs, and cognitive restraints), diets and lifestyles (e.g. gluten-free, vegan or vegetarian), social (e.g., friends and family), cultural (e.g., favourite cuisines; familiarity of the food), hobbies, and historical factors (e.g., past experiences and previous eating behaviour). Secondly, contextual factors are required such as environmental changes (e.g., air quality, time, location, temperature), user's body conditions (e.g., physical activity, sleep per day, heart rate, and blood pressure), and food/ ingredient availability in the household. Thirdly, user's nutritional and health problems can be useful, so that the recommendations are nutritionally appropriate for the user. Lastly, user's demographics are important to consider, such as age, height, weight, gender, occupation (Min et al., 2019; Tran et al., 2018; Trattner & Elsweiler, 2017). Based on all these factors, constraints or rules can be made to filter out irrelevant food items. Furthermore, mobile or sensing devices, such as a watch or fitness bracelet, or health and fitness mobile apps (e.g. MyFitnessPal, Endomondo and Fitbit) can be used to measure personal or contextual real-time factors (Min et al., 2019; Tran et al., 2018). A recent development in sensing devices is a visual food analysis, that can measure the food intake of a meal based on a photo the user made (Min et al., 2019).

4.2 Types of Recommendation Systems in the Food Sector

There are different ways to categorize food RSs. For example, Trattner & Elsweiler (2017) decided to divide food RSs into recommendations for recipes, meal plans, groceries, and menus. However, this study will divide the food RSs based on the study of Tran et al. (2018), as this categorization focuses more on the function and the food RSs in general. Furthermore, there are more types of food related things (e.g. restaurants, food items, ingredients, and coffee shops) that are not covered by the division of Trattner & Elsweiler (2017). According to Tran et al. (2018) food RSs can be divided into four types, based on the information they use for their recommendations.

The first type of food RSs focuses on user preferences. These RSs focus on the user's food preferences derived from for example, the user's food ratings or eating history (Min et al., 2019; Tran et al., 2018; Trattner & Elsweiler, 2017). An example is Fatchum from Cruz, Alpay, Depeno, Altabirano & Bringula (2017), that recommends recipes based on the user's search terms or ingredient input (see Figure 4).

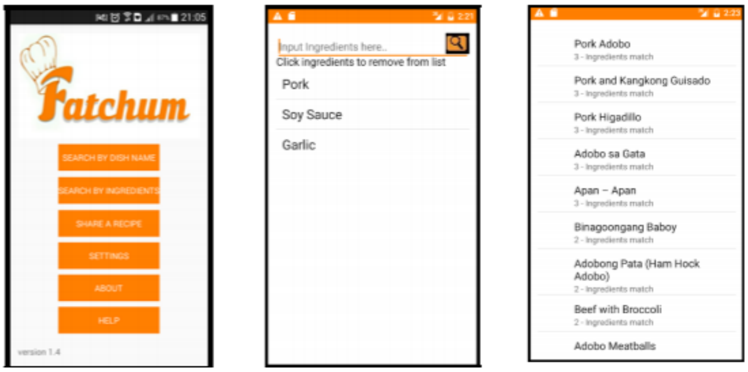

Figure 4 Lay-out Fatchum recipe RS (Cruz et al., 2017, p. 13)

The second type of food RSs focuses on health and nutritional needs of users. For example, by substituting unhealthy ingredients by healthy ingredients or by generating a healthy food plan (Min et al., 2019). According to Trattner & Elsweiler (2017), this is the most studied food RS type. The recommendations are, for instance, based on user's health information and contextual information (Min et al., 2019; Tran et al., 2018). To estimate the healthiness of a meal nutrition and health resources (e.g., USDA or BLS), a visual food analysis (e.g. recognizes food and estimates food quantity from a photo) and/or nutritional food standards (e.g., Food Standards Agency's (FSA) and World Health Organisation's (WHO)) are used in the recommendation approach. Also, a traffic light system can be used to inform the users about the healthiness of the food item, with red being unhealthy, green being healthy, and orange being neither unhealthy nor healthy (Min et al., 2019; Trattner & Elsweiler, 2017). One example of this food RS type is the RS from Alian, Li & Pandey (2018). It recommends healthy meals to American Indians with diabetes based on the user's health situation, and food and nutrition guidelines (see Figure 5 and 6). Furthermore, it keeps track of the physical activity and food intake and gives a daily food summary.

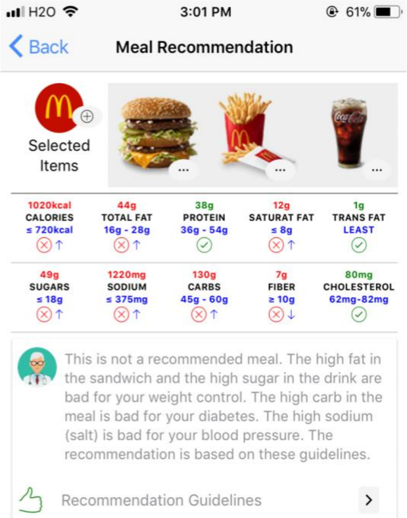

Figure 5 Lay-out Meal Recommendation (Alian et al., 2018, p. 73047)

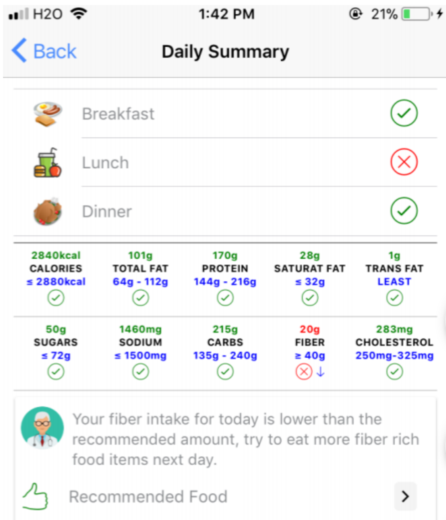

Figure 6 Lay-out Daily Summary (Alian et al., 2018, p. 73048)

The third type is a trade-off food RS, that considers both user preferences and health and nutritional needs. According to Tran et al. (2018) this type leads to more optimal food recommendations. The reason for this is that by considering user preferences the recommended food items are more attractive and relevant for the user. This in turn makes the user more engaged and interested in using the food RSs. Furthermore, by considering the user's nutritional needs, physical activity, demographics, and health problems the recommended food items are healthier for the user. An example of a trade-off RS is SousChef from Ribeiro, Vasconcelos, Vieira & de Barros (2018). SousChef is a meal planner for the Portuguese elderly that keeps track of the user's food intake, user food preferences through meal ratings, and activity monitoring (see Figure 7). It also serves as grocery list.

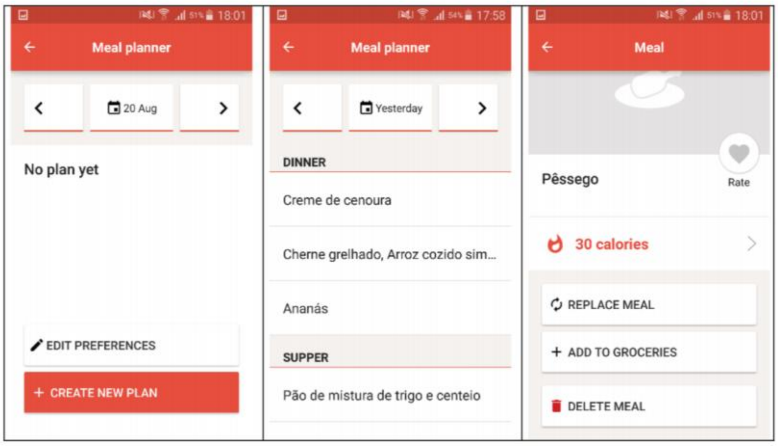

Figure 7 Lay-out Meal Planner SousChef (Ribeiro et al., 2018, p. 120)

The fourth type is group food RSs, as people often make food decisions with friends, families, or colleagues. For instance, people often decide together what they are going to eat during a Christmas dinner (Tran et al., 2018; Trattner & Elsweiler, 2017). However, this type will not be discussed in this paper, since there is a lack of research in this area and this paper focuses on food RSs for individual users.

4.3 Classification of Food Recommendation Systems on the Online Consumer Decision-Making Process

In total seventy-three articles were analysed, of which thirty-five articles were from the reference lists of the three literature reviews, and thirty-eight articles were from own research. Although it was possible to look at all search results from Scopus and Web of Science, Google Scholar retrieved too many search results (10.800). So only the first twenty pages of the search results were used, due to time constraints. The descriptive information of the included articles can be found in Table 1 and the thematic analysis can be found in Tables 2-4.

As can be seen in Table 1, most studies in this analysis were from 2019, followed by 2015, 2017 and 2018. Furthermore, most food RSs were used to recommend recipes and after that meal planning. The main approach used was the hybrid approach, followed by knowledge-based and context-based approaches. Next to this, no studies used a demographic or social-network based approach. However, eight studies included demographic characteristics (Ali et al., 2018; Cruz et al., 2017; Elsweiler & Harvey, 2015; Ge et al., 2015; Harvey & Elsweiler, 2015; Ho & Chang, 2018; Rehman et al., 2017; Subramaniyaswamy et al., 2019) and three studies included information from a social media network in their RS (Chu & Tsai, 2017; Freyne et al., 2011; Jiang et al., 2019; Rathi et al., 2017). Next to this, almost all studies recommended alternatives to the user, which helped them with stage 3: evaluating alternatives. Moreover, the most used RS type was user preference, followed by the trade-off RS type. Lastly, there are more articles that did an experiment with their RS, than articles that explained their RS. All experiments tested the performance (e.g. prediction accuracy, quality or effectiveness), except for the following three studies: Adaji, Sharmaine, Debrowney, Oyibo & Vassileva (2018), tested if there was a connection between personality types and recipe categories; Cruz et al. (2017), tested if there was a relation between the demographics of the participants and how they rated the RS; and Freyne, Berkovsky, Baghaei, Kimani & Smith (2011), tested the effect of personalized and non-personalized tools on user interaction, information access and user motivation with the RS.

As can be seen in Table 2-4, all restaurant RSs are user preference RS types and only the trade-off RS types are focused more on meal planning than recipes. Furthermore, the main approach for user preference and trade-off RS types was the hybrid approach, and for the health and nutrition RS type it was the knowledge-based approach. Also, collaborative filtering was only found for the user preference RS type. For all food RSs types stage 3: evaluating alternatives, was used the most. Next to this, only grocery stores helped the user with stage 1: problem recognition. Moreover, the user preference food RS type had more experiments than explained models, while for the other two food RS types it was the other way around. In the 'Discussion & Conclusion' section more information will be given about these findings.

The last finding is that although most studies focus on food or users in general, five articles are made for a specific regional cuisine: Calabrian food items RS (Agapito et al., 2017), Filipino recipes RS (Cruz et al., 2017), Chinese regional recipes RS (Guo, Yuan, Mao & Gu, 2017), Balinese food stalls RS (Kadyanan, Dwidasmara, Mahendra, Mogi & Sudarma, 2019), and Indian recipes RS (Maheshwari & Chourey, 2019). Furthermore, eleven articles are specially made for certain users: meal plan RS for elderly (Aberg, 2006; Espín, Hurtado & Noguera, 2015; Ribeiro et al., 2018), recipe RS for American Indians with diabetes (Alian et al., 2018), restaurant RS for tourists (Effendy, Nuqoba & Taufik, 2019), recipe RS for users that suffer from a chronic disease (Ivaşcu, Diniş & Cincar, 2018), meal plan RS for obese youth (Jung & Chung, 2016), recipe RS for toddlers (Ng & Jin, 2017), food item RS for people suffering from common diseases (Rehman et al., 2017), food item RS for travellers (Subramaniyaswamy et al., 2019), and recipe RS for people with health problems (Ueta, Iwakami & Ito, 2011).

Table 1 Descriptive information of the included articles

Year	*1986-2010*	*2011*	*2012*	*2013*	*2014*	*2015*	*2016*	*2017*	*2018*	*2019*	*2020*
	8	3	4	1	3	11	3	11	13	14	2
Type of food*	*Food item*	*Groceries*	*Meal planning*	*Recipes*	*Restaurants*						
	6	5	17	*39*	8						
RS approach[1]	*CB*	*CF*	*CxB*	*Hybrid*	*KB*						
	6	2	*11*	30	*24*						
Stage	*Problem recognition*	*Searching for information*	*Evaluating alternatives*	*Purchasing*	*Post-purchasing evaluation*						
	4	*4*	65	0	*0*						
RS type	*User preferences*	*Health & nutrition*	*Trade-off*								
	37	11	25								
Type of study	*Explain model*	*Experiment*									
	31	*42*									

**: there is one study that is both a food item and meal planning RS and one study that is both a recipe and meal planning RS, those are counted double*

[1]*: content-based= CB; collaborative filtering= CF; CxB= context-based; KB= knowledge-based*

Table 2 Thematic analysis of user preference food RSs

Author(s) (number)[1]	Year	Topic of the study	Type of food	Type of study	RS approach[2]	Stage[3]
Adaji et al. (4)	2018	Their recommendations are based on the personality types of the user and users/ online recipe reviews with the same personality type. They tested if there was a connection between personality types and recipe categories	Recipes	Experiment	Hybrid: CB, CF	3
Bushra & Hasan (4)	2019	QuickyCook recommends recipes that contain (almost) all ingredients that the user want to include. They use the recently developed database called Recipe 1M. They measured the performance of the RS	Recipes	Experiment	KB	3
Chu & Tsai (1)	2017	RS that predicts user's preference of restaurants by combining metadata, textual and visual information (photos) in blogs. They tested the performance of their RS	Restaurants	Experiment	Hybrid: CB, CF	3
Cruz et al. (4)	2017	Fatchum recommends Filipino recipes based on the user's search terms or searches recipes by ingredients. Participants tested the usability of the RS based on design-related factors. The researchers also looked if there was a relation between the demographics of the participants and how they rated the RS	Recipes	Experiment	CB	3
Effendy et al. (4)	2019	The RS ranks culinary destinations for tourists based on user positive and negative criteria. The user can apply a weight of importance for each criteria. They test the performance of their RS	Restaurants	Experiment	CxB	3
Elahi et al. (2)	2015	RS that interacts with the user and recommends recipes based on the user’s long-term preferences (ratings and tags of familiar recipes) and short-term preferences (ingredients that the user wants to include). They evaluated the accuracy of the recommendations	Recipes	Experiment	KB	3
Forbes & Zhu (1)	2011	RS that combined content information of the ingredients with the collaborative filtering method. They tested the prediction accuracy of their RSs	Recipes	Experiment	Hybrid: CB, CF	3
Freyne & Berkovsky (1, 2, 3)	2010	Users evaluated the accuracy of two RSs with different data gathering strategies to recommended recipes based on the user's positive ratings. The first one gathers food items ratings and the second one gathers recipe ratings	Recipes	Experiment	Hybrid: CB, CF	3
Fu, Liu, Yong, Yao & Hui (1)	2014	They tested the performance of their RS that base the recommendations on user restaurant ratings on multiple factors (geographical, user and restaurant information) to improve restaurant recommendations	Restaurants	Experiment	CxB	2

Gao et al. (1)	2019	The RS predicts user's food preference based on user's ingredient preference, photos of dishes, and preferences of similar users. They compared the performance of their RS with other food RSs	Recipes	Experiment	Hybrid: CB, CF	3
Ge, Elahi, Fernaández-Tobías, Ricci & Massimo (1, 3)	2015	Their RS extends CF method by including user’s positive/ negative tags and recipe ratings. They tested the effect of using tags in their RS algorithm increase prediction accuracy and compared this to algorithms that do not use tags	Recipes	Experiment	Hybrid: CB, CF	3
Guo et al. (4)	2017	The RS recommends recipes from Chinese regional cuisines with similar flavours as the user's flavour preferences (is determined with the user's recipe ratings). Professional chef's evaluated the RS performance	Recipes	Experiment	CxB	3
Hammond (3)	1986	CHEF builds new recipes and finds recipes that satisfies (almost) all of the user's requests. It can detect faulty recommendations and can build a restriction to avoid this in the future. It stores failure and successful recommendations in its memory	Recipes	Explain model	KB: CaB	3
Hinrichs & Kolodner (3)	1991	JULIA is an interactive RS that recommends meals based on constraints from the user. They tested the effectiveness of JULIA when solving different types of problems	Recipes	Experiment	KB: CaB	3
Kadyanan et al. (4)	2019	They test the accuracy of their Balinese food stalls RS made for Bali. The recommendations are based on user data, food stall ratings, and food ratings	Restaurants	Experiment	Hybrid: CB, CF	3
Kawano, Sato, Maruyama & Yanai (1)	2013	RS that recommends recipes from an online recipe database based on the ingredients the user wants to include. The user points the camera to the ingredient and the RS recognizes it with a visual food analysis	Recipes	Explain model	KB	3
Kodali, Dabbiru & Rao (4)	2019	They recommend restaurants based on their similarity between the user's previous food eaten/ places visited, and cuisine the user prefers. The prediction accuracy of their RS is tested	Restaurants	Experiment	Hybrid: CB, CF	3
Kuo, Li, Shan & Lee (2, 3)	2012	Menu planning based on both requested ingredients by the user and a knowledge graph (that shows the relationship between recipes of whether or not they can be used in one menu)	Meal plan	Explain model	KB	3
Lawrence, Almasi, Kotlyar, Viveros & Duri (3)	2002	Recommends new grocery products based on purchase history of the user and other users and expected appeal of the product to the user. They measured the performance by calculating how many people bought the recommendations with the current RS compared to the older version	Groceries	Experiment	Hybrid: CB, CF	1

Li et al. (4)	2018	The RS bases the restaurant dish recommendations on the user dish ratings, user information, contextual factors, and food attributes. They test the performance of their RS with Chinese foods	Recipes	Experiment	Hybrid: CF, CxB	3
Lin, Kuo & Lin (1)	2014	Based recommendations on recipe, user ratings, and recipe features information (e.g. preparation, course, cuisine)	Recipes	Explain model	Hybrid: CB, CF	3
Maheshwari & Chourey (4)	2019	Their system pairs food and ingredients to innovate new dishes or suggest alternative ingredients for people who are allergic for a certain ingredient. They focus on the Indian cuisine	Recipes	Explain model	KB	3
Pratibha & Kaur (4)	2019	The RS recommends recipes based on user information and contextual factors e.g. the food items available in the kitchen, preparation time of the user, and weather	Recipes	Explain model	CxB	3
Rathi, Rander & Sanghvi & Shah (4)	2017	Data from online reviews, likes, social media content, and comments are collected from different online sources to recommend local food eateries that match the user profile preferences	Restaurants	Explain model	Hybrid: CB, CF	3
Saito, Asada, Ysohitomi, Kato & Tabuse (4)	2018	RS that recommends a recipe based on yesterday's dinner recipe, impression words chosen by the user (e.g. sweet, spicy, warm), past successful recommendations, and recipes with the same ratings. They also tested the performance of their recommendations	Recipes	Experiment	Hybrid: CB, CF	3
Sano, Machino, Yada & Suzuki (3)	2015	They propose two RSs that recommends products on discount by e-mail, one based on transaction data and the other based on transaction data and store manager data. They evaluated the performance of 5 recommendation methods and found out that singular value decomposition is appropriate for the 1st RS and CF for the 2nd RS	Groceries	Experiment	Hybrid: CB, CF	1
Skjold, Øynes, Bach & Aamodt (4)	2017	IntelliMeal recommends recipes based on the ingredients the user (dis)likes. The RS continuously learns the user's preferences as the user can give feedback. They evaluated the performance of the RS	Recipes	Experiment	KB: CaB	3
Svensson, Laaksolahti, Höök & Waern (2)	2000	Recipe recommendations based on the ingredient categories, ingredients, and user clubs (formed by a 'club owner', that recommends recipes to its members). It allows users to interact with each other	Recipes	Explain model	Hybrid: CB, CF	3
Teng, Lin & Adamic (1, 3)	2012	Recommendations are based on nutritional information and the complement and substitution ingredient networks (from a recipe-sharing website). They tested the prediction accuracy of their RS	Recipes	Experiment	CB	3

Trevisiol, Chiarandini & Baeza-Yates (3)	2014	They tested the performance of RSs algorithms that can be used to predict user preferences by extracting positive/ negative food words from menu reviews and ratings. These algorithms can be applied in several RSs that suggest food items or menus from restaurants	Food item & Meal plan	Experiment	CF	3
Ueda, Morishita, Nakamura, Takata & Nakajima (4)	2016	Recommends recipes based on the user's mood (6 aspects: body, mental, taste, time, price, and modification). Students rated recipes on each mood aspect, and this data was used to make a connection between recipes and user's mood	Recipes	Explain model	CxB	3
Varatharajan, Guruprasad & Mathumitha (4)	2020	RS that recommends restaurants based on the user food preferences, restaurant ratings, the user's current location, and ratings of users with the same taste	Restaurants	Explain model	Hybrid: CB, CF	3
Vivek, Manju & Vijay (4)	2018	They compared the performance of an RS that uses a user based CF approach (similarity between users and user ratings) and of an RS that uses an item based CF approach (similarity between recipes) RS method. The user based method performs better	Recipes	Experiment	CF	3
Yamamoto, Kando & Satoh (4)	2016	RS recommends recipes that users will choose based on their cooking history, ingredient preferences and how challenging a recipe is for them. They test the prediction performance of their recipe RS	Recipes	Experiment	CxB	3
Yang et al. (1, 3)	2015	PlateClick is an RS that learns user's food preferences via a visual quiz to recommend recipes. They use a recipe network to learn the similarity between the food images. They evaluate the performance of the RS	Recipes	Experiment	CxB	3
Zeng, Nakano, Morita, Kobayashi & Yamaguchi (1)	2018	RS dialogue system that explicitly elicits user taste and texture preferences through human-robot interaction. The knowledge base is based on a recipe database and an analysis of taste and texture derived from Twitter messages	Recipes	Explain model	KB	3
Zhang, Luo, Chen & Guo (4)	2020	They compared the performance of their multi-view RS with that of single-view RSs. They used multiple images (drink, food, inside & outside of the restaurant) to recommend restaurants to the user	Restaurants	Experiment	Hybrid: CF, CxB	3

[1]*: 1= article from Min et al. (2019); 2= article from Tran et al. (2018); 3= article from Trattner & Elsweiler (2017); 4= recent article from own research*

[2]*: case-based= CaB; content-based= CB; collaborative filtering= CF; CoB= constraint-based; CxB= context-based; KB= knowledge-based*

[3]*: decision-making stages: 1= problem recognition; 2= searching for information; 3= evaluating alternatives; 4= purchasing; 5= post-purchasing evaluation*

Table 3 Thematic analysis of health & nutrition food RSs

Author(s) (number)[1]	**Year**	**Topic of the study**	**Type of food**	**Type of study**	**RS approach[2]**	**Stage[3]**
Agapito et al. (4)	2017	DIETOS recommends healthy and diet-related Calabrian food for healthy users and users with a chronic disease. It is based on the users health profile. The RS shows the user the nutritional information and locality of the food	Food items	Explain model	KB	3
Alian et al. (4)	2018	The RS recommends a healthy lifestyle to American Indians with diabetes based on patient profile, food & nutrition guidelines, physical activity log, and food intake log. It gives a daily food summary	Recipes	Explain model	KB	2
Jiang et al. (4)	2019	Market2Dish recommends healthy food based on the user's health profile (elicited from their social media texts and videos) and a recipe dataset. It interacts with the user and also calculates the user's calorie intake	Recipes	Explain model	KB	3
Jung & Chung (4)	2016	They tested the performance of their RS that suggests dietary menus for obese youth. They include the user's health, personal and contextual information and use the SeeMe5 nutritional dataset	Meal plan	Experiment	Hybrid: CF, KB, CxB	3
Maia & Ferreira (4)	2018	Their RS uses the user's current location, recipe attributes (cuisine type, ingredients), and user's dietary group. They test the performance of the RS with three different recipe datasets (derived from food.com, kochbar.de, and epicurious.com)	Recipes	Experiment	Hybrid: CxB, CF	3
Mankoff, Hsieh, Hung, Lee & Nitao (3)	2002	Use shopping receipts to keeps track of the nutritional content of foods they have eaten and suggest healthier food alternatives that the user can buy next time	Groceries	Explain model	KB	1
Müller, Mika, Harvey & Elsweiler (3)	2012	System that uses the BLS nutritional database to automatically calculate the nutritional content of recipes sourced from the internet	Recipes	Explain model	KB	2
Nag et al. (1)	2017	Use restaurant and nutrition databases, expert knowledge, user health information, and contextual factors to recommend a healthy dish	Recipes	Explain model	CxB	3
Ohata, Nishihara & Yamanishi (4)	2019	This RS recommends meals-out (restaurant dish or pre-cooked food) that supports a balanced nutritional intake based on what the user has eaten that day (user's food log). They let people evaluate the effectiveness of their RS	Recipes	Experiment	CB	3
Rehman et al. (4)	2017	Diet-Right recommends food to people suffering from common diseases that must fulfil their nutritional needs requirements. They create a user profile	Food items	Experiment	KB	3

	2011	based on demographics. They tested the accuracy, performance, and convergence time				
Ueta et al. (2, 3)	2011	They use nutritional information and the user's health profile to recommend recipes that can solve the user's health problems. The user does not need to have nutritional knowledge and can use natural language (e.g. I want to cure my acne). They measured the performance of their RS	Recipes	Experiment	KB	3

[1]: 1= article from Min et al. (2019); 2= article from Tran et al. (2018); 3= article from Trattner & Elsweiler (2017); 4= recent article from own research

[2]: case-based= CaB; content-based= CB; collaborative filtering= CF; CoB= constraint-based; CxB= context-based; KB= knowledge-based

[3]: decision-making stages: 1= problem recognition; 2= searching for information; 3= evaluating alternatives; 4= purchasing; 5= post-purchasing evaluation

Table 4 Thematic analysis of trade-off food RSs

Author(s) (number)[1]	**Year**	**Topic of the study**	**Type of food**	**Type of study**	**RS approach[2]**	**Stage[3]**
Aberg (2, 3)	2006	Meal planning system that provides healthy food recipes for elderly dealing with malnutrition. The recommendations are based on the advice of health-care professionals, but also includes user's food taste	Meal plan	Explain model	Hybrid: CB, CF	3
Ali, Amin, Kim & Lee (4)	2018	RS that provides educational, diet menu plans, and physical activity recommendations. They use expert knowledge as guidelines and include user information (e.g. health, preferences, demographics) and contextual information	Meal plan	Explain model	Hybrid: CxB, KB	3
Bianchini, De Antonellis & Melchiori (1)	2015	PREFer is a menu RSs that matches users' preferences and recipe features while also improving the nutritional habits of the user	Meal plan	Explain model	CB	3
El-Dosuky, Rashad, Hamza & El-Bassiouny (2, 3)	2012	They recommend food items to the user based on their user profile, healthy heuristics (to include more healthy food), and food databases from the USDA. They compared the performance of their RS algorithm with that of traditional RSs algorithms (TF-IDF, B. Cosine, Jaccard, and SemRel)	Food items	Experiment	KB	3
Elsweiler & Harvey (1, 3)	2015	RS that predicts the user's food preference based on their profile. It creates daily meal plans that meet both user food preference (recipe ratings and	Meal plan	Experiment	CB	3

		demographics) and nutritional guidelines from international health agencies. They tested the performance of their RS				
Elsweiler, Harvey, Ludwig & Said (2, 3)	2015	They discussed two ways (one recipe or a meal plan) to incorporate both user preferences and healthy nutritional aspects in a food RS. Integrate both user preferences and nutritional aspects into recipe and meal plan recommendations	Meal plan & Recipes	Explain model	CB	3
Espín et al. (4)	2015	NutElCare is an RS for elderly where they can create a healthy diet plans that satisfy their nutritional needs and taste preferences. The system uses WHO nutritional databases and nutritionists can monitor if the user follows the recommendations	Meal plan	Explain model	Hybrid: CB, KB	3
Freyne et al. (3)	2011	eHealth portal is a diet compliance system that has 3 tools: a meal planner, social network activity feed, and a social comparison tool. They tested the effect of personalized and non-personalized tools on user interaction, information access and user motivation	Meal plan	Experiment	Hybrid: CB, CF	2
Ge, Ricci & Massimo (1, 3)	2015	Their RSs recommend recipes that uses a user profile based on user demographics, user's long-term and short-term preferences and user's health. They use a calorie count in their recommendation algorithm. The computer interacts with the user	Recipes	Explain model	KB	3
Gutiérrez, Verbert & Htun (4)	2018	PHARA is a mobile app RS that gives the user nutritional information (e.g. calorie intake and nutrition guide) about products in the grocery store and they recommend similar or healthier product alternatives. It recognizes the food products based on their visual components	Groceries	Explain model	CxB	3
Harvey & Elsweiler (2, 3)	2015	A web-based system that creates daily meal plans based on the user's taste profile, recipe ratings, demographics, and nutritional requirements	Meal plan	Explain model	KB	3
Ho & Chang (4)	2018	Healthy diet RS that uses the users information (preferences, demographics, exercise habits, health situation) to classify users into categories. Based on the category, meal packages are supplied to the user every week. Users evaluate the performance of the RS	Meal plan	Experiment	Hybrid: CF, KB	3
Ivaşcu et al. (4)	2018	The RS recommendations for users suffering from a chronic disease are based on the user's health information (e.g. past diseases, allergies) derived from the health care institution and user's food preferences	Recipes	Explain model	KB	3

Khan & Hoffmann (3)	2003	MIKAS base recommendations on user health requirements and food preferences. The user can interact with a hospital dietitian. They evaluate the performance of the RS	Meal plan	Experiment	KB: CaB	3
Khan, Rushe, Smyth & Coyle (4)	2019	They compared the performance of their RS (includes contextual factors, user preferences and user health information) with a content-based RS. Their RS can also predict the user's preference of recipes the user has not rated before	Recipes	Explain model	Hybrid: CxB, CF	3
Llerena, Rodriguez, Gómez-Abajo & Castro (4)	2017	Prototype RS that makes a user profile (from a questionnaire about personal, medical, and contextual factors). The RS adjusts the recommendations based on the user's menu ratings	Meal plan	Explain model	CxB	3
Ng & Jin (1)	2017	TodRec assist parents with feeding their toddlers by suggesting recipes. They use both user preferences and nutrition guidelines of the US. They compare the performance of TodRec with commonly-used recipe websites	Recipes	Experiment	Hybrid: CB, CF	3
Nouh, Lee, Lee& Lee (4)	2019	Healthy food items are recommended based on the user's health profile, feedback, and food preferences. They evaluated the performance of their RS; it improves by including user feedback	Food items	Experiment	Hybrid: CB, CF, CxB	3
Ntalaperas, Bothos, Perakis, Magoutas & Mentzas (4)	2015	DISYS recommends dishes in a restaurant that are both healthy and tasty for the user. It considers user preferences, user diet, physical activity, and health indices. The user can interact with the DISYS	Recipes	Explain model	Hybrid: CxB, KB	3
Ribeiro et al. (1)	2018	SousChef recommends healthy meals for Portuguese elderly based on the Portuguese nutritional guidelines. It keeps track of the user's food intake, user food ratings, and activity monitoring. It also serves as grocery list	Meal plan	Explain model	CxB	3
Salloum (4)	2018	PIN is an RS based on user's health information and food preferences. The RS also looks at the meal-food compatibility (e.g. eggs are compatible with breakfast). They evaluated the performance of their RS	Meal plan	Experiment	KB	3
Subramaniyaswamy et al. (4)	2019	ProTrip recommends food to travellers with a disease or diet based on user information (demographics, preferences health situation), preferences of other users, and nutritional value. ProTrip interacts with the user and provide nutritional information to the user. They evaluate the performance of ProTrip	Food items	Experiment	Hybrid: CB, CF, KB	3
Talekar, Raghavendra & Vaddatti (4)	2019	NutriSmart recommends healthy food items in the grocery store based on other user reviews and the user profile (made after the user fills in a questionnaire about food habits, nutrition, and user preferences)	Groceries	Explain model	Hybrid: CB, CF	1

Toledo, Alzahrani & Martínez (4)	2019	They made an RS based on user preferences and nutritional information. The RS has a pre-filtering stage in which they exclude foods that do not match the current user's situation (e.g. daily exercise). They tested their RS performance	Meal plan	Experiment	KB	3
Yang et al. (1, 3)	2017	Yum-me is an RS that include both user's health goals (diet and nutritional needs) and user's food preferences (based on a visual quiz). The RS adjust the recommendations based on the user's feedback (Yummy or No way). They evaluated the effectiveness of Yum-me	Recipes	Experiment	KB	3

[1]*: 1= article from Min et al. (2019); 2= article from Tran et al. (2018); 3= article from Trattner & Elsweiler (2017); 4= recent article from own research*

[2]*: case-based= CaB; content-based= CB; collaborative filtering= CF; CoB= constraint-based; CxB= context-based; KB= knowledge-based*

[3]*: decision-making stages: 1= problem recognition; 2= searching for information; 3= evaluating alternatives; 4= purchasing; 5= post-purchasing evaluation*

4.4 Challenges and Current Solutions for Food Recommendation Systems

There are several challenges and solutions for food RS discussed in the literature reviews.

1. *Predicting the user's food preferences*: according to Min et al. (2019), Tran et al. (2018) and Trattner & Elsweiler (2017) solutions to predict user food preferences are using psychology and neuroscience research methods; user food data from social media and recipe-sharing website (e.g., Yummly, Allrecipes, Meishijie, Foodspotting); user ratings; mobile and sensing devices; and user food journal. However, the accuracy of food RSs is poorer than RSs in other domains, as food preferences are complex and influenced by (contextual) factors that can be hard to obtain or model.
2. *Food journal*: food journals are a solution to better predict user's food preferences. In a food journal users can keep track of their eating history, for example their portion size and calories. Yet, a food journal costs a lot of the user effort to keep track of what they eat, and users easily forget or give wrong information (Min et al., 2019; Tran et al., 2018). To decrease the user effort a visual analysis can be made of a photo the user made, to recognize the food ingredients, food categories, cooking instructions and estimate food intake (Min et al., 2019). However, more research is needed to improve the food recognition of the visual analysis.
3. *User ratings*: user ratings are also a solution to better learn the user's food preference. Unfortunately, it is challenging to collect enough user' ratings while keeping the food RSs convenient and saving the user effort. Furthermore, it is difficult to persuade users to keep rating dishes, recipes, or food items (Tran et al., 2018).
4. *Accurately measuring the nutritional value*: one solution is to standardize the names and quantities. Nevertheless, different names and units or quantities are still used for the same recipe, ingredient, or food item. Furthermore, food can be prepared in different ways, which influences the nutritional value (Tran et al., 2018; Trattner & Elsweiler, 2017).
5. *Food availability*: including the availability of food in the household is a solution to save the user money and prevent food waste. However, this requires a lot of effort from users to register all food items they consume and have in stock (Min et al., 2019; Tran et al., 2018).
6. *Balancing between a big database and user satisfaction*: a big database is an advantage as the food RSs has more food items to recommend that better match the user's health situation or food preferences. Nevertheless, food RSs should find a balance between the amount of food items included in the database and user satisfaction with the system's response time. For example, if the database is too large, the RSs has to check more constraints or rules, which will take longer and can lead to user dissatisfaction (Tran et al., 2018).

5. Discussion & Conclusion

5.1 Discussion

This literature review created an overview of three recent literature reviews and seventy-three studies in the field of food RSs for individual users and how they influence consumer decision-making. With this overview the research question can be answered: *How have the recommendation systems for individual users been applied in the food sector?* The analysed articles were mostly applied in the recipe domain, which is in line with the research from Trattner & Elsweiler (2017). However, no studies were found on RSs for coffee shops or ingredients. An interesting finding was that all restaurant RSs focused on the user preference, as they do not consider health in their recommendations. Also as mentioned before, almost all food RSs can be applied for all different types of cuisines or users, except for sixteen articles. The majority of the studies in this analysis were from 2015, 2017, 2018 and 2019, which can be the result of the search strategy, as for the current studies only studies from 2015-2020 were allowed.

5.1.1 What Types and Approaches of Recommendation Systems have been Applied in the Food Sector?

The types of RSs are user preferences, health and nutrition, trade-off, and group food RSs types (Tran et al., 2018). The user preferences and trade-off types are implemented most frequently in food RSs. This finding was not expected, as Nyati et al. (2019) stated that most researchers focus on healthy food RSs. Nevertheless, according to Ghasemaghaei (2020) it is important to understand the consumer decision-making to improve food RSs, so this can explain why many researchers are focused on the user's food preferences.

In terms of RS matchmaking approaches, the hybrid, knowledge-based and context-based approach were used the most, which was predictable as they are common approaches to be used (Alyari & Navimipour, 2018; Tran et al., 2018; Trattner & Elsweier, 2017). Nevertheless, the content-based approach was only used six times, and the collaborative filtering approach was only used twice. This was not expected since they are also popular recommendation approaches. It is interesting to say that both collaborative filtering approaches were used for user preferences. However, eighteen hybrid approaches use the content based approach and twenty-three hybrid approaches use the collaborative filtering approach. So, it can be assumed that those two approaches are combined more often with other approaches, than that they are used individually. Another finding was that no studies were found that solely used a demographic or social network-based approach (Alyari & Navimipour, 2018; Li & Karahanna, 2015). Nevertheless, it might be better to develop hybrid approaches that include demographic and social network information, as there are more (contextual) factors that need to be taken into account (Min et al., 2019; Tran et al., 2018; Trattner & Elsweiler, 2017).

5.1.2 How can these Food Recommendation Systems be Classified Based on the Consumer Decision-Making Process?

After analysing all studies with the online consumer decision-making model based on Darley et al. (2010) and Maçik (2016) it can be concluded that the majority of food RSs help the user with stage 3: evaluation of alternatives. This finding can be explained with the model in Li & Karahanna (2015) since RSs in general collect user information (e.g. preferences or health situation) to build a consumer profile. Based on this information a food RS can recommends food that matches the criteria of the user profile (Li & Karahanna, 2015). Next to this, only grocery food RSs created new needs or wants for grocery products that the user has not bought before. These RSs thus aid the consumer with stage 1: problem recognition. Lastly, a few food RSs helped the user in stage 2: searching for information. This food RSs then provides the user with information that helps them select or rank their selection criteria.

5.1.3 What are the Current Challenges and Solutions for Food Recommendation Systems?

As can be seen, there were six solutions and challenges found. The main challenge is accurately predicting the user's food preferences, which is in agreement with Schäffer et al. (2017). The main reason given by Tran et al. (2018) and Trattner & Elsweiler (2017), is that food decisions are complex, continuously changes, and is influenced by different (contextual) factors. Moreover, online consumer decision-making is also complex as it is influenced by many external factors (Darley et al., 2010; Maçik, 2016). This challenge can be the reason, why most research is still focused on the user preference food RS type. A solution to solve this challenge is to use psychology and neuroscience research methods. Other challenges according to Tran et al. (2018), Trattner & Elsweiler (2017) and Min et al. (2019) are incorporating a food journal, as it costs a lot of the user's effort and the user can easily forget or give wrong information. This can be solved with a visual food analysis. Next to this, including food availability saves the user money and prevents food waste, but requires user effort. Furthermore, a trade-off needs to be made between user satisfaction (e.g. saving users effort and convenience) and a big database or a lot of user ratings. Lastly, accurately measuring the nutritional value is still difficult as the names and quantities of recipes, ingredients and food items need to be standardized.

5.2 Implications

This paper provides a comprehensive overview of the current researches on food RSs. This is useful information for researchers, as they can use the challenges and future research suggestions as inspiration for their own research. For instance, the researchers can focus on developing a good quality and standardized evaluation method for the performance of food RS. Next to this, the results can help (e-commerce) food companies with designing new and improved food RSs. Companies can look at the list of food RSs available and implement those ideas and useful designs in their own food RS. For instance, grocery stores can use the information of Nutrismart from Talekar et al. (2019) to develop a food RSs for their own supermarket. This will lead to less losses in potential sales and higher revenues for the company (Ghasemaghaei, 2020). Moreover, nutritionists or dietitians can use Tables 2-4 to see what current food RSs exist that can aid their patients in eating healthier. For example, the food RS from Ali et al. (2018) makes diet menu plans, educates its users, and recommend physical activity based on expert knowledge and sensory devices. Lastly, the improved food RSs that can be made with this literature overview will benefit the consumer. For instance, an effective RSs in general can improve the customer's shopping experience; the user's satisfaction with the system and search process; the loyalty and relationship with the company and product or service; and the confidence of consumers in their decision (Häubl & Trifts, 2000; Huseynov & Yildirim, 2016; Verruck & Nique, 2017; Yang et al., 2017). In other words, it will improve the user's decision quality by reducing the user's cognitive effort and search costs (Pederson, 2000). A specific advantage of a food RSs is that they provide information on food and recommend food that is both healthy and tasty for the user, which can change the user's eating behaviour in a positive way (Tran et al., 2018).

5.3 Limitations

There are some limitations that need to be considered. First of all, the method used was not a systematic literature review, which can make it less comprehensive, more biased and subjective, and less easy to replicate (Alyari & Navimipour, 2018; Siddaway, Wood & Hedges, 2019; Snyder, 2019). Also, the literature review was done by one person. This means that there was no inter-rater agreement on the interpretation of the articles (Siddaway et al., 2019). This can harm the reliability and internal validity of the research, since two researchers can discuss and double check the interpretation of the other. Nevertheless, the steps for the literature review were explained thoroughly to achieve transparency, which improved the quality and credibility of this research.

Moreover, as a result of writing this paper in only two and a half months' time, it was decided to exclude unpublished research, as it seemed unattainable within this short time frame. However, according to the publication bias this can threaten the internal validity of the conclusion, since published studies are more likely to have significant results (Siddaway et al., 2019). For example, there could be meal planning or grocery food RSs that are not published. That is why a future systematic literature review might be useful to including also unpublished research.

Furthermore, it was decided in the 'Analysis & Results' section to refer to the three literature reviews of Tran et al. (2018), Trattner & Elsweiler (2017) and Min et al. (2019) instead of the original articles, except for section 4.3. This can make this paper less transparent, as people cannot immediately see in which original article these assumptions or results were found. However, this strategy was used to make it easier to compare the information of the literature reviews. Furthermore, due to the limited time of this research it was decided to spend more time on searching for more recent articles than reading the original articles.

Finally, this research only focused on the food RSs types, approaches, categorisation of studies based on the online consumer decision-making process, challenges and solutions, and future research suggestions. Nonetheless, due to the limited time the external factors, such as individual, social influence, situational, and economic variables that influence the consumer decision-making process and other contextual factors that can be used to build a user profile for food RSs were not analysed (Darley et al., 2010; Maçik, 2016). The same holds for the types of evaluation methods that were not incorporated in the article analysis. Moreover, as explained before, group food RSs were also not covered in this paper. That is why another literature review can be useful that will include these interesting topics in their research.

5.4 Future Research

The future research directions in the food RSs based on this research are as followed:

1. *Food types*: more food RSs are needed to be developed in other areas than recipe RSs. For example, food RSs for grocery shopping, coffee shops, ingredients, restaurants, and food items. Something that might be interesting is to develop a restaurant RS that takes the healthiness of restaurant menus into consideration.
2. *Evaluation methods*: a more standardized and specialized method must be developed to evaluate food RSs on prediction accuracy and diversity. Furthermore, full-online evaluations need more attention, as there are very limited researches that do this (Trattner & Elsweiler, 2017). The experimental researches included in this literature review can be used to make an overview of what current evaluation methods exist.
3. *Literature review*: another literature review can be useful that includes topics such as group food RSs, external and contextual factors of current food RSs, unpublished research, and all current evaluation methods of food RSs. Especially the external and contextual factors are interesting, as no research has focused on identifying the most important contextual variables (Tran et al., 2018; Trattner & Elsweiler, 2017). This in turn, will improves the understanding of how food RSs can change eating behaviour.
4. *Food RSs*: more food RSs can be developed that focus on other decision-making stages than stage 3: evaluating alternatives. For example, a food RS can be developed that provide product information or suggests different selection criteria that the user can use when choosing (healthy) grocery products. This helps people with stage 2: searching for information.

The future research direction in the food RSs based on the three literature reviews (Min et al., 2019; Tran et al., 2018; Trattner & Elsweiler, 2017):

1. *User preference*: according to Min et al. (2019) and Trattner & Elsweiler (2017), further research should improve the development of user profiles and the performance of the food RSs. One topic that asks for more attention is implicit methods (e.g., recipe reviews) to elicit user's food preferences, as explicit methods require user effort and cannot fully capture user preferences.
2. *Sensing devices*: the current sensing devices that measure the real-time user's state cannot measure everything. Some topics that need further research are fusing discrete and continuous contextual variables together in a joint model; innovating sensors to measure or

methods to quantify hard or up to now not available variables (e.g., smell and taste); and making more accurate sensors (Min et al., 2019).

3. *Food item database*: according to Min et al. (2019), Tran et al. (2018) and Trattner & Elsweiler (2017) there are only a few publicly available databases, for example Kaggle for grocery products and MIT recipe database. Furthermore, there are not many databases that combine recipes, food images, user comments, expert knowledge, food items or ingredient data. That is why researchers typically make their own dataset, which are often patented and non-standardized making their findings difficult to validate, and their research difficult to reproduce and less reliable (Trattner & Elsweiler, 2017). Thus, a publicly available database is needed that combines different data.
4. *Visualization of food items*: visual food analysis can serve as a solution for food journals, however, they need to be improved as most visual analysis are only effective for RSs in general. The reason for this is that food is nonrigid and has no distinctive or structured form, which makes it harder to visually analyse it (Min et al., 2019; Trattner & Elsweiler, 2017).
5. *Group food RSs*: according to Tran et al. (2018), more research needs to be done to achieve fast consensus in group decision-making and to make meal planning recommendations for one or more than one day (bundled recommendations). Especially group constraints, such as a food allergy of one individual is important to take into consideration. Next to this, more research should focus on the influence of social situations on (group) food choices (Trattner & Elsweiler, 2017).
6. *Other resources*: some resources that might improve food RSs have not yet been implemented, such as the Health Eating Index as nutrition and health resource; Foodsubs as food substitution database to replace unhealthy food items, meals or ingredients with healthy alternatives; Foodlog as information source to learn the user’s food preferences; Enchantedlearning and Wikipedia as food word databases to normalize the ingredient process; Centers for Disease Control and Prevention as health database to implement food RSs in different geographical regions in America (Min et al., 2019; Trattner & Elsweiler, 2017).

References

(publication year)*= studies included in the 'Analysis & Results' Section

Aberg, J. (2006, March 27-29)*. *Dealing with malnutrition: A meal planning system for elderly*. In Proceedings AAAI Spring Symposium SS-06-01: Argumentation for consumers of healthcare, (pp. 1-7). Retrieved from https://www.researchgate.net/publication/221250510_Dealing_with_Malnutrition_A_Meal_Planning_System_for_Elderly

Adaji, I., Sharmaine, C., Debrowney, S., Oyibo, K., Vassileva, J. (2018)*. *Personality Based Recipe Recommendation Using Recipe Network Graphs*. In: Meiselwitz G. (Eds.), In Proceedings International Conference on SCSM, vol 109 (pp. 161-170). Retrieved from https://www.researchgate.net/publication/325462174_Personality_Based_Recipe_Recommendation_Using_Recipe_Network_Graphs

Agapito, G., Simeoni, M., Calabrese, B., Guzzi, P. H., Fuiano, G. & Cannataro, M. (2017)*. DIETOS: a recommender system for health profiling and diet management in chronic diseases. *Computer Methods Programs Biomedicine, 153*, 93-104. Retrieved from http://ceur-ws.org/Vol-1953/healthRecSys17_paper_13.pdf

Ali, S.I., Amin, M.B., Kim, S. & Lee S. (2018, July 10-12)*. *A Hybrid Framework for a Comprehensive Physical Activity and Diet Recommendation System*. In: Mokhtari M., Abdulrazak B., Aloulou H. (Eds.), Proceedings of the ICOST, vol 10898 (pp. 101-109). Retrieved from https://link.springer.com/chapter/10.1007/978-3-319-94523-1_9

Alian, S., Li, J. & Pandey, V. (2018)*. *A Personalized Recommendation System to Support Diabetes Self-Management for American Indians*. IEEE Access, 6, 73041-73051. Retrieved from https://ieeexplore.ieee.org/document/8539994

Alyari, F. & Navimipour, N. J. (2018). Recommender systems: A systematic review of the state of the art literature and suggestions for future research. *Kybernetes, 47*(5), 985-1017. Retrieved from http://dx.doi.org/10.1108/K-06-2017-0196

Anastasiadou, E., Lindh, C. & Vasse, T. (2019). Are Consumers International? A Study of CSR, Cross-Border Shopping, Commitment and Purchase Intent among Online Consumers. *Journal of Global Marketing*, *32*(4), 239-254. Retrieved from https://doi.org/10.1080/08911762.2018.1528652

Ashman, R., Solomon, M. R. & Wolny, J. (2015). An old model for a new age: Consumer decision making in participatory digital culture. *Journal of Customer Behaviour*, *14*(2), 127-146. Retrieved from https://www.semanticscholar.org/paper/An-old-model-for-a-new-age%3A-Consumer-decision-in-Ashman-Solomon/e087fe95c7a5ac2bf20f84859ed723adb377c978

Bianchini, D., de Antonellis, V. & Melchiori, M. (2015, November 1-3)*. *A web-based application for semantic-driven food recommendation with reference prescriptions*. In J. Wang, W. Cellary, D. Wang, H. Wang, S. Chen, T. Li & Y. Zhang (Eds.), Proceedings WISE 16th International Conference (pp. 32-46). Retrieved from https://link-springer-com.ezproxy.library.wur.nl/chapter/10.1007%2F978-3-319-26187-4_3

Bettman, J. R., Johnson, E. J. & Payne, J. W. (1991). Consumer Decision Making. In T. S. Robertson & H. H. Kassarjian (Eds.), *Handbook of consumer behavior* (1st ed., pp. 50-84). Englewood Cliffs N. J.: Prentice Hall. Retrieved from http://www.academia.edu/download/30385453/bettmanjohnsonpayne91.pdf

Bushra, N. & Hasan, M. (2019, December 18-21)*. *QuicklyCook: A User-Friendly Recipe Recommender*. In S. M. Thampi, L. Trajkovic, K.-C. Li & S. Das (Eds.), Proceedings of the 1st SoMMA 2019 (pp. 245-254). Retrieved from https://link.springer.com/chapter/10.1007/978-981-15-4301-2_22

Čavoški, S., Marković, A. (2015). Analysis of Customer Behaviour and Online Retailers Strategies Using the Agent-Based Simulation. *Management: Journal Of Sustainable Business And Management Solutions In Emerging Economies, 20*(77), 13-24. Retrieved from http://management.fon.bg.ac.rs/index.php/mng/article/view/52/41

Chiu, Y., Lo, S., Hsieh, A. & Hwang, Y. (2019). Exploring why people spend more time shopping online than in offline stores. *Computers in Human Behavior*, *95*, 24-30. Retrieved from https://doi.org/10.1016/j.chb.2019.01.029

Chu, W. T. & Tsai, Y. L. (2017)*. A hybrid recommendation system considering visual information for predicting favorite restaurants. *World Wide Web, 20*(6), 1313-1331. Retrieved from https://link.springer.com/article/10.1007/s11280-017-0437-1

Chugh, D. & Bazerman, M. H. (2009). How can Decision Making be Improved? *Perspectives on Psychological Science*, *4*(4), 379-383. https://doi.org/10.1111/j.1745-6924.2009.01142.x

Clement, J. (2019). *Global number of digital buyers 2014-2021*. Retrieved from https://www.statista.com/statistics/251666/number-of-digital-buyers-worldwide/

Cruz, Z. M. C., Alpay, J. J. R., Depeno, J. D. D. D., Altabirano, M. J. C. & Bringula, R. (2017, October 4-7)*. *Usability of "Fatchum": A Mobile Application Recipe Recommender System*. In Proceedings of the 6th Annual Conference on RIIT (pp. 11-16). Retrieved from https://doi.org/10.1145/3125649.3125650

Darley, W. K., Blankson, C. & Luethge, D. (2010). Toward an Integrated Framework for Online

Consumer Behavior and Decision Making Process: A Review. *Psychology and Marketing, 27*(2), 94-116. Retrieved from https://doi.org/10.1002/mar.20322

Effendy, F., Nuqoba, B. & Taufik (2019)*. Culinary Recommendation Application Based on User Preferences Using Fuzzy Topsis. IIUM Engineering Journal, 20(2), 163-175. Retrieved from https://www.researchgate.net/publication/337681301_CULINARY_RECOMMENDATION_APPLICATION_BASED_ON_USER_PREFERENCES_USING_FUZZY_TOPSIS

Elahi, M., Ge, M., Ricci, F., Fernandez-Tobías, I., Berkovsky, S., & Massimo, D. (2015, September 19)*. *Interaction design in a mobile food recommender system*. In Proceedings of the Joint CEUR Workshop on Interfaces and Human Decision Making for Recommender Systems, IntRS 2015 and RecSys 2015, vol 1438, (pp. 49-52). Retrieved from http://www.inf.unibz.it/~ricci/papers/food-intrs-2015.pdf

El-Dosuky, M., Rashad, M., Hamza, T. & El-Bassiouny, A. (2012, December 8-10)*. *Food recommendation using ontology and heuristics*. In A. E. Hassanien, A. B. M. Salem, R. Ramadan & T. Kim (Eds.), International conference on AMLTA, vol 322 (pp. 423-429). Retrieved from https://doi.org/10.1007/978-3-642-35326-0_42

Elsweiler, D. & Harvey, M. (2015, September 16-20)*. *Towards Automatic Meal Plan Recommendations for Balanced Nutrition*. In Proceedings of the 9th ACM Conference on RecSys (pp. 313-316). Retrieved from https://dl.acm.org/doi/pdf/10.1145/2792838.2799665

Elsweiler, D., Harvey, M., Ludwig, B. & Said, A. (2015, October 22-23)*. *Bringing the healthy into food recommenders*. In M. Ge & F. Ricci (Eds.), Proceedings of the 2nd International CEUR workshop DMRS, vol. 1533 (pp. 33-36). Retrieved from http://ceur-ws.org/Vol-1533/paper8.pdf

Elsweiler, D., Trattner, C. & Harvey, M. (2017, August 07-11). *Exploiting Food Choice Biases for Healthier Recipe Recommendation*. In SIGIR '17 Proceedings (pp. 575-584). Retrieved from https://doi.org/10.1145/3077136.3080826

Ergezer, C. (2016). New Method for Reaching Consumers over the Internet: "Search Engine Marketing". *International E-Journal of Advances in Social Sciences*, *2*(4), 15-23. Retrieved from https://dergipark.org.tr/en/download/article-file/232077

Espín, V., Hurtado, M. V. & Noguera, M. (2015)*. Nutrition for Elder Care: a nutritional semantic recommender system for the elderly. *Expert systems, 33*(2), 201-210. Retrieved from https://onlinelibrary.wiley.com/doi/abs/10.1111/exsy.12143

Forbes, P. & Zhu, M. (2011, October 23-27)*. *Content-boosted matrix factorization for recommender systems: experiments with recipe recommendation*. In Proceedings of the 5th ACM conference on Recommender Systems (pp. 261-264). Retrieved from http://sas.uwaterloo.ca/~m3zhu/papers/sys031-forbes.pdf

Fouskas, K., Pachni-Tsitiridou, O. & Chatziharistou, C. (2020). A Systematic Literature Review on E-Commerce Success Factors. In A. Kavoura, E. Kefallonitis & P. Theodoridis (Eds.), *Strategic Innovative Marketing and Tourism*. 8th ICSIMAT Springer Proceedings in Business and Economics (pp. 687-694). Retrieved from https://doi.org/10.1007/978-3-030-36126-6_76

Freyne, J., & Berkovsky, S. (2010, February 7-10)*. *Intelligent food planning: personalized recipe recommendation*. In IUI'10 Proceedings of the 15th international conference (pp. 321–324). Retrieved from https://doi.org/10.1145/1719970.1720021

Freyne, J. Berkovsky, S., Baghaei, N., Kimani, S. & Smith, G. (2011, July 2-6)*. *Personalized techniques for lifestyle change*. In M. Peleg, N. Lavrač, C. Combi (Eds.), Proceedings 13th Conference on AIME 2011, vol. 6747 (pp. 139-148). Retrieved from https://doi.org/10.1007/978-3-642-22218-4_18

Fu, Y., Liu, B., Yong, G., Yao, Z. & Hui, X. (2014, April 24-26)*. *User preference learning with multiple information fusion for restaurant recommendation*. In Proceedings of the SIAM International Conference on Data Mining (pp. 470-478). Retrieved from https://pdfs.semanticscholar.org/d661/d7d7f419df3cc8e4a12b124725e1a07d5d7d.pdf

Gao, X., Feng, F., He, X., Huang, H., Guan, X., Feng, C., Ming, Z. & Chua, T.-S. (2019)*. Hierarchical Attention Network for Visually-Aware Food Recommendation. *IEEE Transactions on Multimedia, 22*(6), 1647-1659. Retrieved from https://arxiv.org/pdf/1810.05032.pdf

Ge, M., Elahi, M., Fernaández-Tobías, I., Ricci, F. & Massimo, D. (2015, May 18-20)*. *Using tags and latent factors in a food recommender system*. In Proceedings of the 5th International Conference on Digital Health (pp. 105-112). Retrieved from https://www.inf.unibz.it/~fricci/papers/p105-ge-2015.pdf

Ge, M., Ricci, F. & Massimo, D. (2015, September 16-20)*. *Health-aware food recommender system*. In Proceedings of the 9th ACM conference on recommender systems (pp. 333–334). Retrieved from https://dl.acm.org/doi/10.1145/2792838.2796554

Ghasemaghaei, M. (2020). The impact of in-depth online recommendation agents on consumer disorientation and cognitive absorption perceptions. *Behaviour & Information Technology*, *39*(4), 414-430. Retrieved from https://doi.org/10.1080/0144929X.2019.1598496

Guo, L.-R., Yuan, S.-Z., Mao, X.-H. & Gu, Y.-N. (2017, October 22-23)*. *A Recipe Recommendation System Based on Regional Flavor Similarity*. In Proceedings of the 2nd International Conference on CIMNS (pp. 421-426). Retrieved from http://www.dpi-proceedings.com/index.php/dtcse/article/view/17457/16961

Gutiérrez, F., Verbert, K. & Htun, N. N. (2018, September 3-6)*. *PHARA: an augmented reality grocery store assistant*. In Proceedings of the 20th International Conference on MobileHCI (pp. 339-345). Retrieved from https://dl.acm.org/doi/10.1145/3236112.3236161

Hammond, K. J. (1986)*. *CHEF: A Model of Case-based Planning*. In Proceedings of the AAAI-86 (pp. 267-271). Retrieved from https://www.aaai.org/Papers/AAAI/1986/AAAI86-044.pdf

Harvey, M. & Elsweiler, D. (2015, September 16-20)*. *Automated recommendation of healthy, personalized meal plans*. In Proceedings of the 9th ACM conference on recommendation systems (pp. 327-328). Retrieved from https://dl.acm.org/doi/pdf/10.1145/2792838.2796551

Häubl, G. & Trifts, V. (2000). Consumer Decision Making in Online Shopping Environments: The Effects of Interactive Decision Aids. *Marketing Science*, *19*(1), 4-21. Retrieved from https://doi.org/10.1287/mksc.19.1.4.15178

Hinrichs, T. R. & Kolodner (1991, July)*. *The Roles of Adaptation in Case-Based Design*. In Proceedings of the AAAI-91, vol. 1 (pp. 28-33). Retrieved from https://www.aaai.org/Papers/AAAI/1991/AAAI91-005.pdf

Ho, C.-S. & Chang, Y.-M. (2018, December 22-23)*. *Design and Implementation of Intelligent Personalized Dietary Meal Recommendation System*. In Proceedings of the International Conference on CCME (pp. 137-140). Retrieved from http://www.dpi-proceedings.com/index.php/dtcse/article/view/28593/27694

Huang, L. (2016). Exploring utilitarian and hedonic antecedents for adopting information from a recommendation agent and unplanned purchase behaviour. *New Review of Hypermedia and Multimedia*, *22*(1-2), 139-165. Retrieved from https://doi.org/10.1080/13614568.2015.1052098

Huseynov, F. & Yildirim, S. O. (2016). Behavioural Issues in B2C E-commerce: The-state-of-the-art. *Information Development*, *32*(5), 1343-1358. Retrieved from https://doi.org/10.1177%2F0266666915599586

Internet World Stats (2019). Retrieved from https://www.internetworldstats.com/stats.html

Ivaşcu, T., Diniş, A. & Cincar, K. (2018, June 25-27)*. *A Disease-driven Nutrition Recommender System based on a Multi-agent Architecture*. In R. Akerkar, M. Ivanović, S.-W. Kim, Y. Manolopoulos, R. Rosati, M. Savić, C. Badica & M. Radovanović (Eds.), Proceedings of the 8th International Conference on WIMS (pp. 1-5). Retrieved from https://dl.acm.org/doi/10.1145/3227609.3227685

Jiang, H., Wang, W., Liu, M., Nie, L., Duan, L.-Y. & Xu, C. (2019, October 21-25)*. *Market2Dish: A Health-aware Food Recommendation System*. In Proceedings of the 27th ACM International Conference on MM (pp. 2188-2190). Retrieved from https://doi.org/10.1145/3343031.3350594

Jung, H. & Chung, K. (2016)*. Knowledge-based dietary nutrition recommendation for obese management. *Information Technology and Management, 17*, 29-42. Retrieved from https://doi-org.ezproxy.library.wur.nl/10.1007/s10799-015-0218-4

Kadyanan, I. G. A. G. A., Dwidasmara, I. B. G., Mahendra, I. B. M., Mogi, I. K. A. & Sudarma, I. W. P. (2019, April 19-22)*. *The Design of Typical Balinese Food Recommendation System Using Hybrid Method of Collaborative Filtering and Slope One Algorithm on Mobile Device Platform*. In Proceedings of the 5th ICCAI (pp. 111-116). Retrieved from https://doi.org/10.1145/3330482.3330490

Kalaiarasan, K., Govindan, S. & Nasaratnam, S. (2018). The Role of Situational Factor on Buyer Characteristics and Purchase Decision among Malaysian Low-Cost Airline Travellers. *International Journal of Economics and Management, 12*(1), 265-284. Retrieved from http://www.ijem.upm.edu.my/vol12no1/14)%20The%20Role%20of%20Situational%20Factor%20on%20Buyer%20Characteristics.pdf

Kawano, Y., Sato, T., Maruyama, T. & Yanai, K. (2013, July 15-19)*. *Mirurecipe: A mobile cooking recipe recommendation system with food ingredient recognition*. IEEE International Conference on Multimedia and Expo Workshops (pp. 1-2). Retrieved from http://img.cs.uec.ac.jp/pub/conf13/130716kawano_0.pdf

Khan, A. S. & Hoffmann, A. (2003)*. Building a Case-Based Diet Recommendation System Without a Knowledge Engineer. *Artif Intell Med., 27*(2), 155-179. Retrieved from https://doi.org/10.1016/s0933-3657(02)00113-6

Khan, M. A., Rushe, E., Smyth, B. & Coyle, D. (2019, September 20)*. *Personalized, Health-Aware Recipe Recommendation: An Ensemble Topic Modeling Based Approach*. In D. Elsweiler, B. Ludwig, A. Said, H. Schäfer, H. Torkamaan & C. Trattner (Eds.), Proceedings of the 4th International Workshop on HealthRecSys (pp. 4-10). Retrieved from http://ceur-ws.org/Vol-2439/3-paginated.pdf

Kim, D. J., Ferrin, D. L. & Rao, H. R. (2008). A trust-based consumer decision-making model in electronic commerce: The role of trust, perceived risk, and their antecedents. *Decision Support Systems, 44*(2), 544-564. Retrieved from https://doi-org.ezproxy.library.wur.nl/10.1016/j.dss.2007.07.001

Kodali, S., Dabbiru, M. & Rao, B. T. (2019)*. *A Cuisine Based Recommender System Using k-NN and Mapreduce Approach*. International Journal of Innovative Technology and Exploring Engineering, 8(7), 32-36. Retrieved from https://docplayer.net/147125732-A-cuisine-based-recommender-system-using-k-nn-and-mapreduce-approach.html

Kuo, F. F., Li, C. T., Shan, M. K., & Lee, S. Y. (2012, November 2)*. *Intelligent menu planning: Recommending set of recipes by ingredients*. In Proceedings of the ACM workshop on multimedia for CEA'12 (pp. 1–7). Retrieved from https://www.researchgate.net/publication/235918443_Intelligent_menu_planning_recommending_set_of_recipes_by_ingredients

Lawrence, R. D., Almasi, G. S., Kotlyar, V., Viveros, M. & Duri, S. S. (2002)*. Personalization of supermarket product recommendations. In R. Kohavi & F. Provost (Eds.), *Applications of data mining to electronic commerce* (2nd ed., pp. 11–32). Springer: Boston. Retrieved from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.89.3308&rep=rep1&type=pdf

Li, S. S. & Karahanna, E. (2015). Online Recommendation Systems in a B2C E-Commerce Context: A Review and Future Directions. *Journal of the Association for Information Systems*, *16*(2), 72-107. Retrieved from https://www.semanticscholar.org/paper/Online-Recommendation-Systems-in-a-B2C-E-Commerce-A-Li-Karahanna/a034274d13a2ac9fa3d1e56248a80c9ba2a877a2

Li, X., Jia, W., Yang, Z., Li, Y., Yuan, D., Zhang, H. & Sun, M. (2018)*. Application of Intelligent Recommendation Techniques for Consumers' Food Choices in Restaurants. *Frontiers in Psychiatry, 9*, 415:1-415:9. Retrieved from https://dx.doi.org/10.3389%2Ffpsyt.2018.00415

Lin, C.-J., Kuo, T.-T. & Lin, S.-D. (2014, May 13-16)*. *A content-based matrix factorization model for recipe recommendation*. In V. S. Tseng, T. B. Ho, Z-H. Zhou, A. L. P. Chen, H.-Y. Kao (Eds.), Proceedings of 18th Pacific-Asia Conference PAKDD (pp. 560–571). Retrieved from https://doi-org.ezproxy.library.wur.nl/10.1007/978-3-319-06605-9_46

Llerena, L., Rodriguez, N., Gómez-Abajo, P. & Castro, J. W. (2017)*. How to Apply the User Profile Usability Technique in the User Modelling Activity for an Adaptive Food Recommendation System for People on Special Diets. *Systemics, Cybernetics and Informatics, 15*(5), 54-63. Retrieved from https://www.researchgate.net/publication/320616813

Maçik, R. (2016). Changes in Consumer Decision-Making Process Influenced by ICT Usage. In G. Mazurek, J. Tkaczyk (Eds.), *The Impact of the Digital World on Management and Marketing* (1st ed., pp. 331-352). Warsaw: Poltext Co. Ltd. Retrieved from https://books.google.co.uk/books?hl=nl&lr=&id=MyjtDAAAQBAJ&oi=fnd&pg=PA331&dq

Macovei, O. (2015). Applying the Theory of Planned Behavior in Predicting Pro-environmental Behaviour: The case of Energy Conservation. *ŒCONOMICA, 11*(4), 15-32. Retrieved from http://journals.univ-danubius.ro/index.php/oeconomica/article/view/2958/2705

Maheshwari, S. & Chourey, M. (2019)*. Recipe Recommendation System using Machine Learning Models. *International Research Journal of Engineering and Technology, 6*(9), 366-369. Retrieved from https://www.irjet.net/archives/V6/i9/IRJET-V6I946.pdf

Maia, R. & Ferreira, J. C. (2018, October 23-25)*. *Context-Aware Food Recommendation System*. In Proceedings of the WCECS, Vol. I (pp. 1-8). Retrieved from http://www.iaeng.org/publication/WCECS2018/WCECS2018_pp349-356.pdf

Malik, A. & Purohit, P. (2020). A Study of Consumer Buying Behavior: A Review. *UGC Care Journal*, *40*(3), 3355-3363. Retrieved from https://archives.tpnsindia.org/index.php/sipn/article/view/712/661

Mankoff, J., Hsieh, G., Hung, H. C., Lee, S. & Nitao, E. (2002, September 29-October 1)*. *Using low-cost sensing to support nutritional awareness*. In G. Borreillo & L. E. Holmquist (Eds.), Proceedings of the 4th International conference on UbiComp (pp. 371–378). Retrieved from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.58.2277&rep=rep1&type=pdf

Min, W., Jiang, S. & Jain, R. (2019). Food Recommendation: Framework, Existing Solutions and Challenges. *IEEE Transactions on Multimedia*, *X*(XX), 1-13. Retrieved from https://arxiv.org/pdf/1905.06269.pdf

Mughal, A., Mehmood, A., Mohi-ud-deen, A. & Ahmad, B. (2014). The Impact of Promotional Tools on Consumer Buying. *Journal of Public Administration and Governance*, *4*(3), 402-414. Retrieved from https://dx.doi.org/10.5296/jpag.v4i3.6680

Müller, M., Mika, S., Harvey, M. & Elsweiler, D. (2012, May 21-24)*. *Estimating nutrition values for internet recipes*. In R. Arriago & A. Matic (Eds.), Proceedings of the 6th International Conference on Pervasive computing technologies for healthcare (pp. 191–192). Retrieved from http://dx.doi.org/10.4108/icst.pervasivehealth.2012.248682

Nag, N., Pandey, V. & Jain, R. (2017, October 23)*. *Live personalized nutrition recommendation engine*. In Proceedings of the 2nd International Workshop on MMHealth (pp. 61–68). Retrieved from https://doi.org/10.1145/3132635.3132643

Ng, Y.-K. & Jin, M. (2017, November 7-9)*. *Personalized recipe recommendations for toddlers based on nutrient intake and food preferences*. In Proceedings of the 9th International Conference on Management of Digital EcoSystems (pp. 243–250) Retrieved from https://doi.org/10.1145/3167020.3167057

Nouh, R. M., Lee, H.-H., Lee, W.-J. & Lee, J.-D. (2019)*. A Smart Recommender Based on Hybrid Learning Methods for Personal Well-Being Services. *Sensors, 19*(2), 431:1-431:21. Retrieved from https://doi.org/10.3390/s19020431

Ntalaperas, D., Bothos, E., Perakis, K., Magoutas, B., Mentzas, G. (2015, October 1-3)*. *DISYS: An Intelligent System for Personalized Nutritional Recommendations in Restaurants*. In N. N. Karanikolas, D. Akoumianakis, M. Nikolaidou, D. Vergados, M. Xenos (Eds.), Proceedings of the 19th PCI (pp. 382-387). Retrieved from https://dl.acm.org/doi/pdf/10.1145/2801948.2801997

Nyati, U., Rawat, S., Gupta, D., Aggrawal, N. & Arora, A. (2019). Characterize ingredient network for recipe suggestion. *International Journal of Information Technology*, 1-8. Retrieved from https://doi.org/10.1007/s41870-019-00277-y

Ohata, T., Nishihara, Y. & Yamanishi, R. (2019, June 10)*. *Foods Recommendation System for Meals-out in Nutrient Balance*. In Proceedings of the 11th Workshop on Multimedia for CEA (pp. 17-23). Retrieved from https://doi.org/10.1145/3326458.3326926

Oke, A., Kamolshotiros, P., Popoola, O. Y., Ajagbe, M. A. & Olujobi, O. J. (2016). Consumer Behavior towards Decision Making and Loyalty to Particular Brands. *International Review of Management and Marketing, 6*(S4), 43-52. Retrieved from https://www.researchgate.net/publication/303789700_Consumer_Behavior_towards_Decision_Making_and_Loyalty_to_Particular_Brands

Pedersen, P. E. (2000). Behavioral Effects of Using Software Agents for Product and Merchant Brokering: An Experimental Study of Consumer Decision-Making. *International Journal of Electronic Commerce*, *5*(1), 125-141. Retrieved from http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.18.222

Pratibha & Kaur, P.D. (2019)*. *A Context-Aware Recommender Engine for Smart Kitchen*. In Panigrahi B., Trivedi M., Mishra K., Tiwari S., Singh P. (Eds.), Proceedings of ICSICCS AISC, vol 670 (pp. 161-170). Retrieved from https://link.springer.com/chapter/10.1007/978-981-10-8971-8_16

Qiu, L. & Benbasat, I. (2010). A study of demographic embodiments of product recommendation agents in electronic commerce. *Journal Human-Computer Studies*, *68*(10), 669-688. Retrieved from https://doi.org/10.1016/j.ijhcs.2010.05.005

Rathi, S., Rander, R., Sanghvi, P. & Shah, S. (2017)*. Eatery Directory Using Recommendation System and Data Mining. *Journal of Computer Engineering, 1*, 39-42. Retrieved from https://pdfs.semanticscholar.org/99c6/26217fb53d543a0fdd66fc7846c1c6b8676b.pdf

Rehman, F., Khalid, O., Haq, N. u., Khan, A. u. R., Bilal, K. & Madani, S. A. (2017)*. Diet-Right: A Smart Food Recommendation System. *KSII Transactions on Internet and Information Systems, 11*(6), 2910-2925. Retrieved from https://doi.org/10.3837/tiis.2017.06.006

Ribeiro D., Ribeiro J., Vasconcelos M.J.M., Vieira E.F. & de Barros A.C. (2018, April 28-29)*. *SousChef: Improved Meal Recommender System for Portuguese Older Adults*. In: Röcker C., O'Donoghue J., Ziefle M., Maciaszek L., Molloy W. (Eds), Proceedings of ICT4AWE 2017, vol 869 (pp. 107-126). Retrieved from https://doi.org/10.1007/978-3-319-93644-4_6

Saito, K., Asada, T., Yoshitomi, Y., Kato, R. & Tabuse, M. (2018)*. A Recipe Decision Support System Using Knowledge Information and Agent. *Journal of Robotics Networking and Artificial Life, 5*(3), 204-207. Retrieved from https://www.researchgate.net/publication/331484364

Salloum, G. K. (2018)*. *Automated knowledge-based nutrition health assessment, recommendation, progress evaluation, and meal planning* (Master Thesis, Lebanese American University, Beiroet, Libanon). Retrieved from https://laur.lau.edu.lb:8443/xmlui/handle/10725/10468

Sano, N., Machino, N., Yada, K. & Suzuki, T. (2015)*. Recommendation system for grocery store considering data sparsity. *Procedia Computer Science, 60*, 1406-1413. Retrieved from https://doi.org/10.1016/j.procs.2015.08.216

Schäffer, H., Hors-Fraile, S., Karumur, R. P., Valez A. C., Said, A., Torkamaan, H., Ulmer T. & Trattner, C. (2017, July 2-5). *Towards Health (Aware) Recommender Systems.* In P. Kostkova, F. Grasso, C. Castillo, Y. Mejova & A. Bosman (Eds.), Proceedings of the 2017 International Conference on Digital Health (DH '17) (pp. 157-161). Retrieved form https://doi.org/10.1145/3079452.3079499

Siddaway, A. P., Wood, A. M. & Hedges, L. V. (2019). How to do a Systematic Review: a Best Practice Guide for Conducting and Reporting Narrative Reviews, Meta-Analyses, and Meta-Syntheses. *Annual Review of Psychology*, *70*, 747-770. Retrieved from https://doi.org/10.1146/annurev-psych-010418-102803

Simon, H. A. (1972). Theories of Bounded Rationality. In C. B. McGuire & R. Radner (Eds.), *Decision and Organization* (1st ed., pp. 161-176). Amsterdam: North-Holland Publishing Company. Retrieved from http://innovbfa.viabloga.com/files/Herbert_Simon___theories_of_bounded_rationality___1972.pdf

Skjold, K., Øynes, M., Bach, K., Aamodt, A. (2017, June 26-28)*. *IntelliMeal - Enhancing Creativity by Reusing Domain Knowledge in the Adaptation Process*. In Proceedings of the ICCBR, vol. 2028 (pp. 275-282). Retrieved from http://www.iccbr.org/iccbr17/ICCBR2017_workshop_proceedings.pdf

Snyder, H. (2019). Literature review as a research methodology: An overview and guideline. *Journal of Business Research*, *104*, 333-339. Retrieved from https://doi.org/10.1016/j.jbusres.2019.07.039

Subramaniyaswamy, V., Manogaran, G., Logesh, R., Vijayakumar, V., Chilamkurti, N., Malathi, D. & Senthilselvan, N. (2019)*. An ontology-driven personalized food recommendation in IoT-based healthcare system. *Journal of Supercomputing, 75*, 3184–3216. https://doi-org.ezproxy.library.wur.nl/10.1007/s11227-018-2331-8

Svensson, M., Laaksolahti, J., Höök, K., & Waern, A. (2000, January)*. *A recipe based on-line food store*. In Proceedings of the 5th international conference on IUI (pp. 260–263). Retrieved from https://doi.org/10.1145/325737.325866

Talekar, P. S., Raghavendra, G. S. & Vaddatti, B. (2019)*. NutriSmart- Food Products Recommendation System. *International Journal of Innovative Science and Research Technology, 4*(5), 773-775. Retrieved from https://ijisrt.com/wp-content/uploads/2019/06/IJISRT19MY474.pdf

Teng, C.-Y., Lin, Y.-R. & Adamic, L. A. (2012, June)*. *Recipe recommendation using ingredient* *networks*. In Proceedings of the 4th annual ACM WebSci Conference (pp. 298–307). Retrieved from https://doi.org/10.1145/2380718.2380757

Toledo, R. Y., Alzahrani, A. A. & Martínez, L. (2019)*. A Food Recommender System Considering Nutritional Information and User Preferences. *IEEE Access, 7*, 96695-96711. Retrieved from http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=8765311&isnumber=8600701

Tran, T. N. T. T., Atas, M., Felfernig, A. & Stettinger, M. (2018)*. An overview of recommender systems in the healthy food domain. *Journal Intelligent Information Systems*, *50*, 501-526. Retrieved from https://link.springer.com/article/10.1007/s10844-017-0469-0

Transfield, D., Denyer, D. & Smart, P. (2003). Towards a Methodology for Developing Evidence-Informed Management Knowledge by Means of Systematic Review*. *British Academy of Management*, *14*(3), 207-222. Retrieved from https://onlinelibrary.wiley.com/doi/abs/10.1111/1467-8551.00375

Trattner, C. & Elsweiler, D. (2017)*. Food Recommender Systems Important Contributions, Challenges and Future Research Directions. *Arxiv Computer Science Cornell University*, 1-16. Retrieved from https://arxiv.org/abs/1711.02760v2

Trevisiol, M., Chiarandini, L., Baeza-Yates, R. (2014, September 1-4)*. *Buon appetito: recommending personalized menus*. In Proceedings of the 25th ACM conference on HT (pp. 327-329). Retrieved from https://doi.org/10.1145/2631775.2631784

Ueda, M., Morishita, Y., Nakamura, T., Takata, N. & Nakajima, S. (2016, November 28-30)*. *A recipe recommendation system that considers user's mood.* In Proceedings of the 18th International Conference on IIWAS (pp. 472-476). Retrieved from https://dl.acm.org/doi/10.1145/3011141.3011192

Ueta, T., Iwakami, M. & Ito, T. (2011, December 12-14)*. *A recipe recommendation system based on automatic nutrition information extraction*. In H. Xiong & L. B. Lee (Eds.), Proceedings of the 5th International Conference on KSEM (pp. 79-90). Retrieved from https://doi-org.ezproxy.library.wur.nl/10.1007/978-3-642-25975-3_8

Varatharajan, N., Guruprasad, J. & Mathumitha, K. (2020)*. Restaurant Recommendation System Using Machine Learning. *International Educational Applied Research Journal, 4*(3), 1-4. Retrieved from http://iearj.com/upload/01-Guruprasad.pdf

Verruck, F. & Nique, W. M. (2017). Bothering Consumers: When Recommendation Agents Don't Really Make Our Life Easier. *Revista Base (Administração e Contabilidade) da UNISINOS, 14*(4), 240-252. Retrieved from http://www.redalyc.org/articulo.oa?id=337254294001

Vivek, M.B., Manju, N., Vijay, M.B. (2018)*. *Machine Learning Based Food Recipe Recommendation*

System. In Guru D., Vasudev T., Chethan H., Kumar Y. (Eds.), Proceedings of International Conference on Cognition and Recognition, vol 14 (pp. 11-19). Retrieved from https://doi-org.ezproxy.library.wur.nl/10.1007/978-981-10-5146-3_2

Wang, C., Lin, S. & Yang, H. (2016). Impersonate human decision making process: an interactive context-aware recommender system. *Journal of Intelligent Information Systems*, *47*, 195-207. https://doi.org/10.1007/s10844-016-0401-z

WHO (2020). *Obesity and overweight*. Retrieved from https://www.who.int/news-room/fact-sheets/detail/obesity-and-overweight

Xiao, B. & Benbasat, I. (2007). E-Commerce Product Recommendation Agents: Use, Characteristics, and Impact. *MIS Quarterly*, *31*(1), 137-209. Retrieved from https://misq.org/e-commerce-product-recommendation-agents-use-characteristics-and-impact.html

Yamamoto, S., Kando, N. & Satoh, T. (2016, November 11-14)*. *Continuous Recipe Selection Model Based on Cooking History*. In Spiro E., Ahn YY. (Eds.), Proceedings of the 8th International Conference on SocInfo. Lecture Notes in Computer Science, vol 10046 (pp. 138-151). Retrieved from https://doi.org/10.1007/978-3-319-47880-7_9

Yang, L., Cui, Y., Zhang, F., Pollak, J. P., Belongie, S., Estrin, D. (2015, October 19-23)*. *PlateClick: Bootstrapping Food Preferences Through an Adaptive Visual Interface*. In Proceedings of the 24th ACM International on CIKM (pp. 183-192). Retrieved from https://doi.org/10.1145/2806416.2806544

Yang, L., Hsieh, C.-K., Yang, H., Dell, N., Belongie, S., Cole, C., Estrin, D. (2017)*. Yum-me: A Personalized Nutrient-based Meal Recommender System. *ACM Transactions in Information Systems, 9*(4), 39:1-39:31. Retrieved from https://arxiv.org/abs/1605.07722

Yang, K., Song, Y., Wu, C., Yang, P. & Wang, C. (2020, January 31- February 2). *An Exploratory Study of the Promotion Effectiveness of Recommender Systems*. In Proceedings of the 2020 the 3rd International Conference on Computers in Management and Business (ICCMB) (pp. 135-140). Retrieved from https://doi.org/10.1145/3383845.3383850

Yang, Z., Ou, C., & Ziying, Z. (2017, August 10-12). *Investigating the impact of recommendation agents on e-commerce ecosystem*. In Proceedings of the 23rd American Conference on Information Systems (AMCIS 2017) (pp. 1-5). Retrieved from https://aisel.aisnet.org/cgi/viewcontent.cgi?article=1146&context=amcis2017

Zeng, J., Nakano, Y. I., Morita, T., Kobayashi, I., Yamaguchi, T. (2018, October 16)*. *Eliciting User Food Preferences in terms of Taste and Texture in Spoken Dialogue Systems*. In C. Velasco, A. Nijholt, M. Obrist, K. Okajima & C. Spence (Eds.), Proceedings of the 3rd International Workshop on MHFI (pp. 6:1-6:5). Retrieved from https://doi.org/10.1145/3279954.3279959

Zhang, X., Luo, H., Chen, B. & Guo, G. (2020)*. Multi-view visual Bayesian personalized ranking for restaurant recommendation. *Applied Intelligence*. Retrieved from https://doi-org.ezproxy.library.wur.nl/10.1007/s10489-020-01703-6

Zhu, D., Kuo, M. Munkhbold, E. (2016, July 10-14). *Effects of E-Customer Satisfaction and E-Trust on E-Loyalty: Mongolian Online Shopping Behavior.* In T. Matsuo, A. Kanzaki, N. Komoda, A. Hiramatsu (Eds.), Proceedings of the 5th IIAI International Congress on Advanced Applied Informatics (IIAI-AAI) (pp. 847 – 852). Retrieved from https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=7557730