Narrative Review

Digital applications for diet monitoring, planning, and precision nutrition for citizens and professionals: a state of the art

Alessio Abeltino[1,2,†], Alessia Riente[1,2,†], Giada Bianchetti[1,2], Cassandra Serantoni[1,2], Marco De Spirito[1,2], Stefano Capezzone[3], Rosita Esposito[4], and Giuseppe Maulucci[1,2,*]

[1]Department of Neuroscience, Metabolic Intelligence Lab, Università Cattolica del Sacro Cuore, Rome, Italy
[2]Complex operational unit of Physics for life science, Fondazione Policlinico Universitario "A. Gemelli" IRCCS, Rome, Italy
[3]Gruppo Fastal Blu Sistemi, Rome, Italy
[4]Chirale S.r.l., Digital Innovation Hub Roma, Rome, Italy
*Correspondence: *G. Maulucci,* Department of Neuroscience, Università Cattolica del Sacro Cuore, Largo Francesco Vito 1, 00168, Rome. E-mail: giuseppe.maulucci@unicatt.it.
†A.A. and A.R. contributed equally to this review.

The objective of this review was to critically examine existing digital applications, tailored for use by citizens and professionals, to provide diet monitoring, diet planning, and precision nutrition. We sought to identify the strengths and weaknesses of such digital applications, while exploring their potential contributions to enhancing public health, and discussed potential developmental pathways. Nutrition is a critical aspect of maintaining good health, with an unhealthy diet being one of the primary risk factors for chronic diseases, such as obesity, diabetes, and cardiovascular disease. Tracking and monitoring one's diet has been shown to help improve health and weight management. However, this task can be complex and time-consuming, often leading to frustration and a lack of adherence to dietary recommendations. Digital applications for diet monitoring, diet generation, and precision nutrition offer the promise of better health outcomes. Data on current nutrition-based digital tools was collected from pertinent literature and software providers. These digital tools have been designed for particular user groups: citizens, nutritionists, and physicians and researchers employing genetics and epigenetics tools. The applications were evaluated in terms of their key functionalities, strengths, and limitations. The analysis primarily concentrated on artificial intelligence algorithms and devices intended to streamline the collection and organization of nutrition data. Furthermore, an exploration was conducted of potential future advancements in this field. Digital applications designed for the use of citizens allow diet self-monitoring, and they can be an effective tool for weight and diabetes management, while digital precision nutrition solutions for professionals can provide scalability, personalized recommendations for patients, and a means of providing ongoing diet support. The limitations in using these digital applications include data accuracy, accessibility, and affordability, and further research and development are required. The integration of artificial intelligence, machine learning, and blockchain technology holds promise for improving the performance, security, and privacy of digital precision nutrition interventions. Multidisciplinarity is crucial for evidence-based and accessible solutions. Digital applications for diet monitoring and precision nutrition have the potential to revolutionize nutrition and health. These tools can make it easier for individuals to control their diets, help nutritionists provide better care, and enable physicians to offer personalized treatment.

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INTRODUCTION

In recent years, the field of digital health has been rapidly advancing, leading to the development of numerous digital applications for diet monitoring, diet generation, and precision nutrition. These solutions aim to help individuals optimize their diets and improve their overall health and wellbeing by significantly enhancing the accuracy and precision of diet tracking and diet generation with the help of advanced technologies and sophisticated algorithms.

The recipients of digital nutrition solutions can be divided into three categories: citizens, nutritionists, and physicians and researchers employing genetics and epigenetics tools.

These tools have enabled citizens to more effectively track and monitor their diet, their physical activity, and their progress toward their health goals. Some of the popular digital nutrition solutions used by citizens include mobile applications like MyFitnessPal, LoseIt!, and Fitbit. These digital nutrition solutions provide personalized recommendations for diet, exercise, and lifestyle changes based on an individual's goals, preferences, and health conditions.

More specialized digital applications are employed by nutritionists to analyze and generate diets for their clients. These more advanced applications allow specialists to provide a range of functionalities, such as meal planning, nutrient analysis, and recipe creation. Some of the most popular ones include Nutrium, Practice Better, and Healthie. These tools also provide communication and collaboration features that enable nutritionists to work closely with their clients and monitor their progress toward their health goals, helping them to manage their workload and provide better care for their clients.

Physicians also employ digital nutrition applications to analyze and generate diets for their patients. However, unlike nutritionists, they also use genetics and epigenetics tools for research purposes, in some cases to provide personalized recommendations for their patients. These advanced digital tools analyze an individual's DNA and epigenetic markers to identify their unique nutritional needs and create a personalized diet plan. Some of the most popular digital nutrition applications used by physicians include GenoPalate, Nutrigenomix, and DNALife, which each provide a comprehensive analysis of an individual's genetic and epigenetic data to identify potential health risks and create a diet plan that is tailored to their unique needs. In the following paragraphs, we outline the beneficial effects of self- or other-directed monitoring of nutrition.

Beneficial effects of digital self-monitoring in nutrition

Diet self-monitoring involves tracking and recording one's food intake and related factors, such as physical activity and emotions, to gain insights into eating habits and thus make informed decisions about diet. This practice is widely used in weight management programs, but it has also been shown to have numerous other health benefits. This paragraph will broadly discuss the evidence-based benefits of diet self-monitoring, including weight loss, improved diet quality, and better glycemic control in diabetes management.

A goal of weight loss is one of the most common reasons for engaging in diet self-monitoring. The practice of keeping a food diary has been shown to be effective in promoting weight loss in both overweight and obese individuals. A study of 3621 people[1] assessed associations between the use of self-monitoring tools, social support, and loss of weight in an online weight management program, demonstrating that the self-monitoring tools induced significant weight loss (13% in women, 19% in men, $P < .001$). In an 18-week study of 56 participants, a clear correlation emerged between self-monitoring and weight control. Participants who consistently monitored their dietary intake experienced significant weight loss. After 12 weeks, the average weight loss was 1.83 kg and after 18 weeks, 1.28 kg. These findings suggest that consistent vigilance may contribute to successful weight control.[2] A digital web-based application (ArMOnIA[3–5]), which integrates dietary, anthropometric, and physical activity data and provides a personalized estimation of energy balance, was used to undertake a single-arm, uncontrolled prospective study with voluntary self-monitored adult participants for 7 months. Hierarchical clustering of adherence parameters yielded 3 behavioral approaches: high (HA), low (LA), and medium (MA) adherence. The average body mass index (BMI) decrease differed significantly between the LA and HA groups.[3] This suggested that self-monitoring increased awareness of food choices and portions, which in turn helped individuals make healthier choices and reduce their overall calorie intake.

Diet self-monitoring can also lead to improved diet quality. By tracking their food intake, individuals become more aware of their dietary habits and are better able to identify areas in which they need to make improvements. This can lead to increased consumption of nutrient-dense foods, such as fruits, vegetables, and whole grains, and decreased consumption of energy-dense, nutrient-poor foods, such as fast food and processed snacks. In the following study,[6] for example, it was shown that using a PDA for self-monitoring was associated with a significant increase in fruit and vegetable consumption, as well as a reduction in the intake of refined foods, supporting the assumption that this practice has a beneficial effect on the quality of the diet.

Diet self-monitoring can also be beneficial for individuals with diabetes. Indeed, keeping track of food intake, blood glucose levels, and medication use can help people with diabetes better manage their condition and maintain healthy blood sugar levels. A recent study found that self-monitoring of blood glucose levels was associated with significant improvements in glycemic control and a reduced risk of complications in individuals with type 2 diabetes.[7] Throughout the study, the use of Diabeto, a computer-assisted dietary education system, significantly improved patients' dietary knowledge and eating habits. This included reducing calorie intake for those initially consuming excess calories, increasing carbohydrate intake for those with a low initial carbohydrate intake, and reducing fat intake for those with a high initial fat intake. These findings underscore the importance of dietary self-monitoring in managing metabolic diseases such as diabetes.[8]

Here, we will explore the main applications available for citizens for nutritional self-monitoring. The digitalization of self-monitoring involves the use of digital technologies, including mobile applications wearable devices, and online platforms, among others. We will explore some existing commercial applications in this field that are available for citizens.

Beneficial effects of other-directed precision nutrition

Precision nutrition[9,10] is a personalized approach to nutrition that considers an individual's unique genetic, metabolic, and lifestyle factors. This approach is gaining popularity as research continues to uncover the many benefits it offers.

One of the main benefits of precision nutrition is its ability to support weight management. Several studies have found that individuals who follow a precision nutrition plan tailored to their unique needs are more successful at losing weight and keeping it off compared with those who follow a one-size-fits-all approach.[11] This is likely, since precision nutrition considers an individual's specific metabolism, hormonal balance, and dietary preferences, which can have a significant impact on weight loss success. Another benefit of precision nutrition is its ability to improve athletic performance. Indeed, as highlighted in a recent article on sport nutrigenomics,[12] personalized nutrition tailored to an athlete's genetic profile can significantly enhance their physical performance. This is because precision nutrition considers an athlete's unique energy needs, nutrient requirements, and training schedule, all of which can have a significant impact on athletic performance. Precision nutrition has also been shown to improve overall health and reduce the risk of chronic diseases. A study found that individuals who followed a precision nutrition plan tailored to their specific genetic risk factors were able to significantly reduce their risk of developing type 2 diabetes, compared with those who followed a generic plan.[13] Another study found that precision nutrition was able to significantly reduce the risk of heart disease and stroke in individuals with high blood pressure.[14,15] These findings suggest that precision nutrition may be a powerful tool in preventing and managing chronic diseases.

With the rise of digital technologies, precision nutrition has also undergone a significant transformation, allowing for greater customization and scalability of interventions, by providing personalized dietary advice and support. By leveraging mobile applications, wearable devices, and online platforms, among other tools, precision nutrition interventions can provide tailored recommendations based on an individual's unique characteristics, such as genetics, lifestyle, and health status. This review will explore the potential of the main applications available for nutritionists and physicians for planning precision nutrition interventions.

METHODS

Both the published literature and the gray literature were searched to select the most suitable articles and patents for this review. We based our approach on that used by Soldani et al.[16] Not only were reference databases such as PubMed, Scopus, ScienceDirect, and Google Scholar used, but also generic web search engines like Google. "Saturation" was used as a stopping criterion: the search was stopped when no new results/relevant concepts emerged from the search results. The inclusion criteria were: relevance to the topic; discussion of digital applications (devices, machine-learning algorithms, etc) in the field of precision nutrition and clinical nutrition, and consideration of citizens, professionals, and/or researchers in the sector as final consumers; publication in the last 30 years. Commercial solutions were also investigated.

For research of a technical–industrial nature, according to Garousi et al[17] it is possible to identify the material of interest using appropriate strings in search engines (eg, Google). The keywords used are related to the various devices/algorithms considered relevant. A number of different searches were used, making it possible to obtain a broad overview, as done by Soldani et al.[16] The search identified industrial studies, scientific articles, and patents that had been published from 1995 until 2023, encompassing the scientific progress in this field over around the last 30 years. Differently, the commercial devices investigated were the latest models presented on the market by the respective manufacturers.

For diet planning and monitoring, the keywords used were "diet planning algorithms and devices", "diet monitoring algorithms", and "diet smartphone application." Here, the official websites (listed in Table S1 in the Supporting Information online) were consulted.

In the search for information on wearable and smart devices, reviews and other articles presenting digital innovations for diet monitoring and precision nutrition were searched using as keywords: "wearables for precision nutrition" and "wearables for clinical nutrition." Next, a number of related searches were undertaken for "smart scales," "fitness tracker," "continuous glucose monitoring," and "smart bottles." Subsequently, to obtain all the commercial details on the various devices identified, a search was carried out on the websites of the manufacturers and sales companies of these devices (see Table S2 in the Supporting Information online).

DIET SELF-MONITORING AND PLANNING FOR CITIZENS

One of the most popular types of digital applications for diet monitoring is the mobile application, which allows users to track their food intake, monitor their calorie and nutrient intake, and even receive personalized recommendations based on their dietary needs and goals. Diet monitoring applications are the main digital applications available for nutrition, diet planning, and tracking, and the state of the art is constantly evolving. In Table 1,[3–5,18–27] some of the commercial options available for citizens are presented.

While these applications can be valuable tools for individuals, by the integration of several features (such as calorie, exercise, and water tracking; meal planning; recipe suggestions; and progress tracking), it is important to note that they should be used in conjunction with a balanced and evidence-based approach to nutrition. Users should ensure that they are consuming a variety of nutrient-dense foods[28] and avoiding overly restrictive diets, as well as seeking advice from a qualified healthcare professional if they have specific health concerns.

Another issue is that some of these applications may have limitations in terms of the quality and accuracy of their nutrition information due to reliance on manual data entry by users. Users should be mindful of these limitations and supplement their use of these applications with additional research and advice from qualified professionals.

DIET MONITORING AND DIET PLANNING FOR USE BY NUTRITIONISTS

There are several software programs available to nutritionists for diet monitoring and planning. These programs can help nutritionists create personalized meal plans, track their clients' food intake, and monitor their progress toward their goals. In Table 2,[21,24,29–38] some of the options available on the market are presented.

Although these applications can be valuable tools for nutritionists by efficiently generating an individualized diet and monitoring a client's progress, it is important to note that these applications are only tools, and they should be used in conjunction with a comprehensive approach to nutrition and healthcare. Nutritionists should ensure that they are providing evidence-based advice and monitoring their clients' overall health, rather than relying solely on the data provided by these applications.

Furthermore, despite the possibility of planning meals, analyzing recipes, and integrating them with wearable devices, the major pitfalls of these applications are related to their complexity, limited reporting, and cost. Also, technical issues can make it difficult to obtain the required data from digital applications.

DIGITAL PRECISION NUTRITION SOLUTIONS FOR USE BY PHYSICIANS AND RESEARCHERS

Precision nutrition is an emerging field that uses data and technology to develop personalized nutrition recommendations based on an individual's unique genetic makeup, lifestyle, and health history. There are some applications that process more medical data for precision nutrition than basic calorie and nutrient tracking data. Some of these applications may incorporate features such as tracking gut health or microbiome, genetic testing and analysis, and personalized meal planning based on the user's unique DNA and health goals. A few examples are shown in Table 3.[39]

Table 1 **Examples of digital applications for diet self-monitoring by citizens**

Application	Reference	Description	Offer	Strengths	Weaknesses	Research applications and data utilization
ArMOnIA	Bianchetti et al (2022)[3] Abeltino et al (2022)[4] Abeltino et al (2023)[5]	A web-based application for tracking food intake and exercise developed by the Metabolic Intelligence group of the Catholic University of the Sacred Heart of Rome. It has a database of millions of foods, making it easy to track what you eat. It also integrates with some fitness-tracking devices.	Research	- Comprehensive food database - Integration with fitness trackers - Barcode scanner - Personalized calories goals - Complete calorie consumption count - Precise division of each meal (Breakfast, Snack1, Lunch, Snack2, Dinner, Snack3) - Graph generation of daily intake of calories and macronutrient and micronutrient composition	- Some foods are not included in the database, eg, particular/unusual foods - It requires manual insertion of the foods - It is not available to the public now (only trials)	- It stores food data into a noSQL database, where the data can be found and be analyzed. - Data from Amazfit devices can be found through the use of APIs.
Boden Food Plate	Meroni et al (2018)[18]	A web-based electronic food diary developed by a collaboration between the University of Sydney and the Boden Institute. This platform allows users to record food and drink items consumed throughout the day on virtual plates in the form of visual depictions.	Research	- An embedded database that contains ∼1200 items with fixed serving sizes - The dietary data entered in the electronic food diary is automatically analyzed, and researchers can export the results - The application generates graphs illustrating the adequacy or inadequacy of the diet for total energy requirements and some important nutrients. The graphs can be accessed by both researchers and users.	- Some foods are not included in the database, eg, particular/unusual foods. - It requires manual insertion of the foods. - It is not available to the public now.	- Data are stored and can be retrieved by collaborating with the development team.
Calorie Counter—Cronometer		This application tracks food intake and provides detailed information on the nutrients in the food eaten. It also allows the individual to set goals and track their progress over time.	Freemium	- Graphical interface - Comprehensive nutrient tracking - Comprehensive food database - Customizable nutrient goals - Barcode scanner - Water tracking	- Complexity - High price range (see Table S3 in the Supporting Information online) - Steep learning curve - Limited social features	- The free version can be used for food tracking only - The professional version allows data sharing; thus, the data can be analyzed for research purposes.
Calorie Counter MyNetDiary	Rodder et al (2018)[19] St-Jules et al (2023)[20]	Calorie Counter MyNetDiary is a popular nutrition and weight loss application that offers a range of features to help users track their food intake and physical activity.	Freemium	- Integration with fitness trackers - Comprehensive food database - Dashboard - Barcode scanner - Personalized nutrient goals	- Paid features - Overwhelming interface - Not suitable for special diets - Inaccurate database	- Food data can be exported in an Excel file, allowing the processing and analysis of data for research purposes

(continued)

Table 1 **Continued**

Application	Reference	Description	Offer	Strengths	Weaknesses	Research applications and data utilization
Eat This Much		This application creates personalized meal plans based on your dietary goals, preferences, and schedule. It also generates a shopping list for the week and allows you to track your food intake.	Freemium	- Personalized meal plans - Variety of meal options - Nutritional analysis - Integration with grocery lists - Community Support	- Limited food options - Premium features - Limited flexibility in meal planning - Complex user interface	- It can be used to track one's diet and gives suggestions. - It does not allow data sharing.
Lifesum	Tosi et al (2021)[21] Tredrea et al (2017)[22]	It is a mobile application that provides users with personalized nutrition and fitness plans to help them achieve their health and wellness goals.	Freemium	- Personalized meal plans - Extensive food database - Integration with fitness trackers - Focus on overall wellness - Interactive and engaging - Strong social component - Barcode scanner	- Paid features - Limited meal-planning options - Inaccurate food database - Limited nutrient tracking	- It can be used as a diet tracking application. - It does not support data sharing.
Lose It!	Farage et al (2021)[23]	This application allows one to set goals and track food intake and exercise. It also provides personalized recommendations based on goals and progress.	Freemium	- Easy to use - Comprehensive food database - Integration with fitness trackers - Barcode scanner - Community support	- Premium features - Limited exercise tracking - Inaccurate food database - Inaccuracy in food tracking - No one-on-one coaching - Limited flexibility in meal planning	- It can be used to track diet. - It allows data sharing in an Excel file.
MyFitnessPal	Tosi et al (2021)[21] Levinson et al (2017)[24]	This is a popular application for tracking food intake and exercise. It has a database of millions of foods, making it easy to track what is eaten. It also integrates with many fitness tracking devices.	Freemium	- Comprehensive food database - Integration with fitness trackers - Barcode scanner - Community support - Personalized calorie goals	- Premium features - Limited exercise tracking - Inaccurate food database - Inaccuracy in food tracking - Ads - Limited flexibility in meal planning	- It can be used for data tracking. - It does not support data sharing.

(continued)

Table 1 **Continued**

Application	Reference	Description	Offer	Strengths	Weaknesses	Research applications and data utilization
Noom	Jacobs et al (2017)[25] Kim et al (2022)[26]	Noom is a weight loss application that uses a psychology-based approach to help users change their behaviors and develop healthier habits. It provides personalized coaching and tracking of food intake, exercise, and weight.	Premium (free trial)	- Personalized coaching - Behavioral psychology approach - Comprehensive food database - Integration with fitness trackers - Community support	- High price range (see Table S3 in the Supporting Information online) - Measurements not in SI units - Inaccuracy in food tracking - Long initial questionnaire - Limited flexibility in meal planning - Limited exercise tracking - Time commitment	- It can be used as a food tracker. - It allows data sharing.
Yazio	Tosi et al (2021)[21] Mistura et al (2021)[27]	It is a popular mobile application that allows users to track their food intake, physical activity, and weight loss progress.	Freemium	- User-friendly interface - Customizable meal plans - Integration with fitness trackers - Comprehensive food database - Motivational features - Barcode scanner - Personalized nutrient goals	- Limited free version - Limited social features - Inaccurate food database	- It can be used as a data tracker. - It does not support data sharing.

All the applications are listed in alphabetical order. For each application, the URL is provided in Table S1 in the Supporting Information online. *Abbreviation*: API, application programming interface.

Table 2 **Examples of digital applications for nutritionists available on the market for diet monitoring and planning**

Application	Reference	Description	Offer	Strengths	Weaknesses
Evolution Nutrition		Evolution Nutrition is a software program that allows nutritionists to create personalized meal plans for their clients and track their food intake. The program also provides access to a database of over 10 000 foods and allows nutritionists to set macronutrient and micronutrient targets for their clients.	No free trial (from 59 USD per month)	- Client tracking - Customization - Client engagement - Integration with other applications - Extensive food database	- Learning curve - Limited support - Cost - Technical issues - Limited reporting
Healthie		Healthie is a software program that allows nutritionists to create personalized meal plans for their clients, track their food intake, and monitor their progress toward their goals. The program also includes telehealth capabilities, allowing nutritionists to conduct virtual consultations with their clients.	Free trial for 14 days	- Client communication - Telehealth features - Client management - Mobile application - Insurance billing	- Learning curve - Limited customization options - Cost - Technical issues - Limited integration
Metadieta	Vozzi et al (2022)[29] Mameli et al (2018)[30] Dinu et al (2019)[31]	Metadieta is a nutrition and diet software designed to help specialists in the creation of specific diets.	No free trial	- Comprehensive database - Meal planning - Integration with wearables - Professional counseling	- Limited language support - Limited mobile application functionality - Cost
MyFitnessPal for Professionals	Tosi et al (2021)[21] Levinson et al (2017)[24]	MyFitnessPal for Professionals is a software program that allows nutritionists to create personalized meal plans for their clients and track their food intake. The program also provides access to a database of over 6 million foods and allows nutritionists to set macronutrient targets for their clients.	No free trial	- Client tracking - Customization - Client engagement - Integration with other applications - Extensive food database	- Learning curve - Limited customization options - Cost - Technical issues - Limited reporting
NutriAdmin	Saenz et al (2021)[32]	NutriAdmin is web-based software that offers features for client management, scheduling, and billing. It also includes tools for creating meal plans and tracking clients' progress, as well as a database of foods and nutrients.	Free trial for 14 days (39–129 USD per month)	- Client tracking - Meal planning - Client engagement: - Invoicing and billing - Appointment scheduling	- Learning curve - Limited support - No mobile application - Technical issues - Limited reporting

(continued)

Table 2 **Continued**

Application	Reference	Description	Offer	Strengths	Weaknesses
Nutrihand (hybrid)	Nording et al (2013)[33] Cole et al (2019)[34] Raatz et al (2015)[35]	Nutrihand is web-based software that offers features for creating meal plans, tracking clients' progress, and generating reports. It also includes tools for analyzing clients' nutrient intake and for offering personalized recommendations.	Free trial for 7 days (9–25 USD per month)	- Comprehensive database - Meal planning - Integration with wearables - Recipe analysis - Grocery list creation - Professional counseling	- Limited automation - Reliance on user input - Lack of customization
Nutritics (hybrid)	Stephenson et al (2020)[36] Mahmood et al (2018)[37] Cassidy et al (2018)[38]	Nutritics is web-based software that offers features for meal planning, recipe creation, and client management. It also includes tools for analyzing clients' nutrient intake and tracking their progress.	No free trial (120 USD per month for one license)	- Comprehensive database - Customizable reports - Recipe analysis - Multi-language support - Integration with wearables	- Learning curve - Limited mobile application - Price
Nutrium		Nutrium is a software program that allows nutritionists to create personalized meal plans for their clients based on their dietary preferences, goals, and health status. The program also allows nutritionists to track their clients' food intake and monitor their progress toward their goals.	Free trial for 14 days	- Personalized meal plans - Nutritional analysis - Database of foods - Client communication - Mobile application	- Learning curve - Limited customization options - Cost - Technical issues
Practice Better		Practice Better is web-based practice management software designed for healthcare practitioners, including nutritionists and dietitians.	30-day free trial (29–129 USD per month)	- Client tracking - Customization - Client engagement - Integration with other applications - Appointment scheduling	- Learning curve - Limited support - Cost - Technical issues - Limited reporting

All the software is listed in alphabetical order. For each software product, the URL is provided in Table S1 in the Supporting Information online.

Table 3 **Examples of digital applications for precision nutrition that include medical data**

Application	Reference	Description	Offer	Strengths	Weaknesses
DNAlife		An application that offers personalized nutrition plans based on the user's DNA and provides insights into potential nutrient deficiencies and health risks.	No free trial	- Customized nutrition and fitness plans based on an individual's DNA - Comprehensive genetic testing that covers various aspects of health and wellness - Professional interpretation of results by a team of registered dietitians and geneticists - Integration with various fitness applications and devices for seamless tracking and monitoring - Availability of a mobile application for easy access to personalized plans and recommendations	- High cost - Limited focus on nutrition and fitness, and less emphasis on other aspects of health such as sleep and stress management - Reliance on genetic testing as the sole basis for personalized recommendations, without considering other factors such as lifestyle and medical history - Need for a DNA sample - Limited availability in some countries or regions
Genopalate	Shabani et al (2021)[39]	A DNA-based nutrition application that provides personalized meal plans based on the user's DNA, health goals, and food preferences.	No free trial (but 30-day money-back guarantee)	- Personalized nutrition recommendations based on genetic analysis - Provides meal plans and recipes tailored to individual genetic profiles - Offers additional analysis of taste preferences and food intolerances - Easy-to-use interface and user-friendly reports	- Doesn't support comprehensive analysis - Expensive - Limited information on genetic markers - Limited customization of meal plans and recipes, beyond genetic profile
Nutrigenomix		An application that offers genetic testing to provide personalized nutrition recommendations based on the user's genetic makeup.	No free trial (but 30-day money-back guarantee)	- Personalized nutrition recommendations based on an individual's genetic profile. - The program provides evidence-based information that is backed by scientific research. - The results are easy to understand and come with practical recommendations that can be implemented into an individual's diet and lifestyle. - The program has been used by healthcare professionals to help patients optimize their nutrition and reduce their risk of chronic diseases.	- Expensive, and not all insurance plans cover the cost of the genetic testing - It does not consider other factors that may influence an individual's nutrition needs - The program does not provide ongoing support or follow-up - The genetic variations covered by the test may not be relevant or applicable to all individuals
Viome		A personalized nutrition application that uses gut microbiome analysis to provide food recommendations.	Free trial for 14 days	- Personalized nutrition recommendations based on the analysis of an individual's gut microbiome - Comprehensive testing to analyze the gut microbiome, including RNA sequencing - Lifestyle recommendations: in addition to nutrition recommendations, Viome also provides lifestyle recommendations, such as stress management and exercise, to improve overall health and wellness.	- Cost - Limited availability - Limited scientific evidence

All the applications are listed in alphabetical order. For each application, the URL is provided in Table S1 in the Supporting Information online.

These applications have several benefits for the researcher, for citizens, and for nutritionists. Indeed, they can provide researchers with a large amount of data that can be used to identify trends and patterns in how individuals respond to different foods and nutrients, by using new technologies such as machine learning. This can allow the development of more effective personalized nutrition plans to improve health outcomes, supported by the possibility of identifying specific genetic, microbiome and other factors related to the individual's nutritional needs.

However, these applications are relatively new, so there is a need for further research to validate their effectiveness. Additionally, concerns about the accuracy and privacy of genetic and microbiome data should be addressed, to ensure the ethical use of these technologies.

ARTIFICIAL INTELLIGENCE AND MACHINE-LEARNING ALGORITHMS ON NUTRITIONAL DATA

Artificial intelligence (AI) models such as machine-learning, statistical, and mathematical models, have been increasingly used in nutritional applications to empower them with weight prediction, diet planning, and food recognition from images. These models use data such as weight, age, sex, and physical activity levels to generate personalized diet plans and predict weight changes over time. The main applications of AI in Digital Nutrition are as follows: weight prediction, personalized diet plans and food recognition.

In weight prediction, these models can analyze historical data on weight, dietary habits, and physical activity levels to forecast weight changes over time. This information can help individuals and healthcare professionals to make informed decisions about weight management, mainly at a personalized level, and identify potential health risks associated with weight changes.

AI models are also used to generate personalized diet plans based on an individual's dietary preferences, nutritional requirements, and health goals. These models use complex algorithms that consider nutritional content, portion sizes, and food combinations to create customized meal plans that meet an individual's specific nutritional needs.

This technology enables users to take pictures of their meals; the foods are then identified to help in completion of a diet diary. These models use advanced computer vision and deep-learning techniques to analyze the images and extract relevant features, such as color, shape, and texture, to identify the food items and estimate their nutritional content.

In Table 4,[4,5,40–51] the most-used of the available models are shown, along with whether these models are in the form of web or mobile applications.

The use of AI models in nutrition empowers individuals and healthcare professionals to make more informed decisions about weight management, dietary habits, and overall health. By leveraging the power of AI, nutritional applications can provide personalized, data-driven solutions to help individuals achieve their health goals and improve their overall well-being.

Potential applications of large language models in digital nutrition

Among the many machine-learning models, a new and fascinating type that has gained popularity in recent years, due to their remarkable capacity to understand and generate human language, are the Large Language Models (LLMs).[52] These models are trained on vast amounts of text data and use complex algorithms to analyze and understand language patterns, which allows them to generate responses to questions or statements, translate languages, summarize text, and perform other language-related tasks.

LLMs are typically built using deep-learning techniques, such as Transformers, and they require a massive amount of computational power and data to train effectively. The latest generation of LLMs, such as GPT-3,[53,54] can understand and generate natural language with remarkable accuracy and fluency, making them powerful tools for a wide range of applications in fields such as education, healthcare, finance, and more. LLMs could have several potential applications in digital nutrition, some of which might include the following: providing personalized nutrition recommendations, answering nutrition-related questions, generating meal plans, providing support for behavior change, and analyzing and interpreting nutrition-related data.

Based on the user's input, LLMs can analyze their dietary habits, preferences, and health goals, and provide customized nutrition recommendations. These ones can be tailored to the user's specific needs, such as weight loss, muscle gain, or managing a particular health condition.

LLMs can be used to answer questions related to nutrition and diet, such as the benefits of certain foods, how to plan a balanced meal, and the impact of various dietary choices on health. This can help users make informed decisions about their diet and improve their overall health and well-being.

LLMs can be used to generate meal plans based on the user's preferences and dietary requirements. This

Table 4 **Models available for weight forecasting (WF), food recognition (FR), and diet planning (DP)**

Model	Reference	Description	WF	FR	DP	Application
Differential Equation (DE) Revisited	Kevin Hall et al (2007)[40]	This model uses a system of differential equations that can be used to predict weight changes over time by using user-specific information, such as age, sex, height, weight, and physical activity level.	×			Weight Loss DE Plotter
Mathematical model	Hall et al (2011)[41]	This model can be based on the adaptive dynamics of body weight regulation and uses optimization algorithms for the generation of personalized diet plans or weight prediction, by using user-specific information, such as age, sex, height, weight, and physical activity level.	×		×	National Institute of Diabetes and Digestive and Kidney Diseases—Body Weight Planner
Rule-based systems	Kovásznai et al (2011)[42]	These types of models, in this regard, use a set of predefined rules to generate meal plans. The rules are typically based on nutritional guidelines and food group recommendations. The system evaluates the user's dietary needs and preferences and applies the rules to generate a diet plan that meets those requirements. The resulting plan may be adjusted based on feedback from the user or additional information provided to the system. Rule-based systems are often used in conjunction with other models and techniques to generate personalized diet plans that meet the user's specific needs and preferences.			×	NutriGuide, Nutritionist Pro, My Plate Plan
Linear programming (LP)	Dooren et al (2018)[43]	Linear programming is a mathematical optimization technique that can be used to generate diet plans that meet specific nutritional requirements, while minimizing cost or other constraints, such as environmental impact. The model considers various factors such as macronutrient and micronutrient content, dietary restrictions, and food preferences.			×	NutriAdmin, Nutrium
Genetic algorithm	Seljak et al (2007)[44]	Genetic algorithms are a type of optimization algorithm inspired by natural selection, and they can optimize diet plans by evolving a population of plans using selection, crossover, and mutation operators. Each plan is evaluated based on user preferences, and the fittest plans generate new plans for the next generation until an optimal solution is reached. This approach generates personalized plans that minimize environmental impact.			×	Nutrigenomix
Forbes model	Babajide et al (2020)[45]	It is a theoretical equation that quantifies the fat-free proportion of a weight change as a function of the initial body fat, which is estimated by subtracting the fat mass from the total weight. It is commonly used for estimating body-fat percentage based on body weight, height, and age.	×			N/A
Linear regression	Babajide et al (2020)[45]	It models the relationship between weight and independent variables using historical data. It can be used to predict future weights by assuming a linear relationship between variables.	×			Lose It!, MyFitnessPal
Seasonal Auto-Regressive Integrated Moving Average with eXogenous factors (SARIMAX)	Abeltino et al (2023)[5]	It is a linear regression model. It is a seasonal equivalent model, like the SARIMA (Seasonal Auto-Regressive Integrated Moving Average) model, but it can also deal with exogenous factors, which are accounted for with an additional term, helping to reduce error values and improve overall model accuracy. This model is usually applied in time-series forecasting.	×			N/A

(continued)

Table 4 **Continued**

Model	Reference	Description	WF	FR	DP	Application
Decision trees	Babajide et al (2020)[45]	Decision trees are a type of machine-learning model that can be used to predict weight by using historical data and features like age, height, and sex. The algorithm uses impurity measures like entropy to recursively partition the data based on the values of the features. The resulting tree can capture nonlinear relationships between the features and weight, and provide insight into feature importance. However, overfitting can be an issue, which can be addressed through techniques such as pruning, regularization, or ensemble methods like random forests.	×	×		Noom
Support vector machine (SVM)	Babajide et al (2020)[45]	SVMs are a machine-learning algorithm that can be used for weight forecasting by finding a hyperplane that separates different weight measurements in a transformed feature space. The algorithm can handle high-dimensional feature spaces and nonlinear relationships, but requires careful hyperparameter tuning. Therefore, SVMs can classify food based on nutrition, cost, and environmental impact.	×	×		N/A
Convolutional Neural Networks (CNNs)	Aizawa et al (2014)[46]	CNNs are a type of neural network that are particularly used in image classification tasks, including food detection. They work by using convolutional layers that can automatically extract relevant features from the input image. These features are then passed through 1 or more fully connected layers to make a prediction about the content of the image.		×		Calorie Mama AI, Foodvisor, Yummy—Instant Food Recognition, LogMeal
Long Short-Term Memory (LSTM)	Abeltino et al (2023)[5]	LSTM is a neural network architecture suited for time series data, like human weight data. It has a memory component that tracks previous inputs to identify long-term trends and patterns. For human weight forecasting, it takes inputs like age, sex, height, and weight history to predict future weight at different time points. The model is trained on historical weight data, validated against new data, and is a powerful tool for forecasting human weight, particularly for complex or multivariate data analysis.	×			N/A
Gated Recurrent Unit (GRU)	Abeltino et al (2022)[4] Abeltino et al (2023)[5]	The GRU is a type of recurrent neural network used for time series forecasting, such as human weight prediction. It overcomes RNN limitations with gating mechanisms for selective information retention. The model takes in historical weight and relevant data as input to predict future weight. It can be trained using optimization techniques to minimize the difference between predicted and actual values. With proper tuning, the GRU model is a powerful tool for accurate human weight forecasting.	×			N/A
Transformer	Abeltino et al (2023)[5]	The Transformer is neural network architecture for natural language processing, adaptable for time series tasks like human weight prediction. It has an encoder and decoder with self-attention and feedforward networks. The input could include historical weight data and other time-varying features. During training, the attention mechanism identifies informative time steps and features for accurate predictions. It can be trained with back-propagation and optimization techniques for improved performance. Properly trained, the Transformer is a powerful tool for predicting human weight trends and providing insights into weight management.	×		×	N/A

(continued)

Table 4 **Continued**

Model	Reference	Description	WF	FR	DP	Application
Natural Language Processing (NLP)	Pan et al (2020)[47]	Natural Language Processing (NLP) is an AI field that focuses on computer–human interaction through language. In generating diet plans, NLP extracts dietary information from unstructured text such as food logs and dietary restrictions. NLP algorithms analyze and understand text, identifying specific foods, nutrients, and dietary patterns, making personalized recommendations for a healthy diet. It generates meal plans by matching dietary needs with a recipe database or pre-defined meal options. This approach is used in ChatBot-based diet coaching services, in which users interact with a virtual assistant via natural language queries to receive personalized nutrition advice and meal plans.			×	Foodvisor
Case-Based Reasoning (CBR)	Marling et al (1996)[48] Noah et al (2004)[49]	CBR is an AI methodology that utilizes past successful cases to generate personalized diet plans. It involves 4 steps: retrieve the most similar cases, reuse the dietary plans from the retrieved cases, adapt the plans to account for individual differences, revise the adapted plans to ensure they meet the user's specific needs, and retain the new plan for future use. CBR provides a personalized approach that considers individual differences and preferences, making it particularly useful in the context of diet planning. By leveraging past successful cases, CBR can generate effective and tailored dietary plans that can help users meet their nutrition goals.			×	MealPrepPro
Pattern Regulator for the Intelligent Selection of Menus (PRISM)	Noah et al (2004)[49] Kovacic et al (1995)[50]	It is an expert system that uses rules to generate menus. It is based on a diverse menu and eating schedule. A typical day's menu looks like this: breakfast, optional snack, lunch, optional snack, supper, optional snack. Each meal on the menu can fit into one of several distinct patterns. To build a menu, PRISM refines patterns gradually, filling generic pattern slots with specific meals.			×	N/A
Teacher-forced REINFORCE algorithm	Lee et al (2021)[51]	It is a neural machine translation and reinforcement learning system for composition compliance with nutrition enhancement in diet generation.			×	N/A

For all the models, the applications in which they are used are reported. In the WF, DP, and FR columns, the symbol "×" is used to indicate the applications associated with that model. The URL for each model is provided in Table S1 in the Supporting Information online. *Abbreviations:* DP, diet planning; FR, food recognition; N/A, not available; WF, weight forecasting.

can be useful for individuals who are looking to follow a specific diet, such as a vegan or ketogenic diet, or for those who are looking to manage a health condition through their diet.

LLMs can be used to provide support and motivation for individuals who are looking to make changes to their diet and lifestyle. This can include reminders to drink water, encouragement to exercise, and tips for managing cravings.

LLMs can also be used to analyze and interpret data related to nutrition, such as food intake, nutrient levels, and health outcomes. This can help nutritionists and physicians to identify patterns and trends in their patients' diets and make more informed decisions about their care.

Therefore, LLMs have the potential to revolutionize our approach to nutrition and diet, helping individuals to make more informed decisions about their health and well-being, and providing valuable insights for healthcare professionals by enabling personalized recommendations, answering questions, generating meal plans, providing support, and analyzing data.

INTEGRATED WEARABLE DEVICES AND FITNESS TRACKERS

Wearable devices are becoming increasingly popular in various areas of daily life due to their ability to collect real-time data on an individual's health and behavior, such as heart rate, activity level, sleep patterns, and more. The ever-increasing interest from tech companies has brought a multitude of such devices to market, including fitness bands that analyze user's sleep patterns; flexible patches that monitor heart rate, hydration levels and temperature; and smartwatches that track physical activity.[55] The data collected with these devices can be used directly by consumers, who can obtain information on their health in real time. Furthermore, they also can be useful in healthcare, as they can have a crucial role in telemedicine by allowing the remote monitoring of patients.[56,57]

Another medical field in which these devices have been used in recent years is that of clinical nutrition. Indeed, using these devices, it is possible to optimize the subject's nutrition by considering information on their meal intake and integrating it into the context of their daily life. This allows doctors to generate specific and more accurate feedback.

Numerous studies, on the other hand, also indicate continuous glucose monitoring sensors as useful tools for digital and personalized nutrition. Indeed, through blood glucose monitoring, machine-learning algorithms have been developed that are able to predict the glycemic response by considering different aspects of the person, including the diet that they follow.[58] In this way, personalized advice can be provided to control blood sugar, which can also be useful in the context of diabetic subjects.[59] Smart watches are particularly helpful for this application. By integrating a multitude of sensors (such as heart rate, sleep trackers, activity trackers, etc) it is possible to obtain a comprehensive picture of the patient's life and an estimate of the subject's basal metabolic rate. Furthermore, being non-invasive, patients wear them frequently, allowing for the continuous acquisition of these data. This potential is of interest to clinicians, who are also able to share this data easily. In particular, the activity trackers on these smartwatches allow doctors to monitor and evaluate any patient improvements or declines through data on activities of daily living.[60] Furthermore, in Valle et al (2017),[61] the authors obtained promising results in the prevention of weight gain among African American breast cancer survivors through daily weighing self-regulation interventions involving the use of smart scales and smart watches.

Watches, fitness bands, and GPS trackers

These types of devices can track the workouts performed by the user, as well as provide information such as steps taken, heart rate, stress level, and more.[62] There exist several popular wearable devices for fitness tracking on the market. Some examples are[63]: Amazfit,[3–5] the Apple Watch,[64,65] Fitbit,[66,67] Garmin,[64,68] the Huawei Watch D,[69,70] Polar,[71,72] and the Samsung Galaxy Watch[73,74]

Amazfit is a popular brand of wearable devices that offers a range of fitness-tracking products: smart watches, smart bands, and earphones. Some of the popular Amazfit products include Amazfit GTR, Amazfit Bip, and Amazfit T-Rex. These devices offer features such as heart-rate monitoring, sleep tracking, GPS tracking, step counting, and activity tracking. The devices also offer smartphone notifications and have long battery life. Among the products present, there is the Amazfit Bip 3 pro model, which has a remarkable battery life (14 days) and is water resistant at up to 5 atmospheres (ATM) pressure. It features over 60 exercise modes (such as running, cycling, swimming, yoga, etc) and allows you to monitor heart rate, oxygen saturation, stress level, and menstrual cycle.

The Apple Watch is a smartwatch developed by Apple Inc. that can be used to track fitness, receive notifications, make calls, send messages, and carry out other functions. It can track a variety of activities, including running, swimming, cycling, and more. It also has a heart-rate monitor and an accompanying application that allows users to track their progress. It runs on the watchOS operating system and is compatible with iPhones. Among the innovations of version 8, there is a sensor that can monitor a woman's menstrual cycle and ovulation. It is also able to detect accidents and immediately send out a call for help.

Fitbit is a company that produces various kinds of fitness-tracking devices, including smartwatches, activity trackers, and smart scales. Fitbit devices can track metrics such as steps taken, calories burned, and heart rate, and sync with the Fitbit application to provide detailed insights into fitness progress. Among the smartwatches, there is the Fitbit Versa 4, which can collect extensive data on fitness. In fact, it allows planning of a subject's daily training, taking into consideration the daily recovery needs, and allows choice between different types of training (+40 types). Fitbit Versa 4 can also connect with Google apps, read emails and/or text messages, and answer calls.

Garmin is a company that produces a range of GPS-enabled devices, including smartwatches, handheld GPS units, and fitness trackers. Garmin devices are designed for athletes and can track metrics such as distance traveled, pace, and elevation gain. In addition, their devices can track a variety of activities, and they can be connected to a smartphone application so the user can track progress, see information about their health, and set goals. The smartwatches also differ according to the type of physical activity performed. In the generic case of athletes who perform various sports, for example, multisport and triathlon watches have been designed that have different functions. Customized multisport profiles can be created, monitoring data for swimming, calculating training status and loading, and monitoring sleep, recovery, and other functions. The Garmin Forerunner® 965 model, which has various features, including suggestions for daily workouts, can provide advanced training metrics and recovery insights.

The Huawei Watch D is currently the first smartwatch to be declared a medical device in Italy. It has a multitude of sensors (accelerometer, gyro sensor, optical heart-rate sensor, ambient light sensor, skin temperature sensor, differential pressure sensor and Hall sensor) and allows measurement of blood pressure and blood oxygen saturation, and electrocardiogram analysis. It is possible to choose from over 60 different types of training. It has a smart voice assistant, allowing the operator to control music playback, set a new alarm, or know the weather forecast.

Polar produces a large variety of fitness-tracking devices that are designed to help athletes and fitness beginners track their progress and improve their performance. There are several kinds of Polar smartwatches (suitable for different training levels and activities), heart-rate sensors, and accessories like wristbands and straps. For example, the class called Pacer Series is suitable for those who want to use GPS and precise heart-rate monitoring, as well as specialized training, sleep, and recovery tools. On the other hand, for people more interested in sports, the Polar Vantage M class is possibly the most suitable choice. The watches feature GPS and a range of features and performance measures befitting an athlete. The company's devices are known for their accuracy and reliability.

The Samsung Galaxy Watch is a smartwatch that is designed to provide a range of features and functions to help users stay connected and track their fitness. The device runs on Samsung's Tizen operating system and is compatible with Android. Some of the key features of the Samsung Galaxy Watch include fitness tracking, sleep tracking, and the ability to make and receive calls and messages. In version 5, the well-being sensors have been improved, and the sleep coaching mode has been enhanced, as has the automatic training monitoring.

In Table 5,[3–5,64–74] the principal devices are listed with description, costs, strengths, and weaknesses.

To summarize, several examples of smartwatches have been described that have generally similar functionalities, such as monitoring of heart rate, sleep, and oxygen saturation. However, while some models are more suitable for use in everyday life because they also allow you to reply to emails and text messages in addition to the functions related to monitoring physical activity (such as Apple Watch), others can be used by professional athletes because they have specific features for different physical workouts (such as the Polar Vantage M).

Other devices: smart scales, smart water bottles, food tracking, chewing devices, and glucose monitors

Some smart devices have been integrated into digital nutritional solutions, such as devices that can track nutrition or help with nutrition management, but they are not as common as fitness-tracking wearables.

Smart scales. Smart scales are a type of bathroom scale that is equipped with technology to track and analyze a person's weight and body composition. In addition to measuring weight, smart scales can also track metrics such as body-fat percentage, muscle mass, etc. Some of them can also provide estimates of daily caloric needs based on body composition and activity level. To do this, most of these devices take advantage of foot-to-foot impedance (FFI) calculation technology to estimate body composition, using a model that includes several parameters (height, weight, and age).[75] These scales typically connect to a smartphone application or a web-based dashboard via Bluetooth® or Wi-Fi, allowing

Table 5 **Some examples of integrable smartwatches, smart bands, and GPS trackers**

Wearable device	Reference	Description	Cost	Strengths	Weaknesses	Medical device certification?	API?
Amazfit (Bip 3 pro)	Bianchetti et al (2022)[3] Abeltino et al (2022)[4] Abeltino et al (2023)[5]	- Display touchscreen - 14 days of autonomy - Compatible devices: smartphone - GPS: yes	∼€70	- Measurement of various parameters, such as blood oxygenation, stress level, sleep stages - Includes over 60 built-in sports modes - Base-range price (see Table S3 in the Supporting Information online)	- There is no possibility of replying to emails, messages, or calls, only to view them	No	Yes
Apple Watch (Series 8)	Serantoni et al (2022)[64] Hernando et al (2018)[65]	- Display touchscreen - GPS: yes - 10 days of autonomy - Water resistance up to 50 meters - Compatible devices: smartphone and all Apple devices	∼€700	- Many functionalities (oxygen sensor, fall detection, accident detection, training application and others) - Water resistant - Minimal design	- High-range price (see Table S3 in the Supporting Information online)	Yes	Yes
Fitbit (VERSA 4)	Haghayegh et al (2019)[66] Lubitz et al (2021)[67]	- Display touchscreen - GPS: yes - >6 days of autonomy - Water resistance - Compatible devices: smartphone	∼€150	- Bright display - Fast-connecting GPS	- Not suitable for professional athletes	No	Yes
Garmin Forerunner® 965	Serantoni et al (2022)[64] Sivaguru Muthusamy et al (2022)[68]	- Display touchscreen - GPS: yes - Bluetooth: yes - 23 days of autonomy in in smartwatch mode - Compatible devices: smartphone	>€600	- Body battery monitoring - Many preloaded applications - Many features	- High-range price (see Table S3 in the Supporting Information online)	No	Yes

(continued)

Table 5 **Continued**

Wearable device	Reference	Description	Cost	Strengths	Weaknesses	Medical device certification?	API?
Huawei Watch D	Jarchi et al (2018)[69] Zhang et al (2022)[70]	- Display touchscreen + side button (HOME button, HEALTH button) - Waterproof - GPS: yes - Bluetooth: yes - NFC: yes - 7 days of battery life - Compatible with IOS and Android	~€400	- Medical device - Wireless charging - Many features	- High-range price (see Table S3 in the Supporting Information online)	Yes	Yes
Polar (Vantage M)	Climstein et al (2020)[71] Ruiz-Malagón et al (2021)[72]	- Display touchscreen - Waterproof - Compatible devices: PC and smartphone - GPS: yes - Bluetooth: yes	>€200	- Long-lasting battery - Training Load Pro and Recovery Pro - Heart rate reading - Analyzes the effort the individual is making - Multisport sports watch	- More suitable for professional athletes	No	Yes
Samsung Galaxy Watch (5)	Saganowski et al (2020)[73] Nissen et al (2022)[74]	- Display touchscreen - Bluetooth: yes - Compatible devices: smartphone	>€200	- Sleep tracker - Fast-charging battery - Water-resistant smartwatch	- Limited battery life - Not compatible with all available fitness trackers	No	Yes

All the wearable devices are listed (along with their description, cost, strengths, and weaknesses) in alphabetical order. For each device, the URL is reported in Table S2 in the Supporting Information online. In Table S4, in the Supporting Information online, the URLs for the APIs of the scales are reported. *Abbreviations*: API, application programming interface.

users to easily access their weight and body-composition data. Therefore, smart scales are easier to use compared with medical impedance meters, because the electrodes can be reused indefinitely, it is not necessary to position the subject in a supine position, and many indications of body composition are provided.[75]

The following are some commercially available examples of smart scales[76]: Eufy Smart Scale C1, Garmin Index S2,[77] OMRON VIVA,[78,79] Withings Body+,[80] Xiaomi Mi Body Composition Scale 2,[3–5,81] and Tanita.[82]

The Eufy Smart Scale C1 can track up to 16 users, who will be identified by weight and body characteristics. Since there is no Wi-Fi connection, it is necessary to use the smartphone application via Bluetooth to synchronize the data. It is possible to connect with other applications such as Apple Health, Google Fit, and Fitbit to obtain a more complete picture of the user. It has small dimensions, and this makes it very practical.

The Garmin Index S2[77] is another smart scale that takes particularly accurate measurements. The parameters it can evaluate are weight, weight trend, body mass index, bone mass, and others. The high-resolution screen allows the user to view weight graphs over time. Scale data is transmitted via Wi-Fi. It can be synchronized with various fitness applications such as Garmin Connect to see all these parameters directly on the smartphone. In this case, it is possible to register for up to 16 users.

The OMRON VIVA[78,79] can carry out a complete measurement of the person's weight by exploiting bioelectrical impedance analysis (BIA) technology. Various parameters such as visceral fat, fat, skeletal muscle, resting metabolism, body mass index, and weight are evaluated, which clarify the heart health of the user. It is possible to connect it with the "OMRON connect" application but it is also compatible with iOS and Android. It is possible to register complete parameters for up to 4 users, and there is also a guest option.

The Withings Body+[80] is another smart scale that features all the essential functions for health and weight tracking. Indeed, it provides information about body composition, such as body fat, muscle mass, and total body water. The installation is quite immediate, and if the user has other Withings devices, all the data coming from the latter is collected with the scale data in a dashboard. It allows the user to see instant weight trends, providing personalized health insights and setting goals. The application also collects data from third-party applications, such as Apple Health and Google Fit, allowing the operator to view stats like activity levels and compare them with changes in weight and body composition. It features a large tempered glass platform that makes balancing easier. It is also possible to carry out the measurement in child mode and in athlete mode: In the latter case, it is necessary to use a more precise algorithm for defining the body parameters.

The Xiaomi Mi Body Composition Scale 2[3–5,81] provides accurate data on an individual's body composition, which can be monitored with the Zepp Life smartphone application. In particular, the chip used to measure fat can measure up to 13 body composition metrics: body weight, body mass index, body-fat percentage, muscle mass, moisture rate, protein rate, visceral fat rating, basal metabolic rate, and others. The design is minimalistic and features a large bright display and a solid non-slip glass platform. The scale allows up to 16 people to maintain profiles with comprehensive statistics, including fat and muscle mass values, body mass index, and an estimate of basal metabolic rate. There is also the possibility of weighing oneself without transmitting the data (so it works without the application).

The Tanita body-fat analyzer is an innovative device designed for estimating body-fat percentages, employing the principles of bioelectrical impedance. It distinguishes itself from other impedance systems that utilize surface electrodes by having individuals stand barefoot on a metal sole-plate incorporating the electrodes. Consequently, the impedance measurements are acquired through the lower limbs and the trunk of the body.

In Table 6,[3–5,77–82] the smart scales are listed with a brief description, cost, and weaknesses and strengths.

Overall, the examples of smart scales presented have multiple functions capable of creating a comprehensive picture of the subject's metabolism. This can be very useful, providing ready information about one's health. However, in some cases the cost is a bit high.

Smart water bottles. Another type of smart device that plays a role in the nutrition field is the smart water bottle. Specifically, these devices are intended to avoid the problem of dehydration, which has several adverse complications, including confusion and hospitalization.[83] They can track the water intake of the user and remind them to drink water throughout the day. Some models can also sync with fitness-tracking applications to provide a more complete picture of the operator's health and wellness.

The following are some commercially available examples: the Aquio IBTB2BB Bottle with Bluetooth Speaker, the HidrateSpark PRO,[83,84] the LARQ Insulated Stainless Steel Water Bottle,[85] and the TYLT Water Bottle and Portable Power Bank.

The Aquio IBTB2BB Bottle with Bluetooth Speaker is a 16-oz insulated bottle that keeps liquids cold for 24 hours and hot for 14 hours. In addition, there is a detachable Bluetooth speaker at the bottom. It can be

Table 6 **Some examples of smart scales**

Wearable device	Reference	Description	Cost	Strengths	Weaknesses	Medical device certification?	API?
Eufy Smart Scale C1		Size: 280 × 280 × 23 mm Max weight: 180 kg Connectivity: Bluetooth	∼€25	- Easy set-up - Base-range price (see Table S3 in the Supporting Information online) - Well-designed application	- Smaller size than other smart scales mentioned	No	No
Garmin Index S2[77]		Size: 320 × 310 × 28 mm Max weight: 180 kg Connectivity: WiFi and Bluetooth	∼€180	- Minimal design with high-resolution display - Syncs with Garmin	- High-range price (see Table S3 in the Supporting Information online)	No	Yes
OMRON VIVA	Perissiou et al (2020)[78] Ciancarelli et al (2022)[79]	Size: 285 × 280 × 28 mm Max weight: 150 kg Connectivity: WiFi and Bluetooth	∼€100	- Monitors various parameters, providing precise measurements - Possibility of connection with different operating systems	- Sync with the application not very fast - Medium-range price (see Table S3 in the Supporting Information online)	Yes	Yes
Withings Body+	Zhuparris et al (2023)[80]	Size: 327 × 327 × 23 mm Max weight: 180 kg Connectivity: WiFi and Bluetooth	∼€100	- Syncs with Bluetooth or Wi-Fi - Large and non-slip platform	- Medium-range price (see Table S3 in the Supporting Information online)	No	Yes
Xiaomi Mi Body Composition Scale 2	Bianchetti et al (2022)[3] Abeltino et al (2022)[4] Abeltino et al (2023)[5] Alidadi et al (2019)[81]	Size: 300 × 300 × 25 mm Max weight: 150 kg Connectivity: Bluetooth	∼€30	- Works with or without applications - Minimal design - Base-range price (see Table S3 in the Supporting Information online)	- No Wi-Fi connection	No	Yes
Tanita	Jebb et al (2000)[82]	Size: 348 × 320 × 57 mm Max weight: 180 kg Connectivity: Bluetooth	∼€500	- More than 11 values - Separate analysis of fat mass, muscle mass, and muscle quality for each body district	- High-range price (see Table S3 in the Supporting Information online)	No	No

All the smart scales are listed along with description, cost, strengths, and weaknesses, in alphabetical order. For each device, the URL is reported on Table S2 in the Supporting Information online. In Table S4 in the Supporting Information online, the URL for the API of the scales are reported. *Abbreviations*: API, application programming interface; Max, Maximum.

very useful, for example, during training. The speaker is water resistant and offers about 6 hours of playback before needing to be recharged. There is also the possibility of connecting it to the smartphone.

The HidrateSpark PRO[83,84] bottle keeps liquids cold for up to 24 hours; however, it cannot do this with hot liquids. The bottom of the bottle lights up to remind the user to drink, and push notifications can be sent to the phone for this same purpose. It can connect via Bluetooth to the HidrateSpark application (available for iOS and Android) and can sync with Apple Watch, Fitbit, and Garmin. It also includes technology that can help the user find the bottle if it gets lost. It is possible to choose different colors, materials, and capacity of the bottle.

The LARQ Insulated Stainless Steel Water Bottle[85] can keep water hot for 14 hours and cold for up to 24 hours. It is the world's first self-cleaning water bottle that features a water purification system. Using PureVis technology, it can eliminate up to 99% of bio-contaminants such as *E. coli*. It is possible to choose the bottle in different capacities (500 ml and 740 ml).

The TYLT Water Bottle and Portable Power Bank is vacuum insulated to keep liquids hot or cold for up to 12 hours. It also includes a detachable charger for smartphones and tablets that provides up to 2 recharges. The bottle comes with a charging cable and is compatible with iPhone 8 and later, and Samsung Galaxy and Note 8 and later.

In Table 7,[83–85] the smart bottles are listed with their cost, strengths, and weaknesses. To sum up, these types of smart bottles can help users maintain a healthy lifestyle, by providing light notifications or, on the connected application, reminding them to drink; in some cases there is also a Bluetooth speaker, encouraging working out. However, the costs of such devices are quite high.

Chewing devices. Another important measure in the field of precision nutrition is masticatory analysis. There are no commercial wearable devices capable of analyzing masticatory performance, but in the literature it is possible to find some that are able to analyze a user's chewing. This analysis includes many aspects of chewing[86]: sounds generated, force exerted, pressure change in the ear canal, and movement of the muscles involved.

The sounds generated are recorded using acoustic sensors and microphones and subsequently analyzed. Information is obtained on when the food is consumed and the consistency of the food; however, the data collected may have noise components due to the surrounding environment.

Table 7 **Smart bottles**

Wearable device	Reference	Cost	Strengths	Weaknesses	Medical device certification?
Aquio IBTB2BB Bottle with Bluetooth speaker		~€110	- Keeps liquid hot for 14 hours and cold for 24 hours - Rechargeable loudspeaker that also has good performance	- Does not remind you to drink - Does not track water intake	No
Hydrate Spark PRO	Borofsky et al (2017)[84] Cohen et al (2022)[83]	>€60	- Lights up to remind you to drink - Keeps liquid cold for 24 hours	- Cannot use with hot liquids	No
LARQ Bottle PureVis™	Jovanov et al (2016)[85]	>€100	- Self-cleaning water bottle - It can eliminate up to 99% of bio-contaminants, such as *E. coli*	- High price range (see Table S3 in the Supporting Information online)	No
TYLT Water Bottle and Portable Power Bank		~50 USD	- The magazine is removable so that the bottle can be washed in the dishwasher - Can charge up to 2 devices	- Not compatible with all mobile phone models	No

Notes: All the bottles are listed (along with cost, strengths, and weaknesses) in alphabetical order. For each device, the URL is reported in Table S2 in the Supporting Information online.

To measure the force exerted, usually, dental implants with strain gauges are used.[87] They alter oral sensation and cannot be used for long-term monitoring; however, it is possible to have direct access to this type of information.

During chewing, the lower jaw moves to open and close the mouth, causing the ear canal to expand as the mandibular condyle slides back and forth, which produces a pressure change in the duct. In this case, the position of the sensor is familiar, as it is like an earpiece, but there is occlusion of hearing.

During mastication, the opening and closing movements of the jaw are performed by the masseter and temporalis muscles (the main muscles of mastication).[88] In this case, surface electromyography (EMG), piezoelectric sensors, and jaw-movement sensors are used. Various body positions are compatible with the measurement, and the jaw is accessed non-invasively; however, false positives may sometimes be recorded that are related to the subject's movements.

Regarding the first category of device, in a recent study[89] the authors presented an acoustic device in the form of wearable earphones capable of detecting vibrations produced during the act of chewing. By developing an algorithm based on spectral analysis, they were able to classify multiple foods based on the sounds recorded using the device. Similarly, Päßler and Fischer[90] developed a device that analyzes sounds using a microphone. However, in their case the goal was to detect the chewing event and calculate the chewing frequency from the sound.

Regarding the devices analyzing chewing force, Hossain et al[86] detected differences in chewing strength while eating foods of different hardness (with carrot as a hard food example, apple as a moderate food example, and banana as a soft food example), using four wearable sensor systems: (i) a pressure sensor able to measure the pressure variations inside the ear linked to the deformation of the ear canal that occurs during chewing, (ii) a flexible curvature sensor mounted on a rod of the glass in degrees to measure the contraction of the temporalis muscle, (iii) a piezoelectric sensor of strain located on the temporalis muscle, and (iv) electromyographic electrodes located on the temporalis muscle.

Their results indicated that wearable sensors have the potential to be used for measuring chewing strength and assessing food hardness. Another example of this kind of device is presented in the article by Riente et al.[91] The authors developed an electromyographic device to create a personalized masticatory profile. In the case study, they identified different chewing patterns between smokers and non-smokers.

For the third category, photoplethysmography (PPG) sensors are very useful.[92,93] PPG may require only a few optoelectronic components, such as a light source that emits light on the tissue of interest and a photodetector capable of capturing small variations in the intensity of this light due to changes in tissue perfusion. PPG is often used non-invasively and operates using electromagnetic radiation at red or near-infrared wavelengths.

Taking advantage of this technology, Papapanagiotou et al[92] developed a device capable of monitoring blood flow in the ear at the site where it is positioned. This device distinguishes the chewing act from any snacks and chewing bouts. In a later study,[93] however, the authors exploited the PPG sensor technology by integrating it with a microphone and an accelerometer. In this way they have created a practical device, positioned on the earlobe, that is capable of identifying food events and which obtains excellent results.

Regarding devices for detecting the movement of the muscles involved in chewing, there are various kinds of sensors, such as: accelerometers for wrist-motion[94] and piezoelectric sensors for jaw motion.[95] Dong et al[94] report on a watch-like device for continuously monitoring the movement of the wrist to automatically detect masticatory events. The device performed well in distinguishing eating from non-eating activities in real-life tests. Fontana et al,[95] on the other hand, describe a new wearable multisensory device capable of monitoring 24 hours of ingestion behavior. Their device includes a jaw movement sensor to monitor chewing, but also other sensors to monitor gestures and body movement.

Among the various options, the most interesting alternatives include the recording of the masticatory activity of muscles such as the temporal or masseter using piezoelectric or electromyographic sensors. Indeed, this decision is the most useful and accurate solution for practical purposes, as the masticatory muscles are easily accessible. The piezoelectric sensor is also known as a vibration sensor, and it produces a corresponding voltage value when subjected to physical stress.[96] In one application, Kalatanrian et al[96] developed a necklace with a piezoelectric sensor positioned at throat level to recognize chewing activity. Also, this system can estimate the quantity of food consumed and can transmit the data to a mobile phone, where the food type can be categorized.

Nevertheless, EMG technology is often used for chewing analysis, and it is considered a gold standard in the study of mastication.[97] Indeed, EMG sensors can detect the electrical activity of the muscles (in this case, it is typically the masseter muscle in chewing analysis), but it is necessary to be careful when placing the electrodes, which can annoy the user as they have a gel to be attached to the skin. Piezoelectric sensors don't have to be attached to the skin, which can be more comfortable for users but does not allow recording of the electrical activity of the muscle in question.

Zhang and Amft[98] report 3D glasses with bilateral EMG electrodes being used to record the activity of the subject's temporal muscles, with the aim of automatic diet monitoring. Feasibility studies were conducted on the use of the device in daily life, and for classification of foods into 3 degrees of hardness in the laboratory, and good performance was reported. There are already some patents that use this technology to record the activity of the masticatory muscles. For example, Adachi and Morikawa[99] have patented a system in which chewing activity is analyzed using EMG, with the aim of determining whether the person is chewing or doing something else, and whether the act is finished or not. In the interface system included in the invention, there are a number of sections, each analyzing an aspect of the masticatory activity: for example, an amplitude calculation section determines the maximum value of the recorded masticatory signal.

Therefore, in the literature, there are several examples of devices capable of analyzing the act of mastication by considering different aspects and using different types of sensors, with the main purpose of identifying the masticatory act and classifying different types of foods automatically. The next step might be to exploit these devices to obtain data from doctors regarding not only the user's masticatory performance but also the composition of the various meals consumed, thus compiling food diaries.

Continuous glucose monitoring. Continuous glucose monitoring (CGM) is a technology used to track a person's glucose levels in real-time. Unlike traditional glucose-monitoring methods, which require finger-prick blood samples, CGM devices use a small sensor that is placed under the skin to measure glucose levels continuously throughout the day. CGM is an essential tool in precision nutrition, as it allows individuals to monitor their glucose levels closely and make informed decisions about their diet and lifestyle. By tracking glucose levels in real-time, CGM devices can help identify trends and patterns in how the body responds to various foods, exercise, and other factors. This information can be used to create personalized nutrition plans that are tailored to an individual's specific needs and preferences, allowing for more precise and effective management of blood sugar levels. In addition to its use in precision nutrition, CGM technology has also revolutionized diabetes management by giving individuals with diabetes greater control over their glucose levels and reducing the need for frequent finger pricks. CGM devices have become increasingly popular in recent years, with many new products and features being developed to further enhance their accuracy and usability.

The devices differ in their level of invasiveness: invasive, minimally invasive, and noninvasive.[100]

Invasive devices are fully implanted sensors (subcutaneous or intravenous) and interfaced with an external wireless communication device. Many of these sensors include a glucose oxidation enzyme. Communication with the device for data transmission can take place in 2 ways: radio frequency or optical signaling. However, sensors using other technologies have been developed in recent decades. Among them, there is microdialysis, in which a dialysis membrane is placed in a tissue through which glucose-free isotonic fluid continuously flows. During its passage, this fluid "collects" the glucose, which is analysed externally with optical or electrochemical techniques. Another technology that has been employed in invasive devices is spectroscopy: indeed, a single-use invasive optical fiber has been designed that can monitor percutaneous glucose through this type of measurement.

Minimally invasive devices have been developed to measure glucose concentrations in blood or interstitial fluid to avoid the continued presence of a foreign object in the body. Therefore, both the sensor and the data transmission device are located outside the body. In these devices, different techniques are used to estimate the glucose concentration. One of these is iontophoresis, which is based on the generation of a small electric current applied through the skin between 2 nearby electrodes. Sonophoresis can also be used: low-frequency ultrasounds increase the permeability of the skin by inducing the contraction and expansion of gas inclusions in the skin layer, which allows for easier collection of the interstitial fluid. These 2 techniques are the most popular, as they do not cause permanent damage to the skin. However, other types of equipment are often used, such as skin blisters, or micropores and microneedles.

To avoid any invasiveness problem, non-invasive sensors have also been developed, which do not penetrate the skin to measure the glucose concentration but exploit other techniques. These include the use of various spectroscopic techniques to analyze body fluids or gases (such as saliva, tears, or breath), optical technologies that transmit near infrared light through the stratum corneum of the skin, and other techniques.

A particularly interesting example found in the literature is the MiniMed device,[101] that can monitor glucose levels continuously. The MiniMed Continuous Glucose Monitoring System (CGMS by MiniMed Inc.) is a sensor in the style of a Holter that includes 4 components: (i) a disposable subcutaneous glucose-sensing device with an external electrical connector, (ii) a pager-sized glucose monitor, (iii) a connecting cable, and (iv) a communication device that enables downloading of the data stored in the monitor to a personal computer. The subcutaneous sensor continuously monitors interstitial glucose levels in the range of 40 mg/dL–400 mg/dL. The glucose sensor signal is acquired every 10 s, with an average of the signals being saved in memory every 5 min. It is the first ambulatory continuous glucose monitoring system with Food and Drug Administration approval.

On the other hand, there are already several examples of devices capable of continuously monitoring glucose levels on the market. Some examples are the Dexcom G6,[102–104] the Eversense,[105–108] the Freestyle Libre,[109–112] and the Medtronic Guardian Connect.[112–115]

The Dexcom G6 is a sensor placed on the user's abdomen or arm that transmits information every 5 minutes to a corresponding application that can be downloaded to a phone, tablet, or smartwatch. This sensor can integrate other diabetes management devices, such as insulin pumps. However, it is necessary to change the sensor every 10 days.

The Eversense[105–108] measures the glucose concentration in the interstitial fluid through a sensor placed on the upper arm. In this case, the sensor is implanted under the skin and can be worn for 90 days before being replaced. This system automatically sends data to the smart device every 5 minutes. It also alerts the person with an alarm if their blood sugar is out of range.

The Freestyle Libre[109–112] sensor is placed on the back of the upper arm and can continuously measure glucose levels in the interstitial fluid. This system is called "flash," because to take a glucose reading it is necessary to place a smartphone application reader on the sensor. The sensor should be reapplied every 14 days. While it has the benefit of being minimally invasive, some users also report skin irritation from applying the sensor.

The Medtronic Guardian Connect[112–115] sensor is worn on the abdomen, arm, or buttock, depending on the age of the user, to measure glucose concentration through the interstitial fluid. It is also able to collect data indicating when levels are low or high. It is also the only CGM that sends alerts up to 60 minutes before a maximum or minimum level so that the user can act in a preventive manner. The disadvantages of this device include its high price, the need to change the sensor every 7 days and the need for calibration.

It is important to note that these devices are primarily used for people with diabetes to monitor their blood glucose levels, and not necessarily for tracking nutrition.

In Table 8,[102–115] these devices are listed with a brief description, their cost, strengths, and weaknesses.

Various types of sensors for continuous glucose monitoring have been presented in this section, with

Table 8 **CGM devices**

Wearable device	Reference	Description	Cost	Strengths	Weaknesses	Medical device certification?	API?
Dexcom G6	Isitt et al (2022)[102] Guillot et al (2020)[103] Roze et al (2020)[104]	- Sensor duration: 10 days - Subcutaneous sensor	~€65 (only sensor)	- Accurate readings every 5 min	- The sensor's duration before requiring replacement is limited compared to other devices	Yes	Yes
Eversense	Garg et al (2022)[105] Jafri et al (2020)[106] Lorenz et al (2018)[107] Deiss et al (2019)[108]	- Sensor duration: 3 months–6 months - Implantable sensor	>€500	- Long life of the sensor - Readings every 5 min	- A doctor's appointment is required to replace the sensor or make other modifications	Yes	No
Freestyle Libre	Blum et al (2018)[109] Bianchi et al (2019)[110] Fokkert et al (2017)[111] Yeoh et al (2022)[112]	- Sensor duration: 14 days - Intracutaneous sensor	~€65 (only sensor)	- Continuous monitoring - No bites on fingers	- Possible irritation of the skin where the sensor is applied	Yes	Yes
Medtronic Guardian Connect	Yeoh et al (2022)[112] Cohen et al (2018)[113] Funtanilla et al (2019)[114] Christiansen et al (2017)[115]	- Sensor duration: 7 days - Intracutaneous sensor	~€80 (only sensor)	- Readings every 5 min	- Need to replace the sensor frequently	Yes	No

All the devices are listed (along with cost, strengths, and weaknesses) in alphabetical order. For each device, the URL is reported on Table S2 in the Supporting Information online. In Table S4 in the Supporting Information online, the URL for the API of the scales are reported. *Abbreviations:* API, application programming interface; CGM, continuous glucose monitoring.

indications of the advantages and disadvantages of each. Most use a minimally invasive sensor that measures blood glucose through interstitial fluids; however, the main disadvantages of these devices are the limited lifetime of the sensors, and that with this type of measurement (of interstitial fluid rather than blood) there are small inaccuracies in the measurement of glucose concentration.

DISCUSSION AND CONCLUSIONS

Digital applications for diet monitoring, diet generation, and precision nutrition are becoming increasingly popular and have the potential to revolutionize our approach to nutrition and health. Digital nutrition applications have transformed the way individuals, nutritionists, and physicians manage their diets. These tools have made it easier for citizens to take control of their diets, for nutritionists to provide better care to their clients, and for physicians to provide more personalized care to their patients. As technology continues to evolve, digital nutrition solutions are likely to become more sophisticated and accurate, enabling individuals, nutritionists, and physicians to achieve better health outcomes.

Diet self-monitoring is a simple yet effective tool for improving health outcomes, particularly in supporting weight management and diabetes management. By increasing awareness of food choices and portions, individuals can make healthier choices and reduce their overall calorie intake, leading to weight loss and improvement in diet quality. Additionally, self-monitoring can help individuals with diabetes better manage their condition and maintain healthy blood sugar levels. Given the promising effects of diet self-monitoring, healthcare professionals should encourage patients to engage in this practice as part of their overall health management plan. In synergy with self-monitoring, there could be several benefits to the digitalization of precision nutrition interventions by professionals, which represents a promising new approach in the field of nutrition. Firstl, digitalization allows for greater scalability of interventions, as digital technologies can reach many people at once. This is particularly important, given the high rates of obesity and other diet-related chronic diseases globally. Second, digital precision nutrition interventions can provide more personalized and accurate recommendations than traditional approaches. By collecting and analyzing large amounts of data on an individual's genetics, diet, and lifestyle, digital interventions can provide tailored recommendations that are more likely to be effective. Third, digital precision nutrition interventions can provide ongoing support and feedback to individuals, which can improve dietary adherence and long-term outcomes. This is particularly important given the challenges of maintaining dietary changes over time.

Despite the potential benefits of digital precision nutrition interventions, there are also several challenges that must be addressed. One challenge relates to the accuracy and validity of the data used to personalize recommendations. While genetic testing and other technologies can provide valuable insights, much remains unknown about the relationship between genetics, diet, and health. Another challenge is the need to ensure that digital precision nutrition interventions are accessible and affordable to all individuals. There is a risk that these interventions could exacerbate existing health disparities, particularly among those who lack access to digital technologies or who cannot afford personalized interventions. Moreover, there is a need for rigorous evaluation of digital precision nutrition interventions to ensure that they are effective and safe. While there is growing evidence to support the use of these interventions, more research is needed to fully understand their potential benefits and risks. Finally, the miniaturization and the integration of wearable devices and the increasing automation of data acquisition is necessary to reduce the time and the effort required of citizens in providing data to the applications. The future of digital precision nutrition interventions is promising, but there are several areas that require further development and exploration. One key area is the integration of AI and machine learning into these interventions. By leveraging AI and machine-learning algorithms, digital precision nutrition interventions can provide even more personalized and accurate recommendations, as well as identify patterns and trends in data that may not be visible to humans. Automatic recognition is moreover necessary for the compilation of food diaries, to reduce citizen burden and augment reporting accuracy. Moreover, the rapid growth of quantum machine learning has the potential to revolutionize machine-learning algorithms, improving digital precision nutrition both in terms of performance and accuracy.[116–118]

Another area of future development is the use of blockchain technology[119] to ensure the security and privacy of individual data in digital precision nutrition interventions. Blockchain can provide a secure and transparent way to store and share data, which is particularly important given the sensitive nature of genetic and health information. Finally, there is a need for greater collaboration between researchers, healthcare providers, and technology companies to develop and implement digital precision nutrition interventions that are evidence-based, safe, and accessible to all individuals.

Despite these conclusions, some limitations of this review are acknowledged. It is mainly based on existing literature and data available from software vendors. The completeness of the data and potential publication bias could influence our overall assessment. Furthermore, the devices mentioned represent only an illustrative subgroup of the devices currently available on the market. This may limit the completeness of the analysis, and it is possible that there are devices as good or even better than the ones considered here. Readers are encouraged to explore the market further to discover the options best suited to their needs.

Supporting Information

The following Supporting Information is available through the online version of this article at the publisher's website.

Section S1 **References for products**

Table S1 **All digital applications for precision nutrition (for citizens, nutritionists, and physicians)**

Table S2 **All devices for precision nutrition (continuous glucose monitoring, water bottles, smart scales, fitness trackers)**

Table S3 **Price range of dig**

Table S4 **All application programming interfaces available for the devices (smart scales, smartbands, and continuous glucose monitoring) described**

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