Metabolic Phenotype Modelling and Dietary Personalisation: Machine Learning Frameworks for Evidence-Based Nutrition and Lifestyle Intervention Optimisation

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1. Introduction to Personalized Nutrition and Lifestyle Interventions

Introduction

Because of the substantial variation in individual responses to diet and lifestyle interventions, tailoring health recommendations on the basis of individual profiles is becoming increasingly popular. An important asset of personalizing recommendations is the ability to respect how people live, rather than trying to change their behaviors to fit the much more generic approach of one-size-fits-all intervention programs. However, personalizing intervention contents is not trivial, involving a computational challenge to stratify personalized interventions and their dynamical effects across multiple characteristics including diet and lifestyle behaviors, metabolism, context, nodal phenotypes, gene variants, phenotypes, and traits including preferences, health-related quality of life, and potential lifestyle changes. A major aim of personalizing health interventions is to leverage and incorporate personal characteristics, preferences, beliefs, and context to improve individual experiences and adherence, and therefore enhance health outcomes.

Personalized interventions can offer diverging contents based on individual characteristics, being particularly useful to cater for dietary and lifestyle preferences. Contrary to other precision medicine research areas that try to develop standardized solutions, the format of personalizing health interventions using AI/ML methods supports generating results based on specific needs and preferences of individual users. By providing personally useful results, incorporating people's wants, and potential lifestyle changes, personalized interventions can leverage change motivation with a participation effect. A participant-led process in 25 individuals rather than researcher-led categorization of the 824 individuals into 25 groups, with the purpose to enable interpretation by participants rather than to provide interim results to researchers. Qualitative analysis to identify relevant themes in the verbatim transcript data showed that priorities for population communication are on health benefits related to eating more of the healthier group rather than simply reducing consumption of the less healthy group. Improvements in both ease of use and setup time are likely to be needed in order to enhance user engagement, control, and involvement. Ongoing evaluation will capture potential pathways by which the iPelt might be influential.

1.1. Definition and Importance

Personalized nutrition and lifestyle interventions are health recommendation strategies tailored to individuals' personal preferences, circumstances, and life goals, which can be very diverse. Diet variations are associated with different physiological responses to the same foods, highlighting the importance of considering individual differences for better health outcomes. Proper nutrient intake can decrease the incidence of chronic degenerative diseases, and many nutrients act additively, synergistically, or antagonistically upon each other, further underlining the importance of personalizing dietary and lifestyle advice. Social and cultural aspects result in diverse access to and variety of foodstuffs, preparation methods, and food combinations, thereby creating an inseparable bond between food and people, which further supports the development of personalized nutrition. Nevertheless, addressing people's food choices means disentangling habitual diet from biological, psychological, and socio-environmental factors that guide our feeding behaviors. Preferences that drive food consumption are acquired through individual experiences, lifestyles, and cultures. These concepts dictate that dietary and lifestyle interventions will only be effective if the individual's food habits are considered and incorporated with scientific advice.

Discussions on nutritional guidelines and the governmental food supply often chafe against food traditions and changes in individual lifestyles. Decades of accumulated scientific knowledge have been dissipated in public spin-doctoring and the marketing of nutritional products. It is paramount to combine scientific findings with existing food patterns and traditions, as scientific evidence shows that personal and individual choice are major determinants of overall wellness, efficacy of interventions, and adoption of long-lasting changes in behavior: what is the point of a healthy intervention if an individual does not adhere to it and is unable to maintain the changes over time?

1.2. Current Challenges and Limitations

Challenges and limitations. Although additional research is providing in-depth understandings of how personalized recommendations might be optimized, there are still several challenges and limitations concerning the field. In the data science context, the low availability of omics and phenotype data may constrain what can be discovered from machine learning models built on these features. The high complexity of individual profiles and behaviors may lead to relationships that cannot be captured or explained by machine learning, therefore hampering a more personalized exploration of the data. Given the novelty of the field of personalized interventions and health, there may be a lack of infrastructural, financial, or technical resources to conduct the measurement, analysis, and development of tailored interventions. Additionally, there might also be levels of non-adherence and dropout of individuals that could obstruct the reliability and validity of studies, and the interpretation of conclusions to be applied outside of a study setting. Mainstream adoption of personalized nutrition and lifestyle interventions has been limited due to an unmet need for low-cost digital tools, especially video-based tools that facilitate real-time interaction between participants and coaches on assessment and intervention, further leveraging smartphone and wearable capabilities. One issue that has not been addressed consistently in the digital health field is the ethical considerations of obtaining, storing, analyzing, and utilizing physiological, behavioral, and genomic data. This information needs to be accompanied by advanced privacy and consent measures, ensuring the participants are aware of both risks and potential benefits. Addressing these limitations and challenges is an important step in developing more systematic ways of addressing interventions regarding the identification of mechanisms fundamental to health that can be personalized for the unique metabolome of an individual.

2. Role of Machine Learning in Personalized Health Recommendations

Machine learning approaches for optimizing personalized nutrition and lifestyle interventions is a transformational area of research that seeks to develop practical implementation of personalized health recommendations outlined in the previous section. The field is critically dependent on the use of machine learning for deriving personalized interventions, as nutritional needs and lifestyle change processes in chronic illness are governed by complex datasets, the relationships between which can be difficult to disentangle with traditional statistical methods. Moreover, the availability of data on individuals can be directly leveraged by machine learning methods to create models capable of discerning between sick and healthy individuals or identifying other outcomes of interest. The appeal of machine learning approaches in the development of precision health recommendations is also based on an appealing feature of capable machine learning models: their ability to identify patterns in complex, high-dimensional data that include human behavioral variables and their ability to predict future outcomes. This is achieved by machine learning methods learning from data through the process of updating patterns and model weights from information presented in initialized data using loss functions and backpropagation algorithms in supervised or reinforcement learning frameworks.

The iterative process by which machine learning models are trained allows the model to continually refine itself and improve its performance metrics with respect to predicting the initial data. This makes an attractive feature of machine learning models in the context of personalized recommendation systems, especially given the expectation of gradual evolution of an optimized health intervention tailored to an individual's responses over a potentially long process of treatment. It is expected that these iterations over time, learning from increased data, will lead to a more optimized intervention. The field is not without major criticisms, challenges, and potential limitations. Critics have pointed out that machine learning models are heavily dependent on the training data used to create them, and that they can incur bias towards the specific types of individuals used to train them and overfit towards a given dataset.

2.1. Overview of Machine Learning Algorithms

Machine learning underpins the majority of systems aimed at providing health recommendations based on a patient’s individual profile, which can range from dietary patterns and nutritional status to physical activity and fitness. The selection of a machine learning algorithm is crucial and depends on the type of data and the objective of the task. In general, we may broadly distinguish three types of machine learning based on the nature of the data and the results we wish to observe: supervised learning, unsupervised learning, and reinforcement learning.

An ideal solution for providing health recommendations assumes that individual parameters will be taken into account, and the algorithm will be able to provide personalized advice and answers to the user's questions. Even though it may potentially require more resources, such an approach provides the customer with an optimal user experience and significantly increases the probability of achieving the target. In general, predictive models are needed, possibly suggesting whether the lifestyle of the individual should be altered to a healthier pattern. Arising from supervised learning, these computational models predict an output value based on inputs. Decision trees, linear regression algorithms, neural networks, support vector machines, and many others can be used as algorithms for building predictive models. These approaches can assist in personalized nutrition and health applications ranging from basic nutrient requirements to predicting performance outcomes or optimizing best value diets based on validated and reliable dietary assessment tools.

Challenges in this area include that, in some cases, despite a food-specific approach, the machine learning models cannot outperform, or can only partially outperform, the classical statistical techniques. Building an interpretable model is essential in explaining the personalized recommendations made based on the model. A lack of interpretability is seen as one of the reasons that health care is the slowest industry to adopt AI technologies. All these models need to work in real life and potentially need to be scalable. There is a vast literature in personalized dietary and nutrition recommendations using machine learning algorithms, and it is essential to update this literature systematically to provide the latest instructions to companies and academics on the best potential approaches used in different health conditions.

2.2. Data Sources and Feature Selection

Data management in personalized nutrition and lifestyle health recommendation models is fundamental. For this purpose, different approaches and combinations of data modalities have been studied, such as dietary intake, glucose measures, physical activity, genomic composition, metabolic profiling, metabolites of the gut microbiome, physiological measurements, and demographic information. Surveys, especially food frequency questionnaires and 24-hour recalls, as well as combined objective and subjective work through wearable technology and clinical assessments, have also been used to collect data. Close attention needs to be paid to protocols in order to harmonize measures of dietary intake, collections of metabolic profiles, or compounds of the gut microbiome to enhance the data collection experience. Missing data that are the result of lack of adherence to protocols, as well as subject dropouts, can present significant computational challenges in some deep learning algorithms, which can lead to larger proportions of missing data.

Feature selection is a very important strategy in any data modeling problem in order to improve the accuracy of a model and make it more interpretable. Feature selection can help the simplicity and robustness of machine learning models because reducing the feature space and noise and removing irrelevant features usually leads to predicting the target data more effectively and accurately. For personalized nutrition and health recommendations, detection and management of missing data, especially reduced and qualitative bias, are crucial challenges and have important effects on personalized recommendations. Missing or lack of qualitative data will reduce the quality of the input data and result in model preference for recommendation-based solutions that fit best into observed inadequate data rather than valid and true solutions. Moreover, various biases may exist in the datasets, and we also need to analyze the effect of bias on the labeling of samples in the model. Improvement of the robustness and quality of input data can lead to more valid personalized nutrition and lifestyle health recommendations. The amount of data will also impact practicality, speed, accuracy, and acceptability of personalized nutrition and lifestyle health recommendation systems.

3. AI Models for Tailoring Health Recommendations

This systematic review provides an overview of the most common AI methods to optimize personalized nutrition and lifestyle recommendations and highlights existing efforts and opportunities in using turnkey AI to empower both experts and end users with solutions for health and well-being personalization.

To support personalization, the AI field in general and machine learning (ML), in particular, has created prediction models that analyze datasets that can be vast and diverse and then use these analyzed datasets to either compare new data against or to make new predictions based on patterns within the data. For example, predictive modeling is a relevant method to generate dietary options for individuals based on the individual's current time-delimited data and either historical data or large group data.

This predictive modeling outcome can be used to generate recommendations for the individual, hence implementing personalization in the area of AI and health. Further, once these models have been trained by predictive modeling, they can either be implemented by health experts to develop specific recommendations or can be integrated via automated processes into self-management or behavior change platforms, clothing, or other digital or physical tools to ensure the individual personalizes their behavior to support their expected or predicted health improvement. Since they operate on knowledge from the user dataset, including changes over time, the application of these models in dynamic systems provides significant value as health changes occur. Such dynamic adaptability is a clear characteristic of tailored health recommendation models utilizing machine learning and can be implemented in a variety of AI techniques, including rule-based systems, predictive modeling for a statistical outcome, and NLP ratios compared to large populations that automatically personalize depending on a user's input data over time. Key goals of these models are, however, to demonstrate that their personalization can be effective and focus on how the AI integrates human intervention. There is extra research on whether the AI plays an assistive or confined role. Although people respond that they prefer AI to be consultative, confusion persists in training and jokes among scholars about the language that people often use in screening technology that restricts real choices.

3.1. Predictive Modeling for Dietary Recommendations

Optimal nutrition is a multifaceted and extremely complex optimization problem, and traditional mathematical programming techniques are not able to optimally solve it. In an attempt to offer practical solutions, predictive modeling techniques have been applied to optimize personalized nutritional recommendations. Predictive models are trained from historical dietary data and user characteristics to forecast what level of nutrition would be optimal for a given user. Notably, predictive processes are automated, and their final outcomes account for individual and lifestyle user parameters. As a result, they can continually learn and adapt based on user feedback. This perpetual learning scheme is a step forward in process health recommendations, such as diet, which itself is an evolving and adaptive sphere and not a stationary one. Depending on their function, predictive models are commonly divided into regression and classification models. Regression models forecast a user’s nutrient intake, while classification models establish whether a user has a disease or not. More advanced modeling can also be examined, such as causal inferences, which are used to establish the cause-and-effect relationships between different variables. While neither modeling approach is flawless, they do understand different dietary aspects. However, the application of predictive models in dietary recommendations cannot be distilled as merely a quantitative mathematical model. These models rely on quality data fed into them, and the threat of data siloing offers a major challenge in the pursuit of optimized lifestyle modeling. To obtain a robust predictive model, a large quantity of contributing multivariate data is required. Moreover, it must be highly personalized, accurate, and clinically driven. The computational and data input requirements of these predictive models form a large obstacle to their usability. Special care must be taken to ensure the input data to a machine learning algorithm is accurate and individual-specific, or it is likely the recommendation made will be neither accurate nor optimal. Findings on occupational success in generating personalized nutritional recommendations on an individual unit are illustrated.

3.2. Behavioral Intervention Strategies

A complementary approach to using AI models to tailor health recommendations to a participant’s profile is to tailor behavioral intervention strategies to the individual’s predicted behavior. Integrating AI models with these behavioral interventions will enhance the engagement of participants with these interventions, their long-term retention, and ultimately the efficacy of the interventions, such as automating the implementation and adaptation of the intervention strategies according to up-to-date user behavioral profiles provided by the models. Intervention modality preferences and adaptive tailoring have been tested with the example prototype AI system.

Recently, behavioral intervention strategies based on behavioral economics and psychology insights have gained increased attention in computer science and HCI, with the intention to better combat challenging health, environmental, or cybersecurity problems. Some of these possible intervention strategies are based on principles from behavioral economics. Such principles nudge individuals in a desirable direction without restricting their freedom of choice. Goal setting, healthy choice is the default: automatic choice is beneficial for well-being or the environment, while individuals can make another choice deliberately. Prompt for a commitment. Feedback and monitoring are other significant intervention strategies and are important to maintain long-term adherence and behavior change.

Lack of feedback reduces engagement. There is potential in adapting the reinforcement schedule according to the participant profile. AI can also deliver personalized messages to participants. AI could also optimize the mode of message delivery for a participant. It is important for AI to manage the trade-off between respecting such individual variability and achieving effective, scalable AI-driven interventions. Individual variability is one of the challenges faced by the implementation of the intervention strategies.

4. Ethical and Privacy Considerations in Personalized Health Interventions

Privacy and ethical considerations. Personalized health interventions can leverage AI and machine learning to provide users with context-aware health coaching based on their profiles. The use of AI in health technologies raises concerns regarding privacy and data protection, as well as the need to establish mechanisms to ensure transparent data management to foster user trust. It is mandatory to collect and store users' health and other relevant data for the purpose of the intervention. Data collection should have a transparent process, and users must provide informed consent, being aware of the type of data that is collected, what it will be used for, who can access it, and how it will be stored and protected. The data can be personal or sensitive health data, a particular category of data where the consequences of an adverse event can be damaging to individuals, and their management must follow strict protocols. A major concern is related to data ownership, and participants should be made aware of who owns the data and who controls it. Research has demonstrated that data access control and data release control are necessary for trust management in a pervasive healthcare system.

Another important point is about the data analysis algorithms. It has been shown that algorithms for data analysis can introduce bias that is detrimental to preventive and predictive healthcare. If individuals are to receive tailored advice on their lifestyle and health, this should be accompanied by an ethical responsibility to promote health equity. How can harmful bias in decision-support tools be identified and addressed through system certification? Furthermore, essential ethical questions are associated with the accountability and responsibility of the developers of AI systems. The autonomy of decision-making by the developers and the interlinking with socio-technical systems of innovation should be considered. Another potential domain is driven by the responsibility placed on the AI developer or trainer to ensure that the system neither lies nor makes tokenized reasoning. A key driver for fostering trust is transparency, requiring a process of data collection that is as transparent as possible, how data are stored and protected, data analysis, and how the results underpin the presentation of health-related advice given to the individual. It is currently unclear where the boundary is drawn between allowing innovation and safeguarding one's right to privacy. A question is how innovation can best be facilitated, ensuring societal needs and individual rights are balanced. With the increasing digitization of more and more aspects of our lives, this question becomes more critical. While there are clear potential benefits for the prevention agenda—evident in the Personal Health Data use cases identified—a potential danger, of course, is the possibility of data breaches, misuse, harmful confidentiality breaches, and selective use of data by employers, insurance companies, or others. One cannot ignore the risks and dangers, but we should, perhaps, not overemphasize them and at the same time ensure there is a framework that is ethically acceptable, ensuring that one has the necessary privacy elements built in, without stifling the potential solutions that come from the technology that we now have. It is clearly very difficult to find the 'level playing field' here, but with sufficient discussion and moderation, it can be achieved.

5. Future Directions and Emerging Trends

In summary, despite the appearance of multiple practical solutions in personalized nutrition and lifestyle interventions, a number of other approaches and products are expected in the near future. It is believed that advances in technology, particularly artificial intelligence and big data analytics, present an opportunity to address key limitations of personalized health in nutrition. To advance the field, future research should explore the integration of insights from different disciplines, namely nutrition, psychology, and technology. Future personalized approaches in the context of nutrition are expected in the form of the following trends.

1. Real-Time Data and Continuous Monitoring. Future solutions will integrate data from wearables and applications. This data can be used to optimize recommendations and provide updates in real time. For many nutrition AI-based interventions, one significant limitation is the lack of data feedback to guide the adaptive learning process across the

nutritional recommendations that are dynamically updated. To date, few studies have been integrated with wearable body composition technologies to help refine the precision and granularity of the recommendations. A study integrating this technology is underway. There is a global trend toward higher demand for personalized recommendations for managing chronic diseases, so we can expect the application of AI models to personalize nutrition according to disease type.

2. Partnerships Between Technology Suppliers and Healthcare Stakeholders. Many companies are considering or have begun partnering directly with healthcare providers to scale their technologies. They provide the device or solution to the doctors or dietitians to use on their patients. Healthcare providers see this as a direct pipeline to serving customers and feel that they are supported in the use of technology for their clients. Moreover, health monitoring and assessments may be included to give both a mental/emotional and physical comprehensive approach.

3. Scalable Solutions. A basic element of any nutrition AI-based solution should be the ability to turn any solution into a scalable one that can be both B2B and B2C solutions. These solutions will differ between the USA and the EU in terms of the integration of medical and consumer data.

6. Future Direction

The exponential rise in consumers' expectations for a holistic solution to act on their personalized nutrition and lifestyle data forms the backbone of multiple business opportunities for personalized health solutions and beyond. However, personalization in health is an evolving paradigm, and the need for continuous innovative models or algorithmic research to tailor 'one size does not fit all' health solutions will remain. In the years to come, the developed models and/or AI algorithms will need to enhance an individual's emotional engagement and the efficacy of adherence to recommendations. The integration of behaviorally driven design and user experience guidelines from the fields of psychology and consumer insights, and employing principles central to applied gamification, could serve as strong pillars for enhancing emotional intelligence by fostering behavioral and lifestyle changes and adapting to profiles in a positive and motivating way. The growth of personalized health is also expected to leverage artificial intelligence in domains such as problem solving and real-time decision making, automated instrumentation, and process monitoring across the stages of typical food processing workflows. Advancement in the broader field of data analytics is essential for building truly integrated systems capable of effecting health change. Progress in defining and operationalizing responsible and ethical modular frameworks for data governance, user privacy, and deployment of interventions through these potentially trans-sectoral systems is also crucial from the regulatory, industry, and investment standpoints. In summary, such changes should involve vested interest from academia to healthcare systems that will require collaboration on a large scale across multi-sector, disciplined, and stakeholder research perspectives. In designing holistic interventions that leverage personal nutrition opportunities, one can use a combination of behavioral change science, technological innovation, scientific evidence, and user-centric interface design. Collecting truly personalized data is but one smartphone click away! The trend that emphasizes customization is growing and expectations are increasing. A new personalized mindset that aims at achieving custom-fit solutions makes 'personal' the next big opportunity for health-oriented industries. Person-centric online services, especially for health, are expected to grow substantially. Actions will be taken on personalized nutrition recommendations given by the service. Further research to foster the development of state-of-the-art mathematical models, especially for lifestyle management options, will go further to relieve the identified gaps to provide cutting-edge solutions.

7. Conclusion

In this work, we focused on presenting the latest trends and approaches that have been developed for personalizing nutrition and lifestyle interventions. We summarized the available research in the field of machine learning models that can automatically tailor them to an individual's profile and emphasized the necessity for more interdisciplinary collaborations to overcome the challenges. Several case examples were presented to support the importance of using machine learning and artificial intelligence models for tailoring health recommendations and to demonstrate the potential benefits for public health. We presented an approach that consists of dividing the recommendation process into two main stages, namely user profiling and recommendation strategies. We explained how these different stages can be implemented in practice, the challenges that arise from both technical and ethical standpoints, and summarized the precautions and solutions to be taken into account in a hyperconnected world based on data sharing and processing, data privacy, and ethics.

Customized and personalized nutrition interventions, including dietary, lifestyle, and behavioral interventions, have the potential to provide enhanced and positive health outcomes and maximize user engagement by involving users actively in the nutrition-tailored coaching process. Although the development of these approaches carries the promise to revolutionize the way we recommend individualized and personalized nutritional intervention plans, there are many practical and logistical challenges that need to be addressed. Next steps in this area of collaborative research may include the development of data repositories that include detailed information on both participants and healthy and sick people's phenotypic characterization, behavioral data, and molecular information for the joint development of machine learning models. We anticipate that the application of AI will become increasingly complex by considering multiple scales, and it will have a lasting impact on the handling of real-world nutrition and lifestyle interventions. In closing, although challenges remain, we believe that progress in the use of technology in nutrition and lifestyle management is moving forward in a direction that empowers individuals to take ownership of their health and enables professionals to re-engage deeply and with compassion.