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From Traditional Medical Patterns to Artificial Intelligence: The Applicability of Digital Biomarkers in Reinventing Personalised Nutrition

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Abstract: The purpose of this study is to assess the association between digital biomarkers on diet compliance and other health-related outcomes in adults willing to change their eating behaviours. This study employed a mixed-method, cross-sectional design with 100 participants over three months. Basic demographic and clinical data were obtained, and self-monitoring was done using digital biomarkers of diet and physical activity. The dietary compliance level was measured pre- and post-intervention using a dietary questionnaire. Quantitative analyses included paired t-tests, correlation, regression, and mediation analyses to assess the impact of digital biomarkers on nutritional and health outcomes. There was a statistically significant improvement in dietary adherence scores post-intervention ($t = 9.61$, $p < 0.001$). A positive relationship was found between digital biomarker use and diet consumption ($r = 0.45$, $p < 0.001$) and weight loss ($r = 0.32$, $p < 0.05$). Regression analysis indicated that baseline dietary adherence and biomarker use were significant predictors of weight loss ($F(1, 22) = 7.92$; $p < 0.001$ and $F(1, 22) = 7.69$; $p < 0.01$), though the model explained only 20% of variance, suggesting other influencing factors. This study identified usefulness, motivation, and responsibility as key themes related to digital biomarker use. Digital biomarkers hold potential for enhancing personalised nutrition interventions and adherence to dietary recommendations. Future research should focus on data privacy, user involvement, and improving AI algorithms for clinical implementation.

Keywords: biomarkers; digital technology; dietary adherence; health; health behaviour.

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1. Introduction

The evolution of nutrition as a cornerstone of health and well-being has deep roots in traditional medical practices, without which modern dietary science could never have started (Swarnakar et al., 2024). Traditional medical systems like those of ancient China focused on integrating food with medicine (Che et al., 2024). This foundation for integrating food and medicine into health maintenance originated from the same grounds (Lang, Barling & Caraher, 2009). For example, the Huang Di Nei Jing, a typical Chinese medical text, published some guidelines for a balanced diet (Chang et al., 2021). It emphasised the role of food in disease prevention rather than treatment. In that way, it would lay down some of the earliest dietary guidelines, as well as highlight the philosophical and practical foundations that nourished the body and mind. Similarly, traditional Chinese dietary therapy grouped foods into categories—such as "hot," "cold," "neutral," and "strengthening" to treat different health needs, which is the earliest form of personalised nutrition (May, 2024). These historical aspects show that even the traditional patterns of medicine continue to influence the science of nutrition (Alt, Al-Ahmad, & Woelber, 2022).

Unlike these conventional theories, contemporary nutrition science has grown with the help of digital biomarkers, which are parameters that are recorded using digital tools that offer real-time information about the internal state of a person (Arya et al., 2023). The emerging technologies, such as machine learning in nutrition, have also improved the assessment and recommendation systems, especially through the food image recognition techniques (Romero-Tapiador et al., 2024). Digital biomarkers can be used to define the needs, goals, and outcomes of individual nutrition and metabolism, physical activity, and other aspects (Lu et al., 2019; Motahari-Nezhad et al., 2022). Recent AI frameworks, such as automated nutrition analysis models, have further refined how eating behaviours are synthesised and interpreted for personalised dietary guidance (Romero-Tapiador et al., 2023). Digital biomarkers are different from conventional ones as they are based on self-reported information or a set of dietary protocols that do not consider individual characteristics and needs (Bodenstein et al., 2023). For instance, smart clothing and handheld applications let one monitor their glucose level, heart rate fluctuations, or gut microbiota, respectively (Romero-Tapiador et al., 2023; Xu et al., 2024). These technologies are a connection between past dietary knowledge and the current issues faced by the body by providing suggestions that are fitting to an individual's life and genetics (Jonvik et al., 2022).

Digital biomarkers are even more advantageous in conjunction with AI as a way to transform personalised nutrition (Arya et al., 2023; Papastratis et al., 2024). Machine learning is highly effective in analysing large data sets from various sources, such as biomarkers, genetic characteristics, and environment, to produce prognostic models and solutions (Ferrario & Gedrich, 2024; Kourou et al., 2021; Theodore Armand et al., 2024). Applications of machine learning algorithms can help find trends in one's health record that may be undetectable to humans to help in early detection and better planning of diet (Shahid & Khattak, 2022). For example, it is possible to have AI platforms determining how the body of a particular person reacts to certain foods and recommend the right diets for a given goal (Sosa-Holwerda et al., 2024). These innovations not only add to the accuracy of the nutritive cooperation but also increase the opportunities to address the population (Barciela et al., 2024). Digital biomarkers bring the approach of personalised nutrition closer to practice, shifting from the idea of one-size-fits-all diets (Ghosh, 2024; Lu et al., 2019; Tsolakidis, Gymnopoulos & Dimitropoulos, 2024).

This research's goal is to understand how traditional medical patterns, digital biomarkers, and artificial intelligence (AI) can be used to reinvent personalised nutrition. Precisely, the following specific research questions have been formulated: In what way can knowledge of traditional nutritional practices be adopted to enhance current approaches to personalised nutrition? What is the best use of bio signatures for the evaluation and enhancement of dietary behaviours? The place and role of AI in the improvement of the use of digitised biomarkers in developing personalised nutritional plans. In this respect, the answers to these questions can help to fill the existing gap between history and technology in nutrition science.

2. Literature Review

The idea of individualised nutrition has a long history that demonstrates the development of people's thinking about the interaction of nutrition and health (Alt, Al-Ahmad & Woelber, 2022). As far back as ancient civilisations, people have been applying the concept of using diets that are suited to the specific requirements of the individual's body (Alt, Al-Ahmad & Woelber, 2022). For instance, Ayurvedic medicine and Traditional Chinese Medicine (TCM) have long incorporated the concept of the humoral theory of constitution and geographical location in designing the diet (Ansari, 2021). Hippocrates and other ancient writers also posited that food is both a remedy and a toxin depending on the constitution of an individual and their conditions (Elendu, 2024). Thus, respect for the fact that each person is unique can be considered the first step in the development of personalised nutrition (Salloum & Tekli, 2021).

The concept of personalised nutrition started gaining popularity in the second half of the 20th century and more so after the Human Genome Project in 2003 (Matusheski et al., 2021). This monumental discovery offered incomparable knowledge regarding human genetics and the effect it has on health and sickness. Nutrigenomics, which involves the relationship between genes and nutrients, emerged as a new paradigm toward nutritional science reorientation from a nutrient-gene non-specific perspective (Kiani et al., 2022). Producers started on how different genetics affect nutrient requirements and sensitivity, thus coming up with diets based on genotypes. This was complemented by the development of new technologies, such as high-throughput sequencing and bioinformatics, that enabled complex studies on gene diet interactions (Vitorino, 2024).

Over the past few years, an increasing number of studies have been devoted to the concept of digi-biomarkers, which are defined as quantitative signs obtained through digital tools that reflect the state of health of a particular person. Digital biomarkers have become invaluable in personalised nutrition that involves tracking of different parameters, including glucose levels, heart rate variability, and physical activity (Kasimovskaya et al., 2024). Compared to conventional dietary assessments that use qualitative data, digital biomarkers provide more accurate quantitative data to support the development of dietary interventions (Romero-Tapiador et al., 2023; Tanweer et al., 2022). Research has shown that those who use the biomarkers in their diet have better dietary compliance and a generally healthier status than those who do not use the biomarkers.

Current studies have shed light on several applications of digital biomarkers in diet management. For example, the use of continuous glucose monitors (CGMs) has been increasingly embraced by people with diabetes and others interested in metabolic health optimisation (Yu et al., 2024). Such devices allow individuals to track real-time changes in blood sugar levels following ingestion of various foods and make better-informed decisions regarding their diets in relation to metabolic responses. The wearable fitness trackers also measure the physical activity level and the sleep pattern. Such data are invaluable for personalised nutrition plans (George, Shahul & George, 2023).

Artificial intelligence plays a very important role in the effectiveness enhancement of digital biomarkers in personalised nutrition (Tsolakidis, Gymnopoulos & Dimitropoulos, 2024). Such an algorithm analyses large amounts of data generated by digital devices, possibly distinguishing between patterns and connections that would be deemed applicable for dietary recommendations (Min, Jiang & Jain, 2019). For example, machine-learning models can predict how an individual would react to certain foods based on the person's unique metabolic profile and lifestyle factors, as well as genetic predisposition (Panagoulas, Sotiropoulos & Tsihrintzis, 2022). This capability creates very customised diet plans that involve, in addition to nutrient content, personal taste preferences and objectives related to health.

In addition, AI-based platforms are increasingly being used for personalised nutrition interventions on a large scale (Tsolakidis, Gymnopoulos & Dimitropoulos, 2024). Such platforms incorporate easy-to-use interfaces to input users' health data and provide individualised dietary advice from evidence-based guidelines. Health professionals can then use AI technology to better

assist patients requiring improved management of chronic conditions or particular health outcomes to be achieved through diet (Coman et al., 2024).

Despite promising developments in personalised nutrition based on digital biomarkers and AI, the challenges encountered call for attention. These include mainly data privacy: as more persons share their health information on digital platforms, thereby gaining into significant ecosystems of data, securing the data becomes of paramount importance (Jin et al., 2019). Public awareness and education are also necessary on both the benefits and constraints of personalised nutrition strategies (Michel & Burbidge, 2019). The more informed the consumers are about their dietary choices, the more likely they are to seek solutions that align with their values and preferences, which only further underlines the need for transparency in developing and implementing personalised nutrition strategies (Gokani, 2024).

Thus, a historical view of personalised nutrition reflects an extended history of appreciating the individualisation of diets in line with traditional medical insights and modern scientific progress (Singar et al., 2024). In addition, with digital biomarkers, monitoring health and making diet decisions is dramatically changed, while AI technologies continue to help at scale (Kyriazakos et al., 2021). Continued development in this field of research necessitates ethical consideration and public understanding to fully leverage the potential of personalised nutrition for better health outcomes in diverse populations. The evolution from traditional medical patterns to the most advanced technology illustrates how the knowledge of nutrition continues to advance toward a future where dietary advice is tailored precisely to individual needs.

3. Methodology

This research aims to explore potential relationships between the use of digital biomarkers and dietary behaviours within the context of personalised nutrition. Given the exploratory nature of this study and resource constraints, mixed-methods, cross-sectional design was employed. This approach enabled the provision of a detailed study on the use of digital biomarkers. The quantitative research mainly focused on the participants who apply digital biomarkers in the management of their diets.

3.1. Participants

A survey was conducted of 100 adults between 18 and 65 years who currently own and use digital health devices such as wearables and mobile health applications for tracking dietary information and managing their health.

3.2. Sample Selection

In this empirical study, the participants were selected from social media, online discussion forums, and community health programs. The inclusion criteria include the participants aged between 18 and 65 years, having owned and used a digital health device for a minimum of 3 months, and the willingness to participate in all phases of the study. Patients with comorbid conditions that are likely to affect dietary intake were also excluded, including those with end-stage renal disease and pregnant or breastfeeding women. Engaging online platforms and community services was intended for the expansion of recruitment and enhanced recruitment and surveillance. These criteria serve to filter participants in a way that would increase the reliability and validity of the collected data because the participants must have prior experience with digital health technologies.

3.3. Sample Size Justification

The sample size of 100 was calculated based on power analysis in order to achieve a power of 0.80 to detect a moderate effect size of 0.5 at the 0.05 level of significance. This calculation was based on earlier research done in personalised nutrition.

3.4. Data Collection

Baseline Survey: Before proceeding with the study, participants were asked to fill in a baseline questionnaire that included questions on their age, gender, income, level of education, dietary habits, goals and objectives, and current use of digital biomarkers.

Digital Biomarker Tracking: The participants wore gadgets to record physical movement, sleep, and diet for three months. Gathered information consisted of steps taken per day, amount of sleep, diet records, and heart rate variability.

Objective Biomarker Assessment: In addition to self-reported data, participants were provided fasting blood samples at baseline and at the end of the three months. These samples were analysed for key metabolic markers, including but not limited to: glucose, HbA1c, lipid panel (total cholesterol, LDL-C, HDL-C, triglycerides), and inflammatory markers (e.g., C-reactive protein).

Dietary Adherence Measurement: The level of dietary compliance in the study participants was assessed before and after the intervention through a dietary questionnaire called the Dietary Adherence Questionnaire (DAQ). This scale measures the compliance to diet in several areas of focus that include consumption of fruits and vegetables, whole grains, and limited processed foods and sugary beverages, and portion control. The DAQ was chosen because it covers overall healthy eating patterns and has been developed in accordance with the existing dietary guidelines (WHO, AHA, etc.). Although there is no published validation of the DAQ in this particular population, the DAQ is derived from the items that are included in other validated dietary assessment tools and was intended to provide a reasonable estimate of dietary compliance for study purposes.

3.5. Data Validation

To minimise underreporting and overreporting biases in dietary intake data, EI: BMR ratios were used to validate self-reported dietary intake.

3.6. Statistical Analysis

To analyse the study data, SPSS was utilised. For demographic data and baseline data, descriptive analysis, such as means, standard deviation, and frequency distribution, was calculated. To compare the dietary adherence scores, which were obtained using a previously validated scale, between the beginning and end of the intervention phase, t-tests for paired data were used. Regression analysis was determined to be the correlation between the levels of digital biomarkers, such as the frequency of logging and feedback, and the nutritional outcomes, such as changes in the adherence scores, weight loss, and metabolic markers. Additionally, mediational analyses tested digital biomarker engagement (e.g., frequency of data logging) as the mediator between baseline characteristics (e.g., motivation) and nutritional outcomes. The level of significance for all the tests was set at 0.055.

4. Results

4.1. Participants' Demographics

As presented in Table 1, the study involved 100 participants who were selected for the study. The subjects were 38% males and 62% females, and the average age of the sample was 41.2 years (SD = 10.5 years). The participants' mean BMI was 27.5 kg/m² (SD = 4.8 kg/m²). About the use of wearable devices, 65% of participants used fitness tracking wearables, and 35% used smartphone applications. The demographic distribution in this study is consistent with other digital health studies conducted in the population. For instance, one of the first issues that can arise when conducting digital health studies is the issue of generalizability of the participants in the study. The data on participant demographic, clinical, and digital biomarker characteristics are provided in Table 1.

Table 1. Descriptive Statistics of Participants in the Empirical Study (N=100)

Variable	Category/Value	N	Mean	SD	Percentage (%)
Age	Years	100	41.2	10.5	
Gender	Male	38			38.0
	Female	62			62.0
Education Level	Less than High School	7			7.0
	High School Graduate	18			18.0
	Some College	22			22.0
	Bachelor's Degree	33			33.0
	Graduate Degree	20			20.0
BMI	kg/m ²	100	27.5	4.8	
Digital Device Used	Wearable Fitness Tracker	65			65.0
	Smartphone App Only	35			35.0
Dietary Habits	Healthy Eating Index (0-100)	100	65.3	12.1	
Physical Activity Level	Minutes of Exercise per Week	100	150.5	60.2	

4.2. Engagement with Digital Biomarkers

To evaluate the level of participants' interaction with the digital biomarkers, the number of times the participants logged the data and the response to the feedback received from the devices were analysed. Based on the information provided in the protocol, it was determined that participants recorded their food intake 4.2 times a week on average (SD = 1.8). They indicated that they checked the feedback that their devices provided 3.5 times per week (SD = 1.2).

4.3. Statistical analysis

4.3.1. Changes in Dietary Adherence

In this study, paired t-tests were used to compare the dietary adherence scores before and after the three months of the intervention period. These results showed that there was a statistically significant improvement in the dietary adherence scores from the baseline (M = 60.0, SD = 10.0) up to follow-up (M = 75.0 SD = 12.0), $t(99) = 8.25$, $p < 0.001$. The Cohen's d for this improvement was 0.65, indicating a medium effect size.

4.3.2. Relationships Between Digital Biomarker Usage and Nutritional Outcomes

Pearson's correlation was used to assess the correlation between the use of digital biomarkers, compliance with diet and weight loss, and the changes in the HbA1c rate. **Table 2** shows that there was a highly significant positive correlation between digital biomarkers' use and dietary adherence score ($r = 0.45$, $p < 0.001$) and a moderate positive correlation with weight loss ($r = 0.32$, $p < 0.05$). It was also found that there was an inverse relationship between the use of digital biomarker and HbA1c change (-0.25 , $p < 0.05$).

Table 2. Bivariate Correlations Among Key Study Variables (Pearson's r)

Variable	Digital Biomarker Usage	Dietary Adherence Score	Weight Loss (kg)	HbA1c Change (%)
Digital Biomarker Usage	1.00	0.45	0.32	-0.25
Dietary Adherence Score	0.45	1.00	0.58	-0.41
Weight Loss (kg)	0.32	0.58	1.00	-0.63
HbA1c Change (%)	-0.25	-0.41	-0.63	1.00

4.3.3. Regression Analysis

Multiple regression analysis was used in the study to analyse the weights and the factors that may have influenced weight loss. This model used digital biomarkers, the baseline dietary adherence score, age, and gender as independent variables. Regarding the Multiple regression analysis, the study revealed that baseline dietary adherence score ($\beta = 0.42$, $p \leq 0.001$) and the usage of digital biomarkers ($\beta = 0.28$, $p \leq 0.01$) significantly predicted weight loss, with $R^2 = 0.35$, $F(4, 95) = 12.5$, $p \leq 0.001$. This indicates that a person's pre-existing intention towards dietary change and use of digital tracking technology for weight loss are two critical factors in determining the effectiveness of the intervention.

4.3.4. Mediation Analysis

To test the hypothesis, mediational analysis was conducted to determine if the engagement with the digital biomarker influenced the relationship between baseline motivation and nutritional outcomes. The results showed that digital biomarkers had a partial mediation role between baseline motivation and weight loss (indirect effect = 0.12, SE = 0.04, 95% CI [0.05, 0.20]). This implies that the higher baseline motivation has a positive correlation with the level of interaction with the digital biomarkers, which subsequently results in increased weight loss by the patient.

4.4. Qualitative Insights from Participant Interviews

Interpretative findings of the qualitative semi-structured interviews included the following themes regarding participant experience of digital biomarkers:

Enhanced Awareness: The participants' awareness about their eating habits and intake was improved through the use of digital biomarkers that enabled real-time tracking. For instance, one of the participants said, "I used to take lots of calories in a day, but I only realised only when I started taking record of everything with the help of the app. It was a real eye-opener".

Motivation and Accountability: Many participants noted that the data provided by digital biomarkers motivated them to make healthier choices. As one participant explained, "Seeing the numbers go up when I exercised or down when I ate well really kept me on track. It made me feel accountable".

Challenges Faced: Among the challenges, technical problems concerning devices, difficulties in processing large amounts of data, and data security concerns were identified. One participant stated, "Sometimes the device did not sync well, and I found it quite annoying". Also, there is so much data out there that it becomes difficult to sort and analyse it.

5. Discussion

The current study aimed to explore the effects of digital biomarkers on personalised nutrition, including demographics, statistics, and experience. The research highlighted a number of factors regarding the opportunities and realities associated with the effective employ of digital health technologies for enhancing a healthier lifestyle. Our previous studies provide significant evidence that lifestyle, gastrointestinal, and metabolic diseases could be implicated as confounding factors for other chronic diseases with increased mortality, such as liver fibrosis, cirrhosis, neuropsychiatric impairments, and cardiovascular diseases (Trifan et al., 2011; Cojocariu et al., 2019; Bălmuş et al., 2020; Chiriac et al., 2021; Singeap et al., 2021).

Despite being widely used, a recent systematic review showed that their definition significantly varies among the studies, indicating a lack of consensus in this emerging field (Alonso et al., 2024). Digital biomarkers are described as physiological and behavioural data obtained and measured by digital devices such as wearable, portable, implantable, or ingestible devices (Di Martino, Delmastro, & Dolciotti, 2023; Motahari-Nezhad et al., 2022; Theodore Armand et al., 2024). These can offer constant real-time data concerning the dynamic health and other related aspects, which are preferable to conventional clinical monitoring (Alonso et al., 2024). Since we

previously observed that one of the most important causes of therapeutic interventions is the discontinuation of treatments (Trifan et al., 2017), the use of digital biomarkers at hand for the patients themselves could significantly improve their adherence to monitoring and follow-ups (Westerman et al., 2018). Recently, a French initiative proposed an innovative platform to identify nutrition-related behaviour. The design exceeded self-recording of nutritional habits, including spatial tracking and smart household appliance use. In clinical practice, we often use digital biomarkers for monitoring the progress of patients who undergo several interventions. For instance, the use of capsule endoscopy was previously documented by our group as uniquely efficient in monitoring the small bowel physiology in patients diagnosed with occult gastrointestinal bleeding and iron-deficiency anemia (Singeap et al., 2011). Despite the concerns determined by capsule retention, the technique remains a beneficial investigation aiding both the physician and the patient. Advanced mathematical algorithms were also previously used by our group in developing an improved diagnosis biomarker for assessing the stage of liver fibrosis in patients with chronic hepatitis C (Poynard et al., 2012).

With regard to our current results, digital biomarkers were employed to support the concept of individualised nutrition, a practice of providing dietary advice that takes into account the participant's peculiarities, requirements, and preferences. Also, nutritional and lifestyle interventions have been confirmed as effective in assisting treatment approaches of gastrointestinal disorders, such as inflammatory bowel disease (Gîlc-Blanariu et al., 2020). The demographic distribution of the participants in this study resembled other digital health studies, which indicated that people from a diverse cross-section of society are using technology for self-health management. The levels of engagement, as depicted by the number of logs recorded and feedback provided, suggest that participants were highly involved in the use of digital biomarkers to support their nutritional behaviours. However, similar to other previous mHealth-based studies like Marcolino et al. (2018), these engagement levels were found to be moderated by factors that include perceived stress and technical challenges (Marcolino et al., 2018). A recent Swiss initiative to understand the applicability of wearable sensors concluded that the compliance of the patients is vital (Daniore et al., 2024).

The increase in the dietary adherence scores after the intervention period was noticeable from this study, meaning that the use of digital biomarkers is useful in promoting positive behavioural changes (Westerman et al., 2018). There was an increased understanding of the awareness and willingness to follow the dietary recommendations, thus suggesting that real-time data and feedback had a positive impact. These findings support the concept of personalised nutrition and reception of advice that are suitable for a particular person (Braconi et al., 2019).

The regression analysis also provides a rationale for considering digital biomarkers as a tool to deliver weight loss results. The fact that both baseline dietary adherence and digital biomarker usage were predictive of weight loss is consistent with the fact that initial levels of adherence are important, as well as ongoing levels of adherence. This shows that digital health technologies can enhance the desired behaviour and help people attain their health objectives (Awad et al., 2021). This could be encouraging, as major silent epidemics generated by metabolic and nutritional disfunctions are currently increasing the risk for chronic diseases and mortality (Sfarti et al., 2010; Chiriac et al., 2021).

One of the important observations resulting from this study is the ability to get more context and, therefore, bring continuous updates to the participant's lifestyle advice. The study provided evidence for using the data obtained from wearable devices and smartphones to identify the time of eating, estimate personal blood glucose levels, and offer proper recommendations regarding diet and physical activity. This concept is in line with precision nutrition, which acknowledges that postprandial glycaemia is as individual as a fingerprint and depends on various factors, which include sleep, physical activity, and food that is consumed (Stutz et al., 2024).

Several limitations should be considered. A cross-sectional design could prevent establishing a correlation between the use of digital biomarkers and changes in dietary patterns or

health status. In this context, further studies aiming at determining causality should focus on longitudinal or experimental designs, such as randomised controlled trials. Secondly, participant selection via social networks and forums could lead to self-selection, contributing to the limited generalisation of the results. Furthermore, the current study is mainly based on participant self-reporting of dietary habits and digital biomarker use, which can be subjected to recall bias and social desirability bias, respectively. Also, the observation period was relatively short, i.e., three months, thus, the long-term efficiency of the intervention could not be determined. Future research should include a 6-12 month follow-up to determine whether the identified digital biomarkers have had a long-term positive effect on diet and health.

Lastly, due to the control group, the correlation between the dietary adherence changes and the use of digital biomarkers or the contribution of confounding variables could be biased. Furthermore, most of the previous studies have been conducted on clinical samples only, hindering the comparison or extrapolation to healthy individuals. Also, previous research does not provide significant observations regarding the efficiency and safety of long-term biomarker-guided supplementation, thus, the effectiveness of such interventions cannot be determined.

Thus, the most common challenges encountered during the current study included the issue of data privacy, technical malfunction of the devices, and information overload. In this context, the participants pointed out the need for advanced interfaces and data protection. Engagement is another key aspect that is still a significant area of interest for future research to unravel the use of motivation to extend its use for longer periods.

To enhance the application of digital biomarkers in personal nutrition, further studies should be conducted in the following directions: development of new algorithms based on more profound methods for the analysis of multilevel data and taking into account the interconnections between the various biomarkers (Mann et al., 2021). In addition, the effects of long-term biomarker-guided interventions should be further tested to assess their effectiveness and safety in a longer period as well as the effect on different population categories (Ferrario & Gedrich, 2024; Reese-Petersen et al., 2024). The issue of the categorisation of supplements also has to be resolved so that clinicians can recommend nutrition interventions in practice with confidence.

This study indicated that the incorporation of AI in biomarker analysis has benefits and risks. Though machine learning tools and biomarkers can help interpret biomarkers and also identify the best supplements that can be prescribed, they are limited by the fact that they require complete training data sets and clinically validated algorithms (Nascimben, 2024). Also, we previously analysed the awareness of medical personnel on the AI-based solutions used in Gastroenterology (Robea et al., 2024) and found that despite some limitations of the current AI-based solutions, most of the participants acknowledged their usefulness in diagnosis and treatment. Thus, this study helps to address some of these issues by offering information about the use of digital biomarkers in a real-world context and exploring the perspectives of a diverse sample of participants. Despite the mentioned limitations, the current study provides evidence that acknowledges the possible application of the digital biomarkers for nutritional interventions and contributes to the formulation of further perspectives. In this way, the effectiveness of these tools is illustrated, and the necessity of using technology in daily practice is shown. Solving the issues concerning privacy and security, motivation, and development of AI algorithms implies further improvement and efficiency of personalised approaches to nutrition in the future.

6. Conclusion

Our results showed that digital biomarkers could improve patient monitoring, enabling personalised nutrition plan development and contributing to lifestyle changes, such as weight loss. The combination of traditional medical interventions with advanced technology, such as AI-assisted digital biomarkers, could provide individualised and up-to-date lifestyle recommendations. While our results suggested a potential association between digital biomarker use and improved dietary adherence, several limitations, such as data privacy, possible self-selection bias, the short period of observation, and the lack of a control group, encourage further rigorous research to confirm these

findings and establish causality. Also, future studies should be directed towards improving the AI-based algorithms, addressing the data privacy issues, and evaluating the long-term effectiveness and safety in the formulation of customised nutritional plans after common clinical practice interventions.

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