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Review

Artificial Intelligence and Machine Learning Technologies for Personalized Nutrition: A Review

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Abstract: Modern lifestyle trends, such as sedentary behaviour and unhealthy diets, have been associated with obesity, a major health challenge increasing the risk of multiple pathologies. This has prompted many to reassess their routines and seek expert guidance on healthy living. In the digital era, users quickly turn to mobile apps for support. These apps monitor various aspects of daily life, such as physical activity and calorie intake; collect extensive user data; and apply modern data-driven technologies, including artificial intelligence (AI) and machine learning (ML), to provide personalised diet and lifestyle recommendations. This work examines the state of the art in data-driven technologies for personalised nutrition, including relevant data collection technologies, and explores the research challenges in this field. A literature review, following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guideline, was conducted using three databases, covering studies from 2021 to 2024, resulting in 67 final studies. The data are presented in separate subsections for recommendation systems (43 works) and data collection technologies (17 works), with a discussion section identifying research challenges. The findings indicate that the fields of data-driven innovation and personalised nutrition are predominately amalgamated in the use of recommender systems.

Keywords: machine learning; artificial intelligence; personalization; nutrition; recipes; restaurant; data-driven; recommender; recommendation system

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1. Introduction

Imbalanced diets are linked to an increased risk of various non-communicable dis-eases (NCDs) prevalent in modern society, including obesity, type 2 diabetes, and cancer [1–3]. According to the World Health Organization (WHO), at least 2.8 million people die each year due to being overweight or obese, and an estimated 35.8 million (2.3%) of global Disability-Adjusted Life Years (DALYs) are attributed to overweight or obesity [4]. Additionally, as noted by Mariadoss et al. (2023) [5], poor nutrition is also a significant con-tributing factor for specific groups, such as pregnant women, in increasing the risk of cardiovascular diseases (CVDs).

Betts et al. (2016) [6] define personalized nutrition as "developing unique nutrition guidelines for each individual", while precision nutrition "seeks to develop effective approaches based in the combination of an individual's genetic", i.e., genotype, and "environmental and lifestyle factors", i.e., phenotype. Additionally, based on Mathers et al. (2017) [7], population-based interventions have sometimes proved to be ineffective in achieving sustainable eating behaviour changes, while at the same time, evidence suggest considerable interindividual variation in response to the same dietary exposure. Thus, it can be argued that a "one-size-fits-all" approach to proper diet and nutrition is insufficient, since every person has unique needs, and a personalised diet plan is necessary to meet individual requirements. Thus, personalised nutrition (PN), also addressed as "tailored nutrition" or "individualized nutrition", has become increasingly important in recent years to a degree that it is now considered by some as a crucial aspect of a healthy lifestyle and of well-being. PN is also essential for people who already have chronic diseases that require specialised diets and therefore need appropriate nutrition plans [6,8,9]. For instance, a person with type 2 diabetes could benefit from a nutrition low in carbohydrates (Wheatley et al. (2021) [10]), while a person with lactose intolerance requires a diet free of lactose-containing foods such as milk, cheese, and other dairy products. Moreover, PN has been shown to be able to improve the immune system of cancer patients (Shastri et al. (2021) [11]). Hence, PN can help individuals towards the prevention, but also mitigation, of various chronic diseases.

A big rise in the use of recommendation systems for PN has been observed in recent years. Big datasets, along with Artificial Intelligence (AI) models, neural networks, and recommendation systems, are now being used for the generation of tailored meal recommendations that are based on individual user profiles. Such a trend could be expected, as these technologies have been used in the food industry sector for many years now. According to Miyazawa et al. (2022) [12], in 2010, the crossing of AI, machine learning (ML), and Computer Science (CS) with the food industry led to the development of respective applications that utilised big data analysis. Later works, e.g., [13,14], showed how AI- and ML-based approaches can be used for early food disease detection, estimating soil moisture, and more, while Theodoridis et al. (2019) [15] showed how Nutrition Recommendation Systems and similar technologies are used in the field of PN for, e.g., food category recognition, ingredient and cooking instructions recognition, etc. Agrawal et al. (2023) [16] examined the significant impact of AI on the food industry, including the role of AI in PN. Finally, Roy et al. (2023) [17] examined the effectiveness and challenges of these systems in delivering personalized health and dietary advice.

To achieve PN through recommendation systems and other respective technologies, big data collected from individuals regarding their specific needs are needed. For example, data regarding an individual's heart rate, burned calories, daily activity, etc., can be retrieved using smart watches, activity trackers, and more, while data regarding someone's body weight, fat, visceral fat, etc., can be retrieved using smart scales. Even information from the diverse community of microorganisms residing in our gut microbiota can be retrieved using corresponding technologies and methods [18–25]. These and more data can be used as inputs to recommendation systems for generating personalised outputs regarding a user's dietary or wellbeing plan. For example, Amorim et al. (2022) [26] describe a recommendation system in a hospital that uses personal information from in-hospital sensors, such as insulin levels, to adjust patients' daily meals, while Greenberg et al. (2023) [27] present a web application that uses women's personal data, such as age and height, to prevent cardiovascular problems. The outcomes of the above works are showing a quickly expanding field of research. Stefanidis et al. (2022) [28] present a knowledge-based recommendation framework that exploits an explicit dataset of expert-validated meals to offer highly accurate diet plans spanning across ten user groups of both healthy subjects and participants with health conditions. Additionally, Yang et al. (2018) [29] proposed Yum-me, a personalized nutrient-based meal recommendation system designed to meet individuals' nutritional expectations, dietary restrictions, and fine-grained food preferences, while Harvey et al. (2015) [30] presented a recipe recommendation system that proposes meal plans based on foods that a user likes. New data collection technologies are proposed and implemented while new technologies for processing data are arising, expanding the potential of this research field.

Study Purpose, Strengths, and Limitations

This paper aims to present the latest advancements in data-driven innovation for AI and ML technologies in the field of PN along with the data collection technologies that are being used, and to investigate the research challenges for future work. Similar literature reviews on the field of precision nutrition and machine learning do exist. For instance, Livingstone et al. (2022) [31] presented a literature review in the field of precision nutrition. The authors discussed the role and application of "omics" to the prescription of individualized diets for health and wellbeing and the use of ML technologies assisting with integrative purposes. In the same vein, Kirk et al. (2021) [32] conducted an extensive systematic literature review on the same research field, focusing on the state-of-the-art on the use of ML in Precision Nutrition. Their work answers nine research questions and categorises all the re-searched ML models and algorithms regarding task, type, usage, and more attributes, providing a holistic view.

Our work differentiates from these mainly in three aspects, which are the objectives of this paper. Firstly, it encompasses data-driven technologies in general, rather than solely AI-based works in the field of personalised nutrition. This means that it also includes technologies like knowledge graphs, ontologies, optimization algorithms, and more that are not included in the realm of ML and AI. Secondly, we also study data collection technologies that are described and analysed with respect to how they are integrated with the recommendation systems. Finally, our work identifies a series of research challenges that are derived from the literature and associated with specific papers.

In our review, the works are clustered and comparatively discussed, referring to their main scope, data-driven technologies used, system inputs, their technical evaluation and accuracy, and, finally, related datasets. Moreover, the information is displayed in a tabular format with additional explanations regarding the scope of the model and the integration of the various input data types.

A limitation of our work is that it deals mainly with personalized nutrition and does not cover precision nutrition extensively. Exploring the use of data-driven technologies in more nutrition fields would give a more holistic perspective and understanding. Additionally, the time frame of this research is from 2021 to 2024. Therefore, a more extensive review starting earlier could give more and better information with more features to be extracted. Finally, the research databases used are limited to three, and these are all computer science-oriented. The inclusion of works from other databases, e.g., health-oriented ones, could provide a more diverse view.

The examined literature was filtered using the well-established Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) model [33–35]. In Section 2, we discuss the PRISMA model and the specific filters we used. In Section 3, we delve deeper into the use of recommendation systems in the field of PN and present the specific technologies that are used. According to the PRISMA model, the research for recommendation systems in PN is further divided into three subcategories: (a) Nutrition, (b) Recipe, and (c) Restaurant Recommendation Systems. In Section 4, we present the various data collection technologies that are available and review the corresponding data collection or capturing technologies and devices. In Section 5, we discuss the research challenges that are derived from the respective literature. Finally, a conclusion is given summarizing the overall work.

2. Methods

A literature search was performed by adopting the PRISMA guidelines [33–35]. Our study aimed to identify only the latest works in the field of data-driven innovation technologies in personalised nutrition and to categorise them; it was not our aim to delve deeper into a technical comparison of the various systems. The articles were extracted in March 2024 from three academic databases, namely, Scopus (scopus.com), ScienceDirect (sciencedirect.com), and IEEE Xplore (ieeexplore.ieee.org).

Inclusion criteria: We used the text *"Personalized nutrition recommendation"* in the corresponding search bars of all three academic databases.

Exclusion criteria (by automated tools, i.e., using filtering options of the three databases):

- *Publication date* was outside of the time frame 2021 to 2024;
- *Document type* was not an article, review, or conference paper;
- *Publication subject area* was not computer science;

- *Publication was not peer-reviewed;*
- *Publication language* was not English;
- *Duplicate entries* were excluded as well.

Exclusion criteria (non-automated):

- *Publication title and keywords*, *abstract*, or *full text* indicated that the publication was out of the scope and objectives of the present review, i.e., indicated that the publication was irrelevant to AI and ML technologies for PN

The search was based on the following condition: title-abs-key(personalized AND nutrition AND recommendation) AND (limit-to (pubstage, "final")) AND (limit-to (pubyear, 2024) OR limit-to (pubyear, 2023) OR limit-to (pubyear, 2022) OR limit-to (pubyear, 2021)) AND (limit-to (DOCTYPE, "ar") OR limit-to (doctype, "re") OR limit-to (doctype, "cp")) AND (limit-to (subjarea, "COMP")) AND (limit-to (language, "English"))

The number of records retrieved from the three databases was 3052. From these, 335 duplicate records were removed, while 2125 records were excluded as ineligible by automation tools (i.e., date, document type, subject area, peer reviewed, language), leading to 592 unique records for manual screening. After careful examination of the title, keywords, abstract, and the full text for scientific relevance, 67 records remained and were considered for the present review. The full selection procedure is detailed in Figure 1, while Figure 2 displays the number of works for every year, showing the increasing frequency in this area of science.

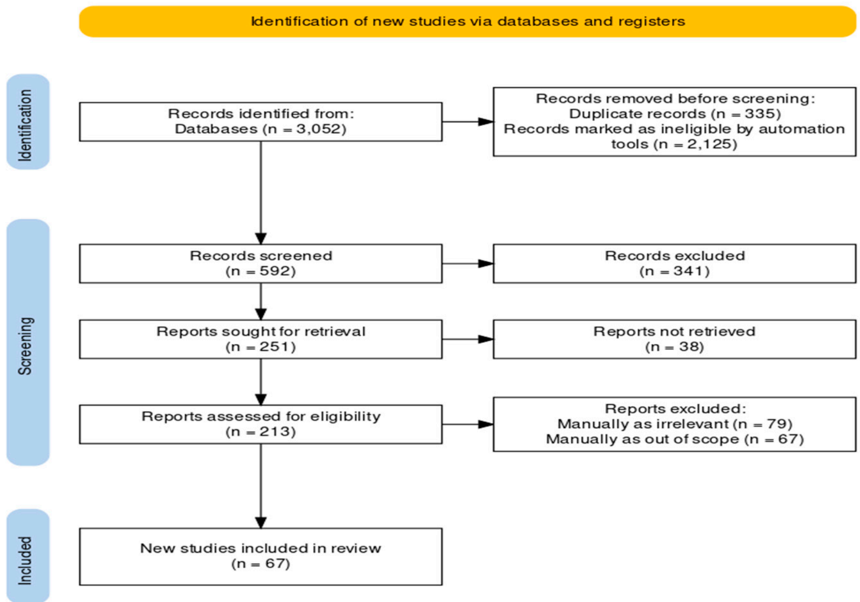


Figure 1. Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) flow diagram of study selection, inclusion, and synthesis.

The final works can be categorised based on their differences and similarities. Drawing from the two similar review works [31,32] and inspired by their categorization methods, we came up to a way to present our findings. More specifically, Livingstone et al. (2022) [31] divided the various "omics" categories, briefly discussing the works while also using a tabular format to summarize this information. In the same way, Kirk et al. (2021) [32] divided and briefly discussed the various machine learning tasks, algorithms, evaluation metrics, etc., while also using a tabular format. Therefore, we decided on dividing and categorizing our research based on commonalities and differences. Three main categories based on the scope of the recommendation system are used (nutrition, recipe, and restaurant) to distinct the final works while grouping the works that use the same or similar methods. Additionally, we identified several commonalities among the works. Specifically, most employed one or more technologies for their recommendation systems, utilized datasets, and incorporated multiple inputs. Some works also integrated their recommendation systems into platforms. Furthermore, we observed that some used devices for data collection. Consequently, we summarize this information in two tables.

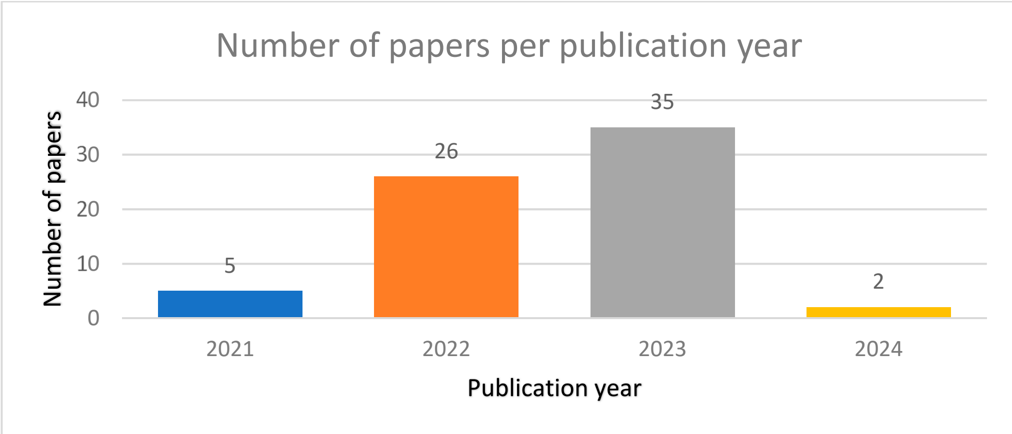


Figure 2. Bar chart displaying the number of works retrieved for every year from 2021 to 2024 (based on the PRISMA model). The increasing number of works is an indication of the rapid growth of this field.

3. Results

3.1. Recommenders in Personalised Nutrition

Recommendation systems are vital components in personalised nutrition, delivering accurate and customized results based on individual needs and preferences. Notably, they outperform older—frequently manual or semiautomatic—methods in terms of time efficiency, affordability, and sometimes even accuracy. These advantages, coupled with surging technology penetration and the increasing processing power of mobile devices' Central Process Units (CPUs) and Graphical Process Units (GPUs), are propelling the field of data-driven PN research forward, resulting in a constant stream of novel studies exploring both improved accuracy and novel technological applications. Applying the PRISMA model to our literature review search, we identified three main categories of recommendation systems:

- **Nutrition Recommendation Systems**. Generate daily or weekly meal plans tailored to individual profiles, leveraging AI, ML, or other computing technologies, as well as multidimensional data.
- **Recipe Recommendation Systems**. Suggest personalised recipes based on individual profiles, preferences, and other data.
- **Restaurant Recommendation Systems**. Recommend appropriate selections from restaurant menus to individuals based on their profiles.

The following subsections delve deeper into these categories, presenting the corresponding literature searches, results, and technologies. First, we summarise the relevant literature, mentioning the works and their findings. Subsequently, we present net graphs and tables of the used databases, technologies, and more, highlighting their frequency of appearance and other relevant metrics.

3.1.1. Nutrition Recommendation Systems

This section explores Nutrition Recommendation Systems, a category focused on personalised meal plan generation through the synergistic application of various digital technologies and dietary databases.

The reviewed studies commonly utilized anthropometric data, including sex, age, height, weight, etc., along with other relevant information, to provide informed recommendations. For example, Haseena et al. (2022) [36] constructed a ranking framework based solely on factors like age or weight to identify suitable nutrition plans, following four stages: gathering user data, generating fuzzy weights using the fuzzy Analytic Hierarchy Process (AHP) (a method used to assign weights to different criteria or factors in decision-making processes, considering uncertainty and imprecision in human judgments; "https://en.wikipedia.org/wiki/Analytic_hierarchy_process (25 August 2024)"), evaluating plan compatibility with cuckoo optimization (The Cuckoo Optimization Algorithm (COA) is an optimization technique inspired by the brood parasitism behaviour of some cuckoo species. These cuckoos lay their eggs in the nests of other bird species, relying on the host birds to incubate and raise their offspring. This natural behaviour forms the basis of the algorithm, where solutions to optimization problems are metaphorically represented by eggs in nests; "https://en.wikipedia.org/wiki/Cuckoo_search (25 August 2024)"), and ranking options with the fuzzy Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) (a decision-making technique that evaluates and ranks alternative options based on their distance from the ideal solution and the anti-ideal solution, aiming to identify the most desirable option; "https://en.wikipedia.org/wiki/TOPSIS (25 August 2024)"). This system incorporates popular dietary approaches like the Mediterranean and low-fat diets, providing diverse personalized recommendations. Similarly, Lakshmi et al. (2023) [37] employed Fuzzy AHP and Fuzzy TOPSIS for personalized nutrition planning, considering individual differences in age, body mass index (BMI), dietary preferences, lifestyle, and blood sugar levels. These fuzzy logic-based methods effectively rank dietary alternatives, like balanced and diabetes-specific diets, catering to nuanced preferences and health requirements, promising more precise nutritional guidance.

Zhang et al. (2022) [38], departing from personalized data, employed a novel many-objective optimization (MaOO) approach using caloric intake data from the MyFitnessPal database. Addressing the limitations of traditional recommendation techniques, the authors proposed a multi-objective approach with four objectives: user preferences, nutritional values, dietary diversity, and user diet patterns. Three representative MaOO algorithms—strength Pareto evolutionary algorithm 2 (SPEA2), Non-dominated Sorting Genetic Algorithm (NSGAII), and SPEA2+shift-based density estimation (SDE)—were leveraged to optimize these objectives simultaneously in two scenarios. In Scenario 1, three objectives were optimized, while Scenario 2 optimized all four objectives, including user diet patterns. Evaluation using the hypervolume indicator yielded values of 59%, 62%, and 73% for the three algorithms, respectively.

Salloum et al. (2022) [39] proposed Meal Plan Generation (MPG), a system that automates the creation of personalized meal plans by integrating personal information, caloric intake, and user preferences. Using an adaptation of the Transportation Optimization Problem (TOP), MPG generates plans that meet caloric needs while accommodating individual preferences. Evaluation involves established nutrition health literature procedures and transportation optimization techniques, demonstrating MPG's ability to produce healthy, personalized meal plans aligned with user preferences. Furthermore, Rout et al. (2023) [40] introduced a machine learning model for diet recommendations based on users' nutritional data and physical conditions, addressing concerns about non-communicable diseases from unhealthy diets. Employing K-means clustering and Random Forest (RF) algorithms, the study analysed nutritional data and user profiles to offer tailored diet advice, enhancing health outcomes and nutritional awareness.

Kaur et al. (2022) [41] presented a food recommendation system targeting Polycystic Ovary Syndrome (PCOS) in women, integrating personal information and food images to manage weight and nutrient intake. They enhanced pre-trained Convolutional Neural Network (CNN) models with additional layers to classify food images and suggest suitable food items based on macronutrient requirements. Evaluation against other models showed high accuracy rates, achieving a 95% accuracy rate for classifying sample food classes and a 90.7% accuracy rate for twelve food image classes. Similarly, Aguilar et al. (2022) [42] introduced a Bayesian network into semantic segmentation methods for food images, achieving improved accuracy in multi-class segmentation and uncertainty estimation. The Bayesian versions achieved 99% accuracy in UNIMIB2016, 88% in UECFOODPIXComplete, and 77% in Food201, outperforming the original versions. Romero-Tapiador et al. (2023) [43] presented a recommendation framework which employed the analysis of eating behaviours through food image datasets. CNNs were used to generate personalized datasets and to provide insights on healthier dietary habits via a user-friendly platform. The results showed 99.53% accuracy and 99.60% sensitivity, demonstrating the potential to significantly enhance dietary monitoring and recommendation systems. Azzimani et al. (2022) [44] utilized Red–Green–Blue-Depth (RGBD) images and user data on anthropometric information, allergies, and chronic diseases to estimate the nutrient content in meals. Advanced image processing techniques and a Multi-Task Fully Convolutional Network (MFCN) were employed for image segmentation and volume estimation. Dietitians evaluated the system, indicating its potential for PN and menu planning.

In addition to user preferences and ratings, health data integration can provide crucial insights into the user's health status and history. For instance, Shandilya et al. (2022) [45] introduced MATURE, a food recommendation system refined to incorporate user health data, ensuring that the recommendations aligned with current health needs. Rigorously validated against other recommendation systems, MATURE demonstrated a superior performance in meeting mandatory health requirements. Xu et al. (2022) [46] presented ElCombo, a personalized meal recommendation system for the elderly, leveraging a Knowledge Graph (KG) integrating foods, nutrients, and health data. Compared with elders' choices, ElCombo significantly improved diet quality, diversity, and adherence to health requirements. Utilizing Particle Swarm Optimization (PSO) and K-means clustering, Hosen et al. (2023) [47] developed an optimized recommendation system for thyroid patients, delivering personalized food recommendations based on historical patient data and nutrient-rich foods beneficial for thyroid health. Validation indicated its superiority over traditional algorithms, offering more accurate dietary advice for managing thyroid conditions.

Introducing innovative approaches to health management, Larizza et al. (2023) [48] presented the V-care app, targeting childhood obesity through gamification and personalized nutrition recommendations. With quizzes and a virtual coach, the app engages users in learning about healthy habits, earning an average score of greater than 3 in user evaluations. Similarly, Lodhi et al. (2023) [49] discussed a personalized nutrition approach for individuals with chronic kidney disease (CKD), employing KGs to provide tailored advice. Evaluation through a case study yielded an average usability score of 8.5/10. Addressing Type 2 Diabetes management, Burgermaster et al. (2023) [50] introduced the Platano mHealth app, offering personalized nutritional guidance based on meal logs and blood glucose levels. User feedback indicates that over 78% found the app easy to use, highlighting its effectiveness in supporting health management.

Islam et al. (2023) [51] utilized electroencephalography (EEG) signals to develop a personalized meal recommendation system, analysing user brain responses to meals to determine palatability. Employing a hierarchical ensemble ML model and TOPSIS approach, they constructed personalized meal suggestions considering user preferences and nutritional requirements, validated through confusion matrix, f1-score, and Area Under the Curve (AUC) score evaluations. The incorporation of EEG signals enhanced the system's ability to understand user preferences, while the ensemble ML model improved the accuracy by combining predictions from multiple models. Similarly, Yang et al. (2022) [52] proposed a PN service leveraging genetic testing, physical examination, dietary habits, and medical history to compute disease risk and nutrition requirements, providing tailored nutrition solutions via a user-friendly mobile application.

Fu et al. (2023) [53] introduced "Food4healthKG", a KG integrating food, gut microbiota, and mental health data from various sources, facilitating food recommendations and queries. Evaluation against expert responses showed system accuracy levels ranging from 90% to 95%. Similarly, Yang et al. (2023) [54] focused on PN plans for immune system improvement, combining DNA testing, physical examination, and lifestyle evaluation to compute tailored plans. Evaluation of their personalized vitamin D supplementation solution demonstrated effectiveness in reducing vitamin D deficiency risk. Furthermore, Yang et al. (2022) [55] developed a PN platform for Chinese users, leveraging genetic, lifestyle, and physical examination data to generate personalized nutrition packs. The study highlights the ease of collecting and utilizing genetic data for accurate PN recommendations, employing business process management techniques for efficiency. These works showcase the potential of integrating diverse data sources for personalized nutrition and health improvement.

In addition to the above works, Geng et al. (2023) [56] proposed a heuristic optimization-based recommendation model, leveraging Trajectory Reinforcement-based Bacterial Colony Optimization (TRBCO) to balance accuracy and diversity in personalized recommendation systems. Evaluation against benchmark datasets demonstrated TRMOBCO's superior performance compared to contemporary and state-of-the-art optimization algorithms. Sahal et al. (2022) [57] explored Personal Digital Twin (PDT) technology for personalized healthcare, emphasizing its potential for improving decision making and treatment selection, particularly in PN. Chivukula et al. (2022) [58] contributed to the field by developing an ontology model in the food domain, facilitating informed dietary decisions based on health conditions. The ontology model was evaluated for its utility in answering queries using SPARQL Protocol and RDF Query Language (SPARQL), demonstrating its effectiveness in providing appropriate food recommendations. These approaches offer innovative solutions for enhancing personalized recommendation systems and improving health outcomes.

Kaur et al. (2023) [59] discussed a Clinical Decision Support System (CDSS) for neonatal nutrition in the Neonatal Intensive Care Unit (NICU), leveraging a Nutrition Recommendation Ontology (NRO) to generate personalized feeding plans and achieving a validation accuracy of 98%. Martinho et al. (2023) [60] contributed to AI systems in healthcare by developing an ontology to manage diet and energy consumption for patients with obesity, diabetes, and those needing tube feeding, aiming to improve health outcomes through personalized dietary recommendations. Similarly, Rostami et al. (2024) [61] introduced the Healthy Group Food Recommendation System (HGFR), prioritizing both user preferences and nutritional value, outperforming other models in database comparisons, and promoting healthier eating choices for groups.

Palacios et al. (2023) [62] proposed Baby-Feed, a user-friendly web app which provides age-appropriate food recommendations for infants to prevent rapid weight gain, with over 87% of parents finding it easy to use and effective, rating it 4/5 stars. Wang et al. (2023) [63] focused on personalized recommendations for carbohydrate–protein supplements, employing ML techniques like backpropagation neural networks to tailor intake for endurance sports enthusiasts, achieving a mean absolute error (MAE) of 470.77 compared to 500.85 for the traditional model, Gradient Boosted Regression Trees (GBRT). Cunha et al. (2023) [64] introduced an advanced nutrition control recommendation system utilizing Internet of Thinks (IoT) devices and ML models in real time to offer personalized dietary and exercise plans, demonstrating accurate BMI prediction within a small time window of three days. These studies highlight the efficacy of ML in personalized nutrition recommendations, suggesting future enhancements for broader dataset dimensions and model robustness.

The literature review reveals a nuanced landscape characterized by diversity not only in technological approaches, but also in the scope of the research endeavours. Within this spectrum, certain studies such as [41,42] employ images as their primary input, while others [45,55] rely on personal and health data. The technological repertoire is equally expansive, encompassing a range from AI CNN models and Bayesian networks to ontologies and addressing the TOP. Moreover, despite a shared overarching goal of delivering PN, the strategies employed exhibit notable variations. For instance, in the study conducted by Islam et al. (2023) [51], the methodology revolved around generating PN through EEG signals, while Sahal et al. (2022) [57] adopted a distinct approach utilising DT.

3.1.2. Recipe Recommendation Systems

An alternative paradigm identified through the literature review involves the integration of PN objectives with the utilisation and management of recipes. By harnessing extensive datasets comprising recipes and nutritional information, coupled with data-driven AI technologies, the creation of individualised recipe recommendations becomes feasible. For example, Neha et al. (2023) [65] delineated a methodical approach to extract and predict information from recipes by employing advanced ML models (Parallel-CNN, Naïve Byes, Fuzzy rule, Artificial Neural Network). This approach adeptly addresses the diverse requirements of users, including dietary preferences, allergies, food intolerances, and more. The results of this work show that Parallel-CNN outperforms the other models with 95% accuracy, 91% precision, and a 95% f1-score, as well as a value of 0.1872 regarding the model loss attribute.

Wang et al. (2022) [66] proposed an intelligent recipe recommendation model, optimizing weekly meal plans to accommodate user restrictions and nutritional needs using the Hungarian algorithm and integer programming, ensuring personalized balanced diets. Buzcu et al. (2022) [67] introduced a Virtual Coaching System (NVS), integrating user-specific factors like allergies and preferences to offer personalized recipe recommendations via an ontology-based approach, validated through user surveys showing a preference for interactive explanation-based interactions over conventional recommendation systems. Shubhashree et al. (2022) [68] presented a recipe recommendation system incorporating allergies and personal information which employed K-Nearest Neighbour (KNN) clustering and the Euclidean distance algorithm to generate personalized diet tables, outperforming other algorithms with 95% accuracy. Likewise, Ribeiro et al. (2022) [69] presented a recipe recommendation system considering user-specific allergies and cultural preferences to craft three-week meal plans. It was validated through simulated user profiles, highlighting the importance of diverse data to meet food preferences, restrictions, and nutritional needs.

Wu et al. (2022) [70] introduced visual-aware food analysis (VAFA), employing deep learning models ATNet and PiNet to classify food items from multimedia inputs like images and descriptions, achieving state-of-the-art performance in food classification and recipe recommendation precision, respectively. The interaction with the recommendation system is facilitated through a web application. Forouzandeh et al. (2024) [71] presented a Health-aware Food Recommendation System with Dual Attention in Heterogeneous Graphs (HFRS-DA), utilizing unsupervised learning on graph-structured data to recommend healthy and popular recipes, outperforming existing methods with superior performance on the Allrecipes dataset. RahmathNisha et al. (2023) [72] outlined the development of the web-based Intelligent Nutrition Assistant Application (INAA) employing AI and ML algorithms to provide personalized dietary recommendations. It was validated through a user study with 50 participants, with future plans to enhance the system with advanced ML techniques and expanded food database.

Li et al. (2022) [73] introduced a novel post hoc agnostic model to explain the output of Recipe Recommendation Systems, aiming to enhance user understanding and confidence in the system's recommendations. The model elucidates the relationships between network variables and user preferences, validated through comparison with four state-of-the-art recommendation system explainable models. By incorporating nutrition-aware criteria variables, the system offers more personalized and health-conscious recommendations, potentially improving the effectiveness of recommendation systems and leading to increased user satisfaction and adoption. In parallel, Li et al. (2023) [74] pioneered an innovative methodology by integrating KGs into Recipe Recommendation Systems, enabling users to transition between different behavioural patterns based on evolving preferences. The system, evaluated on the Food.com and MyFitnessPal datasets, outperformed other models on various metrics, highlighting its effectiveness in providing tailored recommendations.

Kansaksiri et al. (2023) [75] introduced "Smart Cuisine", which utilizes AI technologies, including the Generative Pre-training Transformer (GPT) model, to offer personalized recipes and nutritional advice, enhancing sustainable cooking practices. By processing food images and employing natural language processing, the system generates recipes and provides nutritional guidance. Tests on the Recipe1M dataset showed higher accuracy in predicting well-known recipes, demonstrating the system's potential to revolutionize meal preparation. Similarly, Safitri et al. (2023) [76] introduced CookPal, a GPT-3-based chatbot aimed at promoting healthier eating habits by offering personalized recipe suggestions. Operating on a desktop platform with a focus on data privacy, CookPal demonstrated high accuracy in providing dietary advice (86%) and received positive feedback (4.5/5 in a scalar size of 1 to 5) for its potential to facilitate healthier lifestyle choices.

In conclusion, the use of Recipe Recommendation Systems for promoting healthy eating habits has gained significant attention, showing substantial potential for further development. The literature review highlights a range of methods for tailoring recipe suggestions based on individual preferences, dietary restrictions, and nutritional needs. These approaches employ various techniques, including KNN and Euclidean distance. Despite the diversity in inputs, from physiological data to dietary preferences and allergies, there is a notable trend toward utilizing web-based platforms as intermediaries between recommendation systems and users, as observed in Section 3.1.4.

3.1.3. Restaurant Recommendation Systems

The third category of recommendation systems derived from the PRISMA model is Restaurant Recommendation Systems. With the abundance of data available on the internet, and with the use of data-driven approaches, it is possible to develop recommendation systems that can suggest restaurants or specific restaurant menu items based on users' preferences and nutritional needs. By providing personalised recommendations, such systems can help users make better decisions when ordering food while at the same time promoting healthier eating habits.

Two innovative systems exemplify this trend: MenuDecoder, an AI-powered restaurant app proposed by Hasan et al. (2022) [77], and the "meals-plates exploration cycle" recommendation system from Takahashi et al. (2023) [78]. MenuDecoder leverages AI algorithms and a vast database of restaurant menus to offer personalized meal recommendations based on user preferences and nutritional needs. A qualitative usability study demonstrated high user satisfaction with the app's design and helpfulness. On the other hand, the recommendation system introduced by Takahashi et al. (2023) [78] enhances the dining experience by aiding users in selecting suitable plates for their meals. It employs machine learning for plate shape estimation and text classification, utilizing datasets from recipe platforms and e-commerce websites to establish meal–plate relationships, catering to user preferences and characteristics of both meals and plates.

In conclusion, the use of data-driven approaches in Restaurant Recommendation Systems for personalised nutrition can have significant benefits. This is a promising area for future research.

3.1.4. Summarization

In this section, we summarise key information for recommendation systems that were presented previously in a single easy-to-use table (Table 1). For each recommendation system, we provide: "Reference No.", "Method/Model/Technology", "Datasets", "Inputs", and "Platform". The first column presents the number of the reference that corresponds to the paper or work presented in each row. The second column refers to the technologies used to generate the personalisation (e.g., AI model, method, ontology, KGs, etc.). Additional information is given in parentheses, indicating the use/role of the model. The third column presents the datasets used, including novel datasets that were created as part of the scientific work. The fourth column presents the input provided to the recommendation system, e.g., what information is fed to the AI model, ontology, etc. Here, additional information is also given inside parentheses, explaining the integration of the various data inputs. Finally, the fifth column refers to any means the scientists used to collect inputs or communicate with the users. Such platforms vary and range from paper questionnaires, where users fill the information by hand, to mobile applications that employ a friendly user interface.

Table 1. Overview of the works presented in Section 3 (recommendation systems for personalised nutrition), indicating method/model/technology (the "*" indicates that this work includes numerical measurements regarding the algorithm's efficacy and/or user acceptability. The reader can refer to the work on Section 3 for additional information), datasets, inputs, and data acquisition platform used. Additionally, the last row, named Notes, is referring to where a system uses clinical data (*) and genetic data (**). For more information, the reader can refer to the corresponding work.

Reference No.	Method/Model/Technology	Datasets	Input	Platform	Note
		A. Nutrition Recommendation Systems			
Haseena et al. (2022) [36]	Cuckoo (optimization) Fuzzy AHP (multi-criteria) Fuzzy TOPSIS (decision making) *	-	Physiological data (use the data as values for the comparison matrix)	Questionnaire	*
Lakshmi et al. (2023) [37]	Fuzzy AHP (multi-criteria) Fuzzy TOPSIS (decision making)	-	Physiological data, dietary data, health data (use the data as values for the comparison matrix)	-	*
Zhang et al. (2022) [38]	MaOO (optimization) *	MyFitnessPal	Dietary data, nutrition values	-	*
Salloum et al. (2022) [39]	TOP (optimization) *	-	Physiological data (use a loss function)	Questionnaire	*
Rout et al. (2023) [40]	KNN (clustering) RF (classification) *	Kaggle (calorie dataset)	Nutrition values, physical activity (clustering the data)	Web application	*
Kaur et al. (2022) [41]	EfficientNet (B0-B7) (classification) VGG16 (classification) VGG19 (classification) ResNet50 (classification) ResNet100 (classification) *	Food101	Physiological data, RBG images (compute BMI and caloric needs from physiological data and use food images to calculate caloric income and what to recommend)	Web application	*
Aguilar et al. (2022) [42]	Bayesian network (probabilistic modelling) *	UECFOODPIX, UNIMIB2016, Food201	RGB images	-	*
Romero-Tapiador et al. (2023) [43]	CNN (classification) *	food images (AI4Food-NutritionDB)	Physiological data, preferences, physical activity, food images (construct the user profile from all the above data and then create food image datasets with different eating behaviours)	Mobile application	*
Azzimani et al. (2022) [44]	SVM (classification) MFCN (segmentation) *	Morocco FCT	Physiological data, health data, RGBD images (construct the user profile from the physiological data and health data and then include the information of food image)	-	*

Table 1. *Cont.*

Reference No.	Method/Model/Technology	Datasets	Input	Platform	Note
Shandilya et al. (2022) [45]	Content-based recommendation system (recommendation system) *	CKD, USDA	Health data, preferences, rating (item feature-based classification, then extract mandatory features from the user's profile and finally with the extraction of the preferred features they generate recommendations)	-	*
Xu et al. (2023) [46]	KG (reasoning) NLP (natural language) *	User Profiles, Food Dataset	Sociodemographic, nutrition and health, dietary preferences (rule-based relation among the KG schema)	-	*
Hosen el. al. (2023) [47]	PSO (optimization) k-means (clustering) SOM (clustering) NLP (natural language) *	American food chart	Dietary data, health data, contextual info (clustering the data)	-	*
Larizza et al. (2023) [48]	-	Use their own DB	Demographics, physiological data, lifestyle (construct child profile using the above data)	Questionnaires	*
Lodhi et al. (2023) [49]	KG (reasoning) Ontology (reasoning) *	-	Health data, demographics (construct user profile with the data and then extract proper nutritional recommendations based on rule-based and data-driven approaches)	Web application	*
Burgermaster et al. (2023) [50]	-	-	Meal logs, health data, food images (these data are for constructing the user profile)	Mobile application	*
Islam et al. (2023) [51]	TOPSIS (decision making) *	-	EEG signals, food nutritional (extract features from EEG collection and survey data and then recommend foods and menus)	Questionnaires	*
Yang et al. (2022) [52]	-	-	Genetic data, physical data, diet style, habits, medical data (construct user profile with the above data)	Mobile application, Questionnaire	**
Fu et al. (2023) [53]	KG (reasoning) Ontology (reasoning) *	FoodData Central dataset (FDC), FoodOn, Chinese Food Ontology, KEGG, MENDA, MiKG, MeSH	Health data, food, gut microbiota data (the KG works with queries as inputs and returns the relationship among the above three categories)	-	*
Yang et al. (2023) [54]	-	-	Health data, physiological data (construct the user profile)	Mobile application, Questionnaire	**
Yang et al. (2022) [55]	LIMS (data management processes) Bioinformatic pipelines Genetic Interpretation System, CRM *	AutDB, DisGeNET, OMIM	Physiological data (construct the user profile)	Mobile application, Questionnaire	**

Table 1. *Cont.*

Reference No.	Method/Model/Technology	Datasets	Input	Platform	Note
Geng et.al. (2023) [56]	Heuristic Optimization, TRBCO *	Shaffer, Fonseca, Kursawe, Poloni, ZDT1-6, Movielens-1M	Ratings (use of rating to recommend a meal)	-	*
Sahal et al. (2022) [57]	DT	-	Dietary data, physical activity, contextual information (they do not mention how they integrate these data)	-	*
Chivukula et al. (2022) [58]	Ontology *	-	(The ontology works with queries as inputs and returns the relationship among the tis classes)	-	
Kaur et al. (2023) [59]	Ontology *	Clinical data	Clinical data, weight, gestational age (SPARQL queries to the ontology using the above data)	-	*
Martinho et al. (2023) [60]	Ontology	FoodOn, Joint Food Ontology Workgroup (JFOW)	Preferences, allergies, meal intake, demographics (Queries to the ontology using the above data)	Mobile application, Web application	*
Rostami et al. (2024) [61]	Clustering (encoder and decoder), deep neural networks *	-	Preferences, health factors of foods (construction of a user-rating matrix with the above data)	-	*
Palacios et al. (2023) [62]	ADDIE *	-	Food frequency (construct user profile and feed it to the model)	Questionnaire Web application	*
Wang et al. (2023) [63]	BP Neural Network Model, Gradient Boosted Regression Trees (GBRT) *	-	Health data, physiological data, physical activity, contextual information (input the above data into the models and generate personalized advice)	-	*
Cunha et al. (2023) [64]	RNN, LSTM, GRU *	FitBit fitness tracker data	Food intake, physical activity, physiological data (input the above data into the models to predict BMI, weight, muscle mass, etc.)	-	*
			B. Recipe Recommendation Systems		
Neha et al. (2023) [65]	CNN, Naive Bayes, Fuzzy Rule *	-	Text data of ingredients and recipes (input of the above information to the models)	-	*
Wang et al. (2022) [66]	Integer programming	-	Physiological data, health data, preferences (input of the above data to the model)	Web application	*
Buzcu et al. (2023) [67]	Ontology	OWL-based ontology	Allergies, preferences, type of cuisine (queries to the ontology using the above data)	Web application	*

Table 1. *Cont.*

Reference No.	Method/Model/Technology	Datasets	Input	Platform	Note
Shubhashree et al. (2022) [68]	KNN, Euclidean *	-	Physiological data, dietary data, preferences, restrictions (construct user profile with the above data and feed them to the model)	Web application	*
Ribeiro et al. (2022) [69]	MaOO *	-	Physiological data, food type, allergies (construct user profile using the above data and feed them to the model)	Mobile application	*
Wu et al. (2022) [70]	ATNet, PiNet	Created their own DB	Food images (input the above data to the model to classify them)	Web application	
Forouzandeh et al. (2024) [71]	NLA, SLA, GAT, GNN *	Allrecipes	Rating, recipes (combination of user profiles and ratings of recipes to produce healthy recipes recommendations)	-	
RahmathNisha et al. (2023) [72]	Decision trees, KNN, and SVM *	Kaggle (food and nutrition)	Physiological data, food image (physiological data re used to construct user profile and food images to extract features and then recommend a food)	Web application	*
Yera et al. (2022) [73]	KG *	Coolpod, Allrecipe, Yammly, USDA, Created their own DB	(This model does not use any inputs)	-	
Li et al. (2023) [74]	KG *	Food.com, Food KG	Health data, preference data (two KGs are used for each data to extract features and then combine these outputs)	-	*
Kansaksiri et al. (2023) [75]	Meta-AI, NLP *	Recipe1M	Food images, OpenAI-powered chat service (input food images into the model to extract ingredients)	-	
Safitri et al. (2023) [76]	GPT-3, NLP *	Created their own DB	Contextual information (user texts with the chat-bot)	Desktop application	
			C. Restaurant Recommendation Systems		
Hasan et al. (2022) [77]	AI *	Dataset of restaurant menus	Preferences, menu image (menu item extraction from menu image and combined with preferences to recommend a menu)	Web application	*
Takahashi et al. (2023) [78]	Flow graph, CRF	Cookpad	Preferences (This model does not take any data as input. It is a flow graph which is being trained by the user and leads the user to preferred recommendations)	-	

3.2. Data Collection Technologies

A subject that emerges from the literature examined above is the usage of various sensors, devices, technologies, or processes to gather users' nutrition/health related data. Data acquisition is typically carried out via two distinct processes: (i) user questionnaires or (ii) automated data gathering utilising a multitude of diverse devices ranging from communication devices to wearable sensors and from cameras to medical devices.

Sonkusale et al. (2022) [79] listed an extensive array of sensors specifically designed for measuring and extracting vital body information. These sensors, readily available in the market, play a pivotal role in supporting PN applications. Furthermore, a more in-depth technical analysis is presented in the review paper by Ates et al. (2022) [80], offering a comprehensive and more technical examination of various wearable sensor technologies. This review emphasizes the end-to-end process that transforms raw sensor data into meaningful insights that can inform PN applications. The synthesis of insights from these papers underscores two key points: the abundance of diverse devices and sensors available for PN and the evolving technological landscape that underpins their functionality.

This section presents the data collection technologies that are integral to the field of PN, drawing insights from the literature. It is structured into four subsections, each delineating distinct categories of data collection technologies based on their unique nature, scope, and roles in PN research, and a fifth subsection that summarizes this information.

3.2.1. Wearable Sensing Devices

An avenue for collecting data in the realm of PN involves the utilization of wearable sensors. When discussing wearable devices, we typically refer to items like smart watches and activity trackers, but there are also other devices, such as smart glasses and smart headphones, that can monitor metrics like heard rate, blood pressure, and sleep performance and feed this data to recommendation systems.

The CarpeDiem app, as discussed by Migliorelli et al. (2023) [81], integrates data from wearable devices and user questionnaires to analyse physical activity, sleep patterns, and nutritional habits, offering personalized recommendations to promote healthier lifestyles. A pilot study assessed its effectiveness in driving long-term behavioural changes, emphasizing the utility of combining objective and subjective health data. Meanwhile, Wang et al. (2022) [82] presented NutriTrek, a wearable electrochemical biosensor engineered to continuously analyse sweat for various metabolites and nutrients, including essential amino acids and vitamins. Its wireless communication facilitates real-time monitoring of nutritional needs, showcasing the potential of wearable sensors for developing effective personalized nutrition plans through non-invasive and convenient data collection.

Khan et al. (2022) [83] proposed iHearken, a headphone-like wearable sensor system, employing ML techniques to automatically recognize food intake types in real-life settings. Through four phases, including data acquisition and classification using Bidirectional long short-term memory (Bi-LSTM) models, iHearken achieves high accuracy (97.422%), precision (96.808%), recall (98%), and F-score (97.512%), demonstrating superior performance in food recognition compared to other models. This research underscores the potential of wearable sensors and ML for dietary monitoring. Similarly, Xiao-Yong et al. (2023) [84] introduced a smartwatch-based health management system utilizing physiological data transmitted via 5G and NarrowBand-Internet of Things (NB-IoT) technologies. The system offers continuous monitoring and feedback for medical diagnosis and disease prediction, acknowledging challenges like power consumption and transmission range that require attention for improved effectiveness.

In conclusion, wearable sensors are an excellent way of gathering data from users and feeding them to recommendation systems. With wearable devices, a recommendation system can be frequently updated with users' physiological data and generate more accurate and on-site recommendations.

3.2.2. Cameras

Currently, cameras can be found almost everywhere and in every device, from smartphones with multiple cameras with great resolution to embedded cameras on wearable devices like activity trackers. The work by Azzimani et al. (2022) [44] involves an innovative technique that employs advanced image processing methods to accurately calculate the nutrient content of items depicted in RGBD images that were captured before and after a meal. Similarly, Aguilar et al. (2022) [42] attempted to enhance the accuracy of existing image recognition networks using Bayesian networks. Given an image of one or multiple food plates, the enhanced model can better recognise the foods on the plate. Along the same lines, in the work presented by Wu et al. (2022) [70], images are fed to the AI algorithm for food classification, ingredient recognition, and nutrition analysis to produce a nutrition report for the user. The evaluation and accuracy of these tree works was further discussed in Section 3.1.1.

All in all, cameras with the synergy of AI and ML algorithms can produce significant information for the recommendation systems. From calorie estimation to volume estimation and from food recognition to ingredient recognition, the power of RGB and RGBD images plays a crucial role in the field of PN, with much more to give in the future.

3.2.3. Smartphones and Applications

Smartphones play a multifaceted role in the realm of PN. They are harnessed for diverse purposes, such as capitalizing on their high-quality cameras to capture high-resolution images [42,44,70]. Additionally, the development of mobile applications dedicated to PN has emerged as another avenue [52,54,55,69,85]. An example is the work of Zamanillo-Campos et al. (2023) [86], which discusses the development and evaluation of DiabeText, a personalized mHealth intervention aimed at supporting medication adherence and lifestyle change behaviour in patients with type 2 diabetes in Spain. The testing of the app showed a high level of personalization and patient-centredness. These applications, equipped with user-friendly interfaces, facilitate the input of personalised information and display results from recommendation systems. Furthermore, smartphones leverage wireless connection technologies like Bluetooth to link with various wearable devices. Notably, Martínez-Rodríguez et al. (2022) [87] underscored the efficacy of combining wearable sensors with mobile applications, showcasing superior outcomes compared to methods that do not integrate smartphone applications.

Additionally, gamification emerges as a significant factor in driving user engagement with PN mobile applications, as emphasized by Al-Rayes et al. (2022) [88]. Similarly, Oc et al. (2022) [89] explored motivational technology characteristics through the U-Commerce lens, introducing the gaming, instructing, sharing, and teaching GIST model based on user preferences for gaming, instructing, sharing, and teaching features. This model, built on four principles, aims to cultivate autonomous motivation among users, facilitating more effective and sustainable engagement with PN applications.

In conclusion, smartphones and their synergy with mobile applications and wearable sensors can provide not only a user-friendly interface for users to interact with a PN application, but also a means by which valuable data and information can be collected by the recommendation systems.

3.2.4. Other Sensing Devices

In addition to wearable devices, a diverse array of non-wearable sensing devices holds substantial promise for personalised nutrition. Such devices range from simple smart scales to smart forks and even EEG signal-capturing devices or DNA kits. As was mentioned previously, Islam et al. (2023) [51] retrieved brain data using EEG signals as inputs for their recommendation system, while Yang et al. (2023) [54] used DNA kits to collect genetic information from the users.

Likewise, Wilson-Barnes et al. (2022) [19] employed a volatile organic compound (VOC) sensor to analyse the breath of research participants in two population groups at nutritional risk: (i) adults with poor-quality diets (PQD, fewer than three portions of fruit and vegetables per day) and (ii) adults with iron-deficiency anaemia. The analysis results were subsequently used to investigate correlations of specific compounds with the two groups.

In summary, pivotal health and nutrition-related information can be gleaned from advanced non-wearable sensing devices; however, the process of obtaining, analysing, and applying the data is often more intricate compared to wearable sensors. Beyond the sheer volume of these devices, users may encounter challenges, such as the need to visit hospitals or specialized facilities. Moreover, the complexity of these devices can render them difficult to use and potentially expensive.

3.2.5. Summarization

In the table below, we provide an overview of the various data collection technologies that were presented in this section (Table 2). For each technology, we identify the data-capturing sensor or device used; its data output, which is used as input to the method or model employed; and finally, the scope of the method/model used in the respective work.

Table 2. List of the data collection technologies presented in Section 4, indicating sensors/devices used, method/model input (which is also the output of the sensor/device), and method/model scope.

Reference No.	Sensor/Device Used	Method/Model Input (Sensor Output Data)	Method/Model Scope
Wilson-Barnes et al. (2022) [19]	VOC	Human breath	Nutrient estimation
Aguilar et al. (2022) [42]	Camera	RGB of a plate	Food recognition
Azzimani et al. (2022) [44]	Camera	RGBD of a meal	Meal personalisation
Islam et al. (2023) [51]	EEG	EEG signals	Affects of different meals
Yang et al. (2022) [52]	Mobile	Genetic testing, physical examination, diet style, habits and customs, medical history, exercise data	Tailored nutrition solution
Yang et al. (2023) [54]	Mobile, DNA kit	Lifestyle questionnaire, physical examination results, DNA data	Evaluating users' immune status, nutritional deficiency risk
Yang et al. (2022) [55]	Mobile, DNA kit	Analysing genetic data, lifestyle data, physical examination data	Genetic interpretation report, personalized nutrition report, customized nutrition packs
Cunha et al. (2024) [64]	Food scale, body scale, smartwatches	Food intake attributes, physical activity metrics, body parameters	BMI prediction, personalised feedback, goal monitoring
Ribeiro et al. (2022) [69]	Mobile	Food preferences, restrictions, nutritional needs	Meal recommendation system
Wu et al. (2022) [70]	Camera	RGB of a meal	Food classification
Migliorelli et al. (2023) [81]	Activity tracker	Step counter, physical activity, pulse, sleep hours and sleeping efficiency	Physical activities, cardiovascular activities, sleep patterns, nutritional habits
Wang et al. (2022) [82]	NutriTrek	Age, BMI	Health monitoring, precision nutrition
Khan et al. (2022) [83]	Headphone-like	Chewing sounds	Food intake type
Xiao-Yong et al. (2023) [84]	Smartwatches, mobile	Pulse, heart rate, blood oxygen	Health management

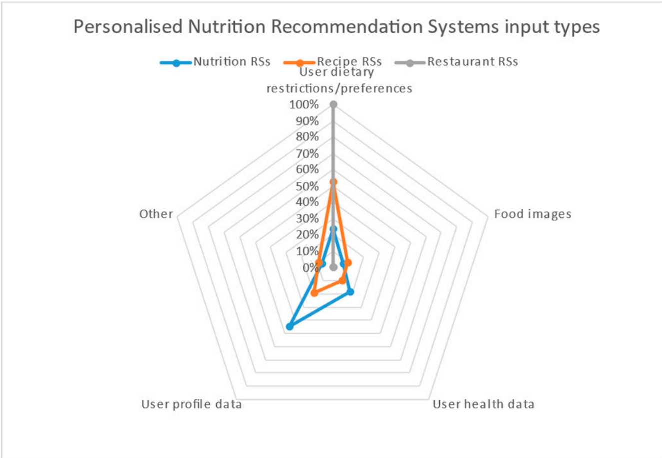
Table 2. *Cont.*

Reference No.	Sensor/Device Used	Method/Model Input (Sensor Output Data)	Method/Model Scope
Zamanillo-Campos et al. (2023) [86]	Mobile	Patient-elicited data	Tailored brief text
Martínez-Rodríguez et al. (2022) [87]	Mobile, activity tracker	Blood pressure, body weight, water intake, fruits intake, vegetables intake, physical activity	Personalised reminders, behavioural tips, educational material, progress tracking
Oc et al. (2022) [89]	Smartwatches, smart wristbands, mobile	Preferences	Gamification

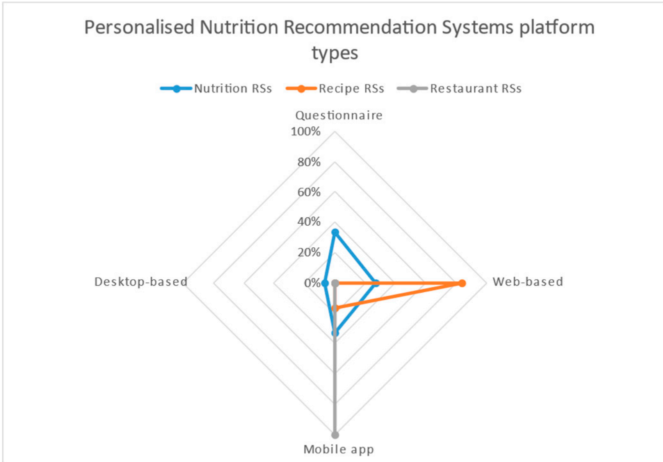
4. Discussion

In this section, we discuss and summarise the findings from the preceding literature review, shedding light on the research challenges that emerge. Upon examining all presented works, certain features have been identified as not only pivotal to each individual study, but also shared across multiple works. A synthesis of such common features was performed, and the result was presented in tabular format to show how each work/method incorporated them. Specifically, we focused on the methods/models/technologies presented in the various works, and for each, we identified the specific datasets, input types, and presentation platforms that were used. The surveyed works employed a diverse array of methods, and even when multiple works employed the same method, they often leveraged different technologies. Across the presented works, various approaches were adopted, including image recognition models (Azzimani et al. (2022) [44]), heuristic optimizations (Heuristic optimization refers to a problem-solving approach that employs practical, experience-based techniques to find good enough solutions for complex optimization problems, especially when traditional methods are computationally infeasible; "https://en.wikipedia.org/wiki/Heuristic_(computer_science) (25 August 2024)") (Geng et al. (2023) [56]), Bayesian networks (Bayesian networks are probabilistic graphical models that represent a set of variables and their conditional dependencies using directed acyclic graphs, enabling efficient reasoning and inference under uncertainty; "https://en.wikipedia.org/wiki/Bayesian_network (25 August 2024)") (Aguilar et al. (2022) [42]), DT (Digital Twin is a virtual representation of a physical object, system, or process that is used to simulate, analyse, and optimize its real-world counterpart through real-time data and advanced algorithms; "https://en.wikipedia.org/wiki/Digital_twin (25 August 2024)") methodologies (Sahal et al. (2022) [57]), deep convolutional neural networks (Deep convolutional neural networks are a type of artificial neural network designed to process and analyse grid-like data structures, particularly images, by using multiple layers of convolutional filters to learn spatial hierarchies of features automatically and adaptively from the input data; "https://en.wikipedia.org/wiki/Convolutional_neural_network (25 August 2024)") (Kaur et al. (2022) [41]), ontologies (Formal representations of a set of concepts within a domain and the relationships between those concepts, used to model domain knowledge in a structured and interpretable way for purposes such as information sharing, integration, and reasoning; "https://en.wikipedia.org/wiki/Ontology_(information_science) (25 August 2024)") (Buzcu et al. (2022) [67]), and more. It is evident that the reviewed works demonstrate significant diversity by employing multiple and distinct approaches, highlighting the breadth of methodologies within the field.

Conversely, when it comes to input types, commonalities emerge among the studies' recommendation systems. For instance, users' physiological data represent a recurring input type [36,41,55], while food images play a central role in [41,42,44,70] and more. Specifically, input types have been categorised into four main groups: user profile data (including personal information, physiological data, genetic data, physical activity, habits, etc.), user health data (including allergies, diseases, medical history etc.), user preferences/restrictions (including dietary preferences/restrictions, food ratings, dietary patterns, preferred cuisine, cultural aspects etc.), and food images (e.g., RGB or RGBD images). The radar chart depicted in Figure 3a visually represents how frequently each input type is used in the reviewed works.



(**a**)



(**b**)

Figure 3. Two radar charts regarding the inputs and the platforms of recommendation systems correspondingly. (**a**) Radar chart displaying how common each input type is. (**b**) Radar chart displaying how common each platform type is.

One significant finding related to the datasets used by the reviewed works is that, in most instances, the researchers employed pre-existing, well-established datasets. However, there are cases where bespoke datasets tailored to the specific research goals are used, as evidenced in Wu et al. (2022) [70]. A second noteworthy observation is the considerable diversity across the used datasets. For instance, [44,45,73] utilised national databases containing nutrition values for various foods, while in Zhang et al. (2022) [38], physiological data were extracted from the MyFitnessPal app. In contrast, Geng et al. (2023) [56] employed ten heuristic optimization benchmark datasets, and Yang et al. (2022) [55] relied on a database for autism as well as a database detailing gene–disease association. Additionally, [41,42,74] incorporated databases of food images, while Buzcu et al. (2023) [67] adopted a Web Ontology Language (OWL), showcasing the rich spectrum of data sources and methodologies employed by researchers in this field.

In terms of presentation platforms, the reviewed works exhibit commonalities, as nearly half of the works in Nutrition Recommendation Systems and almost all the works in Recipe Recommendation Systems used a platform or a method for users to interact with the recommendation system and for the recommendation system to collect information and data from the users. For instance, [36,52,54,55] utilised questionnaires for user interaction, while [41,66,68] opted for web-based applications. In general, presentation platforms have been categorised into four main groups: user questionnaires, mobile applications, web-based applications, and desktop-based applications. The radar chart depicted in Figure 3b visually represents the usage frequency of the various presentation platform types among the works, highlighting the prevalent approaches adopted by researchers for facilitating user engagement and data collection in recommendation systems.

The ultimate role of personalized Nutrition Recommendation Systems is to assist individuals in changing/sustaining their dietary habits to improve their health outcomes, such as balancing BMI, achieving weight loss, and preventing disease. To fully assess the effectiveness of these systems, long-term studies involving human participants are necessary. While our focus in this paper is on the technical evaluation and validation of these systems, as outlined in the introduction, we acknowledge that there is one study that has conducted such an experiment. Yang et al. (2023) [54] demonstrated that personalized nutrition and nutritional supplements significantly improved the immune system of elderly participants by tailoring nutrient intake based on individual genetic profiles, health indicators, and lifestyle factors. This personalized approach led to a marked improvement in immune markers, such as a 30% increase in T-cell activity and a 25% reduction in inflammation-related markers, enhancing overall immune function and reducing susceptibility to infections and autoimmune conditions.

Drawing upon the differences and similarities between nutrition RSs and recipe RSs, it is not clear whether adding recipe recommendation over nutritional recommendation has additive value. However, one benefit of recipe RSs over nutritional ones is stated in Ribeiro et al. [69], who stated that the creation of multiple meal recommendations extended control over users' diets, unlike single-recommender systems.

Finally, several reviewed works have taken the additional step of integrating their recommendation systems into practical applications, such as web or mobile platforms, which are currently available and can be used online. For example, Safitri et al. (2023) [76] presented an application named CookPal, which is a web site where a user can either upload an image of one or more products or write those products and the algorithm will produce a recipe with these products. Additionally, Hasan et al. (2022) [77] provided a web site where users can find useful articles about foods, recipes, restaurants, and more.

Research Challenges in Recommendation Systems for Personalised Nutrition

The field of PN revolves around customising dietary recommendations and interventions for individuals, considering their distinct characteristics, including their profile, genetic information, metabolism, microbiome composition, lifestyle, preferences, and health status. For example, Andres et al. (2023) [90] focused on data engineering issues like data collection, cleaning, integration, and processing, alongside the design and implementation of efficient data pipelines and storage systems, while Sedrakyan et al. (2023) [91] discussed the importance of integrating sustainable food consumption into recommendation systems, the limitations of existing food recommendation systems, and privacy, among other challenges.

Despite the considerable potential of existing PN approaches to enhance health outcomes, a careful examination and analysis of various reviewed works reveal several research challenges that demand attention. This chapter enumerates the research challenges derived from a meticulous review of the literature.

Data Collection and Integration. PN often requires extensive collection of multimodal data that can range from personal user profiles to microbiome and genetic data, and from physical activity data to clinical data. The majority of the above works used more than one type of data as input to obtain a more accurate result, like [38,43,52]; therefore, more diverse datasets are needed.

- *Research challenge: Integration of diverse datasets and development of standardised protocols for multimodal data collection and analysis*

Several data collection devices or methods are either costly or time-consuming (or both) for the user [19,51,54,55].

- *Research challenge: Friendlier and more easily accessible means (devices, methods, etc.) for data collection.*

Precision and Accuracy. Achieving precise and accurate recommendations for individuals is challenging due to the complex interplay of multiple factors. Combining multiple technologies and data, like [36,41,55,63], can diverse the accuracy of a system.

- *Research challenge: Understanding the interactions between genes, diet, lifestyle, the microbiome, and more via novel sophisticated analytical methods and respective computational tools.*

Increasing data diversity leads to more accurate results [37,38,43,51,79,80].

- *Research challenge: Improvement of existing or development of novel technologies (e.g., smart devices) for gathering of additional data.*

Genetic Variation and Gene–Diet Interactions. Genetic variation plays a crucial role in individual responses to dietary factors. People respond differently to the same dietary interventions due to variations in genetics, metabolism, and other factors. Only three studies [52,54,55] include genetic data, indicating the need to address this research challenge.

- *Research challenge: Developing personalised recommendation systems that account for genetic variability.*
- *Research challenge: Identifying relevant genetic variants and understanding how they interact with specific nutrients or dietary patterns via large-scale studies and advanced statistical techniques.*

Long-Term Effects. Studying the long-term effects of PN interventions is essential to understand their impact on health outcomes. Many studies have conducted surveys that included humans, like [66,74,78], for a couple of months, but not for more.

- *Research challenge: Conduct long-term studies with large sample sizes while overcoming any respective logistical challenges and financial constraints.*

Long-Term Results. To evaluate recommendation systems more comprehensively, there is a need for more long-term studies involving human participants, rather than focusing solely on technical aspects.

- *Research challenge: Conduct long-term studies with large numbers of real users using diet recommendation systems, carefully monitoring their responses throughout the process (nutrition behavioural changes, real health changes/outcomes achieved, etc.).*

Behaviour Change. PN recommendations often require individuals to make significant changes to their dietary habits and lifestyle. Studies like [48,70,81,88] have tried to leverage the challenge to motivate a user to keep using a diet, but more effort is needed in this direction.

- *Research challenge: Understand how to effectively motivate and support individuals in making sustainable behaviour changes.*

Ethical and Privacy Considerations. PN almost inevitably involves the collection and use of sensitive personal data. The study of Safitri et al. (2023) [76] is an example of developing a system focusing on users' data privacy.

- *Research challenge: Facilitate privacy protection and address ethical concerns related to data ownership, consent, and potential discrimination.*

In addition to the challenges identified in the reviewed papers, below, we further highlight the research challenges put forth by Food2030 [92], aiming to offer a more comprehensive perspective on this subject. These challenges are not met (with one exception) in the above studies, and therefore, it is urgent to address them in featured works. While the overarching scope of Food2030 is "to achieve a resilient food system that is fit for the future", specific requirements put forth include the need to also deliver co-benefits for peoples' health, the world's climate, the planet, and communities. Hence, the imperative for the coexistence of PN and sustainability remains an ongoing consideration and represents a crucial aspect that could be seamlessly integrated into recommendation systems. The challenges that Food2030 addresses can be summarized as follows.

Carbon footprint. One of the major challenges faced by modern society is the carbon footprint associated with food production and consumption.

- *Research challenge: Utilisation of technologies such as blockchain to trace the origin of food/products or geolocation systems to track their journey from farm to fork, with the aim of contributing to reductions in the carbon footprint.*
- Research challenge: Development of technological solutions to facilitate precise calculations, with the aim of contributing to reductions in the carbon footprint.

Waste. Food waste is a pressing problem in contemporary societies, particularly in more developed countries with high populations and demand.

- *Research challenge: Development of technological solutions for improved accuracy of estimations regarding required quantities of food/products at each stage of the supply chain.*

Prices. Accessibility to affordable food/products remain a challenge in several impoverished nations worldwide (Wang et al. (2022) [66]).

- *Research challenge: Development of technological solutions for the analysis of pricing disparities, ultimately working towards greater affordability and accessibility.*

Sociocultural aspects. Reshaping societal behaviours can lead towards a more environmentally conscious and sustainable way of living.

- *Research challenge: Development of solutions/methods for incorporating technology in education and societal restructuring towards a greener and more sustainable society.*

In summary, the research challenges for data-driven innovation in the field of PN span across diverse domains. A critical focus is on the data sphere, demanding large-scale, precise, and readily accessible datasets. Ethical and privacy concerns emerge prominently, particularly in the utilization of personal user data. The inherent variability among individuals poses a significant challenge for recommendation systems in PN, striving to tailor recommendations to each user effectively. Developing user-friendly applications and platforms is another substantial hurdle. Furthermore, the long-term effects of employing recommendation systems as well as their seamless integration with Food2030 goals pose complex challenges. Achieving harmony with existing technologies and exploring new ones becomes pivotal, especially concerning sustainability, food waste, and other challenges outlined in Food2030. Consequently, the multidimensional nature of challenges in this research field necessitates comprehensive consideration across various facets.

5. Conclusions

This review paper describes a review of data-driven innovative technologies in the realm of PN, offering a comprehensive and holistic overview of the various technologies and their applications in this research field. Adhering to the PRISMA model, the reviewed works cover the period from 2021 to date, emphasising the synergy between computer science and PN.

The findings indicate that the predominant approach to amalgamating these two fields involves the use of recommendation systems. These systems are further categorised into Nutrition, Recipe, and Restaurant Recommendation Systems. The diversity in technologies and methods employed by these recommendation systems is noteworthy. Common across nearly all recommendation systems are the inputs utilized, including user data and food images. Another shared feature is the mediums employed to gather inputs, typically questionnaires, web-based apps, mobile apps, and desktop-based apps.

A dedicated chapter delves into the technologies employed for data collection, highlighting the crucial roles of wearable and non-wearable sensors, cameras, smartphones, and mobile applications. The development of user-friendly interfaces for these recommendation systems, coupled with the integration of wireless connected devices for data provision, holds the potential to guide individuals towards healthier lifestyles using mobile apps for personalized nutrition.

Finally, this literature review identified several research challenges. The paper lists the most significant challenges within the realms of nutrition, computer science technologies, and sustainability, offering a comprehensive perspective on the research field.

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