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SURVEY

Integrating Digital Food Nudges and Recommender Systems: Current Status and Future Directions

AYOUB EL MAJJODI[1], ALAIN D. STARKE[1,2], AND CHRISTOPH TRATTNER[1]

[1]MediaFutures, Department of Information Science and Media Studies, University of Bergen, 5007 Bergen, Norway

[2]Amsterdam School of Communication Research (ASCoR), University of Amsterdam, 1012 WP Amsterdam, The Netherlands

Corresponding author: Ayoub El Majjodi (ayoub.majjodi@uib.no)

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ABSTRACT Recommender systems are widely regarded as effective tools for facilitating the discovery of relevant content. In the food domain, they help users find recipes, choose grocery products, and generate meal suggestions. While they address the challenge of choice overload, their direct influence on promoting healthier food choices remains limited. Digital nudges could further assist in guiding users toward healthier decisions, enhancing the accessibility and visibility of healthy options when integrated into a recommender system. This review examines to what extent food recommender systems have so far successfully incorporated digital nudges for healthy food promotion and which challenges still remain. We present a classification and analysis of various digital nudging strategies employed for this purpose, as well as opportunities for future research. We emphasize that various nudging techniques have the potential to support users in making healthier food choices within food recommender systems. Furthermore, user-centric evaluations represent the most effective approach for assessing the performance of these systems.

INDEX TERMS Food recommender systems, personalization, digital nudging, online decision-making, health, food choices.

I. INTRODUCTION AND MOTIVATION

Recommender systems are considered a fundamental technology on websites and significant digital food platforms [1], [2], [3]. Recommender systems help users navigate the problem of choice overload [4], [5], reducing the set of relevant options by retrieving and presenting content to a user they may like. The primary filtering mechanism of a recommender system is the analysis of past user-item interactions, assuming that previously liked items will also be liked by a user in future interactions [6].

Recommender systems are integrated across various domains. They have been shown to positively impact both users and service providers [7], [8], [9]. Whereas in many domains they focus on hedonic or taste-driven goals, such as finding music to listen or products to buy, food is often more versatile, with users also pursuing goals related to nutrition and sustainability [10], [11].

Recommender systems can play an important role in digital health promotion [12], by mitigating unhealthy eating. The World Health Organization reports that the global number of overweight adults has reached approximately 2.3 billion in recent decades [13], with overweight and obesity being significant contributors to the rising prevalence of chronic diseases [14]. Given these alarming statistics, recommender systems can be designed to not only neutrally cater to user preferences, but to also support healthier food choices [15]. In doing so, they mainly simplify the selection process through personalized suggestions, from meal recipes to restaurant recommendations. Despite their potential benefits, implementing those systems faces inherent challenges due to the complexity of food choices [11], [16], which are shaped by item characteristics, individual preferences, contextual variables, user mood, and social environments.

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Human food choices are influenced by a range of determinants [17]. These include more biological factors [18], such as basic tastes (i.e., sweet, salty, bitter, and sour) and the olfactory senses, which shape our perception of food flavor. These biological influences are mediated by genetic factors [18], bodily functions, and metabolic processes. In addition, external factors also significantly impact food choices. This includes social and environmental influences [17], [19], such as attitudes, beliefs, motivations, values, social status, and interpersonal relationships [20], [21]. The knowledge and skills acquired throughout an individual's life further affect dietary decisions [19], [20], [22]. Furthermore, changes in global food systems have led to shifts in eating patterns, contributing to an increase in the consumption of unhealthy foods [21]. Despite the long list of 'food determinants' identified by research, it remains difficult to predict food choice and behavior, when combining multiple contextual factors [23], [24].

Recommender systems have significantly advanced the modeling of food choice behavior. They apply sophisticated statistical and mathematical models in conjunction with information retrieval techniques [25]. However, not all interaction factors can be effectively modeled [16]. Figure 1 illustrates different factors that influence food choices in the context of recommender systems. In grey, the traditional process of a food recommender system is depicted, as originally presented by Elsweiler et al. [25]. It demonstrates how various food choice factors can be integrated into the modeling of such systems, which aim to present relevant food items to a user. These systems typically take user characteristics and food attributes as inputs (cf. Figure 1, Part (A)) to predefined algorithms and recommendations approaches (cf. Figure 1, Part (B)), which generate personalized food recommendations. The goals of these systems vary, from recommending ingredients similar to those preferred by the user to offering recipe suggestions based on past user ratings [12]. In later research, food recommender systems have started to incorporate nutritional content or users' health conditions or preferences to generate tailored nutritional advice. Despite these advances, efforts to optimize recommendations for health outcomes have remained limited. For example, Chen et al. [26] focus on how nutrition data, such as calorie content and nutrient balance, can improve the health value of recommended recipes. However, the current literature suggests that food recommender systems tend to prioritize popular content, which is often associated with unhealthy dietary standards [27], [28], [29].

Recommender algorithms tend to overlook *how* content is presented, which also significantly impacts user preferences. User preferences are often context dependent [30] and can be influenced by various presentation factors (cf Figure 1, Part C). Insights in how end users are affected by presentation factors offer an opportunity to guide users towards healthier food choices, thereby by enhancing the overall effectiveness of food recommender systems [11], [31], [32]. Any changes made to an interface (i.e., the choice architecture) that lead to predictable choices, e.g., due to cognitive biases, can be defined as 'nudges'. Originally introduced by behavioral economists Richard Thaler and Cass Sunstein [33], nudges were primarily examined outside of the digital realm, such as in cafeteria [33], [34]. Effective examples that steer behavior include putting healthier products at eye-level sight in supermarkets or placing healthier meals the front and end of a cafeteria line [33].

The implementation of nudges in digital contexts arrived later. In 2016, Weinmann et al. [35] introduced the concept of "digital nudges," defining them as interventions designed to modify user interfaces in ways that steer user behavior toward desired outcomes. Digital nudging has been increasingly adopted on various online platforms. For example, gain-framed nudges emphasizing personal health benefits, such as improved fitness and reduced stress, were shown to significantly increase intentions to use public transit, highlighting how individual benefits can effectively motivate sustainable travel choices [36]. Similarly, interventions on online grocery platforms have demonstrated considerable efficacy in fostering more sustainable and environmentally conscious purchasing decisions [37]. Furthermore, repositioning nudges within online food ordering systems have been associated with a significant increase in the selection of healthier food options [38].

Recent research on recommender systems has explored the integration of digital nudges to promote behavioral change and deliver personalized content [39]. For instance, incorporating an explanatory nudge into a food recommender system has been shown to positively influence users' selection of healthier recommendations [40]. Similarly, enhancing user awareness of the healthiness of recommended recipes through the use of multi-color coding of nutritional values (e.g., sugar, fat, salt) as a nudge has been found to encourage healthier food choices [41], while the use of visual appeal can be effective in food search systems [42], [43].

This research investigates how digital nudges have been integrated into food recommender systems to promote healthier food choices. More specifically, it seeks to select digital nudging techniques that can effectively promote healthier food choices within these systems. By examining existing scientific literature, the study explores techniques that warrant further investigation for their potential in this area. We formulate the following primary research question:

- *RQ1: How can digital nudges be integrated into recommender technology to effectively support users in making healthier food choices?*

To systematically organize our study around the main research question, we propose the following sub-research questions:

1. a) *How have digital nudges been integrated in recommender systems to support healthier food choices?*
2. b) *What are the potential future applications of nudges in recommender systems for healthier food choices?*

The paper is organized as follows. Next, in Section II, we expand on relevant background literature for this review

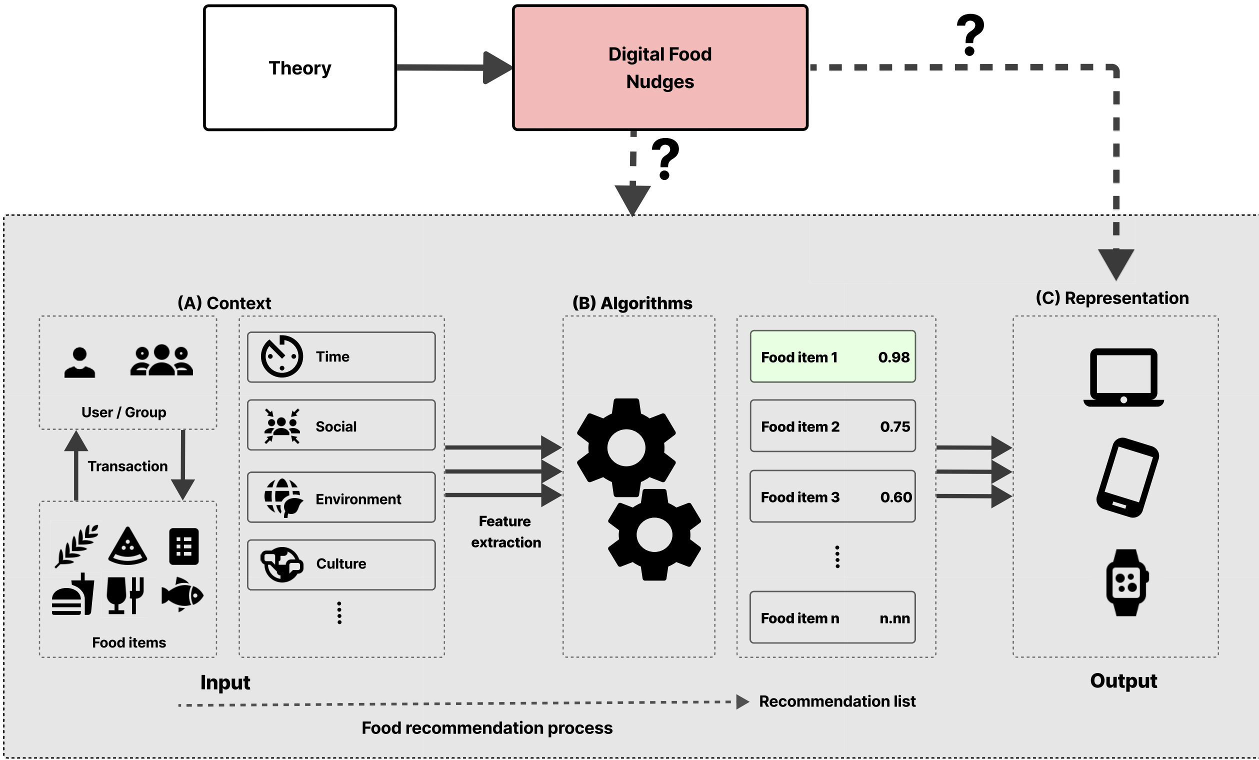

FIGURE 1. **Factors that influence user food choices in the recommendation process include (A) context, (B) algorithms and recommendation lists, and (C) interface representations. The gray section, originally developed by Elsweiler et al. [12], illustrates the original food recommendation process, whereas this paper examines the integration of digital nudges (e.g., highlighted in red) into the process.**

paper. Section III discusses the methodology for performing the literature review. Section IV presents the results in light of our main research question. Finally, Section V discusses future opportunities to integrate food recommendations and digital nudges to support healthier food choices.

II. BACKGROUND

The objective of this paper is to review the current state of the art of digital food nudges integrated into food recommender systems and to reveal future applications of nudges in food recommender systems. The following sub-sections provide a background on current (i) food choice theory, (ii) food recommender system approaches, and (iii) digital food nudges on platforms that not yet been integrated into food recommender systems.

A. FOOD CHOICE THEORY

Human food choice is an iterative process governed by dynamic factors that integrate multiple interacting determinants [44], [45], [46]. Relevant factors can be categorized into those pertaining to the individual, the food item, and the broader environmental or situational context, as articulated in one of the foundational models of food choice [47].

Individual factors influencing food choice are typically categorized into several dimensions. Personal state factors include genetic predispositions, dietary patterns, and physical health conditions. Psychological factors encompass hunger, appetite, and body weight, along with emotional, motivational, and personality characteristics [44]. In addition, personal habits and past experiences contribute significantly to shaping these personal states [48]. The cognitive aspects of food choice are also critical, going beyond mere knowledge and skills to include preferences, personal identity, and sensory evaluations, thus adding complexity to food-related decision-making processes [49]. Attitudes represent implicit evaluations of food, whereas liking refers to the sensory evaluation of food's appeal. Preferences are based on relative evaluations of different food options. A third cognitive dimension is the anticipated outcomes of food choices, particularly in terms of perceived health risks or benefits [50], [51].

Food items can be characterized by a combination of intrinsic and extrinsic factors. Intrinsic factors refer to the inherent properties of the food itself, which encompass sensory attributes such as flavor, taste, aroma, and texture, along with perceptual features such as color, portion size, nutritional content, health benefits, and overall quality [47], [48]. In contrast, extrinsic factors are bifurcated into informational and environmental categories. Informational factors involve knowledge related to the food, including its origin, nutritional profile, and composition. In addition, the social environment influences food choices directly and indirectly through cultural norms, culinary practices, and the social context of consumption, such as specific occasions. The physical environment also plays an important role in determining food availability and accessibility, significantly affecting food choice behavior [48], [52].

Comprehensive models have been developed to explain the factors that influence food choice and decision-making. Sobal et al. [45] model suggests that personal, resource, and contextual factors shape personal food systems based on values, situations, and strategies, which in turn influence food behavior in a feedback loop [53]. Connors et al. [54] expanded this model by emphasizing the role of life course experiences, ideals, and social context in shaping food behavior through similar feedback mechanisms. Sensory factors and packaging information can also trigger emotional responses that directly affect the final food choice [55]. Understanding these interrelated factors is key to promoting healthier eating, with critical determinants including food mavenism, knowledge, market availability, and personal norms [56], [57], [58].

The complexity of explaining final food choices arises from the aforementioned interacting factors and other various determinants [21]. Within the field of recommender systems, the primary focus has been on modeling user food preferences to identify the most appealing recipes, meals, or products. This process is typically framed as a prediction task. Additionally, time and contextual factors have been modeled to a significant extent within food recommendation processes [59]. However, a notable research gap exists between offline food choice theories and the factors that guide user preferences in digital food recommender systems [12].

B. CURRENT APPROACHES IN FOOD RECOMMENDER SYSTEMS

Recommendation technology is typically divided into different recommendation approach categories: collaborative filtering, content-based, knowledge-based, and hybrid methods. Each of these approaches uses some form of interaction between a user and food items or food attributes [6], but they differ in how this is achieved. What they have in common is that they aim to order a set of candidate items into a distinct preference order for a given user. Collaborative filtering algorithms seek out similarity across user-item ratings, such as by identifying which food items are similar or which users like similar food content [16]. Content-based and knowledge-based approaches often represent food items (e.g., recipes) by their metadata or attributes such as ingredients, cooking methods, and metadata [16], [60]. Content-based approaches typically assume that a user liking specific features should maximize the exposure of those features [15], while knowledge-based approaches tap into relations between disclosed user characteristics and food characteristics [61], [62].

Across these approaches, we can postulate that recommender systems aim to maximize a utility function $f(u, i)$. It seeks to predict the most relevant items i' in set of items $\mathbb{I}$ for a given user u in the set of users $\mathbb{U}$, which can be denoted as:

$$\forall u \in \mathbb{U}, \quad i'_{\mathbb{I}} = \arg\max f(u, i) \tag{1}$$

In practice, systems often approximate this utility function using similarity-based heuristics. One common method is cosine similarity, which computes the angle between two user or item vectors:

$$\mathrm{sim}(A, B) = \frac{A \cdot B}{|A|\,|B|} \tag{2}$$

While widely used in collaborative filtering [63], [64], [65], cosine similarity is inherently limited. It captures only static, linear relationships and assumes rational, context-free decision-making. Similarly, the utility function in Equation 1 often omits real-world factors such as choice architecture, and user interface elements, all of which can significantly shape user behavior. As a result, both formulations overlook the influence of digital nudges, subtle interventions embedded in the interface that guide user decisions without restricting choice [66].

To address these shortcomings, recommender systems must evolve from purely preference-based models to aware systems that integrate contextual, social, and cognitive influences. This could involve augmenting utility functions with behavioral parameters, or designing interaction-aware recommendation pipelines that adapt to how and when users engage with content.

These limitations are particularly evident in food recommender systems, where choices are heavily influenced by context, habits, and timing. Traditional collaborative filtering approaches, for instance, assume that users with similar preferences are likely to enjoy similar items [6], [60]. By incorporating taste factors and prior ratings, collaborative-based food recommenders outperform linear models in precision [67], with some neighborhood-based systems achieving up to 85% accuracy in dietary personalization [68].

Over the past decades, content-based food recommendation methods have been the most widely utilized in the literature [60]. The primary distinction of these methods lies in their generation of recommendations through a more in-depth analysis and semantic understanding of item content and user preferences [69]. The item content is represented by features that can range from ingredients to images of prepared dishes. Thus, recommendations are retrieved based on a similarity function that matches the features in a user's profile with those in the system's database.

Knowledge-based recommenders use a different approach. Designers of such systems leverage domain knowledge to score items based on elicited user characteristics and preferences [6], [61]. For example, Cataldo et al. [61] present a knowledge-based food recommender that personalizes recipes by incorporating users' health-related characteristics and personal factors, such as BMI and dietary restrictions. Such approaches would present food content that matches a user's nutritional needs [31]. Knowledge-based approaches are less commonly employed mainly because they limit the food exploration of food options by requiring users to define specific attributes or constraints [3], [16], [70]. The database items are narrowed down according to user criteria and filters, resulting in a selection of predefined food items.

Hybrid recommender systems, as the name suggests, integrate multiple recommendation techniques or components into a single approach [6]. This technique is typically used to reduce limitations present any specific approach, such as the reduced novelty in content-based recommenders [11]. Hybrid systems have shown to enhance both accuracy and performance by drawing on recommendations from diverse sources of information. Chavan et al. [71] demonstrated that hybrid food recommender approach outperform collaborative and content-based filtering regarding recall and accuracy, as they benefit from the comprehensive content analysis inherent in traditional methods.

C. DIGITAL FOOD NUDGES

Beyond recommender algorithms, there is more that can be designed and personalized in a recommender system. The interface is particularly interesting, as different options presented can be reorganized to elicit predictable behavior among users. Hence, users have specific cognitive biases that can be leveraged to steer decision-making towards specific options [72], [73].

This is where nudging theory can play a role in the design of such interfaces. As mentioned earlier, Nudges encompasses various techniques used to support people's behavior and overcome decision biases and heuristics inherent in human thinking systems based on the choice architect in the offline settings [33]. Such techniques have been proven to support and guide informed decision-making across different domains, including the health sector, policy-making, environment, and education [73], [74].

In the context of food choice environments, it is possible to influence individuals to, for example, select healthier options by reducing the perceived effort required during decision-making [75]. This can be achieved by presenting the healthier choice as the more convenient or accessible [76]. The effectiveness of such nudging strategies within physical food environments has been demonstrated in various studies. For instance, research by Bucher et al. [76] has shown that increasing the physical distance of a food option decreases its selection. Cadario et al. [77] introduces a conceptually grounded framework that classifies healthy eating nudges into three distinct, theory-based categories. This framework offers a systematic approach to understanding and differentiating between various nudging interventions to promote healthier eating behaviors. Each category within the framework is anchored in established theoretical principles [33], enabling researchers and practitioners to discern the underlying mechanisms through which each type of nudge exerts its influence. Accordingly, in the present work, we will utilize this framework to categorize the nudging techniques found in literature into three classes, aligning them with the following categorization defined by Cadario et al. [77]:

- *Affectively oriented nudges*: Nudging techniques that encompass interventions designed to enhance the hedonic appeal of healthy food options. This category includes strategies such as "hedonic enhancements", which aim to increase the sensory attractiveness of healthier choices through vivid descriptions, appealing displays, enticing photographs, or aesthetically pleasing containers. Additionally, this category incorporates "healthy eating calls," which are direct appeals that encourage individuals to make healthier choices.
- *Cognitively oriented nudges*: This category includes two types of nutritional labeling: "descriptive nutritional labeling", which offers detailed information such as calorie counts or the content of other nutrients, and "evaluative nutritional labeling", which simplifies the assessment of food items' healthiness through color-coded indicators (e.g., red, yellow, green). A third technique within this category is "visibility enhancement", which aims to inform consumers of the availability of healthier options by increasing their prominence within a food setting.
- *Behavioural oriented nudges*: Interventions that aim to impact people's behaviors without necessarily influencing what they know or how they feel often without people being aware of their existence.

In the contemporary landscape, most human decision-making is made through digital platforms, such as websites and mobile applications [78]. However, individuals are particularly susceptible to making suboptimal decisions within these digital environments. Drawing on the theoretical principles of nudging, Weinmann [35], introduced the concept of "digital nudging" as the use interface design elements to steer individuals' choices or shape users' decisions in online environments. Digital nudges have been explored across various contexts, including privacy, work, and productivity. However, there is growing interest in the application of digital nudges within social contexts, where they are designed to promote more sustainable behaviors, as well as in health-related context, where the objective is to guide users toward actions that are more beneficial to their well-being [79]. In the latter context, digital nudges are highly effective, resulting in a 63% reduction in the proportion of unhealthy food choices and a 30% increase in the selection of healthy food products [80].

D. DIFFERENCES & CONTRIBUTIONS OF THIS WORK

Several attempts have been made to integrate healthiness into food recommender systems, with some studies focusing on generating healthier food options, while others emphasize providing nutritional advice tailored to the user's goals [25], [62], [81]. However, a systematic review on food recommendation systems over the past decade revealed that less than 20% of the literature incorporates nutritional considerations in the process of making food items recommendations [60]. Furthermore, findings by Trattner et al. [27] indicate that the majority of online recipes are generally unhealthy, highlighting the need for food recommendation systems to prioritize the healthiness of recommended items rather than focusing solely on algorithmic accuracy and user preference optimization.

Digital nudging, on the other hand, is a rapidly a growing field of research that has proven to be an effective solution in the area of behavioral change. The strength of these techniques lies in their ease of implementation and evaluation. In the food domain, digital nudges have demonstrated their ability to guide users toward healthier food choices [82], [83]. Given the potential of these technologies, several efforts have been made to investigate the combination of recommender systems and digital nudges to promote healthier food choices. These attempts recognize the powerful role that such integrated approaches can support and guide individuals toward better dietary decisions, thereby enhancing public health outcomes [39].

To the best of our knowledge, no prior research has systematically reviewed the integration of digital nudges with recommender systems specifically to promote healthier food choices. However, the latest work of [84] has focused on using digital nudges and recommender systems in the context of obesity prevention. In contrast, our work systematically identifies and classifies digital nudging techniques for food selection. Figure (1) illustrates how digital nudges are integrated into the process of a food recommender system. Specifically, digital nudges are employed in the interface and representation elements rather than in the algorithm generation phase. This distinction highlights that the primary different between a recommender system and a nudge lies in the design elements enhanced by digital nudges towards the desired proposes [39], [85]. Building on this foundation, we present the work that integrates these digital nudges within food recommender systems and propose a mapping framework that outlines potential combinations for facilitating healthier food choices.

III. METHODOLOGY

This section outlines the search strategy for the literature review and presents the research findings based on the proposed research questions. The paper follows traditional guidelines for conducting a systematic literature review [86], [87].

A. RETRIEVAL: DATABASE SEARCH

The search strategy started with identifying keywords (e.g, recommender systems, digital nudges, health, food) pertinent to our research questions, which were then employed to construct detailed search queries. These queries were subsequently refined to meet the retrieval criteria of each selected academic database. The search, conducted in June 2024, was filtered to include only publications from 2014 to 2024 to ensure relevance in addition to digital nudging was first introduced in the last decade and more research started to become a hot topic in academia with a ten-fold increase of the literature over the last five years [35], [88]. This process yielded a total of 3,130 papers.

Table 1 summarizes the database sources and the corresponding number of records retrieved per database.

TABLE 1. The total amount of literature retrieved from the different sources.

Database	Records
ACM Digital Library [90]	1534
IEEEXplore Digital Library [91]	817
ScienceDirect [92]	748
SpringerLink [93]	16
PubMed [94]	15
Total	**3130**

B. SELECTION: DEFINE INCLUSION CRITERIA

We applied specific inclusion and exclusion criteria to titles and abstracts during the selection phase, concentrating on references to digital nudging and/or recommender systems to promote healthier food choices. This phase, conducted by the first two authors, identified 47 papers that met the inclusion criteria and were subsequently selected for a full-text review. The selection process involved detailed discussions to ensure that each abstract met our criteria and review scope. Figure 2 illustrates the methodology employed for article selection and analysis.

C. ANALYSIS: PAPER EVALUATION AND DATA EXTRACTION

The analysis phase involves a comprehensive review and evaluation of the full texts of papers selected in the previous phase. Out of 47 papers assessed, 19 were included in the final selection. Data is systematically extracted by redefining metadata using a standardized form, which captures details such as the paper title, author, publication venue, nudging techniques, recommendation techniques, datasets, and other relevant information.

The inclusion and exclusion criteria, keywords, and a number of retrieved papers are detailed in [94]. The retrieved paper title, abstract, and the decisions made by the authors is accessible via [95], while the form used for data extraction from full-text readings can be found in [96].

IV. RESULTS

This section begins with an overview of publication statistics and outlets, followed by an in-depth analysis of key findings related to the integration of digital nudges into food recommender systems. Subsequently, it categorizes the digital nudging techniques investigated for promoting healthier food choices, aligning them with previously validated frameworks.

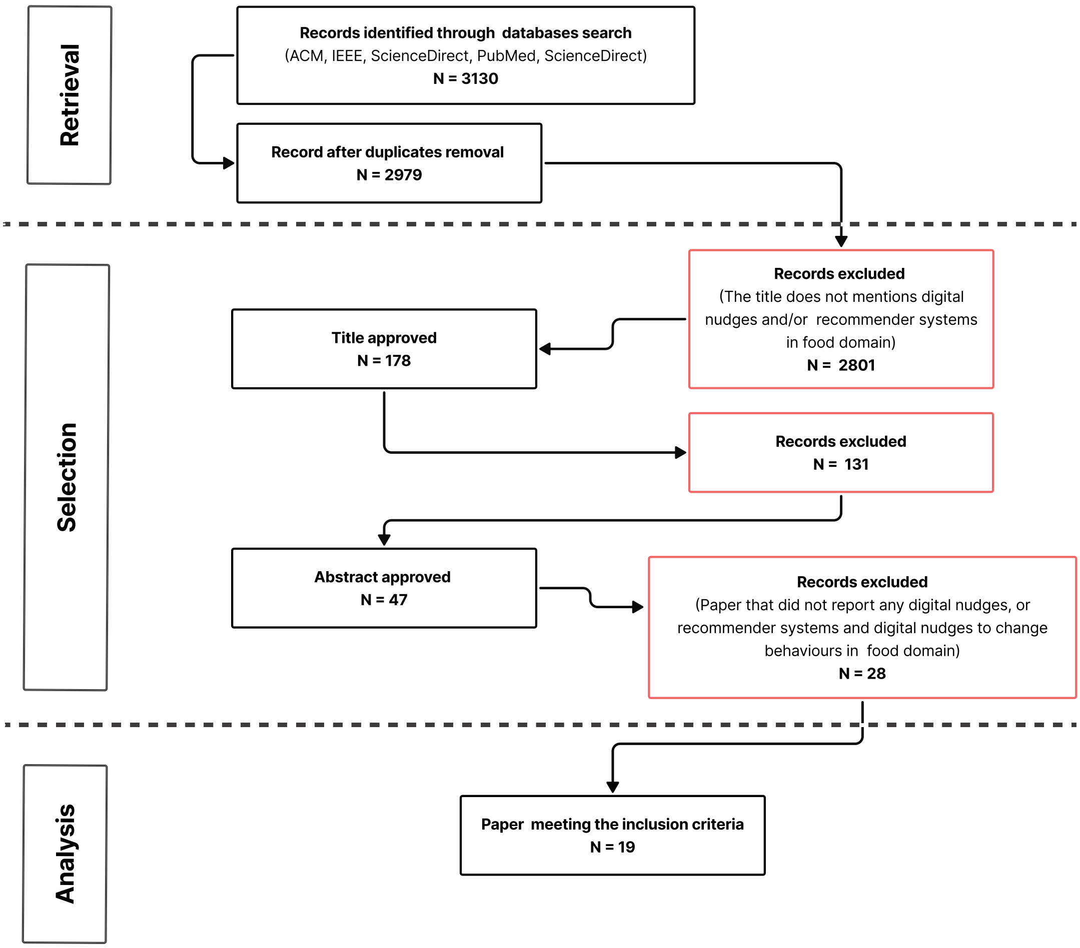

FIGURE 2. Flow diagram revealing the process of how publications were selected or excluded for further analysis.

Finally, the section provides a summary of the datasets, measurement methods, and recruited participants used in the user studies, offering insights into the methodologies employed for evaluating user behaviors.

A. PUBLICATION STATISTICS

A total of 3,130 primary studies were initially retrieved for this literature review, as presented in Table 1. During the selection process based on the inclusion criteria outlined in [94] and after duplicated removal, this number was reduced to 47 studies. In the analysis phase, 19 papers were selected based on the author's abstract and full paper text reading. Most of the studies were published during 2021, while only two contributions were published in the first part of 2024. The distribution of the studies published per year is illustrated in Figure 3.(A). The distribution of relevant papers retrieved from various sources is depicted in Figure 3.(B). The data reveals that the ACM Digital Library [89] contains the largest collection of research on digital nudges and food recommender systems, comprising 70% of the total 19 papers. In contrast, 15% of these papers were published in journals available through ScienceDirect [91]. The IEEE Xplore Digital Library [90] and PubMed [93] contribute the least to the research corpus on this topic, with each source representing 10% and 5% of both conference and journal papers, respectively.

B. FOOD RECOMMENDER SYSTEMS AND DIGITAL NUDGES

Advancements in technology and computational power have significantly enhanced the accuracy of personalization in recommender systems [60]. However, the multifaceted complexity of the food domain necessitates incorporating behavioral change techniques, particularly through digital nudging, within the representation phase of the recommendation process [12]. This integration aims to support individuals in making healthier food choices by employing several nudging techniques on the front-end interface.

Approximately 47% of the 19 reviewed papers successfully demonstrate the integration of recommender systems with digital nudges. Content-based recommender systems emerge as the most frequently integrated technique, utilized in 8 studies and combined with 5 distinct digital nudges. Table 2 outlines the studies that employed content-based

TABLE 2. The integrated digital nudges and recommender systems approaches.

Recommendation approach	Nudging Technique	Studies
Content-Based	Nutritional Food Labels	[71], [98], [99]
	Explanations	[11], [99]
	Positioning	[43]
	Re-ranking	[42]
	Social Norms	[98]
Knowledge-Based	Nutritional Food Labels	[71], [100]
	Notifications	[101]
Collaborative Filtering	Nutritional Food Labels	[102], [100]

approaches for generating recommendations and applying nudges (RQ 1. a)). Notably, nutritional food labels were the most extensively examined, integrated with recommender systems in 7 studies, and tested across all recommender approaches. Integrating digital nudges based on various nutritional food labels into a content-based recipe recommender system has been shown to impact the healthiness of selected recipes compared to conditions without nudges. Specifically, using Multiple Traffic Light (MTL) labeling results in a modest improvement in the healthiness of chosen recipes, as measured by the Food Standards Agency (FSA) score. This effect is measured in both web-based recommender systems and chatbot-based mobile applications [70], [98]. However, a study indicates that when food items are annotated with a combination of nutritional and environmental labels, there is a stronger tendency toward sustainability rather than healthier choices [97]. Interestingly, constructing a TF-IDF-based recipe content recommender system, combined with health-related explanations as nudges, leads to healthier food choices when recipe recommendations are presented as a single list rather than multiple lists [11]. Starke et al. [43] suggest that aligning food recommendations with users' dietary goals can overcome the positional nudge effect on user choice behavior. Conversely, another study found that integrating a simple re-ranking mechanism into various content-based recommenders significantly increased the selection of recipes with lower fat content compared to choices made using a random recommender model [42].

Consistent with previous findings, collaborative filtering and knowledge-based approaches are among the least utilized methods alongside digital nudges in the food domain [12], [60]. However, when nutritional food labels are incorporated as nudges, they have been shown to effectively promote healthier food choices within both collaborative filtering and knowledge-based recommender systems [99], [101]. Additionally, ongoing research has reported the integration of a knowledge-based recommender system with another type of digital nudge, which explicitly sends notifications to users as reminders to make healthy food choices in mobile applications [100].

Integrating digital nudges into personalized content in the food domain has demonstrated significant potential for driving behavioral change. Surprisingly, this direction has received the least attention from both academia and industry [12], [39], as shown in Table 2. The following section reviews and categorizes the primary contributions of digital nudging techniques toward promoting healthier food choices and discusses the impact of each method.

C. DIGITAL NUDGES FOR HEALTHIER FOOD CHOICE

Our analysis identified 20 studies documenting the use of digital nudges. The three most frequently employed techniques were nutritional food labels, positional nudges, and prompts, while feedback, defaults, and menu labeling were the least utilized among the 11 reported techniques. We categorize those nudging techniques into Cadario et al. digital nudging for a healthier choice framework detailed in Table 3.

TABLE 3. Implemented digital nudging techniques for healthier food choices, categorized based on the framework explained in (II-C).

Category	Technique	Studies
Affective	Prompt	[103], [104] , [105]
	Feedback	[103], [104], [106]
	Explanations	[106]
	Incentives	[107]
Cognitive	Nutritional Food Labels	[103], [108], [106], [104]
	Visualization	[109], [110]
Behavioral	Positioning	[103], [104], [111]
	Social Norms	[112], [109]
	Defaults	[111]

Affective-oriented digital nudges have been identified as the most frequently employed techniques, surpassing cognitive and behavioral-oriented nudges, with four distinct methods documented across nine studies, as shown in Table 3. Among these, the combination of prompt and feedback nudges has addressed two key challenges in promoting healthy eating: encouraging mindful, slower eating and fostering healthy eating habits [104]. Incorporating gameful elements into mobile applications, such as providing food explanations, has effectively enhanced users' nutritional knowledge and encouraged healthier food choices [105]. Alternatively, by designing rewards and incentives, users are further motivated to adopt healthy diets that can help prevent the spread of non-communicable diseases. This approach illustrates how a combination of explicit and implicit interventions can promote healthy behaviors in offline settings (i.e., groceries) through digital means [106].

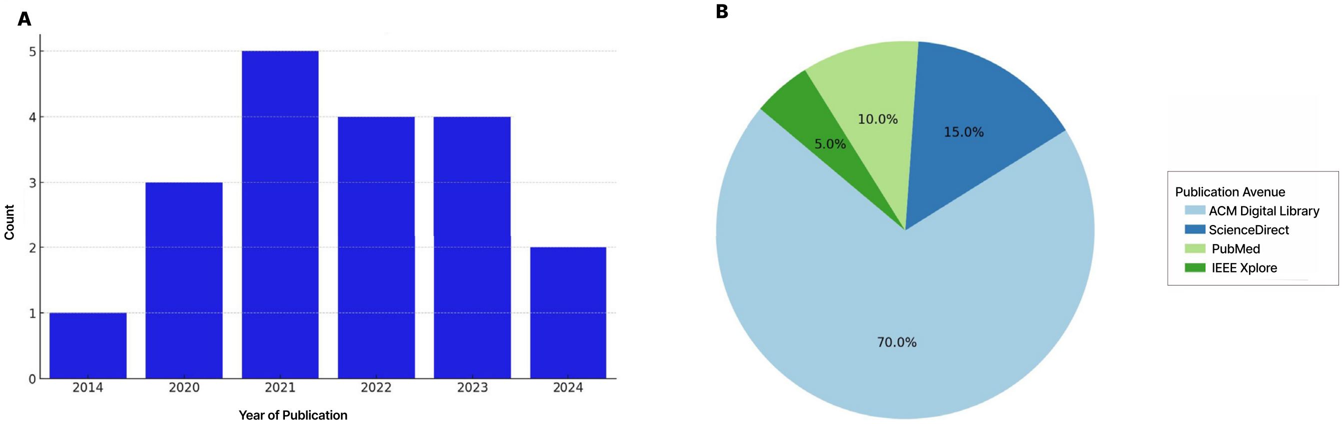

FIGURE 3. Publications statistics: (A) present the number of papers per year. (B) shows the distribution of relevant papers retrieved per avenue.

Nutritional food labels are the most prevalent cognitive digital-oriented food nudges, typically presented in the form of Multiple Traffic Light systems [102], [105], [107]. These labels have proven highly effective, leading to an average 59% increase in healthy and sustainable food choices [107]. Interstenly, a visualization cue as a food nudge linked to a self-report mobile application has proven to lead to effectiveness in user self-tracking their eating behaviors and the nutrition content of the food before making the choice [108], [109].

Reordering and setting healthier options as the default in an online food choice environment have been shown to effectively influence users' shopping behaviors [102], [110]. Similarly, the use of social norms, which has proven effective in driving behavioral change in offline settings [112], [113], has also led to a significant impact on calorie intake in digital environments through the food choices made [111].

Nudging has been widely studied in offline settings across various domains; its application in digital environments has only recently begun to gain significant attention due to its potential for influencing behavior. Despite this growing interest, the long-term effects of digital nudges still need to be explored in the literature. However, one study has demonstrated a notable long-term impact, revealing that using multiple food nudges in a digital environment significantly improved the nutritional quality of food choices in an online canteen setting over a 15-month period [103].

D. DATASETS, MEASUREMENT, AND PARTICIPANT

Food recommender system studies focus on both online and offline evaluations. Offline evaluation helps identify the best algorithms based on recommendation accuracy and requires a source dataset for experimentation [114]. To accurately assess the system's impact, selecting appropriate measurement metrics and involving suitable participants in the experiments is essential [115]. A comprehensive evaluation of a food recommender system must ensure both holistic assessment and research reproducibility. Therefore, we evaluate and extract the data source, measurement metrics, and number of participants from each eligible study [12], [116].

Among the 19 studies reviewed, Only six disclosed their data sources for conducting user experiments and analyses. The Allrecipes.com dataset was notably the most frequently utilized in five studies [42], [43], [70], [98], [99], [101]. A combination of various data sources was reported as the basis for one experiment [100]. The remaining studies opted to keep their datasets private, offering exploration only upon request.

There is a lack of precise details regarding the evaluation metrics for recommendation algorithm performance in the reviewed studies. Only one study provides concrete details on selecting the most accurate recommendation algorithms [101]. While other research suggests using state-of-the-art recommenders or widely adopted approaches appropriate for the context. Concerning health metrics, seven studies reported using international healthiness scores, such as the FSA score, Nutri-Score, or Eco-Score, to assess the healthiness of the datasets utilized and collected [11], [42], [70], [97], [98], [99], [101].

Among the studies reviewed, all provided comprehensive details on the number of participants and the specific user groups involved. The exception was a study that failed to include such information [104]. Additionally, another study suggested conducting a user experiment as future work but did not specify the number or type of users to be involved [100]. Of the studies that did specify participant demographics, few focused on high school and university students [102], [105], whereas the remaining studies encompassed a range of diverse or general population groups. The sample sizes across these studies varied significantly, ranging from a minimum of 5 participants to a maximum of 1331, with a mean of 398.19 and a standard deviation of 425.60 participants.

V. FUTURE OPPORTUNITIES

This section critically examines the gaps identified in current research regarding integrating food recommender systems and digital nudges to promote healthier food choices (RQ 2. b) The analysis is grounded in the reviewed state-of-the-art literature. Subsequently, we highlight emerging opportunities by analyzing the various dimensions of the reviewed studies alongside examples from other domains.

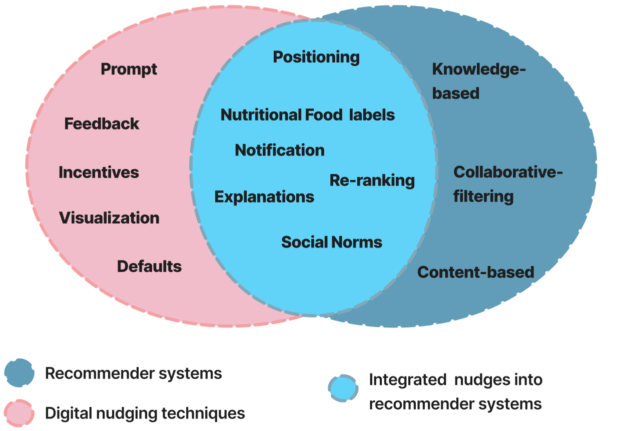

FIGURE 4. Explored digital nudging techniques for healthy food choices. The intersection (light blue) highlights those implemented within food recommender systems.

Existing literature highlights the integration of various recommendation approaches with digital nudging techniques [39]. This study further indicates that several efforts have been made to incorporate such interventions into food recommender systems. Nudging, which involves shaping the design of choice architecture, should therefore be embedded in the presentation phase of the food recommendation process, irrespective of the recommendation algorithms or approaches applied [32], [35], [117], [118]. Out of the eleven nudging techniques we have identified, six techniques have already been tested in a recommender system context. In contrast, five of them have not yet been implemented in a recommender context. Furthermore, there are various combinations of multiple techniques and approaches that warrant further investigation [39]. Figure 4 offers a comprehensive overview of both the explored and unexplored digital nudging techniques within food recommender systems for healthy food choices.

Implementing digital nudges for behavioral change within recommender systems involves several key steps to ensure successful application and evaluation [39], [118]. The first step is to clearly define the context and objectives of the nudge, aiming to support users in making healthier food choices through the recommender interface. The second step involves conducting a comprehensive diagnosis to understand the decision-making process, how user preferences are elicited, and the techniques used for retrieving and presenting recommendations [35], [118], [119]. The third step is selecting appropriate nudges, which requires a thorough understanding of the recommendation process, including the types of interfaces users will interact with, the characteristics of the target audience, and the degree to which nudging strategies should be integrated [11], [70]. The final step focuses on evaluating the impact of these nudges on user behavior. Importantly, this evaluation should extend beyond measuring behavioral changes to include an analysis of the overall user experience, considering system complexity and other contextual factors that may influence food choices [12]. Adopting this holistic and user-centric evaluation approach ensures that nudging strategies not only encourage healthier behaviors but also enhance the usability and overall effectiveness of the recommender system [115].

Extensive research on the design of recommender systems has made it easier to select approaches to generate recommendations in recent years [9], [12]. While, choosing suitable nudging techniques to integrate into the recommendation process remains complex. This review identifies five nudging interventions that have not yet been employed in food recommender systems for healthy food choices. However, we believe that only those outlined below are worth further investigation [39]:

- *Default:* This nudge technique was found to be the mostly used within the nudging and behavioral change literature [118], [120]. In the context of a choice architecture, it is operationalized as a pre-selected option which can still be changed, adhering the libertarian paternalism principles of Nudging [33]. Within recommender systems, it has been shown to be the most studied technique across various domains [39]. To promote healthy choices within the food recommender system, setting the defaults involves pre-selecting the healthiest options from the generated food recommendations for a given use based on the health metric used to evaluate the recipes. Several studies have explored the impact of default settings on user behavior within recommender systems [121]. Starting with a default option often leads users to select it or a similar choice, while also shaping user preferences, which has the potential to encourage healthier behaviors [39], [122]. For example, one study found that users were satisfied when the most sustainable and environmentally friendly trip routes with lower CO_2 emissions were set as the default in a route recommender system [123]. In the food domain, nudging users toward healthier food choices through default settings is worth the exploration regarding the potential of this technique to influence user behaviors in other domains [124].
- *Visualization:* Interventions that increase the salience of items, such as enhancing image quality or emphasizing text, are designed to capture a user's attention [39], [125]. In food recommender systems, visual enhancements, such as high-quality images, highlighting the nutritional attributes, or creating graphics for healthier options, can support more informed and health-conscious decision-making in addition to increasing

user satisfaction [43], [126]. For example, visual cues have successfully encouraged sustainable fashion consumption by drawing attention to second-hand garments and providing sustainability information [127]. Similarly, in book recommendations, nudging users toward off-profile content has increased the selection of books beyond their preferred genres [128].

- *Prompt:* A prompt is defined as a strategically delivered message or reminder aimed at users in specific contexts to influence behavior [129]. It is frequently employed to address situations where individuals are prone to engage in undesirable or unhealthy behaviors, providing timely guidance toward healthier alternatives. The use of prompts has been shown to facilitate effective behavioral change across various domains, including transportation, healthcare, environmental conservation, and education, both in online and offline settings [130], [131], [132]. The integration of prompts within recommender systems has not been extensively explored in the literature [39]. Nevertheless, incorporating reminders to encourage healthier food choices within these systems can be approached in various ways, such as prompting users to consider more nutritious alternatives during decision-making processes. In conversational recommender systems, prompts can further enhance the user experience by facilitating reflection on their choices through explanations and cues [133], thereby supporting more informed and health-conscious decision-making.

Feedback interventions are used as nudging strategies in areas like education and nutrition [84], [134] to provide information about past behaviors to guide future actions [135]. However, integrating them into recommender systems is challenging due to the complexity and risk of increasing cognitive load. Research shows that feedback can sometimes have negative effects [136], [137], while incentives, often applied after a decision, may offer only short-term behavior changes, especially monetary ones. Furthermore, incentives can undermine intrinsic motivation, making it harder to sustain desired behaviors [138], [139]. Implementing such interventions in personalized food recommender systems adds complexities that may overwhelm users [140].

Digital nudges are strategically designed to influence user interactions with the interface and ought to be integrated during the final phase of the recommendation process (i.e., Figure 1 Part (C): representation).

The current study elucidates several areas requiring further exploration. Foremost among these is the insufficient evaluation of used datasets and their quality in compliance with established international health standards [141]. This gap in the assessment process undermines the reliability validity, and reproducibility of the proposed research. Despite advances in algorithmic performance, there is still a critical lack of user-centered experimental designs in the evaluation of food recommendation systems. Traditional offline metrics, while useful for benchmarking, fail to capture how users actually perceive and interact with these systems in real-world contexts. As demonstrated in [115] and [142], incorporating user-centric evaluation frameworks provides a more holistic and robust assessment of system effectiveness. These methods not only account for algorithmic performance but also reflect the nuanced ways in which recommendations influence user behavior and experience over time. Addressing these issues in future research is essential for advancing the field and improving the practical utility of food recommender systems integrated with digital nudges for healthier choices. Another crucial area for further research is the long-term impact of nudging techniques on users' lifestyles and behavior [39], [143]. We are confident that these techniques contribute to a deeper understanding of user decision-making, ultimately fostering awareness and supporting informed choices. Additionally, they have been shown to induce positive habit changes, a benefit well-documented in offline settings [144], [145].

Recommender systems' utility functions (cf. Equation 1) focus on user preferences and item attributes, without accounting for external factors like user interface elements design. This makes integrating digital nudges straightforward, as the utility function does not consider such influences. As a result, nudges can be added to the presentation layer of food recommender systems, using user interface elements to guide user choices [35]. However, significant challenges emerge when attempting to personalize these nudges for individual users within the recommender system interface. Traditional recommender systems typically optimize for engagement and preference-based metrics. In contrast, digital nudging introduces a complementary objective: guiding users toward healthier choices. This dual objective creates an inherent algorithmic trade-off between preserving preference accuracy and achieving meaningful behavioral influence.

A promising approach to addressing this trade-off is the development of multi-objective food recommender frameworks. These systems extend conventional models by incorporating an additional objective function that accounts for the personalization of the nudging strategy itself, rather than the recommended content alone [146], [147]. For example, systems may adapt visual and structural interface elements, such as color schemes, layout configurations, or framing styles-based on individual users' behavioral preferences [148], [149]. By jointly optimizing content relevance and nudge effectiveness, such systems are better positioned to align recommendation accuracy with behavioral change objectives.

However, this personalization of digital nudges introduces an additional challenge: evaluating the impact of such systems. Specifically, measuring the effectiveness of the nudging component within a hybrid recommendation framework remains an open question. Addressing this issue is critical for advancing future research. While user-centric evaluations (e.g., A/B testing) can provide valuable insights into real-world effects, they are often resource-intensive.

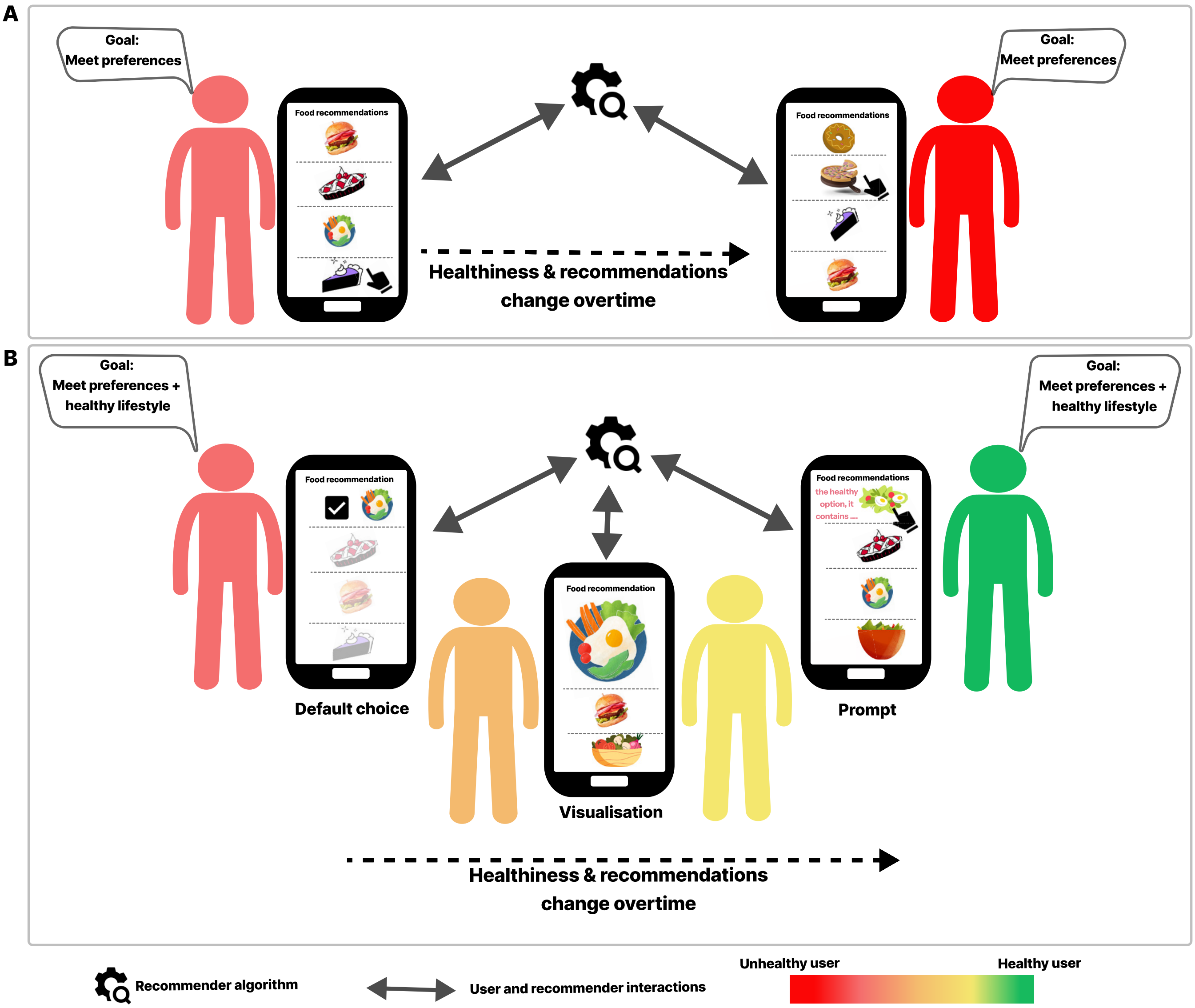

FIGURE 5. The impact of integrating digital nudging techniques into a food recommender system over time. (A) depicts the system without nudging, while (B) illustrates changes in generated recommendations and user choices when nudging is applied.

As a complement, offline simulation environments have been proposed to estimate behavioral outcomes using synthetic or historical interaction data [150], [151]

Moreover, the integration of digital nudges into food recommender systems raises important ethical considerations. Ensuring transparency, user autonomy, and informed consent is essential to avoid manipulative or coercive system behavior. Future work must engage with these ethical dimensions to support the development of responsible, ethically aligned recommender systems [152].

Overall, integrating nudging techniques into recommender systems can enhance their effectiveness by promoting diverse and healthier recommendations. Figure 5 illustrates this concept with an example: (A) depicts user interaction with a recommender system without nudging, whereas (B) demonstrates how incorporating nudging techniques can guide users toward healthier choices. Over time, this approach not only benefits individual users but also enables the recommender system to prioritize healthier options through continuous learning from user data.

VI. CONCLUSION

Food recommender systems have shown their capacity to help users find the desired food content efficiently and alleviate choice overload. Content-based approaches have integrated several nudging interventions, such as nutritional labels and explanations, whereas collaborative filtering and knowledge-based approaches have primarily been tested with nutritional food labels and notification-based nudges. This integration has shown to enhance the healthiness of food choices within these systems. However, various other interventions could be harnessed to further support users in making healthier food choices across different recommendation approaches. For instance, default interventions, which have yielded promising results in other domains, could be applied here. Additionally, visual techniques offer potential; enhancements in image quality or the use of visualization tools can facilitate easier judgments of food healthiness. Consequently, these strategies could contribute to improved user satisfaction and experience within food recommender systems.

This study revealed that various nudging techniques effectively support users in making healthier and more informed food choices. Additionally, incorporating interventions during the presentation phase of food recommender systems has demonstrated significant potential in achieving this goal. The findings from this study contribute to the existing literature by providing a comprehensive summary and review of food recommender systems that successfully integrate digital nudging interventions to promote healthier food choices and encourage healthy eating behaviors.

Using a pre-validated research framework, we systematically analyzed and categorized various nudging techniques within digital environments. Furthermore, we critically evaluated digital nudging strategies that warrant further investigation and explored their potential integration into the food recommendation process to support healthier eating. Lastly, we highlighted the primary limitations identified in existing studies and emphasized the importance of user-centric evaluations for assessing the performance of these systems across various dimensions.

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AYOUB EL MAJJODI received the M.Sc. degree in data science and big data from the National Advanced School of Computer Science and System Analysis, Morocco. He is currently pursuing the Ph.D. degree with the DARS Research Group, University of Bergen. The main focus of his Ph.D. research project lies in recommender systems for the food domain, where he investigates the utility of recommender systems and digital nudging to change people's eating behaviors and help them to attain healthier eating habits.

ALAIN D. STARKE received the Engineering degree in innovation sciences and the Ph.D. degree in human-technology interaction with TU Eindhoven, NL, The Netherlands. He is currently an Assistant Professor with Amsterdam School for Communication Research, University of Amsterdam, NL. His research focuses on how people can be presented effective personalized advice, through both algorithms and interfaces, focusing on domains that involve behavioral change, such as energy conservation and healthy eating.

CHRISTOPH TRATTNER received the B.Sc. degree in computer science and telematics and the M.Sc. and Ph.D. degrees (Hons.) from Graz University of Technology, Austria. He is a Lead Professor in data science and recommender systems with the University of Bergen and the Director of the Research Centre for Responsible Media Technology and Innovation–MediaFutures worth around 26 million EUR. He has published over 150 articles in reputable journals, including *Nature Food*. His research interests include the intersection of behavioral data analytics and recommender systems. He is a ACM Distinguished Speaker and a board member of several leading journals in computer science.