Design Implications Towards Human-Centric Semantic Recommenders for Sustainable Food Consumption

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Abstract. The significance of food is evident in the myriad challenges confronting contemporary society, including the increasing prevalence of diet-related diseases, food waste with its adverse economic, environmental, and social impacts, and the significant impact of food production on environmental issues, among others. As the negative health and environmental impacts of dietary patterns become more evident, there is a growing demand for personalized and sustainable food recommendations to promote healthier and planet-friendly choices. This study aims to enrich the theoretical underpinnings of food recommender systems with an emphasis on sustainable food consumption, by integrating insights from existing research, behavior change theories, and Industry 5.0 digitization concepts on humanity-centered technologies.

Keywords: food recommender · nutrition consumption behavior · sustainable food consumption · human-centric food recommender · privacy-aware food recommender

1 Introduction

The significance of food is evident in numerous challenges confronting contemporary society. Several health conditions such as obesity, diabetes, hypertension, cancer have been linked to dietary practices [1]. The rising prevalence of diet-related diseases has raised concerns about the challenges people face in achieving and maintaining balanced diets. Additionally, the significant contribution of food production to greenhouse gas emissions [2], deforestation, and biodiversity loss [3] emphasizes the potential role of dietary changes on a global scale in mitigating climate change. Food waste is yet another critical issue that necessitates urgent attention due to its adverse economic, environmental, and social impacts [4], in developed countries, consumers constituting a major source of food waste. Scholars have suggested that modifying individual diets could be a crucial aspect of the solution to climate change [5]. The need to address both nutritional and environmental concerns in recommending diets presents a compelling challenge for researchers and practitioners in this domain. As the negative health and

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environmental impacts of dietary patterns become more evident, there is a growing demand for personalized and sustainable food recommendations to promote healthier and planet-friendly choices.

Existing food recommender systems suffer from various shortcomings. For instance, they often lack personalization, relying on generic choices instead of considering individual preferences, dietary restrictions, and cultural backgrounds among others. On the other hand, some food recommenders heavily rely on user data for personalized recommendations, potentially limiting user exposure to food choices that align with their existing preferences and/or conditions [6, 7], failing to address broader food consumption contexts, support behavior change [8] for healthier lifestyles or conscious choices that align with societal concerns. These systems in addition raise privacy concerns over the use of sensitive user data [9]. Additionally, the underlying algorithms lack transparency and may lead to reduced user trust. Furthermore, inaccuracies and slow adaptation to changing conditions (e.g., physiological status, time, location) can result in outdated and ineffective recommendations.

These various factors collectively form the backdrop for further research and development in the field of food recommender systems. In addition, a prominently emerging area of interest in this domain pertains to sustainability assessment, as evidenced by recent scholarly attention [10]. However, the present landscape comprises only a limited number of tools designed to assess the degree of sustainability associated with individual food items.

Despite its significant importance and complex nature, the field of food recommendation remains in its infancy stage, lacking a dedicated theory exclusively focused on this domain [1]. In this study, we aim to construct a comprehensive conceptual map for developing cutting-edge recommenders to promote design and development of sustainable food consumption. This map will interconnect various essential concepts, including insights from existing research in the field (outlined in Sect. 2), theories related to behavior change (presented in Sect. 3), and the next generation digitization concepts rooted in Industry 5.0 - a humanity-centered digitization paradigm (Sect. 4). By integrating multidisciplinary knowledge and leveraging advances in recommender system techniques that accommodate individual preferences, health aspirations, and sustainability targets within a humanity-centered framework, our goal is contributing to new generation recommenders for more effective and responsible food consumption choices. The research aims to serve a starting platform for researchers and designers for human-centric recommenders for sustainable food consumption.

2 Existing Food Recommenders

In the context of food, recommendation systems aim to enhance user dining experiences, encourage healthier choices, and reduce food waste by empowering users to make informed and responsible food consumption choices. There are several types of techniques employed within recommender systems which include: (1) content-based or constraint-based recommendations that suggest items based on attributes and characteristics of previously liked items or restrictions, e.g. previously liked recipes or recipes that are based on restrictions, e.g. gluten-free; (2) collaborative filtering that utilizes user behavior to identify patterns among like-minded users and recommends items based on their preferences that is especially useful when there is limited item information available; (3) hybrid recommenders combine both content-based and collaborative filtering approaches to leverage the benefits of each for more diverse and accurate suggestions; (4) knowledge-based recommenders that use explicit knowledge about user(s) needs and requirements to generate personalized recommendations, which often use rule-based experts systems. Additionally, advanced methods like (5) matrix factorization and deep learning models are employed to capture intricate user-item interactions to deliver more sophisticated and accurate suggestions.

2.1 Algorithms Employed

Content-based recommenders (also referred to as semantic recommenders) analyze the characteristics of food items, such as ingredients, cuisines, or nutritional profiles, to recommend similar options [11]. In collaborative filtering recommenders [12], when presented with a new user (e.g. a traveler), the system recommends an item by drawing upon the favorably rated selections of comparable users (e.g. preferences of previous tourists in a region). In a hybrid system [13], user behavior data (user-item interaction) can be combined for instance with the textual analysis of ingredient lists and cooking methods to suggest recommendations that not only reflects similar user preferences but also considers the intrinsic attributes of food items. In such systems, if for instance a user has interacted with a variety of Italian pasta recipes (collaborative filtering) and has a preference for dishes containing tomatoes and basil (content-based), the hybrid algorithm might combine these insights. The knowledge-based recommender can rely on a structured database of recipes and attributes, while using user input to filter, match, and rank recipes for personalized recommendations [14]. This approach does not require user interaction with explicit ratings or past behavior, making it suitable for scenarios where user data might be limited or where users are seeking inspiration based on available ingredients and preferences. Collaborative filtering can suffer from the "cold start" problem when new items or users have limited interaction data. Knowledge-based recommenders can handle this better since they don't require historical interaction data.

To achieve their objectives, these systems employ different algorithms. Content-based recommenders use algorithms such as vector-based representations, e.g. cosine similarity to measure the similarity between food items based on their attributes, topic model-based or dependency decision tree representations. Collaborative filtering algorithms, use techniques such as matrix factorization decompose user-item interaction matrices to identify latent features to generate personalized recommendations. Matrix factorization dissects the user-item interaction matrix to uncover latent preferences [11]. For instance, it might reveal that a user prefers vegetarian options and spicy foods, even if they haven't explicitly ordered them before. Knowledge-based algorithms employ knowledge graphs that may integrate various aspects of food such as ingredients, nutritional knowledge and medical conditions, and their relations [14]. Deep learning models, on the other hand, can combine images and descriptions of dishes, e.g. using Convolutional Neural Networks (CNNs) to analyze dish images and Natural Language Processing (NLP) techniques for textual descriptions. By fusing visual and textual features, the platform offers personalized recommendations. For instance, when a user interacts with an image of a visually enticing pasta dish with a flavorful description, the model can combine the extracted visual details (ingredients, colors, textures) and semantics of textual cues (e.g. using Word2Vec to convert words into numerical vectors that capture their semantic relationships) to suggest similar recipes that resonate with the user taste. Recent research indicates that visual cues embedded within online recipes accessed by users have the potential to predict user preferences [15]. Another example of using predictive models within food recommender systems include chatbots. Through chatbots or voice assistants, recommender systems can engage in conversations with users to understand their preferences and provide real-time recommendations. Users can ask questions, receive suggestions, and discuss their culinary desires, which can be used by predictive models to refine further recommendations.

2.2 Intended Users

In the context of food recommenders, existing systems can be classified based on different characteristics, such as user groups. In terms of the users these systems can be classified to the following user categories:

- *Individual (children, elderly)*: These systems delve into the intricacies of personal preferences and contexts such as fitness diet, preventive or beneficial diets for health conditions, cost effectiveness, etc.
- *Family*: These systems encompass the broader canvas of shared meals, navigating the delicate balance of accommodating various preferences of various family members and dietary needs into a culinary mosaic that fosters shared enjoyment, catering to both children cravings and adult dietary considerations, next to budgetary choices.
- *Group of users*: These systems aim to support shared decision making, e.g. what restaurant to attend and what to eat together. For example, as people often eat socially, group recommendation becomes important. In group recommendation situations recommendations are optimised to suit multiple taste profiles with the preferences of different users being traded-off or balanced against each other.
- *Farmers for animals*: Such systems for farmers designed to feed animals are personalized tools that utilize data analysis and machine learning that consider factors such as species, age, weight, and nutritional needs to offer tailored feeding plans. These algorithms prioritize health, sustainability, and efficiency. By recommending optimal combinations of feed resources, e.g. organic and hormone-free options, the systems contribute to animal welfare, reduced environmental impact, and resource efficiency. These systems also promote transparency to consumers about how animals are raised, promoting trust in the quality and ethical production of animal products.
- *Farmers for food*: Food cultivation recommenders guide farmers in sustainable practices such as crop selection, precision farming, water-efficient irrigation, energy-conscious strategies, integrated pest management, soil health enhancement, nutrient optimization, climate adaptation, resource monitoring, and real-time decision support. These tools can promote cost-effective andeco-friendly methods, reduce waste, enhance yields, and provide educational resources for informed, sustainable agriculture that in addition can potentially inform other recommenders above to support sustainable food consumption behavior.

– *Supplier*: Food recommender systems benefit suppliers (like local farmers) often in bi-directional systems by expanding market access, reducing waste, and promoting sustainable practices. For consumers, these systems, besides serving standard recommenders, can encourage local sourcing, seasonal eating, environmentally friendly and cost-effective choices, fostering sustainable food consumption patterns and efficient supply chain.

2.3 Food Profiles

In terms of the food categories recommenders can be classified to the following objectives:

– *Product*: Recommenders can encompass food products such as meats, vegetables, and dairy to suggest recipes centered around favored products by users.
– *Ingredient*: ingredient recommendation include fundamental components used in cooking to create dishes, using e.g. user preferred ingredients, dietary restrictions, and allergies to suggest recipes and meals that align with their culinary preferences.
– *Recipe*: Some recommenders offer recipes, a set of instructions that outlines the steps and quantities required to prepare a specific dish, by analyzing user recipe choices, cooking styles, and preferred flavors to choose/compose recipes that match their tastes.
– *Menu*: Some recommenders offer suggestions for menus which contain multiple predefined dishes and possibly appropriate drinks and snacks.
– *Meal*: Recommenders may offer dishes, beverages, and accompaniments that can be consumed together during a dining occasion by analyzing user historical meal choices, taste preferences, and nutritional goals to suggest well-balanced and satisfying meals catering to specific needs and desires.
– *Meal plan*: Recommenders offer guidance for users seeking a structured approach to their daily diet by recommending menu plans that outline a schedule of meals and snacks over a designated period (sequence of temporal occasions), often designed to meet specific dietary goals, such as weight loss, muscle gain, or overall health improvement.
– *Feeding plan*: Recommenders can assist farmers with livestock nutrition, health and management by analyzing animal data and suggesting balanced diets based on nutritional needs, age, and breed. They customize feeding plans, considering ingredient nutritional profiles and cost efficiency. These tools also promote animal health by preventing imbalances and can adjust plans in real-time. By factoring in sustainability and environmental impact, they help farmers make eco-friendly choices. Record keeping and analysis enable long-term optimization.

2.4 Recommender Types in Food Domain

The applications of food recommender systems span across various domains. In terms of the objectives the food recommender systems can be classified to support:

– *Health*: In health-related contexts, food recommendations go beyond just satisfying user taste preferences by also taking into consideration the healthiness of the recommended food items for individuals who suffer from some kind of disease or seek to

prevent illnesses to suggest recovery or preventive diets. The focus here is not only on the immediate appeal of the food but also on its nutritional value and its potential benefits for overall health. Furthermore, while individual meals may be healthy in isolation, recommender algorithms also need to ensure a balanced diet approach when combining them.
- *Recipes*: Recipe recommenders provide personalized recipes based on dietary requirements, cooking skills, and ingredient availability.
- *Cooking*: Cooking-related recommender systems allow users to explore new recipes, offer suggestions on what meals they can prepare based on their available ingredients, cooking skills, and preferred cuisine.
- *Diet*: Diet recommenders design custom diet plans according to individual health goals and nutritional needs. Diet-focused recommenders assist users in achieving specific dietary goals, such as weight loss, muscle gain, or managing medical conditions. These systems analyze the users' dietary requirements and restrictions to suggest suitable meal plans that align with their objectives. The recommendations may emphasize portion control, nutrient balance, and calorie intake, helping users stay on track with their desired diet plans.
- *Grocery*: Grocery recommenders help users create tailored shopping lists and promote healthier food choices.
- *Restaurant*: Restaurant recommenders suggest nearby dining options based on user preferences, reviews, and location.

2.5 Interfaces and Outputs

Recent advancements in the field of food recommender systems have brought about various interfaces for enhancing user experience and satisfaction. These interfaces encompass a diverse range of platforms, including:

- Mobile apps
- Web applications
- Smart plates
- Desktop programs
- Conversational agents

Mobile apps offer on-the-go accessibility, enabling users to receive personalized meal suggestions based on their preferences and dietary restrictions while navigating busy schedules. Web applications extend to larger screens, presenting visually appealing recipe recommendations with interactive features like customizable filters and virtual pantry organization. Smart plates, a cutting-edge interface, merge the physical and digital realms by analyzing the nutritional content of meals placed on them. These plates can suggest healthier alternatives or complementary dishes to balance dietary intakes, fostering mindful eating habits by, for example, analyzing the number of calories in a meal and the time taken to consume it. On the other hand, desktop programs cater to users seeking an immersive browsing experience, allowing them to explore diverse cuisines, cooking techniques, and culinary inspirations through an expansive interface. Conversational agents, powered by natural language processing, introduce a conversational dimension to food recommendations. Users can engage in dialogue with these agents, discussing their tastes, moods, and dietary goals to receive tailored meal ideas and recipe suggestions. These interfaces showcase the transformative potential of AI-driven interactions in shaping culinary preferences and encouraging culinary experimentation.

Food recommenders use a variety of output formats to present recommendations effectively. These may include:

- Text-based descriptions (e.g. recipes)
- Interactive visual elements (e.g. nutrition scores)
- images (e.g. dishes or ingredients)
- Videos (process of cultivating, selecting, harvesting, cooking)
- Nutritional information (e.g. serving size, ingredients, calories, allergen information, glycemic index, health benefits)
- Customizable filters (e.g. search and preference refining features)
- meal plans and grocery lists (e.g. vegetarian breakfast and the ingredients needed for cooking)
- Social sharing (e.g. integration with social media and messengers)

Textual output may contain descriptions or lists of suggested dishes along with relevant details such as ingredients, preparation methods, and flavor profiles. Visual representations of recommended dishes, often accompanied by images or icons, provide users with a quick and visually appealing overview of the options. Users can interact with these elements to explore more details about each dish, such as nutritional content, cooking steps, and variations or find a location of a proposed restaurant. High-quality images of recommended dishes can evoke sensory experiences, helping users get a sense of the final presentation and may prompt them to try recipes that align with their culinary preferences. Recommender systems can also suggest cooking tutorial videos or links to online cooking demonstrations, e.g. with guiding users through the step-by-step process of preparing recommended dishes, thus making it easier for them to follow along and replicate the recipe. Some output formats focus on providing detailed nutritional information for each recommended dish, including calorie counts, macronutrient breakdowns, and dietary information. This allows users to choose options that align with their dietary goals. Users can apply filters based on dietary restrictions, preferred cuisines, cooking times, or specific ingredients. The system then generates recommendations that fit the selected criteria, offering a more tailored and personalized experience. Recommender systems may generate entire meal plans, suggesting combinations of dishes for specific meals throughout the day. Additionally, they can generate grocery lists based on the selected recipes, streamlining the shopping process. Some systems allow users to share their recommended dishes or meal plans on social media platforms, fostering a sense of community and encouraging culinary exploration among peers.

2.6 Challenges with Existing Recommender Algorithms for Food Domain

With regard to the analytics approaches, standard recommendation algorithms perform significantly less well when used for recommending food items than on other problems, such as movies or online purchases in an e-commerce context [1]. Unlike movies or e-commerce products, which may have more universal appeal, food choices are inherently diverse and influenced by various factors that can vary significantly from person to person due to cultural, dietary, and personal factors, making it challenging for standard algorithms to capture such nuances accurately. Context-dependent preferences further complicate the matter. Food choices can be influenced by the time of day, location, or occasion. For instance, users might prefer different types of food for breakfast, lunch, or dinner. Standard algorithms, which typically treat each recommendation as an isolated event, may struggle to incorporate such contextual information, leading to less accurate suggestions. In many recommendation contexts, having a comprehensive and diverse dataset is essential for generating accurate suggestions. However, food data can often be limited to specific cuisines or restaurants, resulting in biased and less varied recommendations. Moreover, the dynamic nature of food menus poses a challenge for recommendation algorithms. Unlike movies or e-commerce products, food menus can change frequently, with new dishes being added or removed regularly. Standard algorithms may not be able to adapt quickly to these dynamic changes, leading to suboptimal recommendations. Additionally, nutritional and dietary constraints need to be considered in food recommendations. Users may have specific dietary preferences or restrictions, such as allergies or cultural dietary practices, which must be taken into account. Furthermore, food choices often involve multiple criteria, such as taste, price, healthiness, and availability. Standard algorithms are typically designed for single-criteria recommendations and may not effectively handle the complexity of multi-criteria food recommendations. Lastly, food recommendations might require additional contextual information other than preferences and historical data, such as financial, seasonal and time constraints, which might not be readily available or challenging to integrate into standard algorithms. For instance, a recipe may be relevant for a user however lack of the time or cooking equipment necessary to prepare the meal can make the recommendation unsuitable [1]. The processing of context information often entails handling data derived from heterogeneous sources with various formats. This can encompass data stream queries, potentially leading to resource consumption that is unaffordable, in addition to data fusion needs [16].

3 Integrating Behavior Change Theories for Sustainable Food Consumption

In the pursuit of addressing pressing global challenges such as climate change and resource depletion, promoting sustainable food consumption has emerged as a critical endeavor. Achieving meaningful shifts towards more eco-friendly dietary choices requires a comprehensive understanding of human behavior and the factors that influence decision-making. This is where behavior change theories come into play. By delving into the intricate interplay of attitudes, motivations, and social dynamics that shape our food choices, these theories can offer valuable insights into how sustainable food consumption can be effectively encouraged and nurtured. While behavior change theories hold significant potential for enhancing the effectiveness of food recommender systems, their extensive application in this context is still relatively limited. While these theories have been widely studied in health promotion and behavior change interventions, their integration into food recommender systems is a developing area of research. Researchers and practitioners have recognized the value of behavior change theories in improving user engagement, adoption of healthier eating habits, and promoting sustainable food choices through recommender systems. However, the comprehensive implementation of these theories, including tailoring recommendations based on attitudes, social influences, and motivations, is not yet mainstream. Some studies have started to explore the integration of behavior change principles into food recommender systems [17], however the full potential of these theories is still being realized. As the field of food recommender systems continues to evolve, there is a growing interest in leveraging behavior change theories to create more impactful and user-centered recommendation strategies. Challenges may include the complexity of adapting theoretical constructs into practical algorithms and the need for personalized data to accurately apply these theories to individual users. Other challenges are related to privacy, trust, and ethical considerations while designing systems that effectively guide users toward healthier and more sustainable eating behaviors.

Integrating behavior change theories within the context of recommenders holds the promise of guiding individuals toward more sustainable food consumption and environmentally conscious dietary habits. When designing food recommender systems, these theories can serve as foundational pillars. *Theory of Planned Behavior* (TPB) [18] can be leveraged to analyze user attitudes towards sustainability and recommend plant-based recipes, aligning with their environmental values and perceived control over food choices. These systems consider user attitudes towards health, social norms related to healthy eating, social influences from eco-conscious communities, sustainability, and their perceived ability and control to make sustainable food decisions.

Similarly, the *theory Social Cognitive Theory* (SCT) [19] supports the notion of humans being influenced by social factors and emphasizes the role of observational learning, social interactions, and modeling in shaping human behavior. This theory can inspire the incorporation of social features within recommender systems by creating a platform where users share their sustainable cooking achievements and engage in discussions by also fostering a sense of community around eco-friendly eating habits. In the context of food choices and dietary behaviors, SCT posits that individuals learn from observing the actions and consequences of others, especially those within their social environment. This includes family members, friends, peers, and role models. People tend to adopt behaviors that they perceive as socially acceptable or that align with the behaviors of those around them. When it comes to sustainable food consumption and using food recommender systems, SCT suggests that individuals are likely to be influenced by the choices and recommendations of their social circles. Recommendations or endorsements from friends, family, or community members can carry significant weight in influencing dietary decisions. Therefore, designing food recommender systems that tap into social influences, provide community-based recommendations, and facilitate social interactions can potentially encourage more sustainable food choices. Practical application of SCT principles into food recommender systems can lead to strategies like showcasing recipes favored by user's social connections, allowing users to share and discuss their meal choices, and highlighting community-endorsed sustainable options. This not only promotes sustainable eating behaviors but also fosters a sense of belonging and social engagement, further enhancing the potential for behavior change.

Yet another theory that can be relevant for behavior change for sustainable food consumption includes the *Health Belief Model* (HBM) [20] which can drive recommendations that emphasize both the health benefits and ecological impact of adopting a sustainable diet. By showcasing the nutritional value and reduced carbon footprint of certain dishes, users are more likely to make informed and planet-conscious choices.

Nudge theory [21], discreetly integrated, can present subtle cues that encourage users to explore sustainable food choices, e.g. meatless or locally sourced options, without imposing strict restrictions. This approach makes sustainable alternatives more salient in their decision-making process. For instance, when searching for protein sources the initial results can showcase legume-based recipes or locally grown vegetables as *default options*. This discreet nudge encourages users to consider sustainable alternatives without explicitly imposing restrictions. When presenting recipe choices, the system can use *visual highlight* or position meatless or sustainable options at the top of the list. By drawing attention to these choices through design elements such as color or placement, users are subtly nudged towards exploring these alternatives first, increasing the likelihood of selecting them. In addition to nutritional information, the recommender system could provide an eco-friendly rating or label for each recipe. For example, recipes with lower carbon footprints or reduced water usage can be marked as environmentally conscious choices. *Community endorsements* are another subtle display of choices that aligns with the principle of social influence and nudge theory, encouraging users to adopt similar behaviors without overtly enforcing restrictions. Nudge techniques can include *time-sensitive notifications* or *alerts* highlighting e.g. special meatless or locally sourced recipes that align with current trends or events. These prompts can gently nudge users to consider sustainable options during specific moments, such as Meatless Mondays or local produce seasons. Recommenders can also analyze user interactions and context information to apply personalized nudges. Additionally, recommenders can incorporate a *progress tracker* that celebrates user adoption of sustainable food choices. Milestones achieved, such as a certain number of meatless meals, could be *rewarded* e.g. with virtual badges or incentives, subtly reinforcing positive behaviors. Incorporating nudge theory into a food recommender system involves strategically applying subtle cues and design elements to guide users towards more sustainable food choices. By discreetly highlighting positive sustainability attributes and making them salient in the decision-making process, the system can encourage users to explore eco-friendly alternatives without imposing strict limitations.

These examples showcase the potential of behavior change theories to shape effective, personalized, and eco-conscious food recommendations.

4 Linking Recommendations with Human-Centric Digitalization Concepts

Food recommenders in the era of Industry 4.0 heavily rely on user data to provide personalized recommendations. However, this can lead to users being only exposed to content that aligns with their existing preferences and conditions, potentially limiting their exploration of new and diverse food choices. Additionally, gathering and analyzing user data for personalized recommendations raises privacy concerns. Users may be hesitant to share their personal information, leading to a lack of data for accurate recommendations or to potential misuse of their data. Some food recommenders may use complex algorithms and machine learning models, making their decision-making processes opaque. Users may not understand why specific recommendations are made, leading to reduced trust in the system. Some food recommenders may not consider the broader context of food consumption, such as cultural preferences, dietary restrictions, or ethical considerations, leading to less relevant or inappropriate recommendations. Among other issues are inaccurate or outdated data that can result in poor recommendations, such as promoting unhealthy or environmentally harmful products. Balancing profitability with such ethical concerns can be challenging for some recommender systems. Last but not least, some food recommenders may struggle to adapt quickly to changing user preferences, conditions or emerging food trends, leading to potentially outdated recommendations.

4.1 Transforming Food Recommenders with Industry 5.0

Industry 5.0 emphasizes the infusion of human values and ethical considerations into technology design. In the context of food recommenders, this means moving beyond a purely algorithmic approach of Industry 4.0 and incorporating human-centric recommendations by considering *broader context* of e.g. cultural, geographical, temporal, ethical, and emotional aspects among others, by incorporating a *semantic approach* instead of solely relying on standard recommender algorithms.. Industry 5.0 leverages psychological insights to drive *behavior change.* Food recommenders can draw from behavior change theories. By thoughtfully integrating behavior change theories into food recommender system design, these enriched algorithms can create user-centric platforms that not only facilitate informed decisions but also empower individuals to embrace and sustain sustainable food consumption practices. As discussed earlier, behavior change theories provide valuable frameworks to align food recommendations with user motivations, beliefs, and social influences. By understanding and applying these theories, researchers and designers can create more effective and user-centered food recommender systems.

As recently suggested by Norman [22] we should talk about *humanity-centered* design of future systems. Under this new paradigm, the value of new technology for humans cannot be prioritized over the impact on the socio-technical and environmental contexts. Therefore, a product that brings high value to people by ineffective use of resources (e.g., consuming too much energy) or by impacting negatively other people cannot be considered humanity centered. Instead of relying purely on data analytics approach, this new "re-humanized" version of digitalization process implies eroding the boundaries between different disciplines. In the domain of food recommenders, this entails crafting conscientious technologies that facilitate human-centric food consumption suggestions. Technological mindfulness also encompasses *involving key stakeholders* in the transformation process, such as *healthcare experts, domain experts e.g. dieticians, privacy and food production policymakers, suppliers, and users* themselves. Engaging relevant stakeholders not only ensures appropriate solutions but also fosters essential values like *trust, privacy, ethics, security, accessibility, usability,* and *transparency* for end-users. Trust and transparency are linked to eXplainable AI (XAI), which employs emerging methods to enhance trust and facilitate *evaluation. Usability*, a determinant of safety (ISO 9241–11) and trust [23], warrants examination in contexts like conversational agents. The predictability [24] of digital agents significantly influences trust, particularly in high-risk decision-making scenarios like health, where trust, comprehension, and explainability are closely interrelated [25].

4.1.1 Explainable Semantic Food Recommenders

In the transition from Industry 4.0 to Industry 5.0, a profound shift in digitization strategies has emerged, one that centers on human values, individual experiences, and the seamless integration of technology within our daily lives. At the heart of this paradigm lies a revolutionary approach to algorithms, that goes beyond mere calculations and enters the realm of semantic understanding. In the context of food recommenders, this transition signifies a departure from the conventional, data-driven algorithms solely based on statistical patterns towards models that are deeply rooted in the semantic understanding of the user preferences and the broader context in which these preferences exist. Semantic algorithms, in contrast to their standard counterparts, possess the capability to comprehend not only what a user likes but also why they like it, by tapping into the intricate interplay of cultural traditions, geographical influences, temporal contexts, ethical considerations, emotional ties, and more. For instance, a semantic algorithm will not just analyze the users' past preferences but can take into account the cultural heritage associated with the event, the regional flavors that resonate with the family background, and even the emotional significance attached to certain ingredients or dishes to craft an experience that is not only delicious but deeply meaningful. The shift towards semantic algorithms can also foster an environment where the food recommender system becomes a trusted culinary companion, one that understands the nuances of individual lifestyles and aspirations, with a capability of offering suggesting local and seasonal ingredients that align with eco-conscious values, and even crafting recipes that evoke nostalgic memories. While this integration of semantic algorithms aligns seamlessly with the principles of humanity-centered digitization, it can also encapsulate the essence of personalization and holistic well-being. By considering the broader semantic context surrounding food choices, these algorithms can empower users to embark on a culinary journey that is not just about sustenance but also about connecting with their heritage, embracing sustainability, and savoring the joys of human experience.

Explainability can enhance user experience [26] by providing clear and transparent insights into why specific recommendations are made, empowering users to make informed choices and fostering a sense of trust; for example, by explaining that a vegan pasta dish is recommended due to its alignment with the user's dietary preference, its rich nutritional profile, and the incorporation of locally sourced ingredients for sustainability, the system can create confidence in user selection and appreciates the system's personalized guidance, e.g."The meal was recommended because it matches your gluten-free options. This recommendation for a quinoa and roasted vegetable bowl also takes into account your nutritional needs with a blend of vitamins and protein, and features locally sourced vegetables to support your sustainability choices".

Semantics can in addition be enhanced by the use of *ontologies*. Within the food domain ontologies can be used to create ontology-based user profiles enabling algorithms to understand user preferences, dietary needs, and culinary context and link with ontologies of nutritional data, ingredient compatibility, culinary techniques and their relationships to provide personalized suggestions with enhanced quality and diversity. Moreover, ontology-based algorithms can facilitate the generation of transparent, explainable and justified recommendations, fostering user trust and understanding. Linked data can provide significant advantages for food recommender algorithms by enabling seamless fusion of data from diverse sources facilitating data integration for more accurate and comprehensive recommendations that leverage a broader spectrum of information from different domains in the context of food consumption and production.

4.1.2 Sustainability Concepts

Sustainability has emerged as a prominent topic in the field of food recommender systems [13]. However, only a limited number of tools are currently available to assess the degree of sustainability of food items. Sustainability recommenders can play a crucial role in promoting environmentally-friendly food choices and reducing food waste. To consider environmental impact in food choices, recommendations must balance user preferences with measures like food miles (distance traveled by food), carbon dioxide emissions associated with food production and transportation, and other environmental/ecological metrics. Recommendations provided by these systems aim to strike a balance between user preferences and environmentally sustainable options, encouraging users to make choices that have a lower ecological footprint.

Eco-assessments are a relatively new concept that quantifies the environmental impact of food. They consider various factors such as greenhouse gas emissions, water use, and land use associated with the production and distribution of each product [27]. Food recommenders use these values to recommend foods with a smaller environmental footprint to promote sustainable consumption habits. These platforms are pioneering the use of alternative ingredient suggestions. They can recommend substitutes for common ingredients that are either healthier, more environmentally friendly, or both. This feature is especially beneficial for people with dietary restrictions or those looking to reduce their environmental impact. In addition, these platforms often can link these suggestions to local farmers to support local agriculture and reduce the carbon footprint associated with food transportation [28].

Some food recommenders also introduce nutritional *health scores* of ingredients by considering various factors such as nutrient composition, dietary guidelines, health impact studies, and user preferences and specific conditions. Nutrition composition assessment takes into account the nutritional content of ingredients, including macronutrients (carbohydrates, proteins, and fats) and micronutrients (vitamins and minerals). Food recommenders often use standardized nutrient databases e.g. the USDA National Nutrient Database or other relevant sources to obtain accurate information on the nutritional composition of each ingredient. Health scores are usually calculated based on dietary guidelines recommended by health organizations like the World Health Organization (WHO) or national dietary guidelines (e.g., USDA's Dietary Guidelines for Americans). These guidelines provide specific recommendations for daily intake levels of various nutrients to maintain a balanced and healthy diet. Many food recommenders in addition incorporate scientific studies and research on the health impacts of different nutrients and food components. These studies help in understanding how certain nutrients can affect health positively or negatively, both in the short and long term. Food recommenders use scoring algorithms that assign weights to different nutrients based on their importance for overall health. These algorithms often take into account factors such as energy density, fiber content, healthy fats, vitamins, and minerals. Some food recommenders allow users to customize their health scores based on personal preferences, dietary restrictions, and health goals. For example, a person following a low-carb diet might prioritize the health score based on lower carbohydrate content.

Different food recommenders, in addition, may employ varying approaches and data sources to compute health scores, and their specific methodologies might not be publicly disclosed due to proprietary reasons, therefore privacy-awareness becomes an important topic in the domain of recommenders in general and food recommender systems in particular.

4.1.3 Privacy-Aware Food Recommender Platforms

In the age of digitalization, privacy-preserving data platforms have emerged as an important tool for promoting sustainable food consumption. By incorporating these mechanisms, privacy-aware novel data platforms for food recommenders strike a delicate balance between delivering personalized recommendations and upholding user privacy. These platforms empower users to make informed food choices without compromising their sensitive information, contributing to a more secure and trustworthy user experience.

Federated learning [29] is a promising privacy-preserving technique that can be employed in food recommendation systems to enhance user privacy while still delivering personalized recommendations. In federated learning, users have full control over their data and its usage. Explicit consent is obtained before any data is collected or utilized for recommendations. The training of machine learning models occurs locally on user devices, and only aggregated insights are shared with the central server. This decentralized approach minimizes the need to transfer raw user data to a central repository, reducing privacy risks. In the context of food recommendation, federated learning operates as follows:

- Data Partitioning: User data remains on their respective devices, ensuring that sensitive information, such as dietary preferences and consumption habits, is not shared externally.
- Local Model Training: Each user device trains a local recommendation model using personal data, considering factors like past food choices, dietary restrictions, and nutritional goals.
- Model Aggregation: The central server aggregates insights from the locally trained model without accessing raw data. This aggregation process captures collective behavioral patterns without compromising individual privacy.
- Global Model Update: The central server updates the global recommendation model based on the aggregated insights. This model is then distributed back to users' devices, ensuring that it benefits from the collective knowledge while preserving privacy.

– Personalized Recommendations: On-device models use the updated global model to generate personalized recommendations for each user, without exposing individual data to the central server.

These platforms, which prioritize user privacy while providing personalized food recommendations, are revolutionizing the way we perceive and consume food. In particular, they stand out for their emphasis on eco-ratings, novel approaches to calculating nutritional value, and suggestions for alternative ingredients that connect with local farmers in a privacy-preserving manner.

In summary, privacy-conscious platforms play a critical role in promoting sustainable food consumption. By highlighting organic ratings, introducing novel methods for calculating nutritional value, and recommending alternative ingredients that connect with local farmers, these platforms enable consumers to make more informed and sustainable food choices. The concepts and interrelationships discussed within this work are additionally depicted via a conceptual framework, as illustrated in Fig. 1.

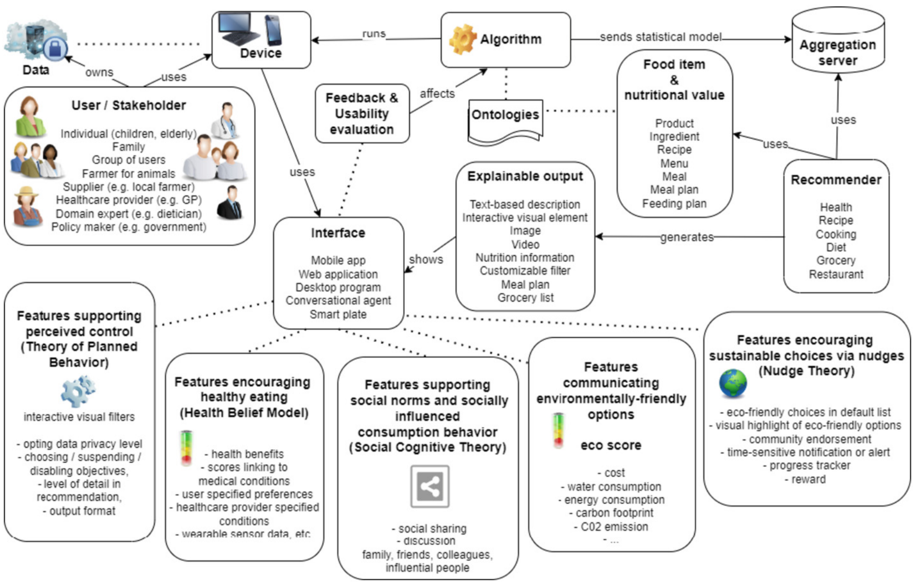

Fig. 1. A conceptual diagram depicting design elements for enhancing recommender systems with privacy awareness and promoting sustainable food consumption.

5 Conclusion

Sustainable food consumption offers diverse benefits, spanning environmental preservation and individual well-being. However, its integration into food recommender systems lacks a unified theoretical foundation, particularly in behaviorally transformative frameworks. While health dimensions are extensively studied, domains like cooking, grocery shopping, and restaurant choices, including menu selections, are relatively underexplored. Algorithms predominantly draw from conventional methodologies, particularly collaborative filtering, often prioritizing individual over group dynamics, which in addition face challenges due to the absence of standardized datasets, compounded by GDPR and copyright limitations on behavioral and recipe data. Notably, a crucial omission is the incorporation of sustainability and environmental considerations, which are increasingly pertinent in modern food consumption paradigms. Initiatives to bridge these gaps and address such critical issues are yet to emerge.

This work enriches the theoretical underpinnings of food recommender systems, emphasizing sustainability by linking the concept of food recommendation with behavior change theories and their applications within the food recommenders. It also situates the food recommenders within human-centric digitization concepts inherent to industry 5.0 such as privacy, trust, explainability, while also connecting relevant stakeholders such as consumers, suppliers, domain experts including healthcare providers, as well as policy makers in the domain. The conceptual map presented in the work offers a foundational platform for the exploration of environmentally friendly human-centric food recommender designs aligned with industry 5.0 principles.

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